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Smart Technology Enabled Residential Building Energy Use and Peak Load Reduction and Their Effects on Occupant Thermal Comfort

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Smart Technology Enabled Residential Building Energy Use and Peak Load Reduction and Their Effects on Occupant Thermal Comfort

by

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Dedication

I dedicate this to my family, who has made me the person I am, and helped me get to where I am today.

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Smart Technology Enabled Residential Building Energy Use and Peak Load Reduction and Their Effects on Occupant Thermal Comfort

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The University of Texas at Austin, 2015

Supervisor: Atila Novoselac

Residential buildings in the United States are responsible for the consumption of 38% of electricity, and for much of the fluctuations in the power demands on the electric grid, particularly in hot climates. Residential buildings are also where occupants spend nearly 69% of their time. As "smart" technologies, including electric grid-connected devices and home energy management systems are increasingly available and installed in buildings, this research focuses on the use of these technologies combined with available energy use data in accomplishing three main objectives. The research aims to: (a) better understand how residential buildings currently use electricity, (b) evaluate the use of these smart technologies and data to reduce buildings' electricity use and their contribution to peak loads, and (c) develop a methodology to assess the impacts of these operational changes on occupant thermal comfort. Specifically this study focuses on two of the most significant electricity consumers in residential buildings: large appliances, including refrigerators, clothes washers, clothes dryers and dishwashers, and heating, ventilation and air conditioning (HVAC) systems.

First, to develop an improved understanding of current electricity use patterns of large appliances and residential HVAC systems, this research analyzes a large set of field-collected data. This dataset includes highly granular electricity consumption information for residential buildings located in a hot and humid climate. The results show that refrigerators have the most reliable and consistent use, while the three user-dependent appliances varied more greatly among houses and by time-of-day. In addition,

the daily use patterns of appliances vary in shape depending on a number of factors, particularly whether or not the occupants work from home, which contrasts with common residential building energy modeling assumptions. For the all-air central HVAC systems studied, the average annual HVAC duty cycle was found to be approximately 20%, and varied significantly depending on the season, time of day, and type of residential building. Duty cycle was also correlated to monthly energy use. This information provides an improvement to previously assumed values in indoor air modeling studies. Overall, the work presented here enhances the knowledge of how the largest consumers of residential buildings, large appliances and HVAC, operate and use energy, and identifies influential factors that affect these use patterns. The methodologies developed can be applied to determine use patterns for other energy consuming devices and types of buildings, to further expand the body of knowledge in this area.

Expanding on this knowledge of current energy use, smart large appliances and residential HVAC systems are investigated for use in reducing peak electric grid loads, and building energy use, respectively. This includes a combination of laboratory testing, field-collected data, and modeling. For appliance peak load reduction, refrigerators are found to have a good demand response potential, in part due to the nearly 100% of residential buildings that have one or more of these appliances, and the predictability of their energy consumption behavior. Dryers provide less consistent energy use across all homes, but have a higher peak power demand during afternoon and evening peak use times. These characteristics also make dryers also a good candidate for demand response. The study of continuous commissioning of HVAC systems using energy data found that both runtime and energy use are increased, and cooling capacity and efficiency are reduced due to the presence of faults or inefficiencies. The correction of these faults have an estimated 1.4% to 5.7% annual impact on a residential building’s electricity use in a cooling-dominated climate such as the one studied. Overall, appliance peak load reduction results are useful for utility companies and policy makers in identifying what smart appliance may provide the most peak energy reduction potential through demand response programs. The results of the HVAC study provides a methodology that can be used with energy use data, to determine if an HVAC system has the characteristics implying an inefficiency may be present, and to quantify the annual savings resulting from its correction.

The final aspect of this research focuses on the development of a tool to enable an assessment the effect of operational changes of a building associated with energy and peak load reduction on occupant comfort. This is accomplished by developing a methodology that uses the response surface methodology (RSM), combined with building performance data as input, and uncertainly analysis. A second-order RSM model constructed using a full-factorial design was generally found to provide strong agreement to in and out-of-sample building simulation data when evaluating the Average Percent of People Dissatisfied (PPD_{avg}). This 5-step methodology was applied to assess occupant thermal comfort in a residential building due to a 1-hour demand response event and a time-of-use pricing rate schedule for a variety of residential building characteristics. This methodology provides a model that can quickly assess, over a continuous range of values for each of the studied design variables, the effect on occupant comfort. This may be useful for building designers and operators who wish to quickly assess the effect of a change in building operations on occupants.

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Chapter 1: Introduction and Motivation

The United States faces significant energy and electric grid challenges. Over the next ten years, U.S. electricity use is predicted to increase approximately 7.5% (US EIA 2013a). The U.S. Energy Information Agency estimates that the peak electricity load in the U.S. will increase approximately 1.5-1.7 times that of the average annual consumption annually (US EIA 2013b). This is particularly pronounced in the hot climates of the U.S. such as Texas, where this peak load in estimated to increase over 10% by 2016, or 2-3% per year, and 16% by 2022 (ERCOT 2013). In addition, since 1982 peak demand growth in the U.S. has exceeded electricity transmission growth by nearly 25% every year (US DOE 2008). Additional concerns include those associated with increased average temperatures across the world due to climate change, predicted to be between 0.3 to 4.8 ºC by 2100 (IPCC 2013). Without significant efforts to mitigate increasing demand and increasing peak load, this threatens the reliable service of electric grids.

Buildings represent an opportunity to address electricity use and peak load demand, as they make up a significant portion of this current energy and electricity use and peak demand. Buildings in the United States consume approximately 74% of total electricity use on an annual basis (US EIA 2013). Residential buildings represent more than half of this building electricity use. Of the residential systems that use energy, 26% on average, is from heating ventilation and air conditioning (HVAC), and 30% is from large appliances, thus these systems make up a significant portion of energy use. On a typical day residential and commercial buildings account for approximately 56% of electricity demand (MW) in the United States. During a peak electricity event, such as those that occur in hot and warm climates in the afternoon in the hottest parts of the summer, building electricity demand represents approximately 76% of total peak load (MW) (ERCOT 2012). Residential buildings account for 51% of this peak, more than twice that of commercial building demand. It is possible to improve the electric grid resilience with: (1) a better understanding of how buildings currently consume electricity, and (2) identification of new opportunities for energy and peak load reduction using buildings.

In recent years an increasing focus has developed in the area of the smart grid to target energy use and peak load reductions. A smart electric grid, includes a virtual network that uses information and digital communication technologies which enable two-way communication between different aspects of the electric grid. This includes, in particular, electricity providers and electricity consumers. Most recently smart grid technology implementations have increased in residential buildings. In 2012 nearly 1/3 of all residential buildings in the United States had smart meters installed; this is projected to increase to over 50% by 2015 (IEE 2012). With the implementation of these meters, utility companies benefit from more easily detection of outages and from reading electricity meters remotely. In addition smart meters collect more granular energy use data for residential properties than previously has been available. Other technologies such as Home Energy Management Systems (HEMS) and home energy meters can also provide more detailed, circuit-level information building energy use monitoring.

In addition to an increasing amount of energy data, the smart grid's communication infrastructure also enables more interaction with building systems and the electric gird. Technologies in residential buildings such as smart appliances, thermostats, and other possible grid connected systems that can communicate and respond remotely to changes and signals from the grid. These technologies can enable demand response and peak load reductions. The adoption of several types of smart thermostats have been implemented the most of the currently available technologies, however other technologies and devices continue to be developed.

Two-way communication via the smart grid, combined with smart technologies, provide an unprecedented amount of information to consumers and utility providers on how and when the energy is consumed by buildings. They also allow control over buildings' main energy-consuming systems that previously has not been possible. The implementation and use of these smart systems is predicted to significantly increase in coming years (Navigant Research 2012). It is thus beneficial to take advantage of the availability of these technologies, and use them to achieve today's and future building energy use goals.

In implementing these changes to buildings to reduce energy use and peak loads, it is also important to ensure that the indoor environment, in particular the occupants of the buildings, are not negatively affected. Buildings are where we spend approximately 90% of our time, approximately 68% of which is in residential buildings (Klepeis et al 2001). Thus it is desired that the changes that are made to a building to achieve the discussed energy goals also continue to provide a comfortable and productive indoor environment for occupants.

This dissertation focuses on residential buildings, and in particular two large energy users in residential buildings, including HVAC systems and large appliances. This is completed through a combination of laboratory and field testing, and modeling. It focuses on:

- assessing the current use patterns of HVAC systems and large appliances;
- .assessing the peak load reduction potential of large appliances, and an improved understanding of the effect that commons problems have on HVAC energy use;

furthermore it quantifies the possible energy savings resulting from earlier detection of a faulty system;

- developing a methodology to evaluate the effects of changes in energy use on occupant comfort.

This dissertation is organized in six chapters, and five appendices. This chapter, Chapter 1, includes motivations for this research and a summary of the research objectives, followed by Chapter 2 which discusses the specific objectives that this research addresses. Chapter 3 provides a summary of the literature review related to the objectives; Chapter 4 discusses the methodologies that were used. A summary of the results and discussion is included in Chapter 5. The final chapter discusses the overarching conclusions of this research and its unique contribution to the literature. Appendices A through E include five full-length journal articles produced by the author as a result of this research

Ultimately, this work provides:

- new knowledge about residential building HVAC systems and large appliances, their potential impact on energy and peak load reduction, and
- a methodology that assesses the affect changes to their performance and use has on occupants.

Chapter 2: Summary of Research Objectives

The overarching goal of this research is to develop methods to reduce residential building electricity use and peak electricity demand through the use of smart, grid-connected technologies and their associated data, and to assess the effect these methods may have on occupant comfort. To achieve this, this research targets two main energy consumers in residential buildings, (a) large appliances, and (b) heating, ventilation and air conditioning (HVAC) systems. Objective (1) aims to define large appliance and HVAC use patterns from larges sets of field-collected residential building data. Objective (2) identifies the opportunity for peak load reduction from smart appliance use and energy use reduction in HVAC systems through continuous commissioning using energy data. Objective (3) aims to develop a methodology to determine the effect these energy use changes may have on occupant comfort. Each of these objectives is discussed in detail in the following sections.

(Objective 1) Determine energy use patterns in residential buildings using large sets of energy use data

As residential building energy use data is increasingly collected and available, it is advantageous to utilize this data to better understand how these buildings are using energy. Two largest types of energy users in residential buildings include HVAC systems, and appliances. This objective focuses on these two main energy users, and includes two investigations related to determining: (a) large appliance energy use patterns, and (b) HVAC systems runtime characteristics. Each investigation is outlined below.

Investigation 1a – Residential Large Appliances Use Patterns

Residential appliances represent approximately 30% of residential electricity use. Much of this use can be attributed to four large appliances found in most homes in the United States, including refrigerators, clothes washers, clothes dryers, and dishwashers. "Smart" appliances connect to the electric grid and can reduce power demand in response to an electric grid signal. To understand the potential for electricity demand response from appliances, this research aims to determine daily use patterns of these large appliances. To date, a very limited number of studies have analyzed home appliance use on a temporal scale, in part due to the difficulty of data collection. The aim is to use a recent, highly-detailed dataset of homes in Austin, TX to understand the current time-of-use patterns of large appliances and the influencing factors on these patterns. This analysis of when appliances use energy aids in improving residential building energy modeling inputs, understanding the effect of the influence of occupants on appliance energy use, and providing information useful for input into quantifying the potential of the use of smart grid-connected appliances to reduce peak energy use.

Investigation 1b - Residential HVAC Operational Characteristics

Heating, ventilation, and air conditioning (HVAC) represents on average 27% of energy use in residential buildings in the United States (RECS 2009). This percentage is larger in hot and humid climates such as Texas. Furthermore, HVAC use has a strong influence on determining the conditions present in the indoor environment, particularly the comfort of occupants. Of homes that utilize HVAC systems in the U.S., 80% of single family homes (53 million housing units), and 60% of multi-family homes (13 million housing units) utilize all-air central systems. Similar to appliances, there is limited information available on HVAC use from field collected data (RECS 2009). The aim is to understand the typical operational characteristics of residential all-air central HVAC systems. In particular, this includes the runtime fraction or duty cycle, and how it varies based on outdoor weather conditions, and the system characteristics. Its relationship to energy use is also studied. Performance of HVAC systems is important to defining the impact of energy and peak load reduction strategies, and on improvements of indoor air quality modeling.

(Objective 2) Investigate use of energy data and technology to reduce building energy use and peak energy loads

The second objective investigates the use of residential building energy data to identify opportunities for energy use and peak load reductions. This objective builds on the insights gained from the energy data on the use characteristics and patterns of HVAC and appliances.. This objective includes two investigations, including, (a) the use of appliance energy data to determine the peak load reduction potential of large "smart" appliances, and (b) the use of energy data to perform continuous commissioning of residential HVAC systems, including the detection of common faults by quantifying changes in the energy use signal.

Investigation 2a - Appliances Peak Load Reduction Potential

Smart appliances that are connected to the electric grid have the potential to provide demand response through turning off or deferring use to non-peak times. The advantage of the use of appliances for demand response, as compared to HVAC, is that the effect on the indoor environment due to changes in the time of use of appliance use is minimal in comparison to changes in HVAC operation. Utilizing, in part, the information developed in *Investigation 1a* on appliance energy use profiles, this research determines the peak load reduction potential of the four studied appliances and the uncertainties associated with this peak load reduction potential. The results of this research can aid in determining which appliances are better suited for demand response purposes.

Investigation 2b – Continuous Commissioning of Residential HVAC Systems Using Energy Data

The under-performance of HVAC systems can cause (1) excess energy use, (2) contribute to higher peak electricity demand, and (3) negatively affect a building's indoor environment. This under-performance has been shown through previous research efforts, to be highly common, particularly in residential buildings, which often do not maintain a regular HVAC service and maintenance schedule. By reducing the occurrence and impact of faults in building's HVAC systems through continuous commissioning, excess energy use can be reduced. Specifically this objective aims to determine, for the most commonly occurring faults, the effect that faults in residential HVAC systems have on the energy signal and HVAC performance. This includes power (kW), runtime (%), energy use (kWh), coefficient of performance (COP) and cooling capacity (kW). Due to the number of different possible faults, two common faults are the focus of this objective. These include condenser air flow reduction and low refrigerant charge. This investigation also quantifies the energy savings associated with the correction of these faults.

(Objective 3) Develop a methodology to assess the effects of energy and peak load reduction efforts on occupant thermal comfort

With changes in building operational strategies such as those outlined in Objective 2, there is a potential that these or other changes may affect the comfort of occupants in the residential buildings. It is important to understand these consequences, to avoid possible negative effects of efforts to conserve energy and improve electric grid reliability. The indoor environment is of particular concern for occupants, who spend

90% of their time indoors. For this Objective, a framework is developed to quantify the effects of energy use changes on thermal comfort of occupants resulting from building operational changes. Using a novel 5-step process, this framework utilizes building energy simulation results generated using a full-factorial design, to build a response surface of occupant comfort. This is simulated using Monte Carlo simulation to determine the degree of discomfort resulting from building operational changes.

Of the many possible energy reduction strategies, changes to use of the building HVAC system arguably has one of the greatest impacts on the indoor environment. Thus assessing the impacts of HVAC operational changes is the focus of use of the methodology developed in this Objective. The developed methodology, however, can be applied to any modeled or field-tested set of scenarios to provide a probabilistic evaluation of the impacts of changes in HVAC, appliance use, or other energy or peak load reduction changes.

Summary of Objectives:

The three objectives covered in this research increase the knowledge of how buildings and building system currently use energy, and how smart technologies can be used to change this energy use to better suit the needs of utility companies and consumers. Both home and residential property owners, as well as utility companies stand to benefit from smart technology enabled methods to reduce energy use and peak loads in buildings. These benefits are in the form of energy and cost savings for home and residential property owners, and increased reliability and grid capacity without significant new infrastructure investment for electric utility and power generation companies. The environment also benefits from reduced carbon and other greenhouse gas emissions from use of less energy and reduced need for inefficient power plants typically used to achieve the peak load demands.

A complete description of the methodology, results, and conclusions specific to each of the Objectives is included in Appendices A to E. Each Appendix includes a journal paper that is published, accepted, submitted, or in preparation for a peer-reviewed journal. These are organized as follows:

Appendix A: "Appliance Daily Energy Use in Residential Buildings: Use profiles and variation in time-of-use". This paper was published in *Energy and Buildings (2014)*.

Appendix B: "Single and Multi-Family Residential HVAC System Operational Characteristics and Use Patterns in a Cooling-Dominated Climate". This paper was published in *Energy and Buildings (2015)*.

Appendix C: "Building Thermal Comfort Evaluations for Mechanically Conditioned Buildings using Response Surfaces in an Uncertainty Analysis Framework". This paper was submitted to *Science and Technology for the Built Environment.*

Appendix D: "Effects of Technology-Enabled Time-of-Use Energy Pricing on Thermal Comfort and Energy Use in Mechanical-Conditioned Residential Buildings in a Cooling Dominated Climate". This paper will be submitted to *Building and Environment*.

Appendix E: "Continuous Commissioning of Residential Central HVAC Systems Using Near-Real Time Energy and Climatic Data". This paper will be submitted to *Energy*.

Chapter 3: Background and Summary of Literature Review

This chapter provides a review of literature related to the topic of research. Each sub-section provides a summary of the literature related to aspects of each Objective. Section 3.1 discusses the organization of the Objectives relative to one-another. Section 3.2 provides a general overview of residential energy use signals, monitoring, and smart grid-connected technologies. Section 3.3 provides a review of previous investigations in residential appliance use patterns and appliance use for energy and peak load reduction. Section 3.4 reviews previous work in residential HVAC operational characteristics, and in the commissioning of residential HVAC systems. Section 3.5 reviews methods of determining the thermal comfort of the indoor environment, and possible effects that energy and peak load reduction can have on thermal comfort. Additional background information and more detailed literature review for each specific research topic is provided in the Appendices.

3.1 Organization of Conducted Research

In residential buildings in the United States, two large users of electricity are the HVA systems) and large appliances. These account for up to 56% and 30%, respectively of total residential use depending on the climate zone (US EIA 2013, RECS 2009), and are the focus of this research. There are four steps that summarize the process of achieving energy and peak load reductions with smart technologies covered in this research, as summarized in Figure 1. Each of these steps relates to one or more Objectives and their respective Investigations.

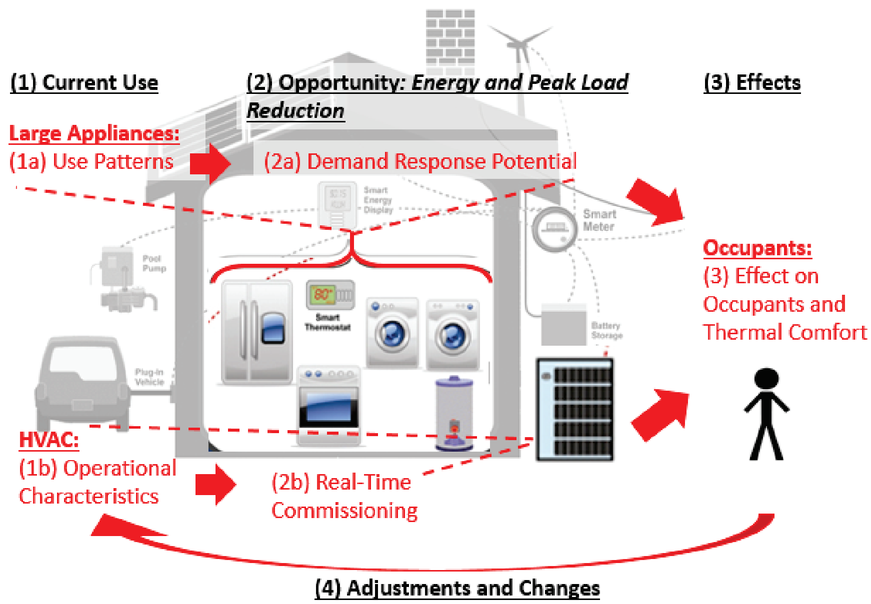


Figure 1: Steps to achieve energy and peak load reduction in residential buildings using smart technologies and their associated data, as they relate to the Dissertation Objectives.

In determining energy use and peak load reductions, it is important to understand first what the current use of these systems are, to provide a baseline for typical use. This includes determining large appliances use patterns (Objective 1a), and residential HVAC operational characteristics (Objective 1b) using energy data. With knowledge of current use, Step 2 is to determine opportunities for energy and peak load reduction, including the demand response potential of large appliances (Objective 2a), and opportunities for continuous commissioning of HVAC (Objective 2b) by characterizing the impact of effects faults and inefficiencies in a HVAC system on energy data and energy use. It is also important to assess the consequences that operational changes will have on the indoor environment, specifically on occupants (Objective 3). Having assessed current use, potential system and operational changes, and the effects of these changes on occupants, as residential buildings and their systems change, the process of additional energy and peak load savings can be achieved and improved by repeating this process.

To date, significant research efforts have been completed to assess reductions in energy use and peak load contributions of buildings. Yet many possible methods remain unexplored, particularly with data related to energy use and grid-connected devices becoming increasingly available.

3.2 Residential Building Energy Use Data and Monitoring

Since energy use data and smart technologies are a central component of this research, it is prudent to provide a brief review of energy monitoring technology and the data they produce.

For residential buildings, the smart grid is implemented in part through the installation of smart meters by utility companies. In 2012, over 1/3 of U.S. residential buildings utilized smart meters; this is projected to increase to over 50% by 2015 (IEE 2012). A smart meter is an electric meter with a one or two-way radio. This radio can communicate energy use data remotely to an electric utility company or in some cases, a residential customer, rather than requiring a manual reading by a utility company employee. A smart meter is a similar size and shape to the long-used analog electricity meter. It meters electricity use at the whole-home level, generally in increments of 15-60 minutes. Non-Intrusive Load Monitoring (NILM) techniques have been developed to disaggregate the whole-home energy use signal by use. Armel et al. (2013), Zoha et al. (2012), Froehlich et al. (2011), and Ehrhardt-Martinez et al. (2010) provide detailed summary of disaggregation techniques developed to-date. However, the lower granularity of current smart meter data presents challenges in disaggregation of the signal, for example separating the HVAC system signal from the whole-home data. Many techniques have been developed to accomplish this disaggregation process, however many also require higher frequency of data collection than smart meters currently provide.

Home energy meters and home energy management systems (HEMS) provide more granular and disaggregated energy use signals on a circuit-by-circuit basis, such as the minute-frequency disaggregated signal shown in Figure 2. This data provides an energy use signal for the whole-home, as well as each individual circuit through the use of “CT” (current transformer) collars which are installed at the breaker panel. This provides a disaggregated energy use signal without the need for disaggregation techniques.

Energy use data includes several different meaningful values that can be studied. For highly granular time interval data, the power (kW) demand of energy-using objects on a residential property is collected over time, where the power at any given data point is the average power collected over the time interval specified. For example, Figure 2 shows a one-minute granularity energy use signal from a home energy monitor of a residential building in Austin TX for one day2. This include the contribution of the indoor supply fan and outdoor compressor and condenser units of the HVAC system. To use this information for achieving peak load reduction, we need both: (1) the power (kW) and (2) the energy use (kWh) of the HVAC and home appliances. Other aspects of the energy use signal that may be studied for HVAC systems include cycle length (min), cycle frequency (hr^{-1}), and runtime fractions/duty cycle (%), where a cycle is a time period between which a system turns ON and OFF.

The energy use data and smart technologies provide the capability for monitoring and control of residential buildings. However, to date, there has been limited published detailed data on how HVACs systems and large appliances use energy. This includes when these systems use energy, and the influence that occupants, systems and environmental parameters may have on their performance and time of use.

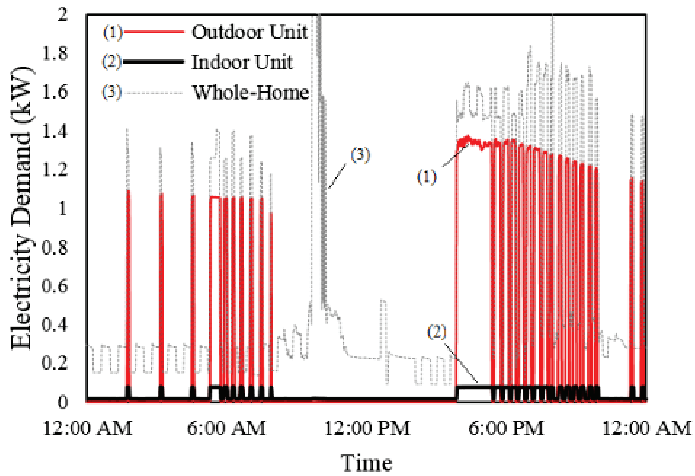


Figure 2: Example of 1-minute whole-home and HVAC indoor and outdoor unit electricity use

3.3 Residential Large Appliances

Approximately 30% of the average U.S. residential building energy use is from household appliances (US EIA 2013a). Common large appliances in residential buildings include refrigerators, clothes washers, clothes dryers, and dishwashers. To accomplish Objective 1a and 2a of understanding current use patterns, and determine their peak load reduction potential, a review of the literature on studies and datasets of information on appliance energy and power demands was conducted. Methodologies used to model energy use trends were also reviewed. Additional background and literature review can also be found in Appendix A.

Appliance Energy Datasets

To determine baseline appliance use, there are several available datasets providing values for annual consumption (kWh) of appliances for a household (US HUD 2009) (US EIA 2009). Figure 3 shows estimated or ranges of average values of the power demand (kW) of large appliances from several sources.3. This figure also includes the penetration factor, or total number of homes utilizing each appliance in residential buildings in the United States (RECS 2009). According to this data, the refrigerator and clothes dryers, on average, use the most total energy (kWh). Clothes dryers utilize the highest power (kW) when in use, followed by dishwashers with drying cycle. Refrigerators have the highest penetration factor and total number installed, followed by washer and dryers, with dishwashers being the least present. Annual energy use information in the available datasets, however, does not provide information to determine when, over the course of each month, day and hour, these appliances are using energy. This is important for comparison with peak electric grid demands to determine peak load reduction potential. For this, more granular energy use information is needed. Furthermore these previous studies do not provide the conditions in which power consumption was measured, nor the characteristics of the appliances measured to determine the reported values of average power consumption. To determine the peak load reduction potential of appliances, additional characteristics of appliance power demands are needed.

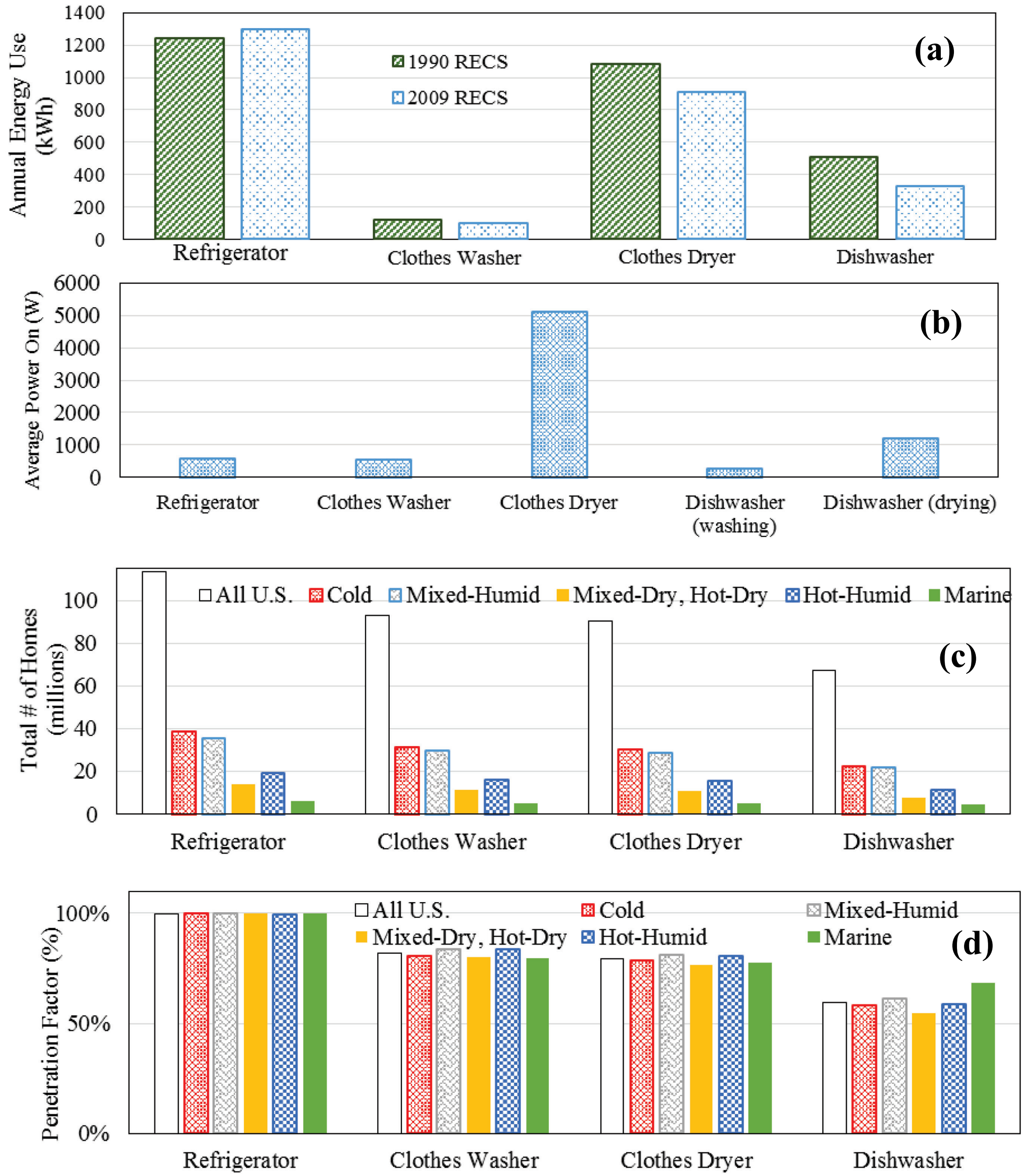


Figure 3: (a) Average annual energy use of large household appliances (RECS 1990, 2009), (b) Average power draw (Watts) when an appliance is ON (EPA 2013) (c) Total number of homes utilizing large household appliances (RECS 2009), and (d) the percentage penetration of large appliances in the United States and by climate zone (RECS 2009).

Appliance Use Patterns

There is limited literature available regarding when, over the course of a day and over the course of a year, the studied appliances are used (Armel et al. 2013), particularly in the United States. The most recent large-scale appliance-specific study to analyze the time of use of appliances in residential buildings was conducted in 1989 (Pratt 1993). This study developed daily profiles for major household appliance use using disaggregated circuit-level data from 288 homes in the Pacific Northwest of the United States (Figure 4). This study also developed variations in appliance energy use by month of the year. Several smaller scale studies have also studied appliance energy use (Hart and de Dear 2004, Parker and Mazzara 1996). These studies, in general found wide variation in the time-of-use over a day, however, the length of study and sample sizes of these studies is limited. The results of Pratt (1993) are used today for building energy modeling of residential buildings, and cost analysis (NREL 2010).

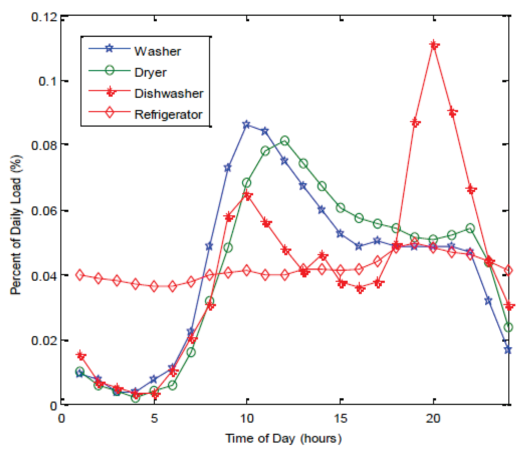


Figure 4: Residential appliance daily energy use patterns derived from 1989 study in Pacific Northwest of U.S. (Pratt 1993)

Appliance use by time of day varies depending on many different possible influences, such as occupant behavior, indoor environmental conditions, age and operational characteristics. Nielsen (1993) attributed 36% of variation in energy consumption of homes to lifestyle and occupant behavior. Of the studied appliances, dishwashers, clothes washers and clothes dryers are more influenced by occupant behavior than refrigerators since they depend solely on the user to determine when to be operated. Arghira et al. (2012), found that the day of the week is correlated with appliance energy use. The Building America Energy Simulation Guidelines for residential buildings in the U.S (2010), based on the findings of Pratt (1993) utilizes a higher energy use for clothes washer and dishwashers on weekends compared to weekdays. It also assumes a higher energy use for dishwashers, clothes washers and clothes dryers in winter months compared to summer months based on the 1989 study.

Environmental conditions, including temperatures, have also been shown to impact the power and energy consumption of appliances, particularly refrigerators (Hart and de Dear 2004). A lower indoor temperature closer to the temperature maintained inside of the refrigerator increases the coefficient of performance (COP) and reduces the power required to operate the refrigerator. The nominal efficiency (nominal COP) of the refrigerator, the amount of opening and closing of the doors that occur, and the amount of food stored, or thermal mass, in the refrigerator/freezer also influence the refrigerator operations. The Building America House Simulation Protocols and B10 Spreadsheet (Hendron and Engebrecht 2010, Wilson et al 2014) utilize different values for energy use of refrigerators by month of the year, with the highest values being in the warm summer months.

Building energy simulation models (BEM) such as EnergyPlus (DOE 2007) uses, for all internal loads occurring during the simulation period: (1)a combination of a normalized daily use profile, (2) an annual energy use value (kWh), and (3) in some cases, a seasonal or weekday/weekend multiplier to model an hourly energy use schedule. The normalized daily use profile provides a value for each hour of a 24-hour period that represents the percent of daily energy use used in that hour. The normalized load profiles are used for all days of the simulation period in energy modeling, meaning the load shape of a particular appliance is the same for all days. These are, in some cases multiplied by a seasonal or weekday/weekend multiplier to adjust the relative energy consumption between the months of the year and days of the week. The same normalized load profile, however, is used, for all days, only the magnitude is changed. When a seasonal multiplier is used for each month, it is multiplied by the normalized daily use to increase or decrease the relative energy consumption for the days of that month. Some month's values are increase while others are decreased. A similar multiplier is used for weekdays and weekends. However, other influences beyond changes in use for weekday, weekends, and month of the year are not taken into account. With newer appliance use data and information about the occupants who use these appliances, there are opportunities to improve upon existing appliance use models, and to determine the impact of additional influencing factors on appliance use.

Appliances and Peak Load Reduction

To determine the peak load reduction large residential appliances can contribute, a review of studies on smart appliances was conducted. Peak load reduction requires that an appliance reduces the power (kW) the appliance consumes by changing the operation of the appliance, or by switching the appliance off such that it is used at a non-peak use time instead. Appliances such as clothes washers, clothes dryers and dishwashers are occupant-controlled. Length of use, use frequency, and energy use depend on occupant needs, occupant-chosen settings, as well as properties of the appliances. For these appliances changing their use to a different non-peak time presents a 100% reduction in use. Refrigerators, however are on at all times and less occupant dependent, and must maintain the required temperature inside of the unit. A smart appliance can communicate with electric grid to respond to pricing or demand response events. Recently manufactured appliances accomplish electricity demand reduction using a delayed start in the case of user-dependent appliances, or by reducing or turning off the heating elements and running for a longer period of time with a lower power demand (Sparn et al 2013). Table 1 shows a summary of several smart technology energy and peak load reduction strategies.

Table 1: Summary of energy and peak load reduction strategies for residential large appliances using smart technology

Residential Smart Device	Energy Savings Settings[1]	Peak Load Reduction[2]
Refrigerator	Disable defrost cycle Increase set point temperature	Increase freezer temperature Delay defrost cycle Disable anti-sweat heater Dim lighting
Clothes Washer	Shorter cycle	Delayed start
Clothes Dryer	Sensor drying, low-heat settings	Delayed start Reduced heat
Dishwasher	Disable heated drying	Delayed start Turn off heated drying

[1]*Energy Star 2014*
[2]*Sparn et al 2013*

However, this study (Sparn et al 2013) was only for appliances in a controlled laboratory environment rather than utilizing data and use patterns from field collected data. Pratt et al (2010) conducted a cost-benefit analysis of the use of smart appliances as spinning reserves in which energy use is curtailed for a period of 10 minutes or less, finding that there significant benefit to the use of smart appliances for this purpose. In this analysis the appliance use patterns from Pratt (1993), along with data from AHAM (AHAM 2009) were used. The conclusions of this study, however, indicate that further work is needed to better quantify the contribution smart appliances at different times of the day.

Summary of Appliance Use Research Needs

In summary, existing information on appliance energy use provides annual consumption information (kWh), and a large scale study was conducted in 1989 to study the time of use of household appliances in the Pacific Northwest region of the U.S. However limited information is available on typical appliance power (kW) demands, and no known additional recent studies have been conducted focusing on the time of use of appliances. These are important for building energy modeling inputs, electric grid load modeling, and estimation of the impact of appliances on peak electricity loads. Additional and more recent information is needed to expand the currently available studies. A recent research work quantified the magnitude of load reduction for several smart appliances; however, this has not been modeled at the community scale or compared to peak electric grid loads. To better estimate the impact of new or retrofitted smart, grid-connected appliances, further study is needed in this area.

3.4 Residential HVAC Systems

Approximately 40% to 56% of the average U.S. household electricity use can be attributed to HVAC system use (US EIA 2013a), with up to 55% of HVAC electricity use being from air conditioning use depending on the climate conditions. To accomplish Objective 1b and 2b, an understanding of available information on HVAC use patterns and influences, and on what effects that faults and inefficiencies have on this use is needed. This section summarizes the literature on studies and datasets of information on HVAC operational characteristics, including the HVAC duty cycle, and influences on HVAC use . Methodologies for fault detection and diagnostics were also reviewed. Appendix B and E also contain additional background and literature review..

HVAC Use Datasets

HVAC use is highly dependent on the climate zone in which a building is located. The RECS (2009) dataset provides annual energy use (kWh) by climate zone (Figure 5a), total number of homes with air conditioning and heating (Figure 5b), and the penetration of heating and air conditioning (Figure 5c) by climate zone. However, this information does not provide information on the power (kW) of a residential HVAC system, nor the amount of time that the HVAC system is ON.

Several small-scale studies have been conducted on residential buildings to determine the operational characteristics of HVAC systems, including the runtime fraction or duty cycle. Previous field studies include the study of 37 homes in North Carolina, 17 homes in Florida, and 17 homes and light commercial buildings in Texas (Norris et al 2009, Ward et al 2005, Stephens et al 2011, Thornburg et al 2004). These previous studies have collected data on the runtime fractions of a small number of homes, and most for a time period of less than a year. Also, there is little knowledge on operational characteristics of multi-family housing HVAC systems.

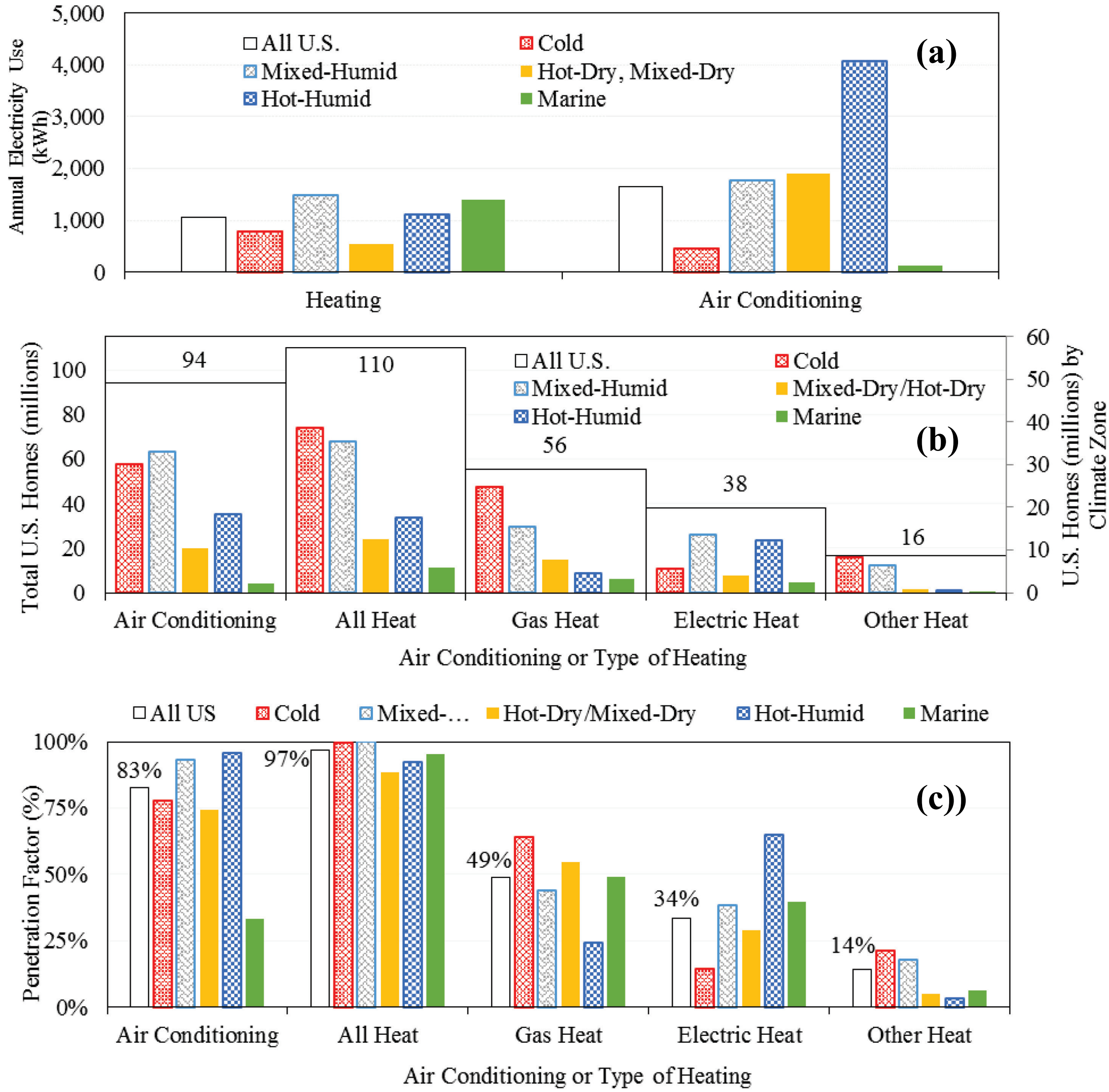


Figure 5: (a) Average annual electricity use (kWh/year) for heating and cooling by climate zone (RECS 2009) (b) Total number of homes utilizing heating and air conditioning in the U.S. (white) and by climate zone (colors), and (c) the percentage penetration of HVAC systems in the United States and by climate zone and type of HVAC system (RECS 2009)

El Orch et al. (2014) discussed the need for additional information to better characterize runtime fractions in residential buildings. Previous studies that have required HVAC runtime fractions for assessment of indoor pollutant level and human exposure, have assumed or estimated these values, or used energy modeling to determine them (Gall et al 2011, Waring et al 2008, Thornburg et al 2011, Klepesis et al 2006, MacIntosh et al 2010). This is particularly important for the hot and humid climate zone which has the greatest percent use of this type of HVAC system in residential buildings.

HVAC Commissioning and Fault Detection

Previous research efforts have explored the possibilities of fault detection and diagnostics for packaged unitary systems, which include split systems for residential buildings, and roof top units (RTUs) for small commercial buildings (Farad and O'Neal 1990, 1991, 1993, Bultman et al 1993, Breuker 1997, Breuker and Braun 1998, Grace et al. 2005, Pak et al 2005, Yang et al 2007a, Yang et al 2007b, Kim et al 2009, Palmiter et al 2011, Yoon et al 2011). Common faults in packaged unitary HVAC systems in the literature include: (a) high or low refrigerant charge, (b) refrigerant line restrictions, (c) presence of non-condensables, (d) airflow restrictions to the evaporator and/or condenser, (e) expansion valve failure, (f) short cycling, and (g) sensor failures. The faults that have the greatest impact on system performance are low refrigerant charge and airflow restrictions to the condenser (SCE 2012a). However, most of the literature has focused on roof top units for light commercial buildings. A summary of literature published through 2012 is discussed in Braun et al. (2012). A limited number have also focused on residential heat pumps and split systems (Kim et al 2009,Yoon 2011, SCE 2012a,b, 2013).

To determine the occurrence of faults, these studies measured a range of variables, including environmental parameters (e.g. indoor and outdoor air temperature, dew point, relative humidity), and HVAC system dependent parameters (e.g. refrigerant flow rate, pressure, and temperature, compressor power, and air flow rate and pressure in various component of air handling unit). These parameters are measured for use in determining HVAC capacity (kW) and efficiency (%), the two variables commonly used to understand an HVAC's energy use in a given set of conditions. To evaluate and compare the impact of different faults in terms of changes to efficiency or capacity, Braun et al (2012) developed a measure called the Fault Impact Ratio (FIR), which is a ratio of changes in equipment efficiency or capacity.

Of the existing research in HVAC fault detection there has been limited focus in residential building systems. Few studies have focused on the use of only energy and smart system data to establish the effects of changes in the level of fault on the HVAC energy signal. This includes how both the power and the runtime are affected. There also is little assessment of the energy savings potential of the earlier identification and correction of an HVAC fault. Additional research in this area is thus needed.

Summary of Research Needs

The existing literature and data discussed in Section 3.4, *Residential HVAC Systems*, provides information to understand the energy and electricity use of residential HVAC systems, segmented by climate region and several other factors. However there is insufficient information about the operational characteristics, specifically the duty cycle (%) of these systems, which is important for indoor environmental modeling and applications. Fault detection of residential HVAC systems to date have mostly focused on commercial system applications, most of which have been conducted in laboratory settings, rather than over longer periods of time over a range of test conditions. Thus conducting additional study on the performance degradation of residential HVAC faults in simulated real-world conditions is needed.

3.5 Occupant Comfort Evaluation and the Effects of Energy and Peak Load Reduction Strategies

In reducing energy consumption and peak energy use in buildings, it is also important to maintain a comfortable and healthy environment (Peeters et al. 2009). However, energy savings measures and acceptable indoor conditions can, in some cases, counteract each another. Thermal comfort, as defined by ASHRAE Standard 55 (2010), is a commonly accepted methodology used to define threshold parameters deemed as comfortable for occupants indoors. Conditions that are considered in defining acceptable thermal comfort of building occupants in mechanically conditioned buildings include (1) environmental factors such as: dry-bulb air temperature (ºC), mean radiant temperature (ºC), air speed (m/s), and relative humidity (%); and (2) personal factors consisting of: metabolic rate (met), and clothing insulation (clo) (ISO 2005; ASHRAE 2010). Mathematical models developed by Fanger (Fanger 1967; Fanger 1970; Fanger 1972) provide the basis for the most widely accepted international thermal comfort standards for mechanically conditioned buildings, including ASHRAE Standard 55 (ASHRAE 2010), International Standards Organization (ISO) 7730 (ISO 2005), and EN 15251 (EN 2006). This model uses two parameters – predicted mean vote (PMV), and percent of people dissatisfied (PPD) to gauge the level of satisfaction of occupants. The thermal comfort zone is defined as all sets of indoor conditions in which the PMV is between -0.5 and 0.5 on a scale of -3 to 3, and the PPD is less than 10%.

Methodologies for defining the level and severity of thermal comfort or discomfort over a period of time have been proposed by a number of authors. Among these, the Percentage Outside Range (Carlucci and Pagliano 2012), Hourly Performance Index (Hensen and Lamberts 2012), and Hours of Exceedance (Olesen and Brager 2004) methodologies, discussed in Standard ISO7730 (ISO 2005), count the number of hours inside and outside the thermal comfort zone, represented as a fraction of the total number of hours evaluated.

Building energy modeling (BEM) can be used to evaluate the effects of changes to a building characteristics and operations on thermal comfort over the whole year period. However, BEM can be computationally expensive, depending on the BEM software and time step utilized. Small changes to the modeled parameters also require additional simulations. Various techniques to simplify the evaluation of BEM have been proposed. Eisenhower et al. (2012) developed a simplified normative model and calibrated it to BEM, based on the techniques discussed in other works (ISO 2007; EN 2005). Reduced-order models have also been developed for the purpose of building control strategies (Goya and Barooah 2012; Dewson et al 1993). Cole et al. (2013) developed a simplified building energy model for building control by fitting a reduced-order model to BEM data for energy consumption evaluation. Artificial Neural Networks (ANN) have also been used to develop models to predict building energy use and thermal comfort (Yuce et al 2014, Chang et al 2015, Ashtiani et al 2014). The Response Surface Methodology (RSM) develops a lower-order polynomial model that represents the relationship between a measured response and a set of design (input) variables (Box and Wilson 1951). It has been used in building applications, including modeling naturally ventilated buildings, predicting the air diffusion performance of displacement-ventilations offices, and determine effects of parameters on heat exchangers (Shen et al 2012, 2013, Khalajzadeh et al 2011). It also results in a function that can easily be used as input into uncertainty analysis, such as Monte Carlo simulation. Uncertainty analysis is useful in comparing a set threshold of thermal comfort tolerance to changes in building parameters and HVAC use.

Thermal Comfort and Appliances Use:

No previous literature to-date is known to have considered the possible effects of changing appliance use or time-of-use of large appliances (Objective 2) on the Thermal Comfort of residential buildings. During operation, large appliances contribute to sensible (temperature) and latent (moisture) load in the indoor environment. Manual J (Rutkowski 2011) assumes a total of 352 W internal load for a combined refrigerator and vented range, 249 W and 176 W of sensible and latent load respectively for unvented cooking and dishwashers, and 147 W for vented washers and dryers. In the assumptions made on the latent and sensible loads associated with large appliances adopted by energy modeling software EnergyPlus (DOE 2007), 100%, 30% and 15% respectively of refrigerator, washer, and dryer loads are considered contribute to sensible loads (Parker 2010). 60% of dishwasher use is considered to contribute to internal latent gains.

According to Pratt (1993), the majority of use of appliances occurs in the mid-morning to mid-evening, which also coincides with the warmest portions of the day and peak energy use times. If these appliances are instead operated at non-peak use times in the evening and night hours when temperatures are cooler, the reduce heat and moisture produced during peak times may reduce the time needed for the HVAC system to bring the interior space to the desired condition in the summer months. This could allow for more time in the thermal comfort zone due to less load on the HVAC system. However, there is insufficient research available to quantify these effects. A limited amount of research has been conduction on the cost-effectiveness of the use of appliances with time-of-use pricing and demand response programs (Pratt 2010, Fuller 2012). However only direct energy cost savings have been considered rather than effects on occupants and the indoor environment.

Thermal Comfort and HVAC Use:

As HVAC systems are designed to control the indoor environment, compared to appliance use changes, changes to HVAC operations enabled through smart technology are likely to have the most significant effect on the indoor environment. The correction of inefficiencies in HVAC systems are likely to have positive effects on the indoor environment. For example, correction of short cycling will allow the HVAC system to remove moisture from the air that is possible only through longer cycling (EnergyStar 2005). Correction of airflow and refrigerant faults will improve cooling capacity and efficiency (SCE 2012b, 2013). Thus this allows the system to control the indoor environmental conditions closer to optimum levels.

Reduction in use of an HVAC system to reduce peak energy loads using utility-imposed pricing strategies and demand response programs, however, have a negative effect on the indoor environment. To date, utility-implemented programs have targeted the use of smart thermostats to reduce peak loads using several types of programs, including Demand Response (DR), and Time-of-Use (TOU) pricing. Newsham and Bowker (2010) provides an overview of these different pricing strategies, citing a 0.3 – 1.2 kW per air conditioner unit energy reduction. Many pilot TOU programs have been conducted throughout the United States (summarized in Faruqui and Malko 1983, Faruqui 2010). These studies did not include the effect on occupants, nor did they use smart technologies to automatically respond to changes in energy costs. Little has been done, however, to specifically understand effects that smart-thermostat enabled energy saving strategies have on occupant comfort.

Summary of Research Needs

In summary, there is a commonly used methodology used to evaluate thermal comfort of occupants in mechanically conditioned spaces such as those common in residential buildings in the U.S. There are also several ways that have been developed to evaluate the long-term thermal comfort of a space. However, there is limited research available on methodologies to evaluate and quantify the effects of energy and peak load reduction strategies on occupant comfort. These are needed in order to understand how changes in a building's operation to save energy or power impact occupants.

Chapter 4: Summary of Methods

This chapter provides a review of the methods used in this research to accomplish each of the Objectives. Section 4.1 discusses the dataset of energy use information of residential buildings utilized and quality control methodologies. Section 4.2 and 4.3 discuss the methodologies used to utilize this dataset to determine energy use patterns of large appliances, and their peak load reduction potential, respectively. Section 4.4 and 4.5, respectively, discuss the methodologies used to determine residential HVAC operational characteristics, and data analysis and laboratory experimental methods used to continuously evaluate, the effects of HVAC faults on energy use data and HVAC performance. Section 4.6 summaries the use of the response surface methodology and uncertainty analysis to evaluate the effects of energy and peak load reduction strategies on occupant thermal comfort. Additional detailed information on the discussed methodologies is also included in the Appendices.

4.1 Residential Disaggregated Energy Use Dataset

The residential building energy use dataset used in this research for the study of large appliance and HVAC use consists of one-minute energy consumption data for residential properties in Austin, TX. The residential single family and multi-family homes studied are a part of smart-grid deployment project which began with monitoring energy consumption of 250 homes in 2012 (Rhodes et al. 2014), and has expanded significantly since this time. A home energy monitoring system (HEMS) was installed in each residential property to monitor this electricity use, and is certified to meet the ANSI C12.20 class for 0.5% accuracy (ANSI 2010). This system uses “CT” (current transformer) collars which monitor individual electric circuits. This HEMS is connected to the home's internet router for internet-based data storage. In the event of a loss of internet connection, the HEMS stores the electricity use data collected, which can then be recovered. The HEMS calculates the root-mean-square (RMS) of current and voltage to determine the average real power and apparent power, which is recorded at one-minute increments. Each one-minute value recorded is an average of the sampled data during that one-minute time increment. Additional information on the specifications of the utilized monitoring system can be found in the manufacturer's literature (eGauge 2014).

Circuit monitoring includes electricity consumption data for the whole-house, as well as one or more individual circuits, including individual appliances, and the indoor and outdoor units of the HVAC system for many of the homes. However, not all circuits are monitored for all homes. In addition to the quality control measures conducted through the data collection (Rhodes et al. 2014), additional quality control measures were also completed. False spikes in the electricity consumption data associated with rebooting of the energy meter or when the device's settings are changed, were removed by identifying one-minute long spikes (>20 kW) and re-assigning these data points with the average value of the data point before and after.

The energy data in this dataset is also anonymized such that each home is given a unique identifier. The address, occupants and other personal identifying information were removed. In addition to energy use data, survey data and home energy audit data were collected linked via the home's unique identifier. This information is also discussed in the Appendices. Survey and energy audit data was available for some, but not all households in the dataset.

4.2 Large Appliance Energy use Patterns

For this Objective (1a), one-minute energy consumption data was collected for a period of one year between March 1, 2012 and February 28, 2013 for 40 homes. The homes monitored between these times were monitored with several different types of energy monitoring systems, 45 of which utilized the eGauge system. This system was shown to have the best agreement with the whole-home energy meter data (Rhodes et al 2014). 40 of the 45 available homes were chosen for use in this study because one or more of the large appliances were monitored in these homes, rather than just whole-home energy data. At the time of this investigation, this dataset was the best available data. The residential buildings used for this objective consist of newly constructed single family homes, built in 2007 or later. The characteristics of the appliances monitored is included Table 2. Additional information is also discussed in Appendix A. Energy use data monitored during this period of time for the studied homes was used in the analysis if over a 24-hour period all data were non-null values. Because an hourly use profile was desired for comparison to previous studies, and for use in building energy modeling, the one-minute data was combined into hourly increments by summing the power demand over each hour.

Table 2: Characteristics of large appliances studied for Objective 1a

Appliance	Year	Types	Count	# of People/ Home
Refrigerator	2008-2009	Bottom Freezer (50%) Side-by-Side (44%) Top Freezer (6%)	15	3.4
Clothes Washer	2000-2009	Front Load (60%) Top Load (40%)	12	3.4
Clothes Dryer	2003-2009	---	18	3.2
Dishwasher	2007- 2009	---	9	3.3

A normalized load profile was developed for each appliance based on the residential buildings studied. This method used is similar to the method used in Pratt (1993). However, rather than a daily profile of a ratio of monthly load to average load, an hourly normalized load profile was created similar to those discussed in Hendron and Engebrecht (2010), and to those used as input for load schedules in building energy modeling software such as EnergyPlus (DOE 20077). The equations used to develop these normalized load profiles are listed as Equations 1-3 in Appendix A. The average electricity consumption for each hour of each day for a particular home was averaged and normalized to the total daily appliance electricity use, such that the hourly load represents the percent of the daily electricity load (PDL). The use of these units enables comparison of the studied dataset to previously reported appliance use data. The normalized load profiles of all homes were averaged together over each hour. The standard deviation, minimum and maximum were also calculated for each of the hourly values. Each of the studied homes was given equal weight. For comparison of the similarity and difference to other load curves, the sum of squared residuals (SSR) was used; SSR is a measure of the Euclidian distance in 2-D space, where minimizing this distance for all hours indicates a closer fit between daily load data (Devore et al 2013), and maximizing the distance indicates a difference in the load shape.

In addition to the study of all homes for the one-year period, the electricity use data of the appliances was also divided into segments by weekday and weekend, heating and cooling season, and whether or not the occupants indicated that they worked from home 20 hours or more per week. These segments were studied according to available data from the studied residential buildings, and for comparison to previous findings such as Pratt (1993). Recent data indicated an increasing number of the U.S. workforce that work from home at least part-time (Mateyka and Rapino 2010).

4.3 Large Appliance Peak Load Reduction Potential

To determine the peak load reduction potential of appliances, a one-minute electricity use dataset was utilized consisting of a set of 130 homes. These homes measured the refrigerator, clothes washer, clothes dryer, and dishwasher for a 1-year period. These homes include the homes monitored in *Investigation 1a*. Of the homes monitored during this time period, these homes were chosen since all of the four studied appliances were monitored during the one-year period and all appliance data contained 90% or more of the full year of data. The homes and appliances studied in this Investigation include the newer homes such as those studied in *Investigation 1a*, and some older homes. The appliances in this study are not smart appliances in that they cannot communicate with the electric grid; however, this study assumed that the appliances studied can be retrofitted to have the capability to be smart appliances such that they respond to demand response or peak pricing signals.

The time of year and time of day in which peak loads on the electric grid occur was determined for the Electricity Reliability Council of Texas (ERCOT) region for the year 2014. This region includes most of the state of Texas. Of the electric grids in the United States, the Texas electric grid has one of the lowest reserve margins (NERC 2014). Thus studying this electric grid region to identify opportunities for peak load reduction is of importance. The peak use time of year in warm and hot climates occurs during the summer months (cooling season). Although peak loads can also occur in the winter (heating season) depending on the climate. However in this study, the study was restricted to the summer (cooling season) when the greatest peak loads occur in this area.

Using time-of-use (TOU) pricing structures used by electricity providers in the ERCOT (e.g. Austin Energy 2014), the period of May 1 to September 30 was considered to be the cooling season. Based on the peak use times considered in TOU pricing schedules, the hours between 2:00 pm and 8:00 pm are considered for peak use reduction potential of the studied appliances. For the time period considered, the peak use in ERCOT has historically occurred during the hours of 5:00 pm and 6:00 pm (ERCOT 2012). With a capacity margin goal of approximately 15% (NERC 2015), it is during this time period that load (MW) in ERCOT has previously been below this goal.

Determining the peak load reduction potential of the studied appliances, the average power (kW) value, percent of time ON, and percent (%) reduction from the average power that can be achieved is required for each appliance. The percent penetration, or percentage of households that have each appliance, is also needed. Each of these values are calculated using the methodologies discussed below.

To determine the electricity load (kW) for a particular hour for each studied appliance, the power (kW) of each appliance when ON (Power > 0.05 kW) over the summer of the 1 year period was used to develop a distribution of average power demands. These values were averaged across all homes studied for each appliance. An Anderson-Darling test was used choose the most appropriate distribution of the average power demand.

To determine the time that an appliance is ON during each peak load hour studied, the total percentage of time ON during each hour from 2:00 pm - 8:00 pm was calculated for each appliance for each home. This was calculated by summing the total amount of time (minutes) that each appliance is ON (Power > 0.05 kW) for each given hour over the summer of the one year period of study. This was divided by the total number of minutes in that hour over the studied period of time. Similar to the power value, a distribution was fit to this value for each hour.

To determine the percent (%) of power demand (kW) for each appliance that can be removed by turning it OFF or changing its performance, for clothes washers, clothes dryers, and dishwashers, it is assumed that a delayed start or pause in the cycle is possible and acceptable during peak use times. This means instead of the appliance being ON, the appliance is turned OFF, resulting in 100% peak power reduction. For refrigerators, a 16% reduction in energy use is assumed, following the testing results in Sparn et al (2013).

To determine the percent of homes that utilize each appliance (penetration rate), the American Community Survey data (2012) was used. This dataset provides information on U.S. residential building characteristics and energy use. According to this dataset, and as shown in Figure 3, the penetration of refrigerators, clothes washer, clothes dryers, and dishwashers is 99%, 84%, 81% and 66% respectively in U.S. homes. These penetration rates are similar in all parts of the country (ACS 2012).

Using these values, the maximum hourly peak load reduction potential of all appliance is calculated using Monte Carlo simulation using a maximum of 100,000 iterations. The equation of the total peak load reduction of each appliance for a single home for a given hour is equal to the multiplication of the average power (kW), percent of time ON, and probability of the appliance existing in a home (the penetration factor). This is multiplied by the fixed value of the percent reduction in energy use for each appliance. It is assumed that these variables are independent. The result is presented in the form of the power (kW) reduction for each peak load use hour (2-8 pm). The total demand response of all large appliances is determined by summing the results of the simulations for all of the four studied appliances.

4.4 Residential HVAC Operational Characteristics

To determine the operational characteristics of residential HVAC systems, the energy use of 189 single family and multi-family homes was monitored for a period of one year between September 1, 2013 and August 30, 2014. This includes 161 single family homes, and 28 multi-family apartments. Of the homes monitored during this time period these homes were used in this study since both the indoor and outdoor units of the HVAC system were monitored during the one-year period, and all HVAC data contained 90% or more of the full year of data. This time period of data was used since it provided the greatest number of homes worth of data at the time of the investigation. In all cases the studied household utilized a central HVAC system, including an outdoor condenser/compressor unit, and an indoor air handling unit. The HVAC was controlled by a thermostat which could be set to heating or cooling mode by the occupant. Two types of central HVAC systems were used, including heat pumps and air conditioning with gas furnace heating. Twenty-two of the homes were determined to utilize timed whole-home ventilation systems, all of which are single family homes. All homes studied pay for their utility bills. Table 1 of Appendix B includes information on the characteristics of the participating households (n=128) and average data for the participating multi-family home properties.

The energy data from two circuits, including the indoor air handling unit and the outdoor condenser/compressor unit were used to determine the HVAC operational characteristics. In homes with heat pump units, both the indoor and outdoor units were used together in both the heating and cooling modes. For homes utilizing a gas furnace, both the indoor and outdoor units were in use in cooling mode, but only the indoor unit was used in heating mode since the gas furnace is the heat source. This distinction in energy signal allows to distinguish the two system types.

To determine the runtime fraction for each home, the energy signal was divided to determine when the HVAC system is ON and when it is OFF. A threshold value of 0.05 kW was used, where above 0.05 kW indicates the system was ON, and below was OFF. Since both indoor and outdoor units typically draw a small amount of power while OFF and not in use, the threshold value must be above zero. A parametric analysis of the effect of the threshold value found that a threshold value between 0.04-0.05 kW had the least effect on the runtime fraction values across all homes, including 0.2% change in the median, and 2% for the mean.

To determine when a system was ON or OFF, two energy signals were utilized for each HVAC system, including the indoor and outdoor units. For the heat pump systems, the outdoor unit signal was utilized to define when the HVAC system is ON or OFF. For the gas furnace systems, since the outdoor unit was not the source of heat in the heating season, the indoor unit data was used. The outdoor unit signal was used for cooling season months (March – November) where the average monthly temperatures was above 18.3°C (65°F). The indoor unit was used for the heating season (December – February), where the average monthly temperatures was below 18.3°C (65°F). To indicate indoor fan-only operation (typical for homes with furnace or fan cycling for ventilation purpose) data collection signal filtering was used. For systems that utilize both electric heating and cooling, including heat pumps, the indoor unit is ON when power consumption >0.05 kW and the outdoor unit is OFF when <0.05 kW. This also indicates the use of the indoor fan without heating or cooling, fan ventilation mode installed in 22 of studied homes.

The annual, monthly and hourly runtime fraction were calculated using all available data from the 189 homes, and are the sum of all times where a system is ON over each time interval. The mean, median and standard deviation were calculated. Cumulative energy use (kWh) information on the indoor and outdoor units was also collected. Outdoor temperature data for Austin, TX was obtained from the National Climatic Data Center, US Climate Data Network quality controlled dataset (2014). The monthly, daily and hourly temperatures used represent the average temperature for the given time period and were computed as the average of the high and low temperature for this time period.

4.5 HVAC Continuous Commissioning Using Energy Data

The effect of faults on near real-time HVAC energy use data and performance was assessed in multiple steps. Each of these steps is discussed in more detail below, and are also discussed in Appendix E. In summary, the first step includes identifying the most common problems and faults that occur in residential HVAC systems. Second, a methodology for continuous determination of the state of the system including, the amount of time ON, and the power draw of the studied HVAC was developed using field-collected energy use data. Third, the electricity signal characteristics of a properly functioning HVAC system were determined, including power and runtime, as a function of outdoor conditions. Fourth, two faults, including condenser air flow reduction and low refrigerant charge were introduced into the HVAC system servicing the UTest House test facility, and tested at different severities of faults. Finally, the energy signal and performance characteristics of the faulty and properly functioning system were compared to determine the effect of the studied faults on the electricity signal and HVAC performance. Each of these steps, and additional information about the testing facility, sensors and data acquisition is also discussed in more detail below.

The identification of common problems and faults in residential HVAC systems was accomplished with literature review of survey studies of HVAC performance assessments, and using data on residential building energy audits conducted in the Texas area. The faults that were chosen to study in further detail were selected based on (1) how common they occurred in building energy audit data , (2) the predicted severity of impact on performance based on previous literature, and (3) their predicted impact on energy signal. The two faults with the highest level of occurrence and higher predicted impact were chosen for study.

The relationship between outdoor conditions and the HVAC power (kW) and runtime (%) were determined using test results for one cooling season (May 1, 2014 to September 30, 2014) of disaggregated one-minute HVAC energy use data. These data are from measuring power at the HVAC outdoor units and from weather data discussed in Section 4.1 and 4.5. The outdoor unit energy data was processed to determine three variables, the system state, the amount of time the system has been ON during the current cycle, and power (kW).

The system state classifications includes (a) OFF, (b) Turning ON, (c) ON; transient, (d) ON; steady-state, or (e) Turning OFF. These states are also shown in Figure 6. Following the findings of Section 4.4, the system is OFF (a) if the power signal shows a value of less than 0.05 kW. The system is (b) Turning ON if the previous value was OFF, and the current value is greater than 0.05 kW. When the system status is set to (b) Turning ON, the timer which counts the length of time the system has been ON begins. The system is considered to be still Turning ON until the current value is within 10% of the previous value and the previous state was (b), at which time the status is switched to ON (c). After the timer reaches a value of 7 minutes, the status is switched from (d) ON, transient to (e) ON, steady-state. This division is necessary to ensure that in the evaluation of the relationship of the system's power (kW) to the outdoor conditions, only power values recorded under steady-state conditions are considered. The system is Turning OFF (d) when the previous status was (c) or (d), and either the power is less than 0.05 kW or the current value is 10% less than the previous value. The status is set to OFF (d) once the value of the power is less than 0.05 kW for more than 2 minutes. The power values are recorded only if the system is in state (c) ON; transient or (d) ON; steady state. The real-time determination of these variables is summarized in the Equations in Appendix E.

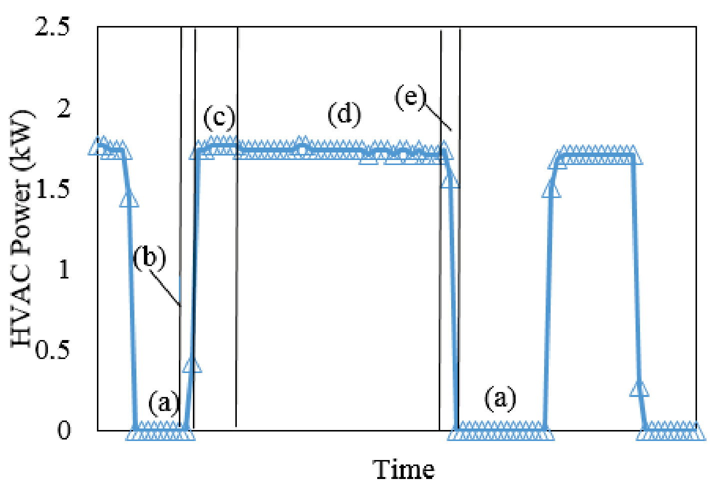


Figure 6: HVAC system state classifications includes (a) OFF (Power < 0.05), (b) Turning ON (previous value = OFF, current value > 0.05 kW, current value = ±10% of previous value), (c) ON; transient (Time ON < 7 min), (d) ON; steady-state (Time ON > 7 min), or (e) Turning OFF (Power < 0.05 kW or current value 10% less than previous). The x-axis represents 2 hour time period.

Note: Timer ON begins counting when the ON transient state is enabled, and ends when the Turning OFF status is enabled.

To determine the runtime fraction for each home, the energy signal was divided to determine when the HVAC system is ON and when it is OFF. A threshold value of 0.05 kW is used, where above 0.05 kW indicates the system is ON, and below is OFF. Since both indoor and outdoor units often draw a small amount of power while "OFF" and not in use, the threshold value must be above zero.

During the laboratory testing additional parameters were calculated to determine the effect of the studied faults on the performance of the HVAC system, as measured by the values of the Coefficient of Performance (COP), a measure of efficiency, and the cooling capacity. The parameters measured include the flowrate through the condenser and through the indoor air handler, the supply and return temperature and relative humidity (RH) of the indoor and outdoor units, the thermostat set point temperature, and the refrigerant line temperatures. The temperature and RH sensors used provide an accuracy of ±0.1°C and ±2.0 % respectively for the ranges of temperature and RH measured. Additional information on the accuracy of the sensors is provided in Appendix E.

To determine the energy signal characteristics of a properly functioning and faulty HVAC system, field testing was conducted at the UTest House test facility in the summer of 2014. Over a period of 1.5 months a series of short-term, near-constant outdoor temperature tests, and a series of long-term multi-day tests were performed. The short-term tests consisted of a constantly running HVAC system that was tested at correct levels of air flow (Fault 1) and refrigerant charge (Fault 2). After establishing the baseline conditions, systematic changes to the level of fault were tested at 20 minute increments. A time period of 20 minutes was chosen to enable the HVAC system to reach steady state between changes. Between each level of fault the system was returned to the correctly functioning state to ensure that the correctly functioning states were similar and permanent damage had not been done to the system by introducing a fault.

The long-term tests were conducted over a period of two days per set of test conditions. Indoor latent and sensible loads were simulated on an hourly basis using the assumptions calculated from the B10 Spreadsheet from the Building Energy Simulation Protocol (NREL 2010). Heat lamps and light bulbs were used to produce sensible heat, while humidifiers were used to produce latent heat. Scheduling and intensity of sensible and latent heat loads were automated using an X10 home automation system. Similar to the short term tests, the baseline, properly functioning system was tested first, and again between each level of fault tested to ensure no degradation in the HVAC performance other than the intentional imposed problem being studied. Additional information on the sensors used and the methodology for testing are included in Appendix E.

4.6 Thermal Comfort Evaluation Using Response Surface and Uncertainty Analysis

A multi-step methodology is proposed to evaluate building thermal comfort. This methodology includes five steps: (1) design variable definition, (2) building energy modeling (BEM), (3) response surface development based on the building energy modeling results, (4) uncertainty analysis using a limit state function constructed using the response surface and a defined occupant thermal comfort tolerance, and (5) result interpretation. Each of these steps is outlined below.

Step 1: Variable Definition for Response Surface Model Development

In evaluating options for construction or operational changes of a building, different design variables are considered. These design variables are used as inputs to build and define the response surface. These design variables can include physical building characteristics, operational characteristics, or climatic characteristics. While the proposed methodology may be applied to develop a response surface for a building using any set of design variables, operational design variables such as HVAC set point temperature, degrees of setback temperature, and set back time period are important variables to considered. This is especially the case for this study, where operational changes are made to an HVAC or appliance for the purposes of energy and peak load reduction. Physical building characteristic and climatic condition design variables may also be used to enable the development of a response surface that can be utilized for different types of buildings located in different locations. To develop a response surface, the number of design variables are chosen, where a greater number of variables develops a more generalized response surface to describe the response of the building. A greater number of variables also requires additional computational time to evaluate combinations of these variables to construct the response function.

Each design variable is defined by its mean value, μ_i a standard deviation, σ_i, and a probabilistic distribution function. Upper and lower bounds are also chosen for each design variable. Values for μ_i, σ_i, and the probabilistic distribution function for each design variable are selected based on documented studies of building characteristics, and operational and climatic considerations (e.g. Persily 1998; Persily 1999; ATTMA 2010; CIBSE 2010; Offermann 2009; ASHRAE 2004; Persily et al 2010; Parker 1990; Roberts and Lay 2013). They may also be chosen following a data collection effort or by using engineering judgment. The upper and lower bounds of each variable define the window in which RSM is assumed to be valid.

In this research, scenarios in which changes to operational characteristics of residential HVAC systems were changed to reduce peak energy use were evaluated. These two scenarios were (a) a 1-hour demand response event, and (b) time-of-use pricing. For (a) two design variables are evaluated, including air exchange rate (ACH, h^{-1}) and the set point temperature of the thermostat ($^{\circ}$C). The demand response event was fixed to occur from 5-6 pm in which the HVAC system was turned off. For (b), five design variables are evaluated, including air exchange rate (ACH), climate region, thermal mass (J/°C-m^2), set-point temperature (°C), and degree of setback temperature (°C). In this scenario, (b), a time-of-use pricing schedule is used, in which peak demand pricing is defined as 2 pm – 8 pm on weekdays, and all other times are considered off-peak. During the peak demand pricing, the smart thermostat controlling the HVAC increases the set point temperature (°C) by the number of degrees specified by the degrees of setback temperature (°C).

Step 2: Building Energy Modeling (BEM) simulations

To establish the desired response surface, input data on the thermal comfort performance of the subject building are needed. Such data include consistent time-interval data of the indoor operative temperature (ºC), or both the dry bulb temperature (ºC) and the mean radiative temperature (ºC). Also, data include relative humidity (%) or humidity ratio (g/kg) of the indoor air. The required data may be obtained using results from building energy modeling or from field-collected building performance studies. In this research BEM is used to produce the indoor temperature and humidity data. It is assumed that air speed criteria (ASHRAE 2010; Gyamfi et al. 2013) for thermal comfort are met in the analyses.

In additional to a consistent time interval for measurements or simulated values, the design period of evaluation over the calendar year must be chosen. A design period is defined by a start day and end day. One year may be used to capture the behavior of the building accounting for all seasons of the year; a single year is a typical period of time used in BEM simulation. If a year-long period is used, there are different thermal comfort zone criteria for heating and cooling seasons (ASHRAE 2010). These seasons and can be determined using monthly average temperatures (MATs) and typical meteorological year (TMY3) data (Wilcox and Marion 2008), or the 99% annual winter and summer and design temperatures as defined by ASHRAE (ASHRAE 2009). All months where the MAT or 99% design temperature is less than 18.9°C may be defined as the heating season, and all months where the MAT is greater than 18.9°C may be defined as the cooling season. Additional information on this methodology is included in the Building America House Simulation Protocols (Wilson et al 2014), which is used as a guideline for building energy simulation of residential buildings. Design times of day must also be chosen for evaluation; the time interval representing the time that the thermal comfort criteria are desired to be met. This is often associated with the times in which the building is occupied.

A nonlinear response surface is constructed using the full factorial design (Hoke 1974). If a large number of design variables are being evaluated, methodologies such as the Fractional Factorial design (Gunst and Mason 2009), Box-Behnken design (Box and Behnken 1960) or D-optimal design (Silvey 1960) may be used to reduce the number of simulations needed and computational time required. These designs are desirable and often used when the extreme points are expensive or impossible to test, or when the Full Factorial Design requires too many runs for the amount of resources or time available. In this research 2-5 variables were considered, thus the full factorial design was used.

The full factorial design requires 3^n simulations, where *n* is the number of design variables utilized in the analysis, including a simulation at each combination of the design variables at three design points, $x_{i,high}$, $x_{i,low}$ and the mid-point. Once the BEM simulation results are generated, two different possible methodologies for evaluating long-term thermal comfort are evaluated for each simulation. These include the percent of time outside the thermal comfort zone (POS), and the average percent of people dissatisfied (PPD_{avg}). POS is the ratio of the number of hours the indoor conditions are outside the thermal comfort to the total number of hours. The PPD_{avg} is the average value of the percent of people dissatisfied. According to ASHRAE 55 (2010), the PPD should be less than 10% to be within the thermal comfort zone.

Step 3: Response Surface Development

The third step is the creation of a response surface (Meyer et al 2011, Khuri and Mukhopadhyay 2010, Meyer et al 1989). Previous literature has found that a second order polynomial function provides a stronger fit to data as compared to a first-order model, and a 3rd order model does not provide a significant improvement in accuracy (Khalajzadeh et al 2011). However, the order of the model may be evaluated to determine the appropriate level of accuracy needed for the application of this methodology. Equation 1 is a second order model, where S is the response surface, made up of n design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ and including a set of model coefficients, b_i (i = 1 to n) for linear variation and b_{ij} (i,j = 1 to n) for quadratic variation, along with a random experimental error term, ϵ.

$$S(\mathbf{X}) = b_o + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} X_i X_j + \epsilon \tag{1}$$

Least-squares regression is used with the selected design variables (Step 1) and the BEM simulations (Step 2) to build the response surface. Backward elimination can be used to keep only the terms of the response surface that are significant if a simplified model is desired. To evaluate the goodness of fit of the model to the data the R^2 (coefficient of determination) value is used. A good fit of the response surface to the data is indicated by an R^2 value close to unity. Evaluation of goodness-of-fit should be conducted on both in-sample data used to develop the response surface as well as on out-of-sample data that were not used to develop the response surface. The out-of-sample data should be within the range of the upper and lower bounds of the design variables considered in the study.

Step 4: Uncertainty Analysis

To address uncertainty in the underlying design variables, a limit state function (Equation 2) is used to quantify the probability of exceeding the acceptable threshold values for POS, and PPD_{avg}. Note that in the use of the response surface created in Step 3 it is assumed that the design variable can be treated as independent random variables.

$$g(\mathbf{X}; T_{acc}) = T_{acc} - S(\mathbf{X}) \tag{2}$$

To achieve compliance with generally accepted standards (ASHRAE 2010), as a part of the design of a building, the maximum allowable values of the POS, or PPD_{avg} must be stated. These POS, or PPD_{avg} values can also be represented as T_{acc} in Equation 2. Monte Carlo simulation (Hammersley et al 1964) is used with distributions for all the design variables and with the developed response surface (Step 3) and the specified maximum values of POS, or PPD_{avg}. A failure in a single Monte Carlo simulation is defined to have occurred when the response surface exceeds the specified maximum values of POS, or PPD_{avg} (T_{acc}) or, effectively, when the limit state function is less than zero. Crude Monte Carlo (CMC) simulation, i.e., Monte Carlo simulation without any additional variance-reduction refinement, is used in this manner to estimate the failure probability. The accuracy of the probability of failure estimates increases with the number of simulations.

Step 5: Result Interpretation and uncertainty of the results

Based on the results of the response surface, the methodology presented in the preceding four steps provides a means of evaluating a range of physical, operational, and environmental characteristics of a building as well as its proposed environment from the point of view of thermal comfort. The results of Steps 1 to 3 provide the response surface function that defines the number of hours outside the thermal comfort zone based on n design variables. Multiple sets of CMC simulations allow the systematic study of the design variables and their importance.

Chapter 5: Summary of Results

This chapter summarizes the results for each of the Objectives. Section 5.1 and 5.2 focus on large appliances, the first of the two studied major energy users in residential buildings. The energy use patterns for each of the studied appliances are described in Section 5.1, and their peak load reduction potential is discussed in Section 5.2. Sections 5.3 and 5.4 discuss the major findings regarding residential HVAC systems, the second major energy user in residential buildings. HVAC operational characteristics and use patterns are presented in Section 5.3. Section 5.4 discusses the evaluation of the effects of the studied HVAC faults on characteristics of energy use data and HVAC performance, and the potential energy savings resulting from the correction of these faults. Finally, Section 5.5 summarizes the evaluation of the proposed thermal comfort evaluation methodology in assessing thermal comfort, and its implementation to determine the effects of HVAC operation schedule and building performance changes on occupant thermal comfort. This thermal comfort evaluation includes the effect of a smart thermostat-enabled demand response event and time-of-use (TOU) pricing. For brevity, only major results are discussed in this chapter; however, additional results, details and discussion are included in the Appendices. Each section begins with a summary of the results, followed by additional details, discussion, graphs, and tables, and refers to the appropriate Appendix for additional results applicable to that section.

5.1 Large Appliance Energy Use Patterns (Investigation 1a)

This section summaries large appliance use patterns, including the normalized hourly appliance use profiles, and segmentations by weekdays, weekends, work-at-home households, and seasonal variations.

Summary of Findings on Large Appliance Use Patterns:

Overall, the normalized appliance use patterns were generally found to be similar to a previous large sample study of appliance use in 1989 (Pratt 1993) which were collected in a different climate zone. The use patterns of user-dependent appliances, including dishwashers, clothes washers, and clothes dryers, were found to vary more between homes and between days than automated appliances (refrigerators). The average standard deviation in hourly normalized energy use between homes is greatest for dishwashers, followed by dryers, washers and refrigerators.

Regarding the segmentation results, of the three studied influencing factors, including seasons, weekdays and weekends, and work-at-home versus non-work-at-home households. Out of these, whether or not the residents worked at home showed the greatest difference overall when considering all appliances energy use. Households where members work at home use up to 28% more of their daily appliance energy use during normal business hours (9am – 5pm) than non work-at-home households. The clothes washer and dryer energy use profiles were most influenced by the residents that work at home, while the refrigerator and dishwasher energy use profile were most affected by whether or not it was a weekday or a weekend. The heating and cooling seasonal variations had the least effect on the normalized use profiles for the appliances studied. This is consistent with the similarities seen between the normalized use profiles of appliances in homes in the hot-humid climate zone of Texas and those observed in the mixed and cool climate zones of the Northwest part of the United States. These are discussed in further detail below, and in Appendix A.

Specific Details and Discussion:

The refrigerator normalized energy use (Figure 7a) is a significantly flatter, more constant energy user, varying, on average, 5 to 9 times less between homes compared with the other appliances studied. The greatest energy use occurs in the afternoon, with the use peaking at 7:00 pm, consistent with the finding of (Pratt et al 1993). The greatest variation in use occurs between the hours of 6:00-8:00 am and 6:00-8:00 pm, consistent with times of meal preparation. Compared to the profile developed by Pratt et al (1993) for refrigerators, this profile values closely match, disagreeing, on average by only 0.04 PDL. Since 1989 refrigerators have become increasingly more efficient due to increasingly stringent regulations. However, with a small difference between the profiles from the previous study (1993), this indicates that these changes do not have a strong influence on the normalized daily time-of-use of energy for refrigerators. Indoor temperatures can also affect efficiency and power draw of the refrigerator, however with minimal differences between the two profiles, this suggests that either the indoor temperatures were similar or that this has a minimal influence on time-of-use patterns. The increased variation in the energy use of the refrigerator during the evening hours can be explained in part by human behavior, through the opening and closing of doors for dinner meal preparation, and placing warm food into the refrigerated space. Both activities result in additional energy use.

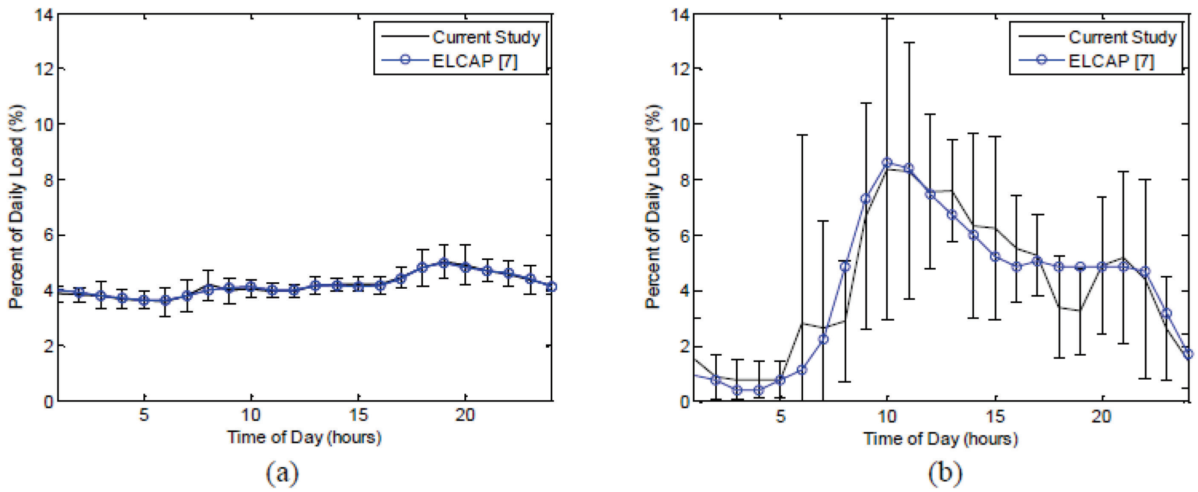


Figure 7: Average normalized energy use profiles for (a) refrigerator and (b) clothes washer, from this study (black) and compared to Pratt (1993) (blue).

The user-dependent appliances, including the clothes washer, clothes dryer and dishwasher had the greatest variation in normalized energy use by hour, varying between, 0.07 - 8.4 PDL, 0.06 - 9.1 PDL, and 0.05 - 8.5 PDL respectively. Figure 7b shows the normalized energy use profile for the clothes washer, to demonstrate this variation in contrast with the refrigerator. Clothes washers and dryers peak (Figures shown in Appendix A) in energy use between 9 am and 2 pm, while dishwashers show distinct peaks in the morning at 9:00 am, and night at 10 pm which is also the time with greatest variation in load across the homes. This variation is more than twice as much as the average variation (4.0 PDL). We also note the profile for clothes washers peaks an hour earlier than the clothes dryers. The greatest variation in hourly PDL occurred at the times when the energy is used most. This includes 10:00 am for clothes washers, 6:00 pm for clothes dryers, and 9:00 am and 10:00 pm for dishwashers. In comparing these use profiles to previous studies, clothes washers and dryer are similar to Pratt et al (1993), but somewhat different than Saldanha and Beausoleil-Morrison (2012). Beausoleil-Morrison found that peak use in washers and dryers is in the evening hours. The hourly values in Beausoleil-Morrison's study vary from the present study on average by 0.59 and 0.61 PDL respectively.

The main difference in the load shapes of the refrigerator and the washer, dryer and dishwasher can be partially explained by the fact that the use of clothes washers, dryer and dishwasher depend strictly on the occupant use, and. unlike the refrigerator, these appliances do not consistently require electricity. Interestingly, unlike the dishwasher load profile, which peaks in the morning and evening hours when those who work away from home would likely be at home, the energy use of the washer and dryer are highest during normal business hours, with the exception of the 6 pm dryer spike. This increased use is similar to the profile found in Pratt et al. (1993). Of the homes studied in the present research, 20 of the 40 homes (50%) indicated that one or more members of the household worked from home more than 20 hours per week, which may explain some of the increased use during this time.

Comparing weekday and weekend use profiles for the studied appliances, the results show time-of-use changes as well. This is shown in Figure 3 in Appendix A. This segmentation of weekdays and weekends is in agreement with Arghira et al. (2012), which found that the day of the week is correlated with energy use. For all appliances, the standard deviation of hourly PDL is greater on weekends than weekdays, explaining some of the variation in use among homes. Comparing the difference in the profiles of the three segmentations studied, the dishwasher shows the greatest difference in profiles between weekdays and weekends. On weekdays there is, on average, a lower percent of daily energy use during normal business hours (9 am – 5pm) as compared to weekdays for all but clothes dryers. This makes sense, since many of the residents work outside of the home and would not be using appliances during this time. Interestingly, refrigerators, the most user-independent appliance, show the greatest reduction in use on weekdays, as compared to the other three more user-dependent appliances. This may be explained because people have less time to cook meals at home that requires use of the fridge and storage of warm food.

Separating the energy use profiles, into those households that work twenty or more hours per week from home and those who did not, (Figure 8) energy use of appliances during normal business hours (9am-5pm) in households where members do not work from home is 2-28% less than households that do work from home. This is important to note, as the number of Americans working from home has increased in recent years. Variability is also significantly lower for those households with no home workers for all but the clothes washer. Comparing the SSR values of the three studied factors, the washer and dryer are most influenced by whether or not the household has someone working at home or not.

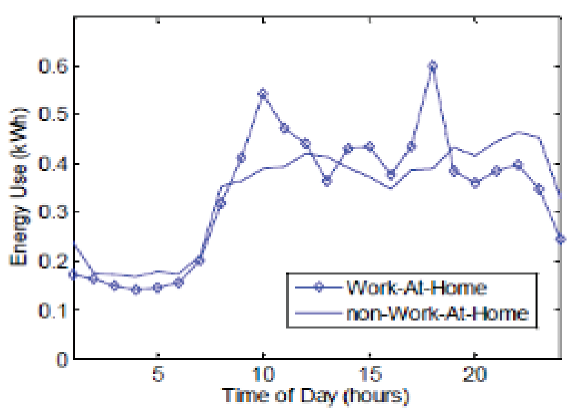


Figure 8: Aggregated work-at-home versus non-work at home household appliance daily average energy use (kWh).

5.2 Large Appliance Peak Load Reduction Potential (Investigation 2a)

This section summarizes the results of the analysis of the peak load reduction potential of the four studied appliances. The study of appliance use patterns, Investigation 1a, shows that all appliances use more than 25% of daily energy use during peak use times, from 2-8 pm. In ERCOT (Electric Reliability Council of Texas) electric grid in which the studied appliances are located, this demonstrates the potential to reduce electric grid peak demand by use of appliance "smart technologies" that schedule the operation of appliances. Clothes dryers utilized the greatest percent of daily load (36%) during peak use times and thus were of interest for this application. The following section focuses on assessment of hourly peak load (power) reduction by presenting results from the Monte Carlo simulation using: average power demand (kW), average percentage of time ON each hour (%), the percent of power that can be reduced (%), and the percent of households using each appliance in the studied region (%).

Summary of Findings on Appliance Peak Load Reduction Potential:

Results show that clothes dryers and refrigerators provide the greatest peak load reduction potential of the studied appliances, followed by dishwashers. Clothes washers provide the least peak load reduction. However, the uncertainty in the peak load reduction is greater for clothes dryers than refrigerators. In addition, since refrigerators' percent of power reduction is assumed to be 16%, based on previous studies, this limits the refrigerator peak load reduction potential per home. If this percentage were to increase, this would enable additional peak load savings that may match or exceed the predicted savings in comparison to the clothes dryer.

Specific Details and Discussion:

The average power demand for each of the studied appliances over the 1-year period of study is shown in Figure 9a-d. This figure shows a histogram of the average power demand of each of the studied appliance when the appliance is ON, and a fitted normal distribution for comparison with the binned data. An Anderson-Darling test was used to determine the best fit distribution for the data. For the average power demand of the refrigerator and clothes washer, a lognormal distribution is used, and for the clothes dryer and dishwasher, a normal distribution provides the best fit. The distributions and their parameters are shown in Table 3. Results show that the average power demand is greatest for the clothes dryer, followed by the dishwasher, clothes washer then refrigerator.

The average percent of time each appliance is ON for each peak use hour (2-8pm) over the 1-year period of study is shown in Table 3. The refrigerator is ON approximately 60-65% of the time, while the clothes washer and dryer are ON 2.9-3.7% of the time. The dishwasher is on the least, at 1.7 to 3.9%. The percentages of time ON were all found to be lognormally distributed.

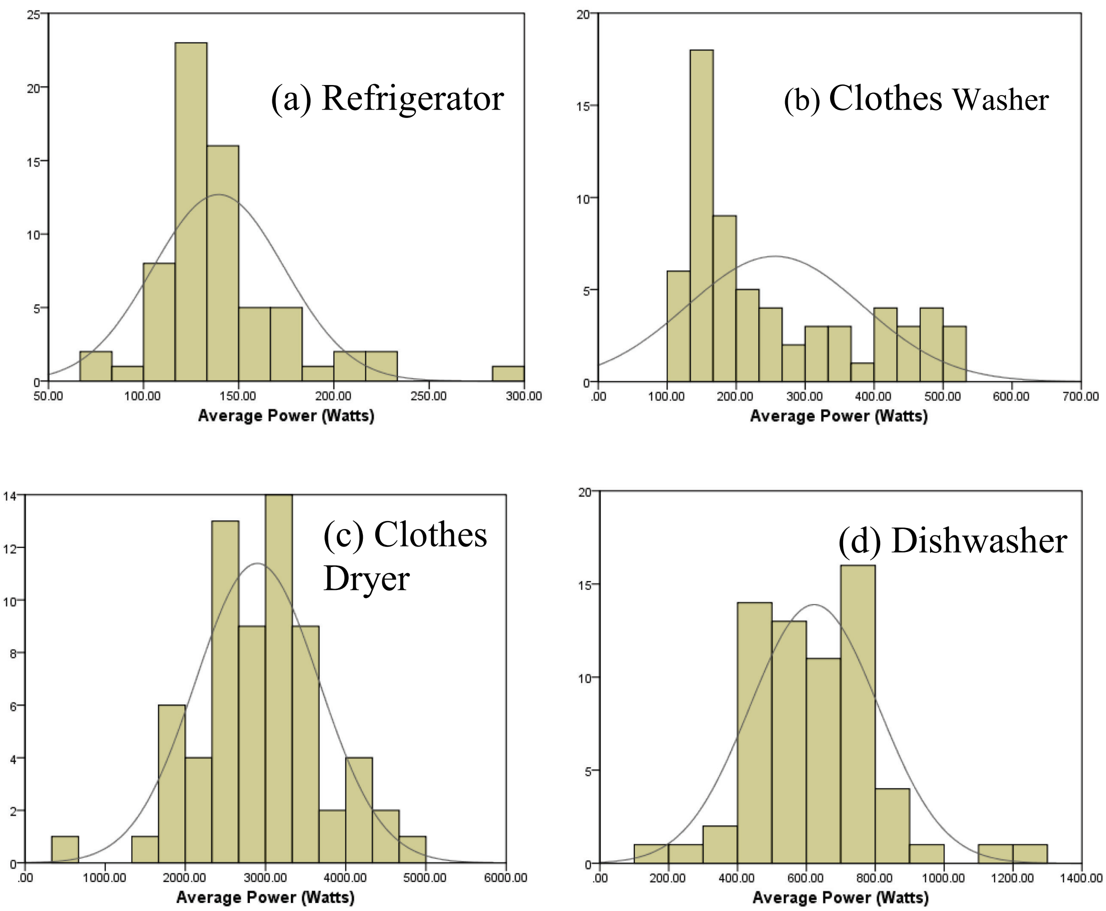


Figure 9: Binned histograms and fitted normal distributions of the average power (Watts) of each appliance when ON over the one-year period of study, including (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers.

Note: the normal distributions shown are for purposes of comparison. The final distributions and their parameters utilized in this research are shown in Table 3.

Table 3 Appliance average power demands and percentage of time ON each hour over a 1-year period

Appliance	Average Power Demand (watts)			Average Percent of Time ON Each Peak Hour						
	Dist. Type	*Param. 1*	*Param.2*	*2pm*	*3pm*	*4pm*	*5pm*	*6pm*	*7pm*	*8pm*
Refrigerator	Lognormal	m = 136	s = 0.22	60%	60%	60%	60%	62%	65%	65%
Clothes Washer	Lognormal	m = 231	s = 0.46	3.7%	3.4%	3.2%	3.2%	3.1%	3.2%	2.9%
Clothes Dryer	Normal	μ = 2904	σ = 773	3.6%	3.4%	3.2%	3.1%	3.1%	3.1%	2.3%
Dishwasher	Normal	μ = 626	σ = 185	2.2%	2.2%	1.9%	1.7%	1.8%	2.9%	3.9%

In addition to power and time ON, the final two parameters include the percent of homes that use each appliance (percent penetration) and the percent reduction in power that is possible. For the percent penetration, these values are shown in Figure 3d of Chapter 3 of this dissertation, with the highest penetration from refrigerators, followed by washer, dryers and dishwashers. The percent of reduction in power is assumed to be 100% for user-dependent appliances, and 16% for refrigerators, as discussed in the Methodology chapter.

To estimate the impact that smart appliances may have on peak load reduction, the entire ERCOT (Electric Reliability Council of Texas) electric grid is considered. This electric grid includes 7.5 million households, and encompasses most of the state of Texas. For assessing maximum potential, an optimistic scenario of 100% penetration of smart appliances in these households is assumed.

The results of the Monte Carlo simulation are shown for each of the four appliances in Figure 10 for the time period of 5-6 pm. This time is the hour where peak load is the highest on the electric grid in ERCOT. The other hours studied (2 – 8 pm) are not shown in this summary for brevity. Figure 10 shows, for each appliance, the cumulative distribution of total peak load reduction in ERCOT. The horizontal axis indicates the total peak load reduction corresponding to a given probability the ERCOT-wide peak load reduction will at least be this value. For example, for refrigerators there is a 50% probability that the peak load reduction from 5-6 pm will be at least 97 MW. Of the four studied appliances the dryer has the greatest peak load reduction potential, followed by refrigerators, washers and dishwashers when comparing the mean values. However, the spread of the distribution of refrigerators is much smaller than that of the clothes dryers, indicating a more reliable load, which may be important when considering the need for a reliable source of demand response potential on a grid-level scale. In looking at the tails of the distributions (Figure 10), refrigerators provide at least 50 MW of peak load reduction potential 95% of the time, whereas dryers provide very little peak load reduction 20% of the time.

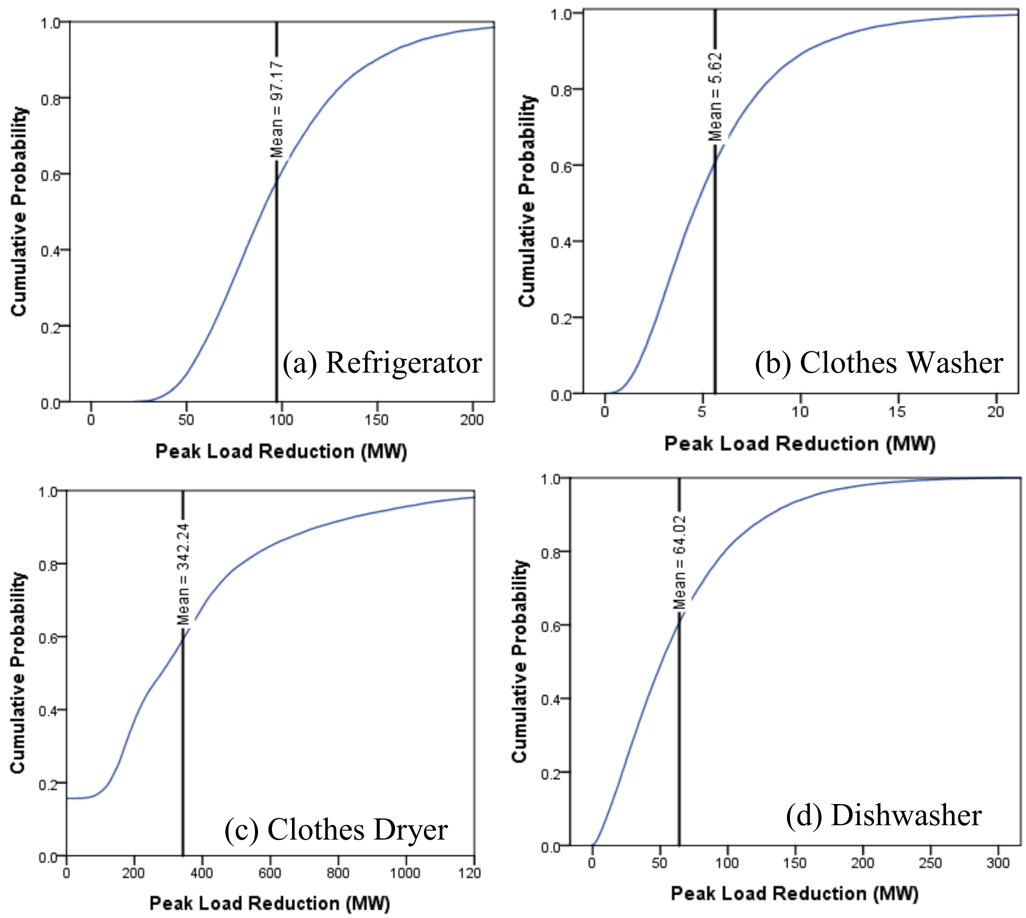


Figure 10: Cumulative probability distributions for (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers showing the peak load reduction potential (MW) from 5-6 pm, the peak use time on the ERCOT (Electric Reliability Council of Texas) electric grid.

Note: The peak load reduction potential is for the ERCOT region, which includes 7.5 million households.

In comparison to demand response programs that currently focus on HVAC energy reduction through the use of smart thermostats, appliances provide a smaller peak load reduction potential. However, changing when appliances are used has very minimal effects on the indoor environmental conditions and thermal comfort of occupants, as compared to changes in HVAC operations.

5.3 HVAC Operational Characteristics (Investigation 1b)

The results regarding the operational characteristics of residential HVAC systems include yearly, monthly, and hourly runtime fractions, as well as the runtime fraction compared to outdoor temperature and energy use. These results are further subdivided by type of HVAC system, and by home type: single family or a multi-family home.

Summary of Findings on HVAC Operational Characteristics:

There are four main conclusions that were determined from this study. First, the average annual HVAC runtime for both single family and multi-family homes is approximately 20% (12 min/hour) in the hot and humid climate of study. While this annual value is consistent with previous research, assuming a single value for annual runtime fraction may be misleading, as the runtime fraction varies, on average between 7% and 40% with each season. Second, the HVAC runtime fraction of the studied homes in the peak heating season and peak cooling season are approximately 1.5 and 4 times greater, respectively, than in the transition spring/fall seasons. Summer runtime fractions average 34-40% across all homes in the peak summer month. Winter runtime fractions average 7-17% while the transition season from 7 to 10%. Third, the hourly profile of HVAC runtime fraction in the cooling, heating and transition seasons are different. In the cooling season the runtime fraction is highest in the evening and lowest in the morning, while in the heating season it peaks in the morning, and it is lowest in the afternoon. The transition season runtime fractions are the most consistent across all hours of the day. Finally, monthly and daily HVAC runtime fractions are lowest where the outdoor temperatures are at approximately 15°C; the farther above and below this range the outdoor temperatures get, the greater the runtime fraction of the heating or cooling system. Additional details concerning these results can be found in Appendix B. Also, results regarding fan-only operation of HVAC system can be found in Appendix B and are not included in this summary for brevity.

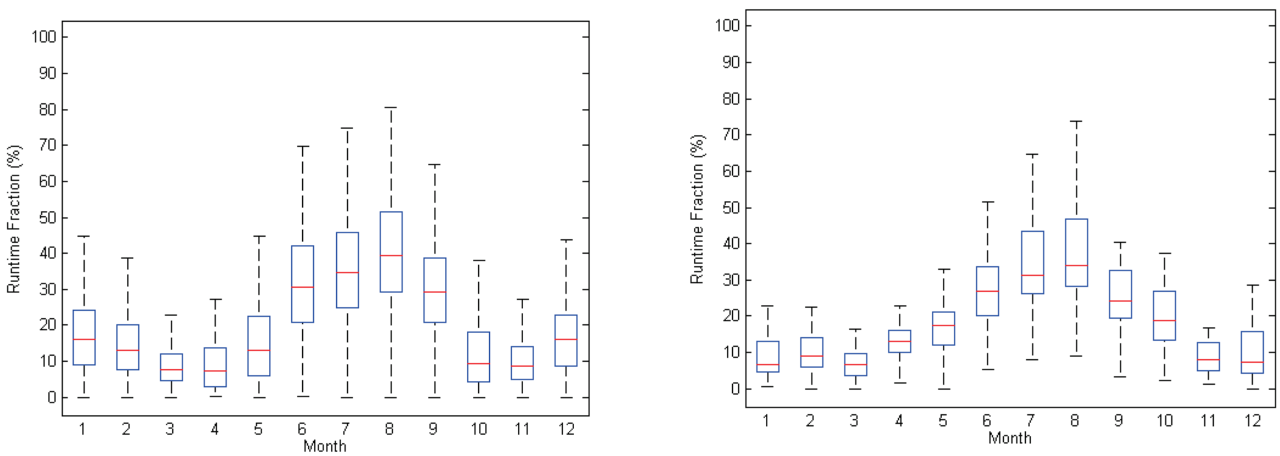
Specific Details and Discussion:

The mean annual runtime fraction of all systems, including both heat pump and gas furnace systems, and for all housing, including single-family and multi-family houses is approximately 20% (12 min/hour), with a standard deviation of 2.8-4.1% (1.7-2.5 min/hour) depending on the home and system type. Table 4 shows the mean, median and standard deviation of the annual runtime fraction (%). The studied multi-family homes have a 2.5% lower annual runtime fraction with a 1.3% larger standard deviation than single family homes. Heat pump and gas-furnace homes have a minimal difference of 0.2% in annual average runtime fraction. The median annual values are lower than the mean values in all cases, ranging from 14.1-16.4% of time.

Table 4 Annual runtime fractions (%) of subsets of 189 homes in Austin, TX

Type (# of homes)	Mean	Median	Std. Dev
Single Family (n=161)	21.0	14.1	2.4
Multi-Family (n=28)	21.3	16.4	3.1
Heat Pump (n= 50)	18.5	15.2	4.1
Gas-Fired Furnace (n=139)	21.1	14.5	2.8

Runtime fractions were determined for each month of data collection, from September 2013 to August 2014 (Figure 11). The mean values for the runtime fractions (center horizontal line of the box plot) for single family (a) and multi-family (b) homes. The upper and lower ends of the box plots represent the 25% and 75% percentile of homes, and the vertical dotted lines show 2.7 times the standard deviation (99.3% of data).



(a) (b)

Figure 11: Monthly runtime fractions (%) of residential HVAC systems, including, (a) single family homes, (b) multi-family homes. *Note: Month 1 corresponds to January, and Month 12 to December.*

Monthly runtime fractions are highest during the months of the peak of the cooling (summer) season, in all cases. Mean monthly runtime values range from 33.9 – 39.5% and median, from 35.4 - 41.1% in August. In addition the peak summer season also has the greatest variation in runtime fraction among the studied homes. The heating (winter) season represents the second highest runtime fractions of the four seasons, with runtimes peaking in December–February. Mean monthly runtime values range from 6.8 to 17.4% and median, from 9.6 to 19.6% in January. The multi-family units show the lowest heating runtime fraction of the four subsets of data. The lowest runtime fraction of the HVAC systems are in the spring and fall seasons, which is the transition between the heating and cooling seasons. During this time, unlike the cooling and heating seasons, the outdoor temperatures are often within the thermal comfort zone of occupants. Of these months, including March – May and October - November, the monthly runtime fractions are lowest in March and November, ranging from 6.6- 9.8% mean, and 8.4-10.7 % median. These transitions periods in the seasons also have the least variation in value among the homes studied.

Average hourly runtime fractions (Figure 12) were computed for all homes following the same methodology. The months of January, August, and March are used to show the heating, cooling, and transition seasons respectively. Hourly runtime fractions vary significantly across all homes. The average standard deviation for the heating, cooling, and transition seasons are 31%, 37% and 28% respectively. Since an hour time increment is shorter than daily or monthly intervals of study, the chances that the HVAC runs nearly 100% or 0% of the time are higher than at larger time increments.

The observed runtime fractions show significant variation; regression analysis was conducted on the annual runtime fraction of single family homes to determine the significance of the effect of influencing factors. The impact of: building age, size, number of occupants, type of HVAC system, and average cooling and heating set point temperatures were analyzed. Regression analysis indicated that of the considered factors listed above, the number of occupants ($p=0.04$) and the reported cooling set point temperature ($p=0.05$) were statistically significant influences on annual HVAC runtime. The third most influential factor was the age of the building, however it was not statistically significant. Of the factors assessed, these were found to explain some of the variation in the annual runtime fraction data (R^2=0.33). There are also many other possible factors that may influence the runtime of an HVAC system than were not captured in the available information in the studied dataset.

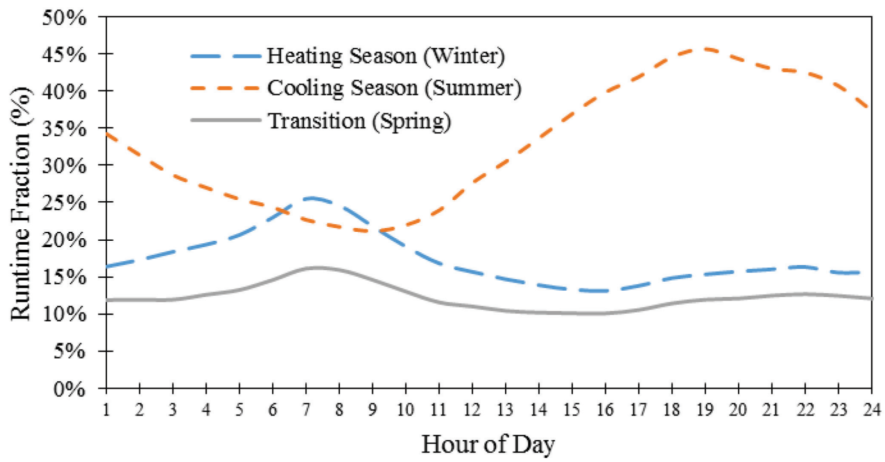


Figure 12: Average hourly runtime fractions (%) for the heating season, cooling season, and transition season across all homes studied (n=189).

In comparing monthly and daily outdoor temperatures (°C) to the runtime fraction (%) of the monitored home's HVAC systems, the minimum daily and monthly HVAC runtime fraction occurs when the monthly and daily outdoor temperatures are 14-15°C. These runtime values are 12% and 8% on average, respectively. The highest runtime fractions occur at the extreme high and low monthly and daily average outdoor temperatures. At outdoor temperatures of 30°C, the average monthly and daily runtime fractions are 46% and 45% respectively.

When the outdoor temperature is close to the desired indoor set point temperature, the HVAC runtime should be low since the difference in indoor and outdoor temperatures are low. As observed in Figure 12, low runtime fractions occur during the spring and fall seasons (transition seasons). During transition months, when outdoor conditions are closer to the thermal comfort zone conditions, as defined by ASHRAE 55, the HVAC is needed less to maintain a desired indoor temperature. Building occupants may also open windows or doors rather than use the HVAC. 15°C is lower than the thermal comfort zone range of temperatures for conditioned spaces of approximately 21°C and 28°C operative temperature (average of air temperature and mean radiant temperature). However the interior temperature of the home is likely different than the exterior. According to the adaptive thermal comfort model used for naturally ventilated spaces, at an outdoor monthly temperature of 15°C, and acceptable indoor operative temperature is between 20°C and 25°C.

In comparing the HVAC energy use (kWh) and whole-home energy use (kWh) to the monthly, daily and annual runtime fractions, HVAC energy use has a stronger correlation to the annual, monthly and daily runtime fractions than the whole-home energy use (Figure 13). This is expected since there are many other factors that contribute to whole-home energy use and its variation, including occupant behavior, and other internal loads.

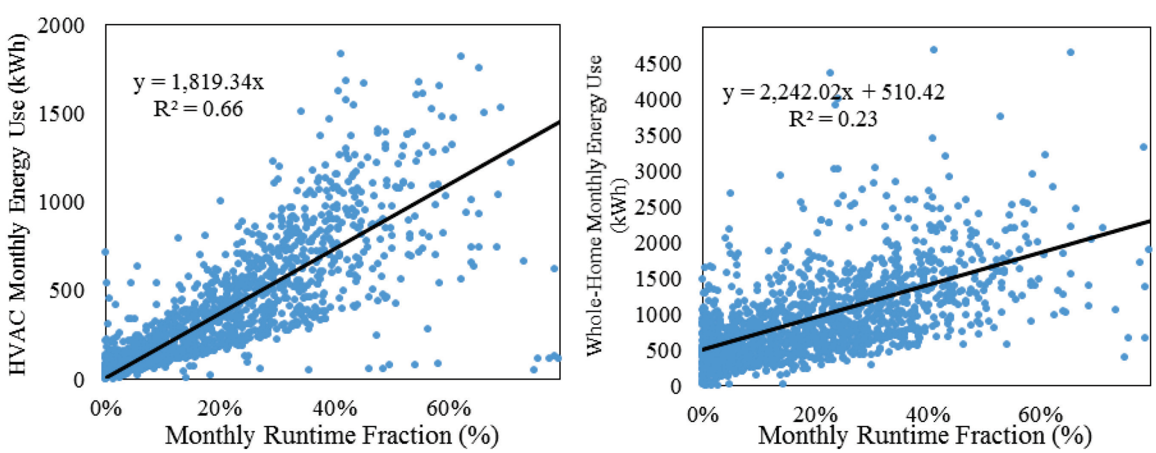


Figure 13: HVAC (a) and whole-home (b) energy use (kWh) compared to the monthly runtime fractions of the studied homes.

Additionally external loads such as sprinkler systems, outdoor lighting or other outdoor energy users may contribute to this whole-home energy use but have no effect on the HVAC system. Since the runtime of an HVAC system is directly associated with how much energy it uses, it is expected that this be a stronger correlation. Factors such as outdoor temperatures, variations in the building envelope properties and solar heat gains of a home, system properties of the HVAC system, as well as other factors may be the cause of the variation in the relationship between runtime and energy use. Monthly energy use also has a stronger correlation to runtime fraction (Figure 13). Monthly energy use compared to runtime provide the strongest correlation which may be explained in part due to outdoor temperatures generally not varying significantly over a month timespan. Outdoor temperature affects the efficiency and operational characteristic of an HVAC system, and whether or not the occupants may feel comfortable opening windows or switching the HVAC between heating and cooling mode. The stochastic behavior of occupants and HVAC use is evident in the more significant variation in daily energy use and runtime. The annual energy use compared to runtime suffers from combining multiple seasons in which occupant behavior, and operational changes such set point temperatures which may vary significantly over this period of time.

5.4 HVAC Continuous Commissioning Using Energy Data (Investigation 2b)

This section investigated the effects of the two studied faults, including condenser air flow and low refrigerant change, on the energy use data and performance of the HVAC. This study includes the assessment of the changes to power draw, runtime, energy use, coefficient of performance and cooling capacity due to these faults. It also include an assessment of the total energy savings associated with the correction of HVAC faults. Only the results for the condenser air flow reduction faults are included in this results section, and additional details concerning these results are in Appendix E.

Summary of Findings of HVAC Continuous Commissioning

All of the studied variables, including the power when the system is ON, the runtime fraction, energy use, cooling capacity, and coefficient of performance were found to be affected by two studied faults in a residential HVAC system. Due to a condenser air flow reduction fault, the power is increased, while a refrigerant charge fault decreases the power at a given outdoor temperature. This is a distinguishing feature of two studied faults. With both types of faults, the runtime and energy use increase, and the coefficient of performance and cooling capacity decrease. Utilizing the established relationships between the fault level, outdoor temperature, and the HVAC runtime fraction values presented Investigation 1b, an annual whole-home electricity savings of 1.4-3.8% can be avoided by correcting a 10%-25% condenser airflow fault, and 3.8-5.7% savings for the correction of a 10-25% low refrigerant fault.

Specific Details and Discussion

To determine the impact of the studied faults on the energy signal and performance the characteristics of the properly functioning HVAC were first investigated. The performance of the HVAC system is dependent on the outdoor temperature. During testing period the outdoor temperature ranged from 16°C to 32°C, with an average temperature of 27.6°C. Figure 14a shows the relationship between outdoor temperature and the power of the HVAC system when it is on. Only the values for when the systems is at steady-state are shown (state (d), as discussed in Figure 6)

Linear regression analysis between outdoor temperature has an R^2 value of 0.908, indicating that the outdoor temperature is able to predict approximately 91% of the variability of the HVAC power usage (kW) when the compressor is ON. Variation in the HVAC power is slightly larger at higher temperatures. For an increase of 1°C the power of the HVAC system increases 30.8 W.

Figure 14c indicates the relationship between the average 24-hour temperature and the runtime fraction (%). A 24-hour period (12:00 am – 11:59 pm) was used since the automated internal sensible and latent loads simulated during this time are set to be the same for each day studied. The results are organized to show the runtimes for each of the three different indoor set point temperatures as separate series. An approximately 2°C increase in indoor set point temperature decreases the runtime by approximately 10-15% for the properly functioning HVAC system. A 1°C increase in average daily outdoor temperature increased the runtime by 4.5-7%.

To evaluate the impact of the two studied faults, including condenser airflow reduction and low refrigerant charge, two types of tests were conducted, including near-constant temperature tests and long-term tests. Impact on power, runtime, cooling capacity are annualized and results are included in Figure 14. Figure 14b and d show the impact on power and runtime due to condenser faults at 10% and 25% condenser fault levels at indoor set point temperatures of 21.1°C, 23.4°C, ad 26.7°C.

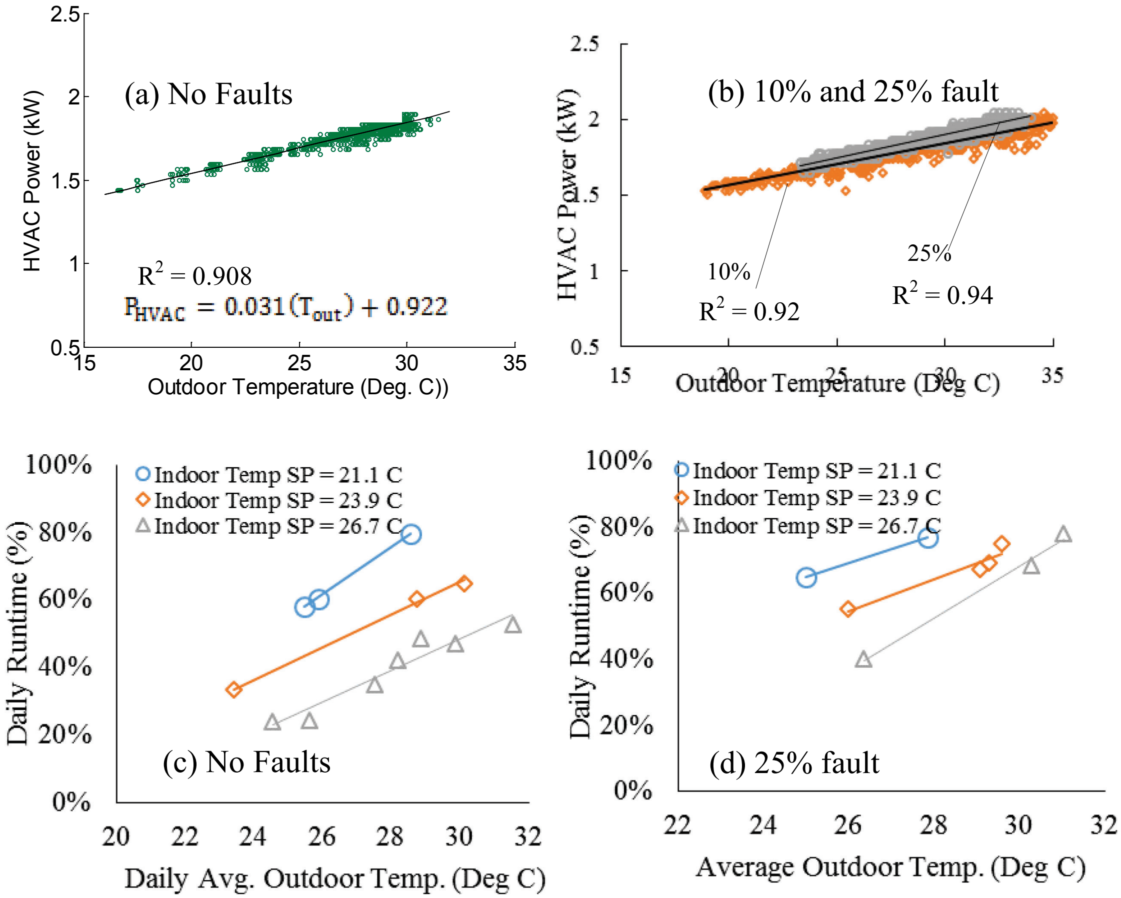


Figure 14: (a) HVAC power draw (kW) of a properly functioning system and (b) power draw (kW) with a 10% and 25% condenser air flow reduction; (c) Daily runtime values (%) for a properly functioning HVAC system at varying daily average outdoor temperatures and indoor set point temperatures and (d) Daily runtimes values (%) for an HVAC system a 25% condenser air flow reduction at varying daily average outdoor temperatures and indoor set point temperatures.

The short term, near constant temperature tests conducted found that the condenser air flow reduction fault increased the power by 3-8% depending on the level of fault. The refrigerant charge fault results are shown in Figure 14d. The short-term tests found a decrease of 6% and 12% in power with a 10% and 25% reduction in refrigerant. These values are consistent at all of the outdoor temperature observed. The runtime of the HVAC system also increases with an increase in the degree of fault.

The cooling capacity and coefficient of performance were also affected by the HVAC faults. Calculating these values using the equations presented in the Methodology section in Appendix E, the condenser flowrate fault decreases the efficiency by 6% and 12% at a 10% and 25% air flow fault. It similarly decreases the cooling capacity, on average, by 4 and 11% at 10% and 25% air flow fault. The specific data are shown in Figure 15a-b.

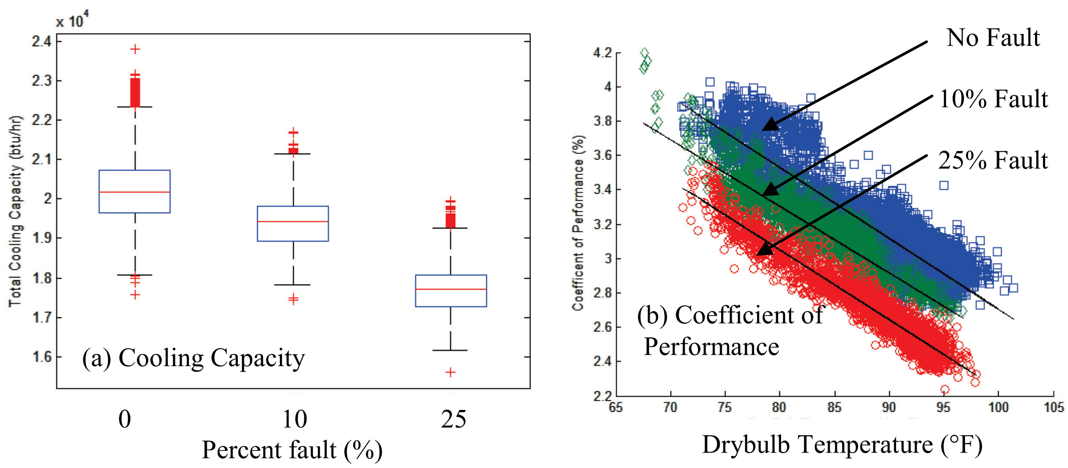


Figure 15 (a) HVAC cooling capacity reduction at a 10% and 25% air flowrate reduction and (b) the coefficient of performance of the HVAC system (%) at the two levels of condenser air flowrate fault

5.5 Thermal Comfort Evaluation Using the Response Surface Methodology and Uncertainty Analysis (Objective/Investigation 3)

This section discusses the results of the use of the response surface methodology to evaluate the effect of operational changes of a residential building's HVAC system on the thermal comfort of occupants. It also compares thermal comfort changes to energy use associated with these changes. This includes evaluation of the response surface methodology as a low-order model of a building's thermal comfort response to changes in operational and physical design variables. Two long-term thermal comfort evaluation indices were investigated which include the percent of time outside the thermal comfort zone (*POS*), and the average percent of people dissatisfied (*Average PPD*). These measures are used for two different scenarios, including time-of-use pricing and a 1-hour demand response event.

This section discusses the time-of-use (TOU) pricing study and its evaluation of *Average PPD*. The effects of automatic setbacks using smart thermostats in response to time-of-use pricing on occupant thermal comfort were evaluated for representative single family residential buildings located in 3 climate zones with dominant cooling loads. Building energy models (BEM) of single family homes are evaluated using a full factorial experimental design to create a response surface. These design variables include indoor set point temperature, TOU degrees of setback temperature, thermal mass, and air exchange rate for each climate zones. These are compared to the relative energy savings resulting from TOU thermostat setbacks while considering other design variables. Further discussion on this methodology and the results of the 1-hour demand response event and the results regarding the *POS* are included in Appendix C. Additional information on the time-of-use pricing study is included in Appendix D.

Summary of Findings of Thermal Comfort Evaluations

In evaluating the use of the proposed methodology as a model for a building's thermal comfort response to changes in operational characteristics, a second-order response surface was found to provide a reasonable fit to building energy model simulation in- and out-of-sample data. It provided a better fit to the data for the Average PPD thermal comfort index as compared to the POS. Regarding influential variables on occupant thermal comfort, thermostat setbacks during peak energy pricing times were found to increase the average percent of people dissatisfied. However, the indoor set point temperature was the most influential of the variable studied in decreasing long-term thermal comfort, while improving HVAC energy efficiency. The thermostat setback (1-4°C) had the strongest influence on thermal comfort in a hot-dry climate, while the most HVAC energy savings is achieved in the mixed-humid climate zone. The results are constructed in such a way that costs and benefits of TOU rates for homes with different characteristics, in climate zones with air conditioning-dominate energy consumption can be evaluated.

Specific Results and Discussion

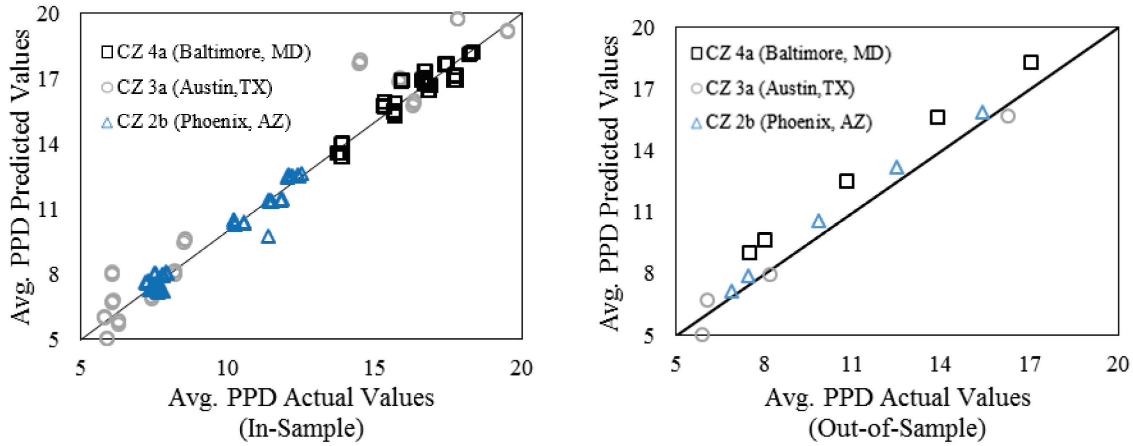
To develop a response surface each of the four design variables were used as inputs to build and define the response surface. Each design variable required an upper and lower bounds of which the variable is evaluated and the model is valid for in the developed response surface. The upper $x_{i,high}$ and lower $x_{i,low}$ bounds of the set point temperatures were chosen to be within the limits of the summer thermal comfort zone. The degrees of setback temperature was chosen to represent the extreme minimum (no setback), to maximum setback from demand response and time-of-use rate trials (Siemann 2013). The upper and lower bounds of the air exchange rate were chosen to cover a range of values common in newer buildings (Offerman 2009). Thermal mass varies depending on the amount of interior walls and furniture inside a residential building. These variables are summarized in Table 5.

Table 5: Design variables used to create thermal comfort response surface model

Type	Variable	Lower bound $x_{i,low}$	Upper bounds $x_{i,high}$	(Geometric) Mean μ_i	Standard Deviation	Distribution
Operational	Summer (Cooling) Set Point Temp. (ºC)[1]	21.1	29.4	25.1	1.7	Normal
	Setback Temp (ºC)[2]	0	4.5	1.8	1.3	Normal
	Air Exchange Rate (ACH) (1/hr)[1,3]	0.10	1.0	(0.26)	(1.04)	Lognormal
Structural	Internal Thermal Capacitance (kJ/°C-m^2)[4]	26.4	39.3	35.1	4	Normal

[1] *Pecan Street Research Institute; Dataset on building energy audits and survey performed in 2013 and 2014 on residential buildings in Texas*
[2] *Siemann 2014*
[3] *Offermann, F. J. (2009).*
[4] *Building America Building Simulation Protocol (2010)*

In predicting the *Average PPD*, the response surface provided a strong fit to in-sample data. The second order response surface model showed a stronger fit than a first order model, with a coefficient of determination (R^2) value of 0.995 to 0.997 for in-sample data fitting in each of the studied climate zones. For out-of-sample data, a set of values for the design variables was created using a random number generator within the range of the minimum ($x_{i,low}$) and maximum ($x_{i,high}$) limits of the experimental design and compared to the predicted values using the response surface. This also shows the strong fit between the model-predicted and the actual values. Parity plots showing the fit of out-of-sample data are shown in Figure 16. For the out-of-sample data, the Average PPD models show a strong fit, with the model for Climate Zone 2a and 4b over-estimating the value of Average PPD slightly (1% and 3% respectively).



(a) (b)

Figure 16: Parity plots comparing the model-predicted values of the Average PPD for in-sample (a) and out-of-sample (b) data. Note: CZ = climate zone, PPD = Percent of people dissatisfied

Regarding influential factors on the *Average PPD*, in all of the studied climate zones, increases in set point temperature and increases in setback temperature also increase the *PPD*. This is shown in Figure 17 in this chapter, and in Figures 5 and 6 in Appendix D. Increased discomfort due to increased set point temperatures is consistent with ASHRAE 55 (2010), in which the percent of people dissatisfied increases with increasing indoor temperatures. Similarly, in all of the studied climate zones, an increase in thermal mass has very little effect on the *PPD*. A home with a larger thermal mass can reduce indoor temperature increase rates because a higher thermal mass introduces a thermal lag or time delay in the flow of heat from exterior to interior. Thus if the thermostat is set back it can take more time for a higher thermal mass building to increase in temperature to where the occupants are uncomfortable. However, the thermal mass in the modeled buildings represents the typical thermal mass of a newly built home. This thermal mass and variation in thermal mass is small in comparison to what has been used to effectively affect thermal comfort in residential buildings in previous studies (e.g. Balaras 1996, La Roche and Milne 2004, Ogoli 2003). In all of the studied climate zones an increase in air exchange rate, increases the PPD and POS. This is consistent with previous findings (e.g. Berardi et al 1991, Rijal et al 2007). If an increased amount of unconditioned outdoor air enters into the indoor environment due to a higher air exchange rate, this can increase indoor temperatures faster, resulting in a longer period of time at a higher temperature.

The most significant second-order RSM terms vary by the climate zone in which the building is located. The set point temperatures and squared set point temperature were significant influences for the *Average* PPD in all of the studied climate zones. Air exchange rate has the most influence in Climate Zones 3a and 2b. Additionally several of the reaction terms were significant.

In evaluating the influence of the degrees of setback on thermal comfort, the *Average PPD* is compared with a constant set point temperature with zero degrees of setback, at each of the different design scenarios. At a degree of setback of zero, this represents a constant set point temperature regardless of the peak pricing. Figure 17 shows that the influence of the number of degrees of setback has a non-linear influence on the long-term thermal comfort indices. Each of the lines in Figure 17 represents a different set point temperature and is labeled as such. The mixed-humid and hot-dry climate zones are included in this figure; additional plots are included Appendix D.

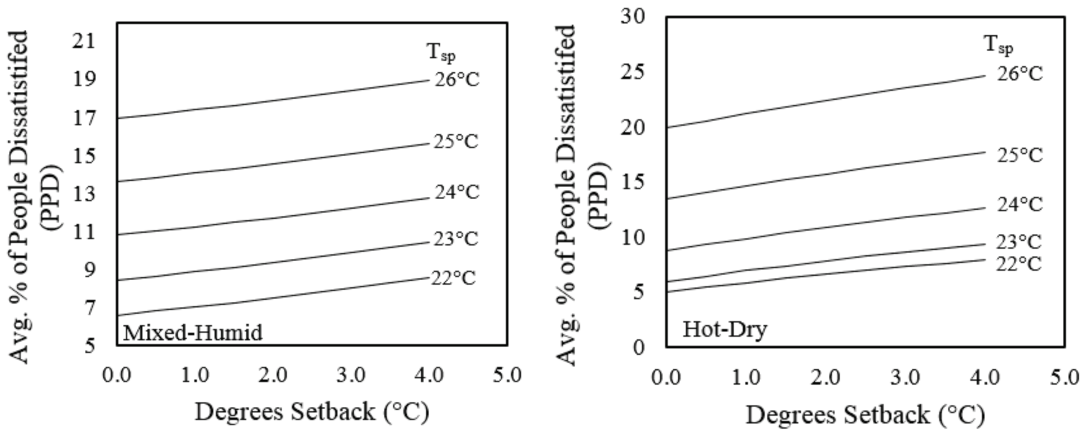


Figure 17: Influence of degrees of setback temperature on the *Average PPD* at a range of indoor set point temperatures for Climate Zone 4a (mixed-humid), and 2b (hot-dry). *Note: Each line represents a set point temperature; a constant value for ACH of 0.4 h^{-1} and thermal capacitance of 35 kJ/°C-m^2 are used in the creation of these graphs.*

The degrees of setback during the on-peak times most strongly influences the thermal comfort indices in Climate Zone 2b (hot-dry). A four degree setback increases the *Average PPD* by 3.5% to 4.5% in this climate zone. In a hot climate with the highest number of cooling degree days in comparison to the other studied climates, this is a reasonable result. With a higher outdoor temperature, this will cause the building's indoor temperatures to increase faster during the setback times, as the building absorbs more solar radiation and transfers heat to the interior with a higher interior-to-exterior temperature gradient. The greatest change in the *Average PPD* is due to changes in the degrees of setback temperature when the set point temperature is lower. Changes to the set point temperature have the strongest influence on thermal comfort in the hot climate zones (2b, hot-dry and 3a, hot-humid). The *Average PPD* varies by approximately 17% across a range of 5°C in set point temperature for Climate Zone 2b (hot-dry), and 19% for 3a (hot-humid). These variations in thermal comfort are 56% and 77% more, respectively, than for Climate Zone 4a (mixed-humid).

Looking at the effects of a larger scale implementation of time of use pricing, probabilistic analysis allowed for evaluation of the effects on a set of homes with a distribution of setback temperatures. Assuming an adoption rate of the degrees of setback temperature for time of use pricing from Siemenn (2014), and the probability distributions of the design variables, Monte Carlo simulation the results are shown in Figure 18. For homes in the hot-dry climate zone a lower percentage of the homes meets the suggested maximum 10% PPD as compared to the mixed-humid and mixed-hot climates. For homes in the hot-dry climate zone approximately 35% and 60% of single family homes have an Average PPD of 10% and 15% respectively, where as in the hot-humid and mixed-humid climate zones, 45-65% and 80% of homes have an Average PPD of 10% and 15%. The hot climate zones also have a longer tail of homes at high values of Average PPD than the mixed climate zone.

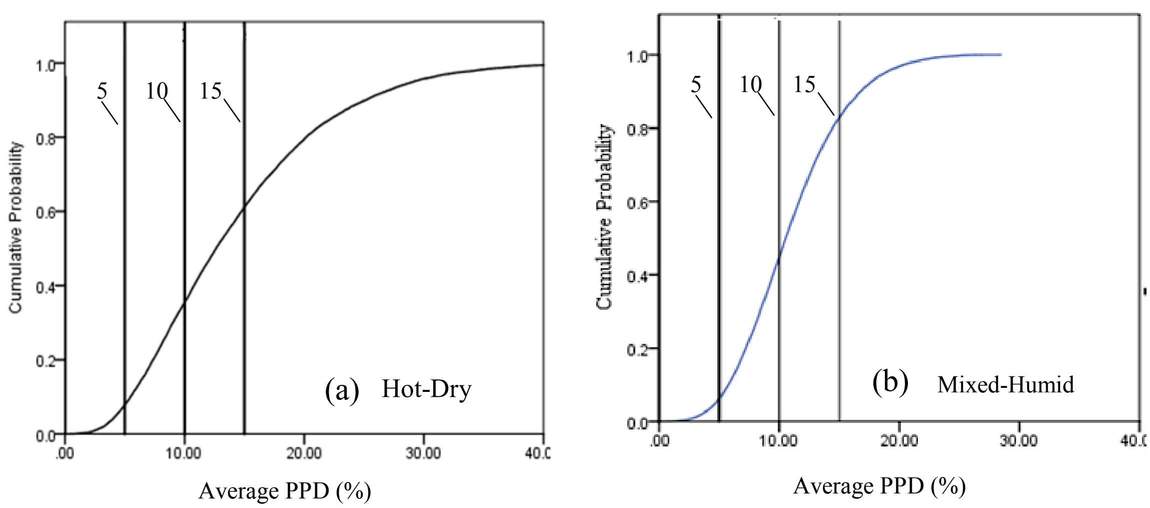


Figure 18: Cumulative probability of the Percent of People Dissatisfied (%) for Climate Zone (a) 2b (hot-dry), and (b) 4a (mixed-humid) resulting from Monte Carlo simulation for a community of homes

Figure 19 shows the comparison of the HVAC energy use to the *Average PPD* at an ACH of 0.4 h^{-1} and a thermal mass of 35 kJ/°C-m^{2}, with variations in set point temperature and degrees of setback. Each cluster of data points has a set point temperature and are labeled as such. The variation in the values in the clusters is due to the change in degrees of setback temperature (0 - 4°C) with the highest degree of setback being the points with the highest thermal comfort dissatisfaction. The left most data point in each cluster corresponds to the condition of zero setback in the thermostat during the peak use times.

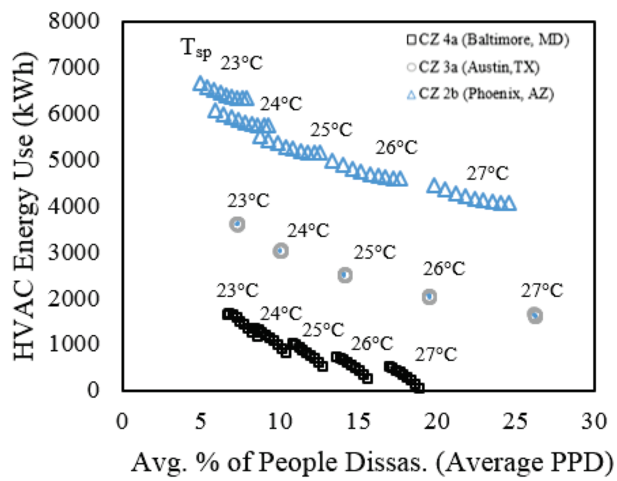


Figure 19: HVAC energy use compared to the long-term thermal comfort indices Average PPD for a new IECC code-compliant single family home in Climate Zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry).

Note: Each cluster of points has a set point temperature as labeled; the variation in the values in the clusters is due to the change in degrees of setback temperature (0-4°C from left to right); a constant value for ACH of 0.4 h^{-1} *and thermal capacitance of 35 kJ/°C-*m^{2} *are used.*

In Climate Zone 2b (hot-dry), the HVAC energy use is highest, followed by Climate Zone 3a (hot-humid) and 4a (mixed-humid). This is consistent with the values of the cooling degree days of the studied climate zones. The thermal comfort of occupants decreases as the HVAC use increase; however, this trend is not linear and depends on which long-term thermal comfort index (Average PPD or POS) is used. As the indoor set point temperature increases, and the degrees of setback increases, the amount of HVAC energy use decreases. An increase in the number of degrees of setback causes the greatest decrease in HVAC energy use in the mixed-humid climate as compared to the other studied climate zones. This is likely due to the less extreme outdoor temperatures and solar radiation in the mixed-humid climate that would not heat the residential building as quickly during the peak use time when the set point temperature is higher. An increase in set point temperature also causes the least increase in occupant dissatisfaction in the mixed-humid climate zone compared to the other studied climate zones.

Chapter 6: Summary of Conclusions

The work presented in this dissertation explored the use of both highly granular building energy use data and the capabilities associated with “smart”, electric grid-connected technologies to better understand residential building energy performance and its effect on occupant comfort. More specifically, the work established in this dissertation first proposes novel ways to utilize detailed residential building energy data to develop insights into how the two largest contributors of residential building energy use, large appliances and HVAC systems, use energy. Secondly, it utilizes energy data collected in the field, results from laboratory experiments and building energy modeling for (1) assessing the potential for peak load reduction of large smart appliances and (2) determining if two common types of HVAC faults may be present and the energy savings associated with their correction in a cooling dominated climate. Finally, this research proposes a novel methodology to assess the effect of changes to building operations, such as those used to reduce building energy use and peak energy load, on the comfort of occupants. This methodology is applied to two commonly used peak energy load reduction scenarios that utilize smart thermostats.

A total of five different research studies were conducted addressing three main Objectives. The introduction, background, methodologies and results are summarized in Chapters 1-5, and are presented in full in five full-length journal articles included in Appendices A-E. The major findings of the three objectives are summarized below.

- Appliance use patterns in the studied hot-humid climate zone are, in general, similar to that of previous findings in other climate zones; the time of day of appliances use is most strongly influenced by whether or not occupants have one or more members that work from home, as compared to seasonal, and weekday/weekend variations.

- Smart clothes dryers and refrigerators provide the greatest peak load reduction potential of the four studied appliances for peak loads that occur in the afternoon and evening; clothes dryers have a higher peak load reduction potential, but the uncertainty of this peak load reduction is higher than that of the more consistent refrigerator peak load savings.
- Annual runtime of residential HVAC in the homes studied located in a hot-humid climate is 20%; however, significant variations in this runtime, which vary by season and time of day, demonstrate representing HVAC runtime as single value is highly simplified. HVAC use is lowest when outdoor temperatures average approximately 15°C, and it increases as temperatures increase and decrease beyond this value.
- HVAC energy use and runtime are most closely correlated when comparing at the monthly temporal scale, and show a linear correlation with increasing variation in energy use with increasing runtime; a 25% and 50% monthly runtime equate to an average of approximately 450 kWh and 900 kWh per month of HVAC energy use respectively for the studied homes. However there is considerable variation in the energy use.
- Faults in residential HVAC systems affect the power, energy use, runtime, cooling capacity and coefficient of performance of these systems; with the correction of HVAC faults of up to 25%, 1.4 to 5.7% of whole-home energy savings can be achieved for HVACs located in hot-humid climate zones. Of the studied values power depends on the HVAC characteristics, however energy use

and runtime also depend on occupant behavior and building characteristics and thus are less useful in determined the occurrence of a fault unless the building's operations and occupant schedules are either consistent or taken into account.

- The proposed methodology which utilizes a response surface and probabilistic modeling to assess long-term thermal comfort of occupants provides a good fit to in and out of sample building energy simulation data, and enables the quick assessment of occupant discomfort associated with building operational and physical changes.
- The thermostat set point temperature has the greatest influence on long-term occupant thermal comfort when considering a home using time-of-use pricing and a smart thermostat; an increased degree of setback temperature of the thermostat during peak use times (2-8 pm) increases the Average PPD.

These specific findings uniquely contribute to an improved understanding of buildings, their energy use and performance. Large, highly-detailed building energy use information and datasets have not historically been available, due in part to the difficulties in the collection and storage of this information. However, moving forward, with increasing implementation of smart meters, home energy meters, and home energy management systems, and other data collecting devices, much more information is being collected and stored. This thesis presents a closer look at how insights can be drawn from this information to improve current assumptions in building energy modeling and indoor air modeling, and to inform energy policy and legislation.

The methodologies presented in this research can be applied to other collected building energy information to assess the use patterns of the same or other types of energy users and technologies. HVAC operational characteristics can be useful in improving indoor air modeling. The use pattern findings presented in this research can also be compared to those collected in other locations, climate zones, and building types. As policy makers and utility companies implement legislation and programs aimed at improving electric grid reliability and energy efficiency, the presented results on peak load and energy reduction could be used to inform these efforts. Similarly, when building owners and operators assess the costs and benefits of implementing energy reduction strategies, the proposed thermal comfort evaluation methodology can be used to assess what affects these changes will have on the comfort of occupants in the considered building.

Implications and Future Work

The number of buildings being built and in use is rapidly growing throughout the world, as is the size (m^2) of the indoor environment (United Nations 2012). In some places, such as Manhattan in New York City, the area of the indoor environment is already nearly three times that of the area of land in which the buildings are constructed (Martin et al 2015). However, as suggested by Stephens et al (2015) and Ramos and Stephens (2014), there is limited documentation of these buildings' characteristics, such as ventilation strategies, air exchange rates, HVAC operations, temperature, humidity, surface temperatures, human occupancy and other parameters. This research contributes to a better understanding of these characteristics and the variations associated with them, particularly for HVAC and large appliances. However additional information continues to be needed. With increasing availability of energy use data, and the increasing interest in the use of sensors and connected technologies, called the *Internet of Things*, to monitor buildings, there are many additional opportunities to contribute to a better understanding of our built environment characteristics. With this additional information on building operational and physical characteristics, this can help to better characterize building environments and their influence occupant health, indoor environmental quality, microbial presence and exposure.

Beyond characterizing the existing building stock, as changes are made to building operational and physical characteristics to improve energy efficiency and reduce buildings' contribution to peak loads, these changes also have additional implications. One of these, occupant thermal comfort, was assessed in this research. In addition, these change may also affect occupant behavior, and the indoor environment. While the study of these topics are not within the scope of this research, it is prudent to discuss these implications as natural extensions to this work. Methodologies suggested in this work, such as the response surface methodology, may also be applied to assess and model the relationships between energy savings and these aspects of the built environment.

First, energy and peak load reduction programs, such as those discussed in this research, may affect occupant behaviors. These programs implemented in residential buildings, provide energy and cost savings to the consumer. Recent literature suggests that while this cost and energy saving may be realized, the additional money gained may also be partially re-spent on other energy-consuming activities or behaviors. This is known as the *rebound effect* (see Sorrell and Dimitropoulos 2008, Sorell et al 2009, Greene 2012), and can be classified as direct or indirect. For example, a direct rebound effect of participating in an HVAC demand response program may be deciding to turn down the thermostat to keep their house cooler using the money saved. An indirect rebound effect may be deciding to reinvest the money buy a larger, less efficient vehicle. These effects have been documented in a number of studies (Druckman et al 2011, Freier-Gonzalez 2011, Thomas and Azevedo 2013) which have estimated both direct and indirect effects together can range from 30-40% in the United States. Some of these rebound effects are measurable looking only at the electricity use signal, while others are not. Further assessing these effects is of interest in future work.

Changes to building characteristics can also have significant implications on indoor air and environmental quality, including the microbiome of the built environment. However, the implications of these changes remains to be fully explored, as discussed in Martin et al (2015). As we spend nearly 69% of our time in residential buildings, and over 90% indoors, this is an important extension of this work. Energy efficiency upgrades and changes to remove faults or building inefficiencies can include changes to residential building parameters including reduction in air exchange rates, introduction of outdoor air ventilation, changes to HVAC operations, improved insulation and fenestrations, among others. Peak load reduction strategies, particularly those which include HVAC cycling, thermostat setbacks, can affect the temperature, humidity, indoor/outdoor air fractions, filtration, pressure differentials, and air mixing. Even small changes to these indoor environmental characteristics can influence microbes (Frankel et al 2012, Kembel et al 2012, Meadow et al 2014), and indoor air pollutants such as inorganic and organic (VVOCs, VOCs, SVOCs) gases, and particulate matter both in the air and on or in surfaces. For example VOCs emissions from consumer and building products have been shown to increase with temperature and relative humidity (Haghighat et al 1998, Lin et al 2009, Masuck et al 2011, VanderWal et al 1997). Similarly temperature, air mixing, and air exchange rate have been shown to influence SVOCs (Liang et al 2015, Clausen et al 2010, Liang and Xu 2015). As strategies are developed to improve energy efficiency and electric grid reliability through changes to buildings and their operations, understanding the implications of these changes on the indoor environment is also an important extension that merits further investigation.

Appendix A

Paper 1: Appliance Daily Energy Use in Residential Buildings: Use Profiles and Variation in Time-of-Use

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Abstract

One of the largest user of electricity in the average U.S. household is appliances, which when aggregated, account for approximately 30% of electricity and 29% of site energy used in the residential building sector. As influencing the time-of-use of energy becomes increasingly important to control the stress on today's electrical grid infrastructure, understanding when appliances use energy and what causes variation in their use are of great importance. However, there is limited appliance-specific data available to understand their use patterns. This study provides daily energy use profiles of four major household appliances: refrigerator, clothes washer, clothes dryer, and dishwasher, through analyzing disaggregated energy use data collected for 40 single family homes in Austin, TX. The results show that when compared to those assumed in current energy simulation software for residential buildings, the averaged appliance load profiles have similar daily distributions. Refrigerators showed the most constant and consistent use. However, the three user-dependent appliances, appliances which depend on users to initiate use, varied more greatly between houses and by time-of-day. During peak use times, on weekends, and in homes with household members working at home, the daily use profiles of appliances were less consistent.

1. Introduction

Currently, buildings consume approximately 40% of site energy in the U.S., over half which is consumed by residential buildings [1]. Residential buildings alone are responsible for over 37% (4.89 EJ) of electricity consumed in the U.S. [1]. In Europe, households are responsible for 25% of total energy needs, including 68% of total building energy use [2]. High peak electricity demands in the afternoon and early evening of the hot months of the year, much of which is due to fluctuation in building use, have further motivated the development of strategies to reduce electric loads during these times. These changes can only be achieved, however, if the current energy use is first understood in detail.

One of the largest portions of electricity use household is from large appliances, which, when aggregated, account for approximately 30% of all electricity used in the residential building sector in the U.S. [1]. This, together with small appliances, home electronics, and lighting, accounts for more than 2/3 of total residential electricity use. Appliances are of particular interest for study due to their high penetration rate, and increasing rate of penetration across the world [3 and 4]. In recent years, appliances have been targeted by manufacturers and utility companies as methods to shift or reduce peak energy use. In addition, unlike changes to heating and air conditioning use, changes to their time-of-use will not significantly affect the comfort of the indoor environment.

Four large appliances including, refrigerators, clothes washer, clothes dryers, and dishwasher, are among the most common large appliances found in U.S. homes. Refrigerators are the most common, followed by washers, dryers and dishwashers [4]. This order of penetration of appliance ownership is similar in other developed and developing countries [3], and continues to increase globally [5]. According to the 2012

American Housing Survey [4], 99%, 84%, 81% and 66% respectively, of all single family homes in the United States have each of these appliances, each with an average annual energy consumption of 1240, 120, 1080, and 510 kWh respectively [6]. New, more energy efficient appliances use up to 40-50% less energy than those sold in 2001 or earlier. This study specifically focuses on directly monitored electricity consumption of appliances. Other indirect impacts on energy due to hot water use, and latent and sensible heat gains that may non-linearly effect whole-home energy use are the subject of on-going research, but not included in this study. While there are many available datasets providing values for annual consumption (kWh) of appliances for a household (e.g. [4][6]), there is, however, limited information available regarding when, over the course of a day, these appliances are used.

Studying this, and the influencing factors associated with these use profiles is important for multiple reasons. This includes an improved understanding of the potential electricity use reductions possible from appliances during peak use times, and improved input values of appliance use to improve the accuracy of residential building energy modeling.

The most recent large-scale appliance-specific study to analyze time-of-use of appliances in residential buildings in the U.S. was conducted in 1989 [7]. This study developed daily profiles for major household appliances use using disaggregated circuit-level data, including the four discussed in the current study. It remains, to the authors' knowledge, one of the largest and most detailed studied to-date on residential appliance use in the United States. A large database of appliance energy use in European households has been complied through the REMODECE—Residential Monitoring to Decrease Energy use and Carbon Emissions in Europe project, which is discussed in [8].

For each country this typically includes several weeks of data for multiple households. Several smaller studies have also looked at time of use of appliances [9][10][11], and have found a wide variation in the time-of-use, with increased use [9] and variability [10] in the mid-morning and evening hours for single and multiple or groups of appliances [9-11]. Refrigerator energy use was found to be the most constant over a 24-hour period with small peaks in morning [7,9] and evening hours [9][11]. Several other studies have focused on appliance use trends [12] and identification [13] in the UK, and on day ahead appliance energy use prediction in France [14] using the IRISE database included in [8].

To predict energy use, previous literature has indicated that factors such as occupant behavior and socio-economic status are important [15]. Nielsen attributed 36% of variation in energy consumption of homes to lifestyle and occupant behavior, and 64% to socio-economic influences. Other factors such as climate zone, number of occupants, income level, age of home, and size of home have also been correlated with home energy use. Compared to whole-home energy use, likely the energy use of appliances such as dishwashers, clothes washers and clothes dryers is more highly influenced by occupant behavior since they depend solely on the user for operation. With human behaviors and lifestyles constantly changing since the 1989 study, such as a more than 35% increase in the number of adults that work one or more days a week from home since 1997 [16], this may affect time-of-use of appliances. Other studies have focused on appliance energy use feedback [17]. Additionally, U.S. federal standards for new appliances set in 1987, which have been consistently reviewed and revised since, have reduced energy consumption of appliances significantly, with a predicted savings of 74 EJ of energy through 2020 [18]. Borg [19] found that in Europe, appliance efficiency did reduce energy loads, but not peak electrical demand.

Additional information is thus desired to better characterize appliance energy use in the current residential building stock. The effects on the time-of-use of these and other factors, such as the influence of residents working from home, and the day of the week have not been studied in detail. Establishing a simple and adaptable methodology to assess appliance use over time will also prove helpful as influences on appliance use patterns change. This is particularly useful to predict the potential influence that "smart" appliances, connected to the smart electric grid, and to provide updated inputs to building energy simulation loads.

This study aims to address the need for a more detailed understanding and analysis of daily energy use patterns and several of the factors that influence them. More specifically this study will explore the following questions:

1) When do appliances use energy throughout the day, and how do their electricity use profiles look?

2) How much do these load profiles vary each hour between homes and what are possible sources causing this variation?

3) If appliance load monitoring is to be conducted in future studies, what is the least amount of time needed to achieve a representative load profile of home appliances?

This paper is organized into three sections. The method used to develop a normalized energy use profiles is discussed, followed by the results of using this method for each of the four studied appliances. These results are compared, and two influencing factors on these profiles are also discussed and analyzed.

2. Methodology

Energy use was monitored in this study, as discussed in Lopes et al. [20] and Crosbie [21]. One-minute energy consumption data was collected for 40 homes in a concentrated area in Austin, TX. These homes are part of a 250-home smart-grid deployment project (data collected by Pecan Street Research Institute) which began monitoring home energy consumption in 2012. These homes consist of newly constructed single family homes, built in 2007 or later. Several different types of home energy management systems (HEMS) were installed in a subsets of homes to monitor energy use. This study is limited to 40 of the 250 homes monitored, since the data collected by the type of HEMS deployed in these 40 homes was, of those installed, found to provide the best agreement with the electricity utility meters. The utility meters represent the upper bound of accuracy available for HEMS.

The HEMS use "CT" (current transformer) collars which are clamped to the individual circuits of each home's breaker box, and an adapter that connects to the home's internet router for data collection. The HEMS provides root-mean-square (RMS) of current and voltage to calculate average real power and apparent power, which is saved at one-minute increments. Circuit monitoring includes consumption data for the whole house, as well as multiple different individual circuits, including individual appliances for many of the homes. Further information on the data collection methodology of these homes is discussed in detail in [22]."

One year of disaggregated energy use data (March 1, 2012 – February 28, 2013) was collected for each of the 40 homes studied. The starting date of monitoring varies, however all but two homes (5%) had begun recording energy consumption data by March of 2012.

To demonstrate the characteristics of the 40 homes sampled in this study, data from home energy audits and resident surveys is compiled in Table 6. Table 6 also includes average demographic and physical characteristics of the homes for U.S. and

Texas building stock. The average number of occupants per home in this study (2.86) is similar to the average U.S. residence (2.6). However, this dataset's homes are larger and newer, and have a higher household income. In addition, a relatively high percentage of households (50%) indicating they work from home twenty or more hours per week.

Table 6: Characteristics of all homes studied vs. homes with each appliance circuit monitored

Category	U.S. Homes (in thnds)[1]	Texas (in thnds)[1]	Homes Studied[2]	Dish-washer[2]	Refrig-erator[2]	Clothes Washer[2]	Clothes Dryer[2]
Housing Units	131,035	9869	40	9	15	12	18
Single Family Homes	61.70%	65.60%	100%	100%	100%	100%	100%
Year Built (2005+)	5.10%	8.50%	100%	100%	100%	100%	100%
Number of Bedrooms (avg.)	2.4	2.5	3.2	3.3	3.4	3.4	3.2
Area (avg.)	158	--	204	218	212	200	202
Household Size (avg.)	2.6	2.79	2.86	2.88	2.69	2.2	2.63
Level of Education							
Less than Bachelors	71.8%	74.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bachelor's Degree	17.7%	17.4%	12.5%	11.1%	20.0%	25.0%	11.1%
Graduate Degree	10.5%	8.6%	87.5%	88.8%	80.0%	75.0%	88.9%
Household Income							
Up to $ 49,999	47.3%	49.2%	7.5%	0.0%	13.4%	16.6%	11.2%
$50 - 74,999	18.3%	18.0%	10.0%	11.1%	6.7%	8.3%	16.7%
$75 - 99,999	12.4%	11.8%	22.5%	22.2%	20.0%	25.0%	22.2%
$100 - 149,000	12.7%	12.2%	27.5%	22.2%	26.7%	25.0%	22.2%
$150 +	9.2%	8.9%	32.5%	44.4%	33.3%	25.0%	27.8%
Work From Home (hr/week)							
None/Not Reported	--	--	42.5%	44.0%	33.3%	41.7%	27.8%
1 – 20	--	--	17.5%	11.1%	6.7%	0.0%	16.7%
21-40	--	--	27.5%	22.2%	40.0%	41.7%	44.4%
41+	--	--	12.5%	22.2%	20.0%	16.7%	11.1%

[1] American Community Survey, 2011, 1-year estimates [23]

[2] Pecan Street Inc data (see Rhodes et al 2014 [22] for data collection methodology)

2.1 Appliance Circuit-Level Data

Appliance circuit-level data was available for a subset of the 40 homes studied. Table 6 also provides information on the number of homes with each of the appliance-specific circuits used, and their corresponding average characteristics. The same subcircuits and appliances were not monitored for all homes. In each of the 40 homes, one or more of the four studied appliances was monitored. From the 40 analyzed houses, 15 homes had dedicated circuit for the refrigerator, 12 homes for the clothes washer, 18 homes for the clothes dryer and 9 for the dishwasher. The characteristics of these appliances are shown in Table 7. Comparing the 40 home average characteristics to those of each set of homes with appliance-specific load monitoring, household size (number of occupants) and home size (m2) are less than 8% different from with the exception of those homes with monitored clothes washer. In each of the subsets over 45% of homes reported working from home twenty or more hours per week. The estimated annual energy use of each of the studied appliances is shown in Figure 20, as compared to the Residential Energy Consumption Survey from 2009 [6].

Table 7: Characteristics of all homes studied vs. homes with each appliance circuit monitored

Appliance	Year	Types	kW (average)
Refrigerator	2008-2009	Bottom Freezer (50%) Side-by-Side (44%) Top Freezer (6%)	0.85
Clothes Washer	2000-2009	Front Load (60%) Top Load (40%)	1.34
Clothes Dryer	2003-2009	---	3.65
Dishwasher	2007- 2009	---	1.25

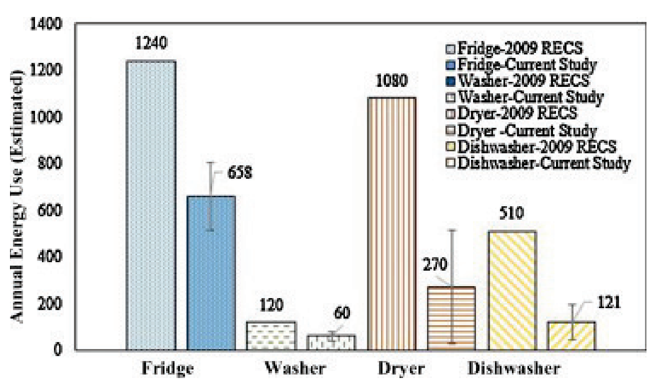


Figure 20: Appliance Average Annual Energy Use (kWh) compared to the Residential Energy Consumption Survey (2009) [6]

2.2 Dataset Quality Control

Several quality control checks were performed on the dataset for its use in this study. The HEMS sometimes records false short peaks, so called "spikes", in electricity consumption, associated with the rebooting of the HEMS. These one-minute long spikes in the one-minute data (>20 kW) were removed and assigned the value of the average of the data points before and after. Over the year studied, a total of 0-7 minute (0-0.001%) data points for each home were identified as spikes for each of the 40 homes. With these spikes eliminated, the data was then aggregated into hourly time steps by summing 60 minutes of data (Watts).. This is consistent with the methodology and units for the widely-used building energy modeling software EnergyPlus [24], BEopt [25] and eQUEST/DOE 2 [26]. The use of kWh units also allows the resulting charts to be compared with previous studies on energy consumption of homes, end-use loads and load shapes.

While whole-home energy consumption was monitored nearly the entire length of the one-year period, some appliance circuits were disconnected for a period of time, resulting in missing data. To address missing field data, [7] suggested filled missing data with previous year's data for the same day. In this study, data was only considered usable in this analysis if over a 24-hour period: (1) all hours provided a non-null value, and (2) at least one hour of data (60 minutes) contained a non-zero value. Table 8 shows the total number of days of available data for each appliance across all homes, including the average, maximum and minimum number of days for each house. On average, washers and dryers were monitored for 44% and 61% of the year, and refrigerator and dishwasher were monitored for 33% of the year-long period.

Table 8: Available days of energy consumption data across 40 homes

	Refrigerator	Clothes Washer	Clothes Dryer	Dishwasher
Days monitored (across all homes)	2068	1752	3975	1330
Mean num. days monitored / house	122	159	221	121
Min. num. days monitored / house	29	29	39	29
Max. num. of days monitored / house	290	297	354	291
Standard Deviation of num. of days monitored per house	108	120	135	115

2.3 Energy Use Data Processing:

To calculate the normalized load profile of a specific appliance across the entire dataset, (a) a normalized load profile was created for each house, then (b) the normalized load profiles of all homes were averaged together over each hour. This method is similar to the method used in [7], however the results provide a normalized load profile comparable to those referenced in [27], rather than a ratio of monthly load to average load. Each home's load profile was given equal weight regardless of the number of days used to create that home's load profile, so as not to weight the average in favor of homes with more available data. To complete (a) for each home, the average energy consumption for each hour $E_{avg,h}$ in each non-null day of data for a particular home was averaged for each of the 24 hours using Eq. 1,

$$\left(E_{avg,h}\right)_a = \left(\frac{1}{N_h}\sum_{i=1}^{N_h} E_{n,h}\right)_a \qquad \text{(Eq. 1)}$$

where h is the number of the hour being averaged (e.g. h=1 represents 12:01-1:00 am), n is the number of the hour of monitoring being considered (e.g. n=4, this is the 4th day of monitoring), N_h is the total number of hours available for hour *h,* and $E_{n,h}$ is the energy use for hour *h* for hour number *n*. This creates an average load profile for house *a* for a particular appliance. To generate the normalized load profile for each hour, $E_{norm,h}$, each hour's average value was divided by the total average energy consumption for this average day, $\sum_{i=1}^{24} E_{avg,h}$, (Eq. 2).

$$\left(E_{norm,h}\right)_a = \left(\frac{E_{avg,h}}{\sum_{i=1}^{24} E_{avg,h}}\right)_a \qquad \text{(Eq. 2)}$$

To complete (b), all homes' normalized load from (a) were averaged by the hour (Eq. 3), where *A* is the total number of homes averaged. Each house's load profiles was given equal weight when averaged to generate the final normalized energy use profile. $\left(E_{norm,h}\right)_{avg}$ thus represents the percent of daily energy use used for a particular hour *h* for the average of the homes considered.

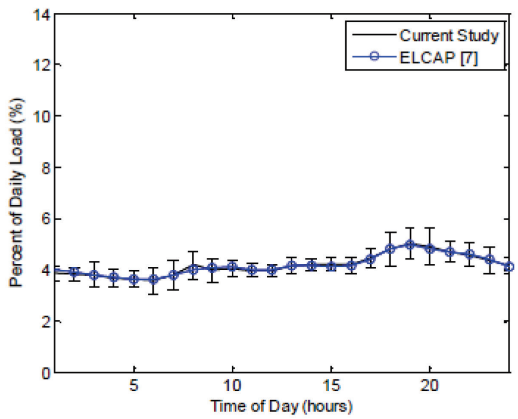
$$\left(E_{norm,h}\right)_{avg} = \frac{1}{A}\sum_{a=1}^{A}\left(E_{norm,h}\right)_a \qquad \text{(Eq. 3)}$$

All appliance circuits for the available homes were processed using this method develop average normalized energy use profiles.

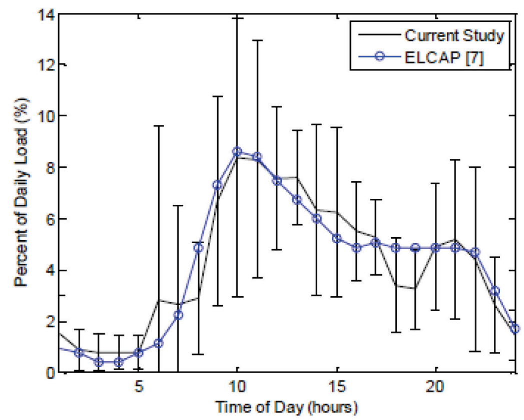
3. Normalized Daily Use Profiles by Appliance

The final normalized energy use profiles for each appliance are shown in Figure 21, with the x axis showing the time of day in hours. $\left(E_{norm,h}\right)_{avg}$, the percent of daily energy use load (PDL) of each hour, is plotted in black. The error bars represent one standard deviation in the value the normalized energy use of that hour among the homes studied.

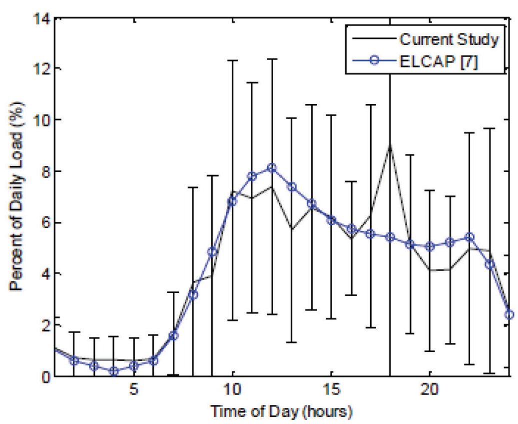
The dashed line is the normalized load profile developed from [7] and used in [25], plotted on the same graph for purposes of comparison. These results use all the energy use data available to develop the observed profiles.



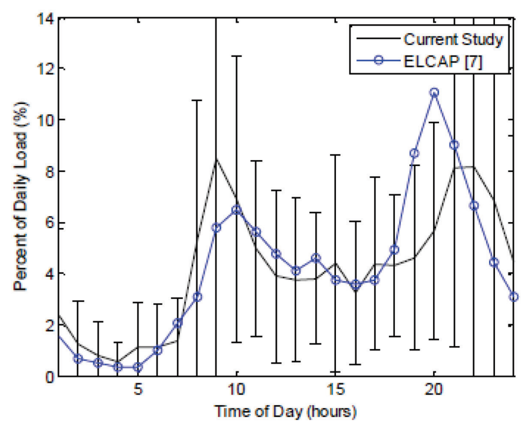
(a)



(b)



(c)



(d)

Figure 21: Average normalized energy use profiles for (a) refrigerator, (b) clothes washer, (c) clothes dryer, and (d) dishwasher from this study (black solid) and from Pratt [7] (blue dashed)

For comparing the normalized daily use curves developed for each appliance to Pratt [7], the sum of squared residuals (SSR), a measure of the overall difference between the new measured data's normalized energy use profile, and the previously developed use profile (Table 9). A small SSR indicates a tight fit between the curves and thus greater similarity, and a large SSR indicating there is a greater difference between the curves. This can also be thought of as the Euclidian distance in 2-D space, where minimizing this distance for all hours indicates more similar fit of the two curves. The refrigerators have the least difference between the previous study [7] (0.001 PDL) and the dishwashers have the most (0.75 PDL).

Table 9: Sum of the squared residuals (SSR), comparing this study's homes to previous study's results [7], and comparing segmentation of homes

SSR	All Days vs. [7] (PDL)	Weekday vs. Weekend (PDL)	Work at Home vs. Not (PDL)	Summer vs. Winter (PDL)
Refrigerator	0.001	0.02	0.01	0.01
Washer	0.27	0.62	0.85	0.71
Dryer	0.44	0.27	1.31	0.32
Dishwasher	0.75	1.06	0.72	0.20

3.1 Refrigerator

The refrigerator normalized energy use is a significantly flatter, more constant energy user than the other appliances analyzed in this study, varying between 3.5 and 5 PDL of total energy use per hour for all hours. The greatest energy use occurs in the afternoon, with the use peaking at 7:00 pm, consistent with the finding of [7] and [10], which also found the greatest use period during this time. The standard deviation for each hour's value is, on average 0.41 PDL. The greatest variation in use occurs between the hours of 6:00-8:00 am and 6:00-8:00 pm, consistent with times of meal preparation. Compared to the other appliances studied, this profile is the most consistent among homes, varying, on average, 5 to 9 times less between homes compared with the other appliances studied.

Compared to the profile developed by [4] for refrigerators, this profile values closely match, disagreeing, on average by only 0.04 PDL.

Influences on the energy consumption of a refrigerator have been correlated with outdoor temperature [9], and can also be influenced by indoor temperature of the room in which the refrigerator is operating. A lower indoor temperature closer to the temperature maintained inside of the refrigerator increases the coefficient of performance (COP) and reduces the power required to operate the refrigerator. The nominal efficiency (nominal COP) of the refrigerator, the amount of opening and closing of the doors that occur, and the amount of food stored, or thermal mass, in the refrigerator/freezer also influence the refrigerator operations. Since 1989 refrigerators have become increasingly more efficient due to increasingly stringent regulations. However, with a small difference between the profiles from Pratt et al. [7] and the current study, this indicates that these changes do not have a strong influence on the time-of-use of energy of refrigerators. The outdoor temperatures and indoor temperatures of homes throughout the monitoring period of this study and those in [7] likely were somewhat different, due to differences in climates between the Pacific Northwest and Texas. However without indoor temperature data, this correlation cannot be confirmed. With minimal differences between the two profiles, however, this also suggests that temperature has a minimal influence on time-of-use of electricity of refrigerators.

The increased variation in the energy use of the refrigerator during the evening hours is logically best explained due to the increased influence of human use on energy consumption, through the opening and closing of doors for dinner meal preparation, and placing warm food into the refrigerated space, requiring additional energy use to cool the food to refrigerator temperatures. The opening and closing of the refrigerator causes a direct loss of cool air in the fridge to the surrounding space. Placing warm food in the refrigerator requires extra energy to cool to the refrigerator’s cooler temperature.

3.2 Clothes washer and dryer

The clothes washer and clothes dryer had the greatest variation in normalized energy use by hour, with each hour varying between 0.07 - 8.4 PDL and 0.06 - 9.1 PDL as seen in Figure 21(b) and 21(c). The greatest period of use occurred between 9 am and 2 pm, peaking at 10:00 am for clothes washers and 12:00 pm for clothes dryers during this high-use time. This is consistent with [7], but somewhat different than [11], which found peak use in washers and dryers in the evening hours. For the clothes dryer a higher peak occurred at 6 pm but with significantly larger variation between homes. The greatest variation among homes’ profiles occurred at 6:00 am (6.8 PDL), and 10:00 am (5.4 PDL) for clothes washers, and at 6 pm for clothes dryers (12 PDL). The average standard deviation among homes was 2.5 and 3.4 PDL respectively.

Similar to the refrigerator, the normalized load profiles of the clothes washer and clothes dryer are closely aligned with the findings of [7]. The hourly values in this study vary on average by 0.59 and 0.61 PDL respectively. The [7] profile for clothes washers peaks at the same time, however, for the clothes dryers, this profile peaks one hour later than [7].

We also note a comparatively lower use at 6 and 7 pm for the clothes washers and a higher use of the clothes dryer at 6 pm.

The use of clothes washers and clothes dryers depend strictly on the resident's decisions.. Unlike the refrigerator, the clothes washer and clothes dryer do not consistently require electricity. This explains the main difference in the load shapes of the refrigerator and the washer/dryer. The spike in the load profile at 6 pm for dryers can be explained from the influence of several homes in the dataset that only ran their clothes dryer at this specific time throughout the period monitored. Likely, with a larger number of homes and a longer monitoring period, this spike and relative influence on the load profile would be smoothed over. Interestingly, unlike the dishwasher load profile, which peaks in the morning and evening hours when those who work away from home would likely be at home, the energy use of the washer and dryer are highest during normal business hours, with the exception of the 6 pm dryer spike. This increased use is similar to the profile found in [7]. Of the homes studied, 20 of the 40 homes (50%) indicated that one or more members of the household worked from home more than 20 hours per week, which may explain some of the increased use during this time. 85% of the homes studied also had 2 or more household members, indicating that one or more of these members maybe home during the day, but not necessarily working from home, and using the clothes washer and dryer during these hours. The number of household members who were at home during the day, however, was not explicitly asked in the resident survey conducted.

3.3 Dishwasher

The dishwashers, compared to the other appliances, had a use profile that differs the most (1.2 PDL) from [7], more than twice the average difference for clothes washers as shown in Figure 21(d). The variation in normalized energy use by hour is similar to that of washers and dryers, averaging varying between 0.05 - 8.5 PDL. The load profile shows a distinct peak at 9:00 am (8.5 PDL), and 10 pm (8.1 PDL) which is also the time with greatest variation in load across the homes (9.9 and 9.2 PDL). This variation is more than twice as much as the average variation (4.0 PDL).

Two of the dishwasher circuits monitored have energy use profiles that indicate the dishwasher is only in the morning and two houses show use only in the evening. Due to the small sample size, these homes had a significant influence on the resulting load profile. Dishwashers, similar to clothes washers and dryers, are also user-dependent, in that they use very little electricity unless specified by the user. Dishwasher use is also typically associated with meals, thus it makes sense that peaks in use would occur around meal times, in this case breakfast and dinner, similar to the observations of [15].

4. Segmentation of Daily Use Profiles:

While the appliance load profiles developed in this study somewhat closely follow that of those developed in 1989 by [7], the variability in the percent of daily energy use used each hour is significant between the homes, particularly for those hours that also have the highest average energy consumption. To assess the source of variation in these profiles, three possible influencing factors are investigated. The first two factors are energy use on weekdays vs. weekends, and energy use of households with members working at home vs. those who do not. These factors affect the relative amount of time spent in the home, and thus also the daily time-of-use of energy due to different behavioral patterns. Energy use during the heating and cooling seasons is also discussed. To compare these factors, the SSR, as discussed in Section 3, is used. A larger value of SSR indicates a greater difference in the two compared profiles. These values are shown in Table 9.

4.1 Weekdays vs Weekends:

Using the same methodology, normalized energy use profiles were created for weekdays and weekends. Figure 22 compares the normalized energy use profiles for weekdays (Monday – Friday) and weekends (Saturday – Sunday) for each appliance. Unlike the assumptions in current energy modeling, where only the total energy use increases on weekends, Figure 22 shows time-of-use changes as well. This segmentation of weekdays and weekends is in agreement with Arghira et al. [28], which found that the day of the week is correlated with energy use. Refrigerators, clothes washers and clothes dryers show lower energy use in the morning hours on weekends than on weekdays, but higher energy use in the afternoon and evening hours. Dishwashers, on the other hand, show higher use in the morning and early afternoon hours and lower use in the evenings. For all appliances, the standard deviation of hourly PDL is greater on weekends than weekdays (Table 10), explaining some of the variation in use among homes. Comparing the difference in the profiles of the three segmentations studied, the dishwasher shows the greatest difference in profiles between weekdays and weekends.

Table 10: Energy use and variability comparison of weekdays vs. weekends

	Average Hourly Variability (standard deviation)			9 am-5pm % of Daily Load		
	Weekend (PDL)	Weekday (PDL)	Less variability on weekdays (%)	Weekend (%PDL)	Weekday (PDL)	Less PDL on weekdays (%)
Refrigerator	0.52	0.47	10%	44	42	2 %
Clothes Washer	3.7	3.1	21%	64	63	1 %
Clothes Dryer	4.2	3.9	7%	63	65	-2%
Dishwasher	5.9	4.2	39%	44	41	3 %

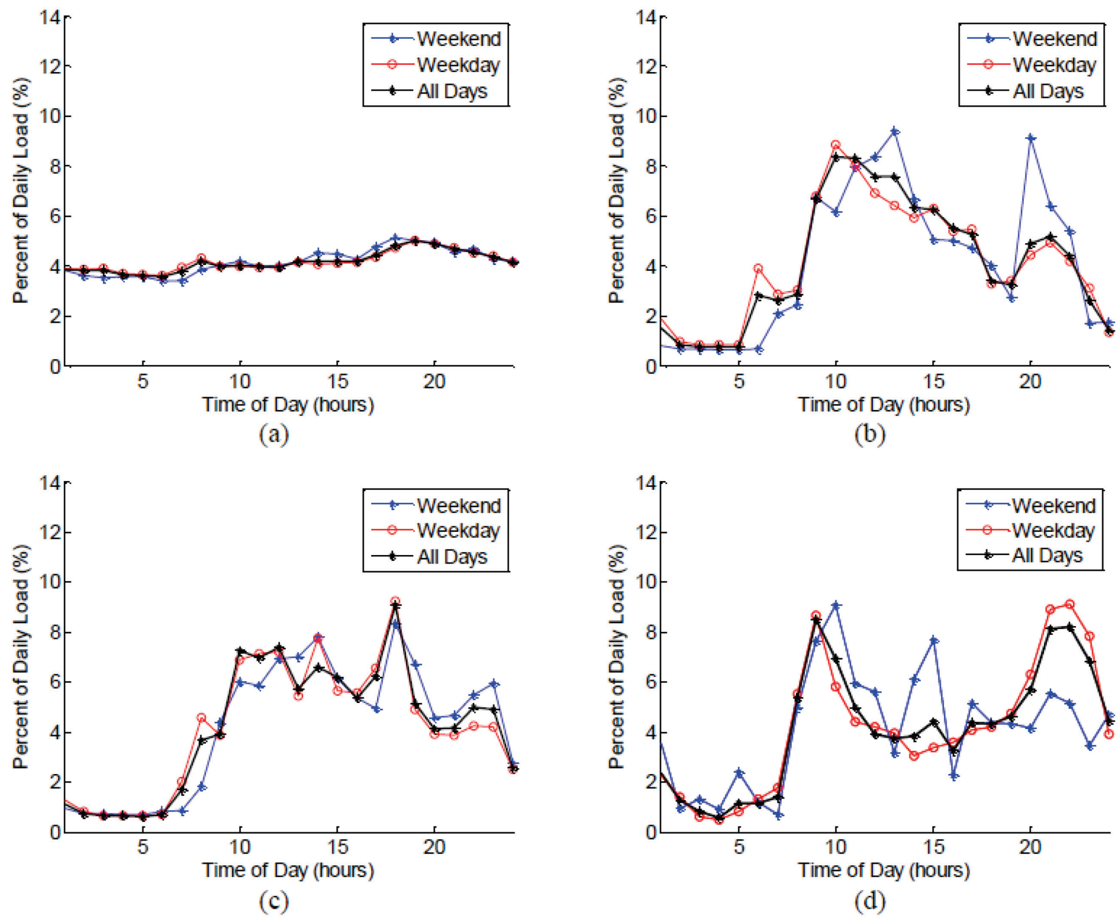


Figure 22: Normalized energy use profiles of (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers on weekdays and weekends

4.2 Working from Home:

Because the use of clothes washers, clothes dryers, and dishwashers is user-dependent, it is worthwhile to investigate the effects of an increased number of hours spent in the home due to household members working from home. The homes considered in this study indicated a significant spread in the amount of time spent working at home (Table 6).

Comparing the weekend and weekday profiles in Figure 22 for all homes, on weekdays there is, on average, a lower percent of daily energy use during normal business hours (9 am – 5pm) as compared to weekdays (Table 11) for all but clothes dryers. This makes sense, since many of the residents work outside of the home and would not be using appliances during this time. Interestingly, refrigerators, the most user-independent appliance, show the greatest reduction in use on weekdays, as compared to the other three more user-dependent appliances. This may be explained because people have less time to cook meals at home that requires use of the fridge and storage of warm food.

Separating the energy use profiles, into those households that work twenty or more hours per week from home and those who did not, energy use of appliances during normal business hours (9am-5pm) in households where members do not work from home is 2-28% less than households that do work from home (Table 11). This is important to note, as the number of Americans working from home has increased in recent years [16]. Variability is also significantly less for those households with no one working from home for all but the clothes washer. Comparing the SSR values of the three studied factors (Table 4), the washer and dryer are most influenced by whether or not the household has someone working at home or not.

Table 11: Energy use and variability comparison of work-at-home vs. non-work-at-home households

	Average Hourly Variability (standard deviation)			9 am-5pm % of Daily Load		
	Work-at-Home (PDL)	Not (PDL)	Less variability on weekdays (%)	Work-at-Home (PDL)	Not (PDL)	Less PDL on weekdays (%)
Refrigerator	0.42	0.38	12%	42	42	2%
Clothes Washer	2.0	2.6	-22%	72	61	18 %
Clothes Dryer	3.7	2.6	45%	72	56	28 %
Dishwasher	4.1	3.5	18%	51	43	19

4.3 Heating and Cooling Seasonal Effects:

The effects of the normalized energy use profiles of the studied appliances in the heating (October to March) and cooling (April – September) were also studied. Of the homes monitored, Austin, TX is a cooling-dominated climate, with 1661 cooling degree days (CDD), and 919 heating degree days (HDD) [29]. The difference in the normalized daily use profiles for all appliances showed the least differences when comparing the profiles generated for the heating and cooling season. The values of the SSR (Table 9), over all were smallest, indicating that this factor is not as influential as the other studied factors.

5. Implications of Results

Home Energy Use:

As an estimate of the implications of the use of the appliance load shapes developed in this study, the average yearly electricity use of each of the studied appliances from the RECS 2009 [6] for refrigerators, washers, dryers and dishwashers respectively are used to provide a relative weight of each appliance's contribution to home electricity use for the profiles developed in [7] and in this research. The relative contribution (%) of each appliance to total large appliance electricity use has remained similar, despite improvements in efficiency of appliances. Of electricity consumed by all four of the studied large appliances, refrigerators, washers, dryers, and dishwashers account for 42%, 4%, 37% and 17% of total annual use in the U.S. in 1990 [30], and 49%, 4%, 34% and 13% in 2009 [6]. If all appliances are combined together to create one representative profile of large appliance electricity use (Fig. 3a), the results of [7] and the current study are similar, with an average difference between profiles of 0.4 PDL for each hour. This profile is most influenced by the dryer and refrigerator, and less by the clothes washer and dishwasher. The dryer use profile, due to the spike at hour 18 (6:00 pm), has an influence on the load shape and causes the spike in the total use profile in Figure 23. Further dividing the profiles by weekday and weekend (Fig. 3b) and work-at-home and non-work-at-home (Fig. 3c) we see a more significant difference in time-of-use. Assuming the same energy use values in [7] for purposes of comparison, the energy use (kWh) is consistently higher during working hours (9am -5pm) for work-at-home households, amounting to 48% of daily energy use, 6% (0.43 kWh) more than non-work-at-home households. Comparing weekdays to weekends, the weekday energy use begins to increase around 6 am on average, while on weekends the energy use remains low until 7 am. Since there are only two of the seven days in a week that are weekends, this trend is not visible unless two profiles are used instead of one. Additionally, energy use during normal business hours is approximately 2% lower on weekdays than weekends. These differences indicate it may be important to consider further study to quantify the effects that working at home has on the use profile, beyond the 40 homes studied in this research. Current profiles may under predict energy use during the day, particularly with increasing numbers of residents working at home.

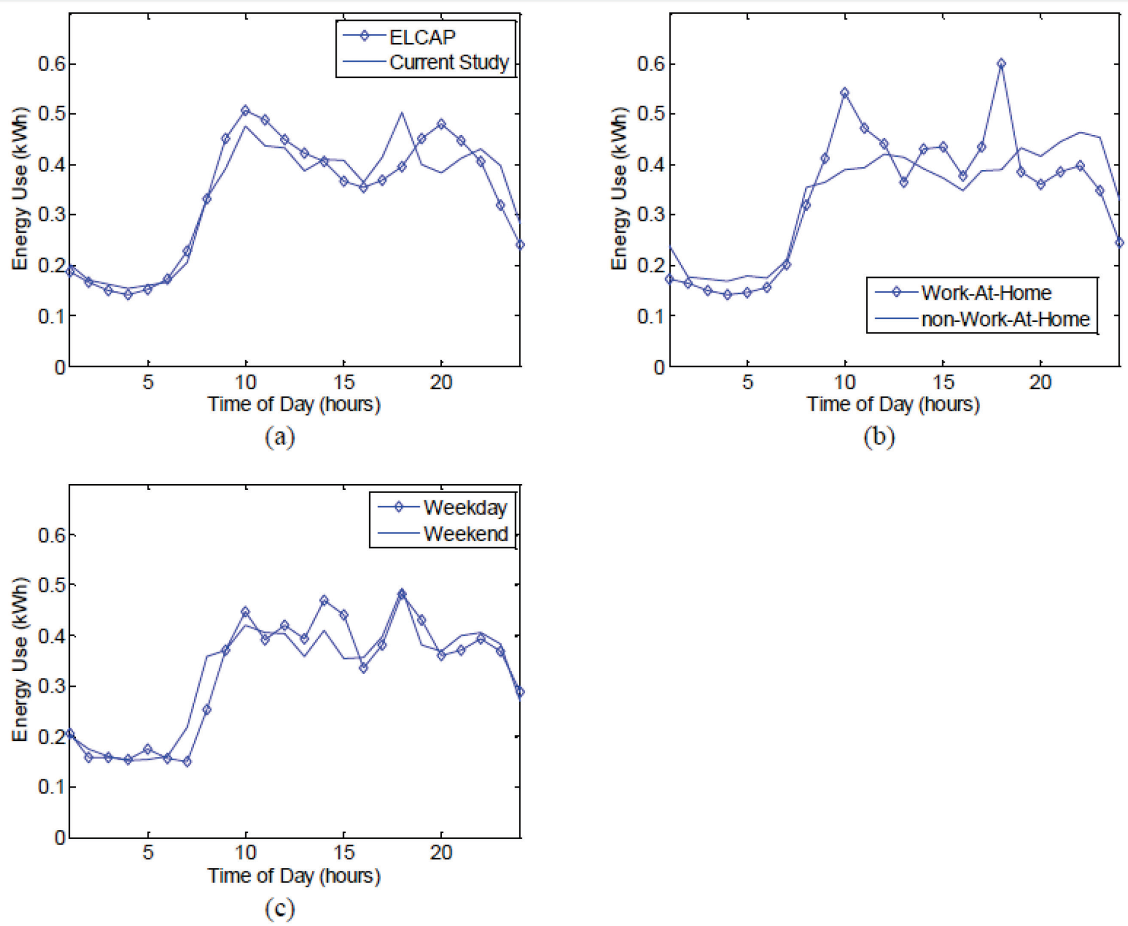


Figure 23: Aggregated daily energy use of all studied appliances comparing (a) this study to [7], (b) homes that work from home and those who do not, and (c) weekdays and weekends.

Peak Electric Grid Load:

In warm climates, including Texas, peak electricity demand is a significant concern for utility companies. Peak demand use is a concern in many other countries as well due to a variety of factors. Using the methodology outlined in this paper, a normalized profile of the Electric Reliability Council of Texas (ERCOT) during the summer months of May to

September [31], shows that, on average, the hours of greatest demand occurs consecutively between 3 pm and 8 pm. This time period, 21% of a day, corresponds to 28%, 29%, 36%, and 27% of total daily load (PDL) of the refrigerator, clothes washer, clothes dryer and dishwasher respectively. All appliances, thus, show potential to provide relief to the electric grid. Clothes dryers, with the greatest percent of daily use coinciding with peak hours on the electric grid (36%), and the second highest average daily energy use among the studied appliances [6], shows the strongest potential for reducing electric grid peak load stress in this climate. This methodology can be applied to other locations nationally and international as well by similarly identifying the peak use times of the grid, and comparing these times to the use profiles of appliances, in applications such as those developed by [32].

Building Energy Simulation

The results of this study are also important for building energy simulation software, which uses energy use profiles of internal energy loads as input data [25] [26] [27]. Energy simulation relies on the accuracy of the profile's underlying assumptions to produce a resulting accurate representation of building energy consumption behavior. This requires a schedule of energy use of all energy-consuming components of a building, including appliances. Residential building energy simulation uses an hourly normalized daily use profile, which is multiplied by an annual energy use value (kWh), and in some cases, a seasonal or weekday/weekend multiplier [11]. These daily use are used to represent use pattern of that appliance for all days of the year-long simulation period. Currently the load shape of appliances for each day of the year is the same since it is derived from a single normalized daily energy use profile, but the relative magnitude of the load for each day is different. The use of multiple load shapes for different days of the year has not been investigated prior to this study, nor has the influence of factors, such as sociodemographic characteristics, time of year, and day of week, on these profiles. As shown in Table 9, the washer and dryer profiles are most influenced by the whether or not the residents work at home, and the refrigerator and dishwasher are most affected by whether or not it is a weekday or a weekend. This demonstrates that including multiple profiles may provide a more realistic representation of energy use of appliances over a day.

6. Limitations

The 40 homes monitored in this research consist of newly constructed, single family homes in Austin, TX. The homes are similar in size to the average newly built homes in the United States, but are limited in number and not necessarily representative of all homes in the U.S. The efficiency of the appliances has an effect on the magnitude of the total energy used by the appliances, but not the normalized use profile, which allows for comparison with previous field collected data from [7] and other sources. The number of appliances monitored within the 40 homes is limited, ranging from 9 to 18 individually monitored circuits. The data utilized, however, represents the total available number of individually monitored appliances in the field collected data.

The range of time of monitoring of energy use of subcircuit level data in buildings has ranged from several weeks [8], to several years [7]. On average, the appliances monitored in this study were monitored for between 159-221 days throughout the one year time period of monitoring (Table 8). To assess how long of a monitoring period is required to capture the normalized load profile of a home's energy use, the average percent change in the 24 hourly values of the normalized energy use profile was calculated for each number of days of monitoring in this study. The absolute value of the percent change was used to develop the trends shown in Figure 24, which shows the upper and lower bounds of these values for all homes studied. These values provide a measure of the influence of an additional day of monitoring has on the normalized daily use profile. A power curve was fit to the upper and lower bounds and is also shown in Figure 24. The equations for the maximum change, representing the worst case scenario, are shown in Equ. 1, where ϵ is the average change in the value of the normalized energy use profile, and n is the number of days monitored.

$$\begin{aligned} \epsilon_{Fridge} &= 2.019n^{-0.913} - 0.0112 \\ \epsilon_{Washer} &= 2.315n^{-0.574} - 0.0863 \\ \epsilon_{Dryer} &= 3.027n^{-0.663} - 0.0573 \\ \epsilon_{DW} &= 2.415n^{-0.547} - 0.1118 \end{aligned} \qquad \text{(Equ. 1)}$$

Table 12 provides a comparison of the number of days required to achieve average levels of change in the profile for each of the appliances based on Equ. 1. The number of days to reach a consistent profile is lowest for refrigerators. This is generally to be expected since human behavior has less of an effect on refrigerator energy use than the other appliances. If a benchmark of 0.05 is considered acceptable, for the user-dependent washer, dryer and dishwasher, a 139-154 day monitoring period is required. The refrigerator, however, only requires 46 days, approximately one-third of the time of monitoring. Comparing these values to the average length of monitoring of the studied appliances (Table 3), only the dishwasher (avg. days = 122) does not meet this threshold, and is a limitation of this study.

Table 12: Days of monitoring required to achieve a desired level of average percent change in the normalized daily use profile

% Change in avg.		0.5	0.1	0.05	0.01
# Days	Fridge	5	24	46	147
	Washer	11	81	139	255
	Dryer	13	87	154	311
	Dishwasher	12	86	140	235

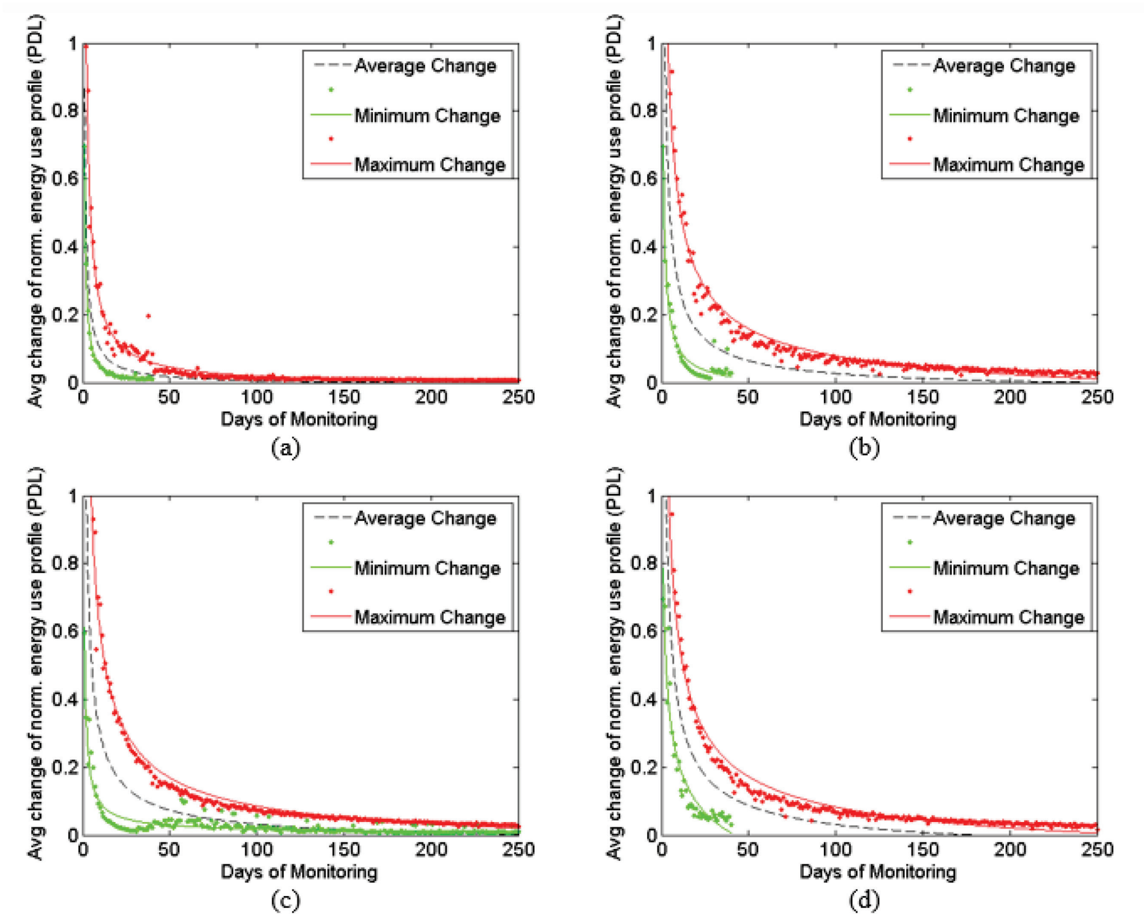


Figure 24: Change in hourly normalized energy use with increasing number of day of monitoring for (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers

7. Conclusions:

In this study a methodology was discussed for use in the development of representative schedule of daily energy use of appliances, in particular daily normalized energy use profiles. Normalized energy use profiles were developed for four large appliances, including refrigerators, clothes washers, clothes dryers and dishwashers using energy consumption data from 40 homes in Austin, TX. The appliances studied in this research are all newer appliances and are used by households similar in size to the average U.S.

household. As more energy efficient appliances come to market and are purchased, the results of this research will be relevant in predicting current and future appliance energy use. These load profiles, with the exception of dishwashers, were similar those found by [7], and those currently used in building energy modeling software. However, the significant variation in the normalized load profiles motivated further investigation as to the cause of this variation. Three factors were investigated that were found to influence the time of use of appliances, including the day of the week (weekday vs. weekend), and whether or not the household reported having one or more members working from home 20 or more hours per week. These factors were correlated with increased energy use of appliances during normal business hours. The influence of the heating and cooling season were also studied, but found to have, in total, a lesser effect on the shape of the use profile than the first two studied factors. Limitations of this study were discussed and the influence of the length of monitoring period on the resulting energy use profiles. The following conclusions can be drawn from this research:

1) Appliance use patterns have not changed significantly since the 1989 study [7] except for in the case of dishwashers, which shows a large peak in use in the morning than in previous studies;
2) User-dependent appliances use patterns vary more between homes and between days than automated appliances; the average standard deviation in hourly normalized energy use between homes is greatest for dishwashers (4.0 PDL), followed by dryers (3.4 PDL), washers (2.5 PDL) and refrigerators (0.41 PDL).

3) Weekday and weekend use patterns of appliances are similar, but the average standard deviation of weekday use patterns between homes is 7-39% lower than on weekends, indicating a more predictable energy use pattern on weekdays.
4) Weekdays and households where no one works at home have more predictable, consistent electricity use patterns than weekends and households where members work at home 20 or more hours per week.
5) Households where members work at home use 2-28% more of their daily appliance energy use during normal business hours (9am – 5pm) than non work-at-home households.
6) The washer and dryer energy use profiles are most influenced by the whether or not the residents work at home. The refrigerator and dishwasher energy use profile is most affected by whether or not it is a weekday or a weekend.
7) Of the influencing factors studied, if all appliances are considered, the heating and cooling seasonal variations have the least effect on the normalized use profiles of the appliances studied. Whether or not the residents worked at home shows the greatest difference.
8) Electricity use varies more between houses during peak use times of day than during low-use times.
9) All appliances use more than 25% of their daily energy use during peak use times, demonstrating the potential to reduce peak use on the electric grid if equipped with smart technologies; clothes dryers utilized the greatest percent of daily load

(36%) during peak use times and thus show the strongest promise for this application according to the studied homes.

10) 139-154 days of user-dependent appliance electricity use data is needed to represent an appliance's daily use profile at a threshold of 0.05% maximum average change in energy use. Refrigerators require approximately one third of the time, or 46 days of monitoring, to achieve the same threshold.

11) Utilizing multiple normalized daily energy use profiles of appliance, rather than one, as inputs into building energy models may help provide a better representation of daily appliance energy use in residential buildings. This include consideration of sociodemographic characteristics such as working at home, and day of the week.

Of particular interest in the finding of this study is the increase in appliance energy use during the day of homes with work-at-home members. As it continues to become more common for adults to work from home [16], this may influence the overall load shape of the residential building sector in the long term.

Through development of normalized daily energy use profiles for each of the studied appliances and assessing influences of variation on time-of-use, a greater and more accurate understanding of appliance energy use is achieved.

The results of a this study can be used to inform utilities, manufacturers of appliances, and consumers about the role appliances currently play in residential energy consumption, and how this varies with time. It is also important to understand when residential home appliances are used in applications such as building energy modeling, a method increasingly used to identify cost-effective methods of retrofitting buildings to reduce energy consumption. Energy modeling relies on the accuracy of its underlying assumptions, which includes time-of-use of appliances. The time-of-use of appliances is also useful for utility companies, who must predict and meet the electricity needs of its customers. Understanding how different factors affect the load profile of appliances will help to predict how appliances will be used in the future, and the possibilities of peak load shifting by altering appliance use patterns.

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Appendix B

Paper 2: Single and Multi-Family Residential Central All-Air HVAC System Operational Characteristics in Cooling-Dominated Climate

Kristen Sara Cetin, Atila Novoselac

(Published in Energy and Buildings (2015))

Abstract

189 conditioned residential single-family and multi-family homes in the cooling-dominated climate of Texas were instrumented with home energy management systems (HEMS) to collect sub-metered data on HVAC operations. This study analyzes the HVAC operation from these homes over a one year period to determine the duty cycles of the HVAC systems. This includes annual, monthly, and hourly HVAC on-off operation patterns. Regression analysis was used to determine the relationship to HVAC energy use and whole-home energy use, and the influence of building and occupant characteristics. HVAC runtimes are found to be approximately 20% per year, but vary, depending on the season and time of day. Daily and monthly runtime fractions are lowest (10%) at average outdoor temperatures of 15°C, and increase with increasing or decreasing temperature. Hourly runtime peaks at 7 pm in the cooling season, while in the heating and transition seasons, it peaks at 7 am. The number of occupants and the indoor cooling set point temperature were found to most strongly influence the HVAC runtime. The results are formatted to be used in various building and indoor air quality applications where the studied phenomena are influenced by HVAC operation.

Key Words: runtime fraction, duty cycle, central air conditioning, single family homes, multi-family homes

Introduction

In the United States people spend 68% of their time in residential buildings [1] and 90% of their time indoors [2]. Therefore, there is a need for residential buildings and their systems to provide a comfortable and healthy indoor environment. This is often accomplished through the use of heating, ventilation, and air conditioning (HVAC) systems, particularly in the summer (cooling) and winter (heating) seasons. Nearly 87% of homes in the United States use air conditioning, including 89% of single family homes, and 84% of multi-family homes [3]. In more extreme hot climates such as Texas, air conditioning penetration is nearly 100%. Air conditioning penetration is lower in many other parts of the world, but is predicted to grow worldwide by 72% between 2000-2100, particularly in the face of predicted climate change [4]. Nearly all homes in the U.S. (97%) [3] also use central heating. Worldwide, the use of central heating is also predicted to increase by 34% by 2100. Since HVAC systems impact energy use, thermal comfort and indoor air quality, it is important to understand how and when these system operate. However, there is limited information available on the operational characteristics, and specifically on runtimes of these HVAC systems, particularly in the United States.

A residential centralized all-air HVAC system typical of U.S. homes cycles ON and OFF to maintain a temperature set by a central thermostat. Of homes that utilize HVAC system in the U.S., 80% of single family homes (53 million housing units), and 60% of multi-family homes (13 million housing units) utilize this type of system [3]. Of the homes located in hot and humid climates, as defined by the Building America climate guidelines [5], 82% (15 million housing units) utilize central all-air HVAC, the highest percent penetration of all climate zones in the United States. HVAC use is greatest in the summer (cooling season) and winter (heating season) months, or when indoor and outdoor temperatures have the greatest temperature differential. This runtime fraction, also called duty cycle, or the percent of time the HVAC system is ON, affects both the energy demand on the electric grid, and the other duties of HVAC systems including dehumidification, filtration and, in some cases ventilation [6].

Impact of runtime fraction on energy systems: HVAC use has a large impact on both overall electricity use, and peak demand on the electric grid [7]. Of the 22% of energy use and 38% of electricity use attributed to residential buildings in the U.S. [8], HVAC systems make up over 52% of this energy use, and 31% of this electricity use [9]. These percentages are greater in the more extreme climate regions. In hot climates such as Texas, HVAC use accounts for over 56% of electricity use of residential buildings in the summer months [10]. Higher runtime fractions of HVAC systems also equate to greater demand on the electric grid. In the summer (cooling season), particularly in warm climates, in the afternoon and evening hours when residential HVAC use is highest across all homes, a greater duty cycle equates to greater loads on the electric grid. The reason for this is a greater percentage of air conditioning units that are running simultaneously. With the development of demand response programs, dynamic and time-of-use pricing, introduced to reduce load on the electric grid during peak use times [11], it is crucial to understand existing runtime fractions of homes. This will enable better prediction of the effects these programs will have on peak electricity demand and better forecasting of energy demand and use trends.

Impact of runtime fraction on the indoor environment: Regarding the indoor environment, the HVAC system operation directly influences building indoor temperatures, relative humidity (RH), ventilation and recirculation rates, air speeds, and building pressure relative to the outdoor environment. Without heating and cooling, the indoor unit central fan may also provide whole-home air recirculation or ventilation. Air recirculation facilitates air movement and mixing. Most all-air residential HVAC system only recirculate the indoor air (no fresh air is added), and ideally the return air volume (m^3/s) is equal to the supply air volume. In this case the HVAC system does not change the indoor-to-outdoor pressure. However, even small differences in supply and return air flow rates caused by leaks in supply or return ducts cause that pressure are positively or negatively pressurized affecting the ventilation rate by infiltration. Thus frequency and duration of HVAC system operation may also have a significant impact on ventilation rates in buildings. In newer homes with a tighter building envelope, a forced ventilation system may be installed which provides additional fresh air indoors by adhering to a minimum ventilation rate, as discussed in ASHRAE Standard 62.2 [12]. This is accomplished either through the use of an exhaust ventilation system which depressurizes a home by pushing indoor air outdoors through a vent, or a supply ventilation system which pressurizes a home though the intake of fresh air into the home. Often these ventilation systems are tied to the operation of the main HVAC system and the intensity of this mechanical ventilation depends on the frequency and duration of HVAC system operation.

Air movement, pressure, temperature and RH resulting from HVAC operation also have implications in particulate matter concentrations and indoor chemistry. This includes devices in a home to aid in the removal of pollutants, such as filters installed in the HVAC indoor unit that remove pollutants from the indoor air such as particles and ozone [13-16]. Their effectiveness in removing pollutants depends in part on how often and how much air is flowing through these filters. HVAC operation also affects indoor air flows and mixing conditions, which can result in changes in deposition on indoor surfaces [17-19] and occupants [20-21], and the formation of secondary pollutants [22-23]. Passive removal materials (PRMs) [24-27] and stand-alone air filter effectiveness [23] are also affected by air speed and indoor air mixing from HVAC operation schedules. Indoor concentrations of particulate matter, ozone, secondary organic aerosols and other byproducts have been linked to human health, as discussed in [28-30], thus additional study and analysis on HVAC runtime characteristics is needed to realistically evaluate the dynamics of pollutant concentration and human exposure.

Considering the efforts to improve energy efficiency and reduce peak power consumption, while providing indoor environmental control, researchers use runtime fraction information for various analyses. However, there is very limited information available on runtime characteristics of central all-air HVAC systems. Previous studies that have required HVAC runtime fractions for assessment of indoor pollutant level and human exposure, have assumed or estimated these values, or used energy modeling to determine them [27, 31-34]. Several small-scale studies have also been conducted on residential buildings to determine runtime fractions. Previous field studies include the study of 37 homes in North Carolina, 17 homes in Florida, and 17 homes and light commercial buildings in Texas [35-38]. These previous studies have collected data on runtime fractions of a small number of homes, and most for a time period of less than a year. There are also no know studies to date that provide runtime characteristics of multi-family housing. As discussed by El Orch et al. [39] additional information is needed to better characterize runtime fractions in residential buildings. This is particularly important for the hot and humid climate zone which has the greatest percent use of this type of HVAC system in residential buildings.

This research aims to identify annual, monthly, daily and hourly seasonal operation trends from data analysis of HVAC energy monitoring data from 189 homes in a hot and humid, cooling-dominated climate. This includes determining the air conditioning and heating runtime fractions of conditioned residential buildings, including single family and multi-family homes with heat pumps and with air conditioners/gas-fired furnaces. The results are divided into sections by time interval frequency including annual, monthly and seasonally hourly runtime data. A second section covers runtime fractions of indoor fan-only operation. The third section identifies trends in HVAC runtime fractions as a function of outdoor temperature to extend the use of this data beyond the hot and humid climate where this study was conducted. This work highlights the importance of the time-varying and outdoor temperature-varying runtime fractions and the implications this has on the indoor environment.

Methodology

The operation of the air conditioning and heating systems was monitored for 189 households in Austin, TX between September 2013 and August 2014. Of the monitored homes, 161 are single family homes, and 28 are multi-family apartments. In all cases the homes utilized a centralized HVAC system, including an outdoor condenser/compressor unit, and an indoor air handling unit. The HVAC is controlled by a thermostat which can be set to heating or cooling mode by the occupant. The results of a survey of a portion of the participating households (n=128) describe the general characteristics of the single family homes (Table 13). Average data for the participating multi-family home properties is also provided in Table 13. The majority of the single family homes studied (86%) are heated using gas heat, while all multi-family homes utilize heat pumps, with the only major differentiating factor between heat pumps and air conditioning/gas heat being the type of heat used. The age of the HVAC system is known for only a limited number of homes (n=12). However, assuming a new HVAC system was installed and has not yet been replaced in homes with known dates of construction built in the last 10 years, the average age of these HVAC systems is 6.9 years. The average indoor cooling and heating set point temperatures of the single family homes have a standard deviation of 1.8°C and 1.7°C respectively across the reporting homes (n=103), with the average maximum setback of 1.8°C higher and 2.0°C lower, respectively. 28% and 29%, respectively, reported a constant set point temperatures in the cooling (summer) and heating (winter) seasons. Indoor set point temperatures were not available for the studied multi-family homes

Twenty-two of the homes utilize timed whole-home ventilation systems, all of which are single family homes. All homes studied pay for their utility bills. The electricity and gas utilities utilize a tiered rate structure that increase in price by total cumulative use per month, but rates do not vary by time of day or week. The single family homes are newer properties on average, as compared to the multi-family homes, and are more than twice as large in area. Despite a large home size, however, the number of occupants in the single family and multi-family homes is similar. For the surveyed homes, the average number of weekdays that someone is home during work day hours is 3.22 days.

Table 13: Residential building characteristics

Type of Home	HVAC system	Mechanical Ventilation	Heating	Cooling	Home Age (yrs)	Area (m^2)	Ceiling Height (m)	Occu-pants (#)	Cooling Set point (°C)	Heating Set point (°C)	Week-days at home
Single Family (n= 161)	Furnace (n=139)	Yes (n=3) No (n=136)	Gas	Electric	8[a]	197[a]	3[a]	2.6[a]	25.2[a]	20.0[a]	3.22[a]
	Heat Pump (n=22)	Yes (n=19) No (n=3)	Electric	Electric							
Multi-Family (n=28)	Heat Pump (n=28)	No (n=28)	Electric	Electric	37[b]	78[b]	2.7[b]	3[b]	--	--	--

[a]*data from results of online survey of the participating household residents in 2013.*
[b]*data provided by the apartment complex management.*

A home energy management system (HEMS) was used to collect energy consumption data in each household including whole-home electricity (kWh) and individual circuit electricity (kWh) at one minute intervals. The HEMS data was found to provide good agreement with utility meter data; more details on the data collection methodology are discussed in [40] and [41]. Following the methodology in [41], the data was quality controlled to remove spikes and to check for missing data. All of the 189 homes contained 90% or more of the data available over the studied one-year time period. HVAC energy use data collection began for some homes as early as January 2012; thus, missing data was filled using the same day and time from a previous year, following the same methodology of other researchers utilizing energy data (e.g. [42]).

Two types of central HVAC systems are used in the studied homes, distinguished by the heating energy source: including (1) heat pumps and (2) air conditioning with gas furnace heating. This is important to note because type of HVAC system in use determines the methodology used to determine the runtime fraction. The type of HVAC system heat source, however, should not affect the resulting runtime fraction.

The energy data from two circuits, including the indoor air handling unit and the outdoor condenser/compressor unit, were used to determine the HVAC operational characteristics discussed in this paper. In homes with heat pump units, both the indoor and outdoor units are in use together throughout the year, in both the heating and cooling modes (Figure 25a). For homes utilizing a gas furnace, both the indoor and outdoor units are in use in cooling mode, but only the indoor unit is used in heating mode (Figure 25b) since the gas furnace is used as the heat source and does not create an electricity signal. This distinction in energy signal distinguishes the two system types. As a part of the occupant survey, occupants also reported that their HVAC system type. For quality control, this data-driven determination of HVAC system type confirmed with the occupant-reported HVAC system type.

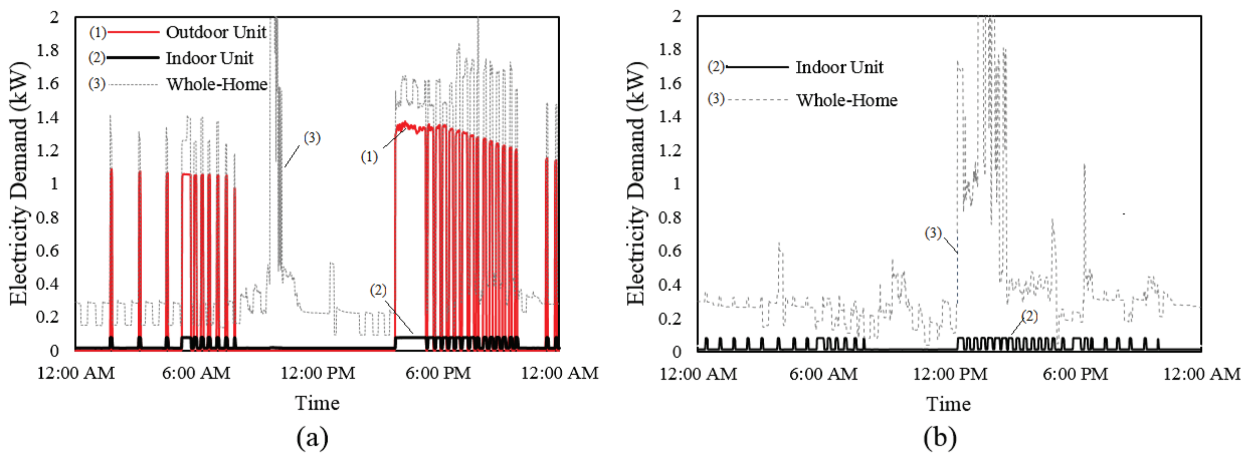


Figure 25: Energy signal for a residential building HVAC system, including the indoor air handling unit, and outdoor condenser/compressor unit. (a) Indoor and outdoor unit ON at the same time, indicating, in winter (heating season), the system is a heat pump; in summer, both heat pump, and air conditioner/gas-furnace units show this same signal. (b) Indoor unit is ON and outdoor unit is OFF, indicating, in winter, the system is using a non-electric source of heat (gas furnace); in summer (cooling season) and transition months, indicating the indoor unit only is ON.

To determine the runtime fraction for each home, the energy signal (illustrated in Figure 25) must be divided to determine when the HVAC system is ON and when it is OFF. A threshold value of 0.05 kW is used, where above 0.05 kW indicates the system is ON, and below is OFF. Since both indoor and outdoor units often draw a small amount of power while “OFF” and not in use, the threshold value must be above zero. A parametric analysis of the effect of the threshold value found that a threshold value between 0.04-

0.05 kW had the least effect on the runtime fraction values across all homes, including 0.2% change in the median, and 2% for the mean.

To determine when a system is ON or OFF, two energy signals were utilized for each HVAC system, including the indoor and outdoor units. For the heat pump systems, the outdoor unit signal is utilized to define when the HVAC system is ON or OFF. The indoor system may also be used, however, the difference between the power draw (kW) when the HVAC system is OFF and ON is approximately four times higher for the outdoor unit (2 kW) than the indoor unit (0.5 kW) showing a more clear distinction between the ON and OFF system states using the outdoor unit. For the gas furnace systems, since the outdoor unit is not the source of heat in the heating season, the indoor unit data is used. The outdoor unit signal was used for cooling season months (March – November) where the average monthly temperatures was above 18.3°C (65°F). The indoor unit was used for the heating season (December – February), where the average monthly temperatures was below 18.3°C (65°F).

For systems that utilize both electric heating and cooling, including heat pumps, when the indoor unit is ON (>0.05 kW) and the outdoor unit is OFF (<0.05 kW), this indicates the use of the indoor fan without heating or air conditioning. This method is also used to identify indoor fan-only operation in the summer (cooling) season in homes with gas heating systems.

The annual, monthly and hourly runtime fraction are calculated using all available data from the 189 homes, and are the sum of all times where a system is ON over each time interval. Both mean and median values are reported, as well as standard deviation, where the distributions are normally distributed. Cumulative energy use (kWh) information on the indoor and outdoor units was also collected. Outdoor temperature data for Austin, TX was obtained from the National Climatic Data Center, US Climate Data Network quality controlled data sets [43]. The monthly, daily and hourly temperatures used represent the average temperature for the given time period and are computed as the average of the high and low temperature for the given time period.

Results

The results are divided into three sections including, yearly, monthly, and hourly runtime fractions, as well as runtime fraction compared to outdoor temperature. These results are further subdivided by type of HVAC system, and by whether the home is a single family home or a multi-family home.

Annual runtime fractions

The mean annual runtime fraction of all systems, including both heat pump and gas furnace systems, and for all housing, including single-family and multi-family houses is approximately 20% (12 min/hour), with a standard deviation of 2.8-4.1% (1.7-2.5 min/hour) depending on the home and system type. Table 14 shows the mean, median and standard deviation of the annual runtime fraction (%). The studied multi-family homes have a 2.5% lower average annual runtime fraction with a 1.3% larger standard deviation than single family homes. Heat pump and gas-furnace homes have a minimal difference of 0.2% in annual average runtime fraction. The median annual values for runtime fractions are lower than the mean values in all cases, ranging from 14.1-16.4% of time. Figure 26 shows a histogram of all homes annual runtime fraction, which peaks in frequency between 15-20%.

Table 14: Annual runtime fractions (%) of subsets of 189 homes in Austin, TX

Type (# of homes)	Mean	Median	Std. Dev
Single Family (n=161)	21.0	14.1	2.4
Multi-Family (n=28)	21.3	16.4	3.1
Heat Pump (n= 50)	18.5	15.2	4.1
Gas-Fired Furnace (n=139)	21.1	14.5	2.8

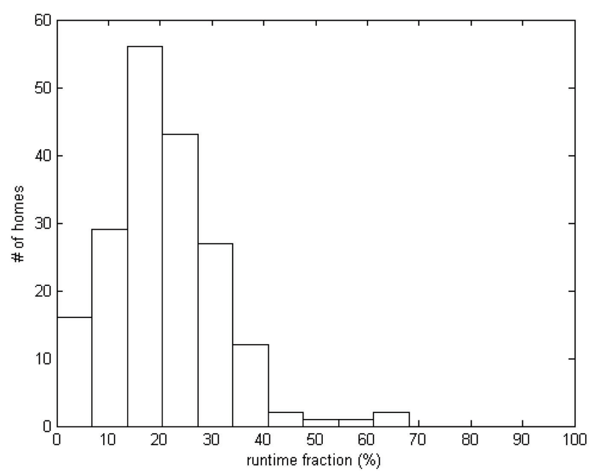


Figure 26: Annual runtime fractions (%) 189 homes in Austin, TX

Monthly/daily heating and air conditioning runtime fractions

Runtime fractions were determined for each month monitored from September 2013-August 2014. Figure 27 shows the mean values for the runtime fractions (center horizontal line of the box plot) for single family (a) and multi-family (b) homes, as well as for homes with the heat pump (c) and gas furnace (d) systems. The upper and lower ends of the box plots represent the 25% and 75% percentile of homes, and the vertical dotted lines show 2.7 times the standard deviation (99.3% of data).

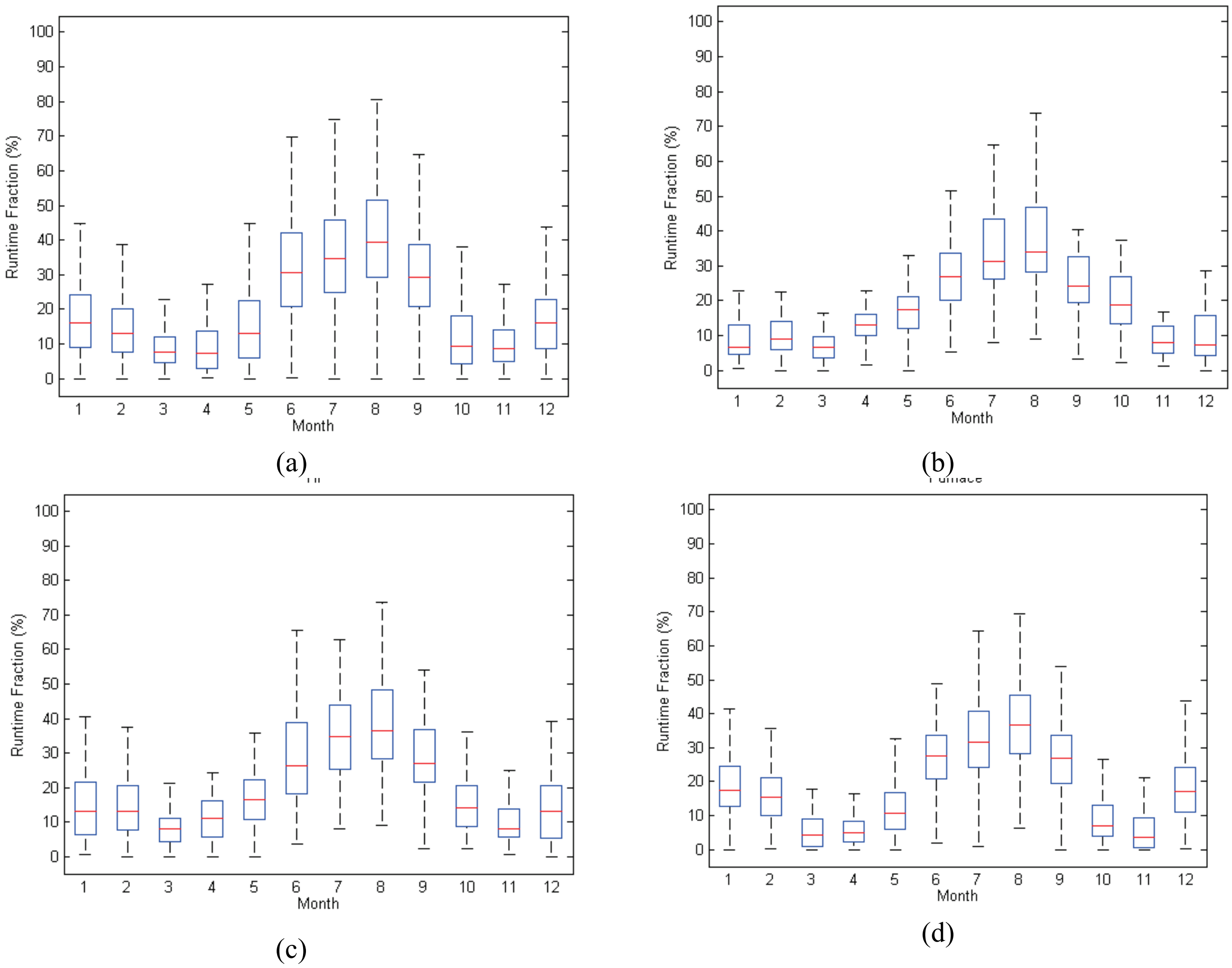


Figure 27: Monthly runtime fractions (%) of residential HVAC systems, including, (a) single family homes, (b) multi-family homes, (c) homes with heat pumps, and (d) homes with gas-fired furnaces.
Note: Month 1 corresponds to January, and Month 12 to December.

The four subsets of data have similar runtime fraction patterns. Monthly runtime fractions are highest during the months of the peak of the cooling (summer) season, in all cases.

Mean monthly runtime values range from 33.9 – 39.5% and median, from 35.4 - 41.1% in August. In addition the peak summer season also has the greatest variation in runtime fraction among the studied homes. The heating (winter) season represents the second highest runtime fractions of the four seasons, with runtimes peaking in December–February. Mean monthly runtime values range from 6.8 to 17.4% and median, from 9.6 to 19.6% in January. The multi-family units show the lowest heating runtime fraction of the four subsets of data.

The lowest runtime fraction of the HVAC systems are in the spring and fall seasons, which is the transition between the heating and cooling seasons. During this time, unlike the cooling and heating seasons, the outdoor temperatures are often within the thermal comfort zone of occupants. Of these months, including March – May and October-November, the monthly runtime fractions are lowest in March and November, ranging from 6.6- 9.8% mean, and 8.4-10.7 % median. These transitions periods in the seasons also have the least variation in value among the homes studied.

Hourly heating and air conditioning runtime fractions

Average hourly runtime fractions (Figure 28) were computed for all homes following the same methodology. The months of January, August, and March are used to show the heating, cooling, and transition seasons respectively. During the peak cooling season the hourly runtime fraction is on average the lowest at 9:00 am (21%), and highest at 7:00 pm (46%). During the peak heating season, the runtime fraction is greatest in the early morning at 7:00 am (25%), and lowest at 4 pm (14%). The transition season (March) is similar in shape to the heating season, but lower in value (10-16%). Hourly runtime fractions vary significantly across all homes. The average standard deviation for the heating, cooling, and transition seasons are 31%, 37% and 28% respectively. Since an hour time increment is shorter than daily or monthly intervals of study, the chances that the HVAC runs nearly 100% or 0% of the time are higher.

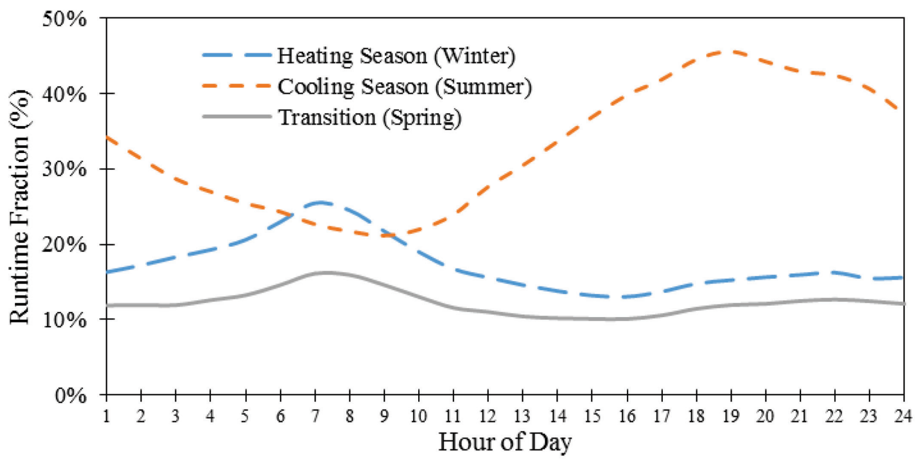


Figure 28: Average hourly runtime fractions (%) for January (heating season), August (cooling season), and March (transition season) across all homes studied (n=189).

Indoor Fan-Only Operation Runtime

Of the 189 homes studied, 22 show timed indoor fan-only operation, all of which are single family homes. Figure 29 shows the runtime fractions for the studied homes with indoor fan-only ventilation for the summer months, and those without it for all months of the year. Only the summer months are shown for the indoor fan-only ventilation homes since only three of the 22 homes utilized heat pumps, and thus for a large majority of these homes, the winter (heating season) runtimes of the indoor unit for ventilation and for heat cannot be distinguished using the electricity signal only.

On average, the median runtime value is 3.1% of the time (1.9 min/hour) for homes with indoor fan-only ventilation. For homes that do not show this pattern, the median value for runtime averaged just under 1.0% (0.6 min/hour). Mean values are 8.4% (5.4 min/hour), and 2.3% (1.4 min/hour) respectively. In both cases, the runtime fraction of when only the indoor unit is ON is consistent across all months studied. The nearly 3 times larger indoor fan-only runtime fraction in homes with timed fan-only ventilation is expected since these homes should be running the indoor fan regularly per ASHRAE 62.2 guidelines [12].

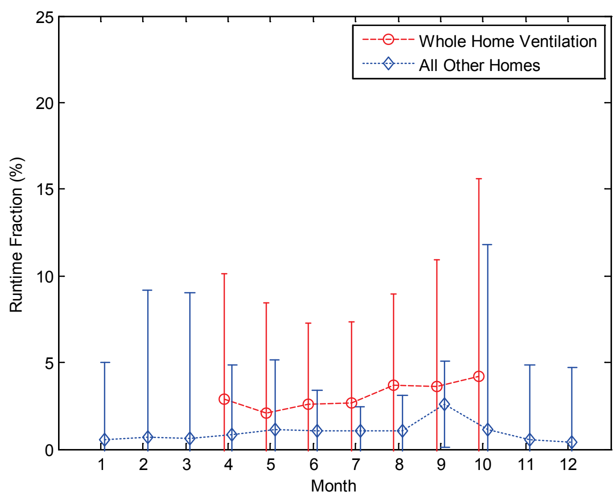


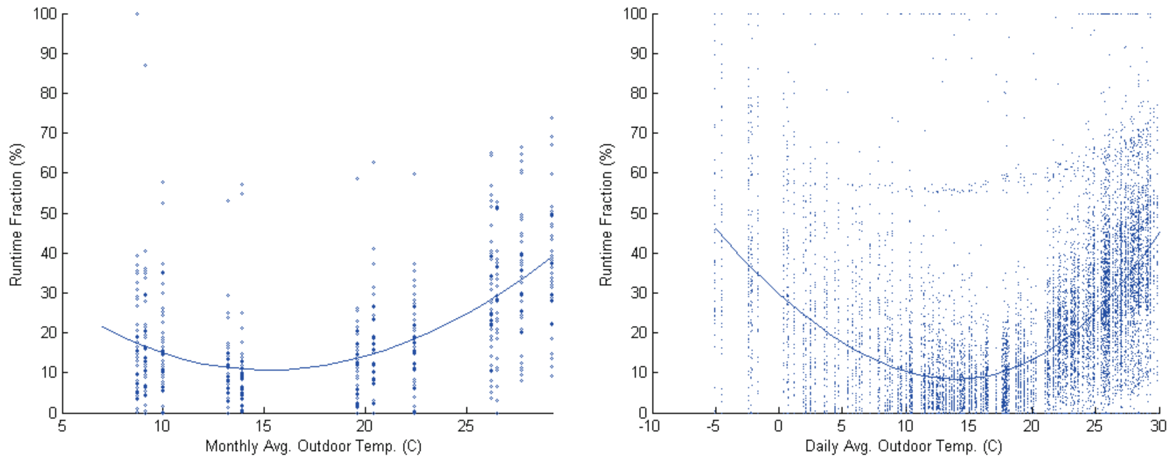
Figure 29: Monthly indoor fan-only runtime fractions for monitored homes with timed fan-only ventilation and those without; *Note: Error bars represent 2.7 times the standard deviation (99.3% of data).*

Relationship to Outdoor Temperature

Monthly and daily outdoor temperatures (°C) are compared to the runtime fraction (%) of the monitored home's HVAC systems (Figure 30). The minimum daily and monthly HVAC runtime fraction occurs when the monthly and daily outdoor temperatures are 14-15°C (57-59°F), and are 12% and 8% on average, respectively. The highest runtime fractions occur at the extreme high and low monthly and daily average outdoor temperatures. At outdoor temperatures of 30°C, the average monthly and daily runtime fractions are 46% and 45% respectively.

A third-order polynomial function is fit to the monthly and daily runtime fractions, showing the relationship of runtime fractions to outdoor temperature. This is determined since year-to-year daily and monthly outdoor temperatures vary, both within the same location and climate zone, and when considering other climate zones. Understanding this relationship between the outdoor temperature and runtime fraction allows for consideration in applying these results to other climate zones with overlapping temperature ranges. This polynomial function is applicable between the ranges of the temperatures observed when developing the curve (-5 to 30°C for daily averages, and 5 to 29°C for monthly averages). Table 15 shows the coefficients of the polynomial function P, where p_0 to p_3 are coefficients of the polynomial function in Equation 1. The R^2 value listed in Table 3 indicates the high variability of the runtime fractions across homes.

$$y(t) = p_0 + p_1 t + p_2 t^2 + p_3 t^3 \qquad \text{Eq. 1}$$



(a) (b)

Figure 30: Runtime fractions (%) of all residential HVAC systems, compared to (a) monthly average temperature (°C) and (b) daily average temperature (°C).

Table 15: Coefficients of polynomial function and coefficient of determination of outdoor temperature and HVAC runtime fraction data

	p_3	p_2	p_1	p_0	R^2
Monthly	-7.5e-6	1.9e-3	-0.052	0.49	0.32
Daily	1.1e-5	8.0e-4	-0.029	0.30	0.31

HVAC and Whole-Home Energy Use

The HVAC energy use (kWh) and whole-home energy use (kWh) are compared to the monthly, daily and annual runtime fractions (Figure 31). HVAC energy use has a stronger correlation to the annual, monthly and daily runtime fractions than the whole-home energy use. Monthly energy use also has a stronger correlation to runtime fraction than does annual and daily values.

Discussion

Historically due to lack of detailed, longer-term datasets, most models, particularly those utilized for indoor environmental research, have assumed a single value for the runtime fraction for an entire year. Previous work's assumed annual runtime fractions range from 16.7% [31,36], to 25% [27,44]. Small scale studies of runtime fractions have found duty cycles between 9 and 34% [35, 39]. The study previously conducted in Austin, TX found a median runtime of 20.6% [37]. This study finds a median runtime fraction of 14.1-16.4%, and an average runtime fraction of 18.5-21.1%.

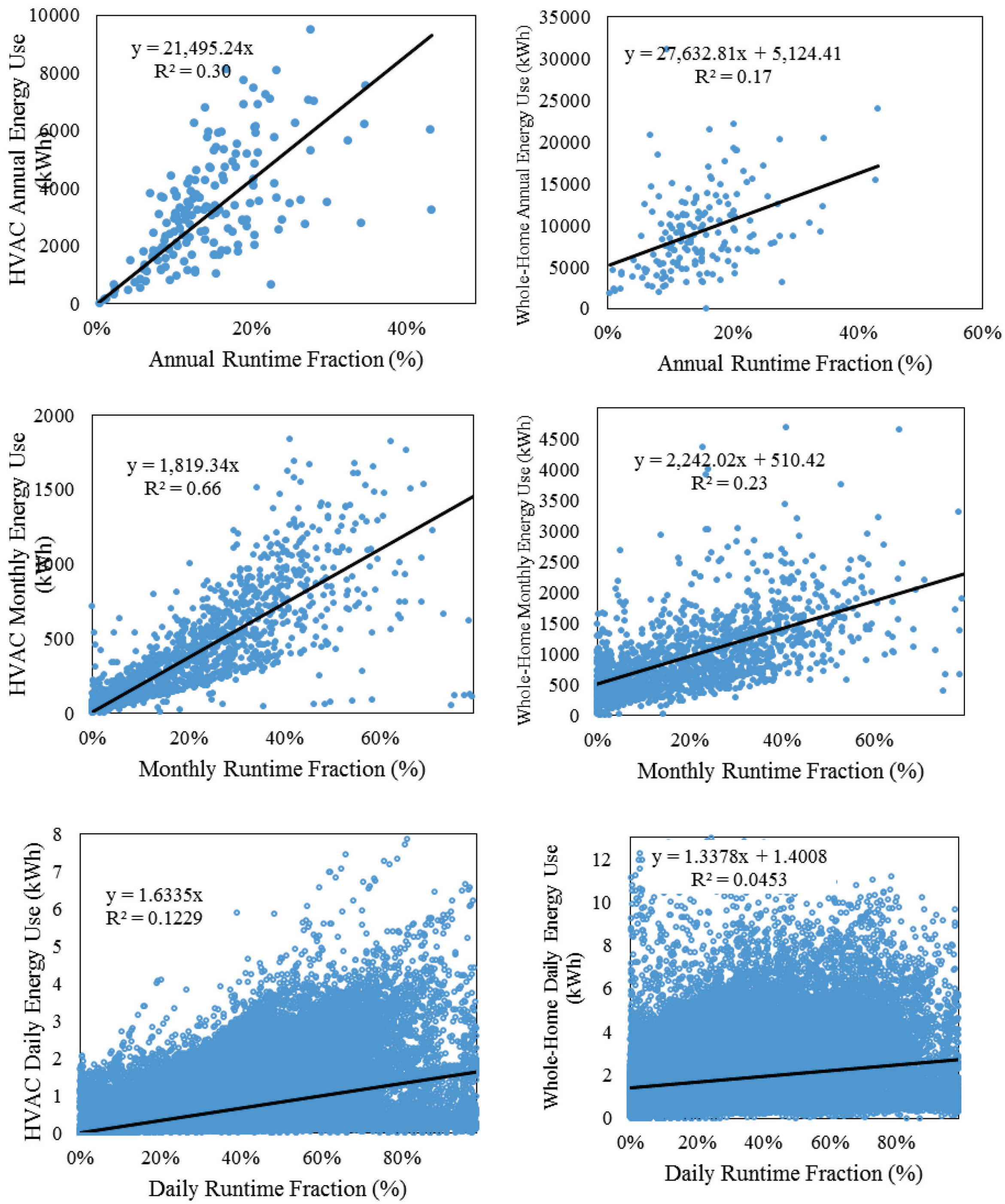


Figure 31: HVAC (left column) and whole-home (right column) energy use (kWh) compared to the annual, monthly and daily runtime fractions of the studied homes.

Comparison to previous studies

The annual runtime fraction found in this study is lower than the previous study in Austin, TX, and within the range of assumed values and findings of previous literature. There are many possible reasons for these differences. The current study utilizes measurements from a larger number of homes over a continuous, uninterrupted period of time, rather than intermittent or shorter periods of time [35,37,39], thus it is not necessarily expected that the annual runtime values would equate to those found in the previous studies. Compared to the previous study in Austin, TX [37], this study utilizes data collected over a year-long period (8760 hours), rather than 100 – 212 hours for the cooling period only. The predicted runtime fraction (Equation 1, Table 15) for daily and monthly runtime at the same average outdoor temperature as the previous study (27.9°C) is approximately 35% for the current study, which is higher than what was found in Stephens et al [37]. Stephens et al. [37] also included light commercial, non-residential buildings, which have different HVAC demands, while the current study does not. Previous studies have also concentrated on single family homes, or single family and light commercial buildings, rather than multi-family and single family homes. The single family homes studied have a higher runtime fraction as compared to the multi-family homes but not as high as those in previous studies.

Influencing factors on runtime fraction

The observed runtime fractions show significant variation. Regression analysis was conducted on the annual runtime fraction of single family homes to determine the significance of the effect of influencing factors where data was available (n=103). These include building age, estimated building volume, number of occupants, type of HVAC system, and average cooling and heating set point temperatures, and were found to explain some of the variation in the annual runtime fraction data ($R^2 = 0.33$). Combined with annual HVAC energy use values (kWh), the coefficient of determination is nearly doubled ($R^2 = 0.64$). There are many possible additional influencing factors. Discussion on the influence of these factors and the results of the regression analysis are discussed as follows

Temperature and Climatic Conditions: Perhaps the most logical influence on the overall runtime fraction and runtime fraction temporal patterns is the outdoor climatic conditions. Since the purpose of an HVAC system is to maintain desired indoor climatic conditions despite changes in the outdoor conditions, when the difference in indoor and outdoor temperature increases, the runtime fraction should also increase since the HVAC must work longer to heat or cool the interior space. This pattern is observed in Figure 30, when compared to both daily and monthly average outdoor temperatures, with considerable variation among the homes studied, which may be due to a variety of influences discussed in this section.

The lowest runtime fractions occur at approximately 15°C. When the outdoor temperature is close to the desired indoor set point temperature, the HVAC runtime should be low since the difference in indoor and outdoor temperatures are low. As observed in Figure 27, low runtime fractions occur during the spring and fall seasons (transition seasons). During transition months, when outdoor conditions are closer to the thermal comfort zone conditions, as defined by ASHRAE 55, the HVAC is needed less to maintain a desired indoor temperature. Building occupants may also open windows or doors rather than use the HVAC. 15°C is lower than the thermal comfort zone range of temperatures for conditioned spaces of approximately 21°C and 28°C operative temperature (average of air temperature and mean radiant temperature). However the interior temperature of the home is likely different than the exterior. According to the adaptive thermal comfort model used for naturally ventilated spaces, at an outdoor monthly temperature of 15°C, and acceptable indoor operative temperature is between 20°C and 25°C.

Building Age: The age of the homes studied may affect the runtime fraction. According to data from the U.S. Residential Energy Consumption Survey [3], the average energy use (kWh/yr) of residential air conditioning and heating systems decreases, the older the age of the home, meaning either the power draw (kW) or runtime fraction (%) of the HVAC system decreases. Stephens et al. [37] found that runtime fraction increased with the increasing age of the home. Because only shorter periods of time during the cooling season were used, it [37] did not capture the annual behavior of the system. However, it is expected this trend would be similar for the heating season. Comparing the annual runtime fraction (%) to the age of the homes in this study for those homes with available information, the runtime fraction decreases slightly with the increasing age of the home. However a strong correlation between the age and annual runtime fraction (R^2 = 0.05) was not observed, and regression analysis indicated this factor was not statistically significant ($p > 0.05$). The age of a home does not capture any energy efficiency retrofits or other modifications to a home that may have been performed that may affect runtime fraction, thus this may explain part of the lack of strong correlation between home age and runtime fraction.

Air Exchange Rate: The air exchange rate (ACH) of the studied homes can also affect the operation of the HVAC system. A higher air exchange rate means more unconditioned air infiltrates into the home through the building envelope, including the walls, floors, and ceilings, while conditioned or heated interior air escapes through the envelope or ductwork. In the summer (cooling) and winter (heating) months, with additional unconditioned air to heat or cool to maintain the desired indoor set point temperature, the HVAC systems needs to be ON for a longer period of time to make up for the lost heating or cooling load from the unconditioned infiltration. A more leaky construction with more unconditioned air also can also mean higher humidity inside a home, particularly in humid climates. While humidity will not affect the behavior of the thermostat and HVAC runtime directly, it may make occupants more uncomfortable at higher temperatures. This may cause them to turn down the thermostat, causing the HVAC to run longer. During the transition months in which outdoor temperature is within the thermal comfort zone the increased ACH may become beneficial. For example, with suitable ambient condition, the HVAC system will be off and occupants may open the windows to allow for natural ventilation. In this case, the ACH would have a small effect on HVAC use.

Previous studies of over 70,000 U.S. homes have found that the age of a home is a significant predictor of the air exchange rate (ACH) of a home [45], with older homes having a higher ACH, or more "leaky" construction, and newer homes having a lower ACH, or "tighter" construction. However, as discussed, older homes may also be retrofitted to reduce the ACH of the home using weatherization techniques. Without testing for the ACH in each of the studied homes, a definitive answer of the ACH cannot be provided, however, as shown in Thornburg et al. [38], ACH and runtime fraction do have a positive but weak (R^2 =0.35) correlation. A similar trend may occur in the homes in this study.

Building Envelope Characteristics: The thermal performance of the building envelope of a residential building can also be an important influence. Newer homes are built with greater amounts of insulation than older homes. Less insulation allows more heat exchange to occur between the exterior and interior of the home, thus with a less insulation, the HVAC system must be on longer to maintain the desired set point. As applicable building codes have become more stringent with time in the U.S., the R-values of the walls and fenestrations have improved. Retrofits, including added insulation, will reduce the heat loss from interior to exterior of the home. The insulation value of the studied homes is not definitively know, however assuming the homes were built to code this, this may also influence the runtime fraction.

The volume of the building (m^3) also has an influence on the runtime as a larger space requires more air to be conditioned for a desired set of indoor conditions. The regression analysis did not show a statistically significant influence estimated building volume, determined by the reported building area (m^2) multiplied by ceiling height (m), on the annual runtime fraction.

Exterior wall surface exposure: The single family homes studied are, on average 8 years old, while the multi-family homes are, on average, 37 years old. However the runtime fractions are also lower for the older multi-family homes, despite likely lower R-value walls. In considering the building envelope for single family versus multi-family homes, while single family homes have all sides of the home exposed to exterior conditions, multi-family homes have a smaller number of exterior walls, and thus a larger number of interior walls that interface with other conditioned housing units. This may explain part of the lower runtime fraction values found for the multi-family homes since the HVAC system requires less use to make up for cooling and heating losses to the exterior.

Building thermal mass: Building thermal mass influences how much heat is absorbed and stored in a building and can have a positive or negative effect on reducing building HVAC energy use and runtime. In hot climates with large temperature swings below and above the indoor set point, a large thermal mass can reduce HVAC use by introducing a thermal lag or time delay in the flow of heat from the exterior to the interior; when the outdoor temperatures increase over the set point temperature this allows the indoors to stay cooler longer without the need for mechanical conditioning. In cold climates in which the set point temperature inside is always warmer than outside, heat flow is always flowing from interior to exterior. In this case thermal mass will not have a significant effect. In the hot and humid climate in which this study is conducted, the thermal mass of the homes studied likely has an influence on the HVAC runtime.

HVAC system characteristics: Several other influences on runtime fraction include, for system characteristics, under or oversized HVAC systems [46-48], indoor evaporator fan speeds [49], and the presence of one or more faults or system inefficiencies [50-51]. An undersized system requires longer runtimes to meet the desired interior conditions since the cooling or heating capacity is lower than needed. Conversely an oversized system often results in short cycling, where the HVAC turns ON and OFF frequently, but for short periods of time. Indoor evaporator fan speeds change the amount of air flowing over the cooling coil and thus affect the sensible and latent cooling and heating capacities. The studied systems, however, utilize constant speed evaporator fans, thus this should not affect runtime fractions in the studied homes. Faults in an HVAC system, such as evaporator or condenser flow rate reductions, and low or high refrigerant charge, can cause degradation in system capacity, which requires the system to run longer to meet the same needs of a properly functioning system.

The age of the HVAC systems studied may also have an effect on the runtime fraction, particularly since such faults or inefficiencies may be more common in older systems. While the studied systems were all single-stage systems, the use of newer systems such as variable speed or multi-stage systems, or in the case of multi-family units, variable refrigerant flow (VRF) systems, would also impact runtime fraction since the rate of cooling is variable. As manufacturers use a variety of techniques to improve efficiency of residential HVAC systems, this must be considered in the use of this research.

The age and size of the studied HVAC systems was reported for only some of the systems in the studied homes and the systems were not tested for faults. However, considering most of the single family homes studied were built within the last 15 years, it is assumed that the age of the HVAC systems in these homes is the same age of the home. In the regression analysis, the age of the home was the third most influencing factor of those studied.

Internal loads and occupant behavior: Internal loads including occupants, plug loads, and appliances can also affect HVAC operations. Higher internal loads can increase HVAC runtime in the summer, and reduce it in the winter. The thermostat set point temperature set by the occupants, the deadband range, and location of the thermostat and return registers determines whether the thermostat tells the system to be ON or OFF. This also includes human behavior such as the opening and closing of doors and windows. The regression analysis indicated that the number of occupants had a significant influence on the annual runtime fraction of the HVAC system ($p = 0.04$). This analysis also indicated that the indoor cooling set point temperature (summer) is influential on the runtime fraction ($p = 0.05$).

Application for other climates

While the monthly, daily, and hourly runtime fractions will be specific to the climatic region of the studied homes, they have important implications for use in indoor environmental models, thus an effort is made in this research to allow for the extension of the use of this data for other locations. The correlation between outdoor temperature and runtime fraction is developed to also be applied for use in other climate regions with overlapping outdoor temperature ranges. Using the curves shown in Figure 30 of runtime fraction vs outdoor temperature, this correlation of temperature vs. runtime fraction could be applied to TMY (typical meteorological year) data for a given location of study. This could be used to determine the runtime fraction of HVAC systems in buildings in other geographic locations.

Limitations and Future Work

It is important to note that there are many factors that affect the runtime fraction of an HVAC system, including the HVAC system characteristics, the building it services, and the climatic conditions in which the building is located. These factors introduce uncertainties into runtime fractions across homes. It is also important to note that the studied central all-air HVAC system is the most commonly used HVAC system type in the U.S., however there are other types of heating and air conditioning systems used throughout the U.S. and world beyond the studied system that are not covered in this analysis.

The runtime fraction of an HVAC system is highly dependent on the seasonal conditions, including outdoor temperature and RH. In the cooling-dominated climate of Texas, the summer season is long, and the winter season is short. Other milder climates may see lower annual runtime fractions than those found here, as the outdoor conditions that correlate with low-runtime fractions of HVAC occur more often. This is a geographic limitation of the presented dataset of homes. The correlation between temperature and runtime fraction shown in Figure 30 also contains a higher level of uncertainty and should be noted if used to apply to other locations.

This study also includes one year of data. Additional data may be helpful in providing additional insights, however one year of data captures the full range of seasonal conditions and temperatures that are typical of the region's weather. Additional data may provide a slightly larger range of performance by outdoor temperature, however this study provides a significantly larger dataset in terms of time of monitoring, as compared to previous studies.

The dataset also includes a limited set of homes (n=189). These homes' physical characteristics and their occupants' characteristics are not necessarily representative of all U.S. homes or homes in other countries, but are a strong improvement from previously presented data.

As discussed, runtime fractions assumptions are typically constant values. More detailed information on HVAC operational characteristics such as this allows for a more detailed modeling based on this variable. For example, in calculations of ozone indoors, ozone is typically present in higher concentrations in the summer months. Using a constant value for runtime fraction may thus underestimate the ozone concentrations indoors since a lower value for runtime would be assumed in the summer months rather than the seasonal values. Similarly in looking at the hourly profiles of runtime fraction, a constant value for runtime would not capture the changes in runtime throughout different hours of the day.

Using this more detailed information on runtime fractions of HVAC systems, developing indoor air models that incorporate time and temperature dependent runtime fraction values would be beneficial to understand the implications of runtime fraction variations. Additionally further study of similarly collected data in a heating dominated climate could provide a more complete picture of HVAC runtime fraction data across multiple climate zones. Considering the influence of other building and human factors on HVAC operational characteristics may also provide additional insights on the prediction of these characteristics. These topics are the subject of ongoing and future work.

Conclusions

This study has conducted analysis on the characteristics of the operation of HVAC systems for 189 homes in Austin, TX for a one year period. The results of this study are intended to build the dataset of information on central all-air HVAC operations to aid in improving indoor air models. The following conclusions can be drawn from this work:

(a) The average annual HVAC runtime for both single family and multi-family homes is approximately 20% (12 min/hour). However, while this annual value is consistent with previous research, assuming a single value for annual runtime fraction is misleading, as the runtime fraction varies, on average between 7% and 40% with the seasons.

(b) The HVAC runtime fraction of the studied homes in the peak heating season and peak cooling season are approximately 1.5 and 4 times greater, respectively, than in the transition spring/fall seasons. Summer runtime fractions average 34-40% across all homes in the peak summer month, and winter runtime fractions average 7-17%, depending on the home and system type. Transition period runtime fractions range from 7-10%.

(c) The hourly profile of HVAC runtime fraction in the cooling and heating season are different; In the cooling season the runtime fraction is highest in the evening (7:00 pm), and lowest in the morning (9:00 am); There is a 21% runtime fraction difference between the highest and lowest hourly average across all homes; The hourly profile of HVAC runtime fraction in the heating season, however, peaks in the morning (7:00 am), is lowest in the afternoon (4:00 pm), and varies by 11% runtime fraction across all hours. The transition season runtime fractions are the most consistent across all hours of the day, averaging between 10-16% per hour.

(d) Monthly and daily HVAC runtime fractions are lowest where the outdoor temperatures are at approximately 15°C; the farther above and below this range the outdoor temperatures get, the greater the runtime fraction of the heating or cooling system.

(e) Indoor fan-only operation averages between 1 and 3% by month. This value is consistent across all months of the year. When comparing homes with regular timed indoor fan-only operation, the indoor fan is ON, on average 3.1% of the time, approximately 3 time more than those that do not.

(f) There is considerable variation in the runtime fractions of the studied homes, which is due to a variety of influencing factors. These factors must be taken into consideration when using the results of this study.

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Appendix C

Paper 3: Thermal Comfort Evaluation for Mechanically Conditioned Buildings using Response Surfaces in an Uncertainty Analysis Framework

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(Submitted to Science and Technology for the Built Environment)

Abstract

An uncertainty analysis methodology is proposed to aid in quantifying the risks of thermal comfort under-performance posed by changes to variations in physical and operational characteristics of a building and its environment. This includes those implemented for building energy savings, peak electricity load reductions, or those due to climatic changes. Using building performance data as input, a Response Surface Methodology (RSM) is used to develop a model to predict building thermal performance for ranges of user-defined design variables. This model is verified for accuracy using in and out-of-sample data. Uncertainly analysis is then used to estimate the probability of achieving an acceptable threshold of thermal comfort performance. A case study is presented to demonstrate the implementation and interpretation of the results of this methodology, which evaluates the effects of a 1-hour demand response event on thermal comfort of a residential mechanically-conditioned building. The case study finds that a second-order response surface provides reasonably accurate model of thermal comfort. For the studied single family home, compared to varying the air exchange rate, the indoor

set-point temperature has a greater influence on achieving an acceptable level of thermal comfort.

Introduction

In many developed countries, on average, people spend 80-90% of their time indoors (US EPA 1989; Leeach et al 2000). The thermal comfort of the occupants, a measure of the satisfaction with the indoor environmental conditions, is thus of great importance. Previous studies have linked thermal comfort to the health, well-being and productivity of occupants (Schellen et al 2010, Akimoto et al 2010), particularly the elderly (Almeid-Silva et al 2014). Conditions that are considered in defining acceptable thermal comfort of building occupants include (1) environmental factors such as: dry-bulb air temperature (ºC), mean radiant temperature (ºC), air speed (m/s), and humidity (%); and (2) personal factors consisting of: metabolic rate (met), and clothing insulation (clo) (ISO 2005; ASHRAE 2010). Mathematical models developed by Fanger (Fanger 1967; 1970; 1972) provide the basis for the most widely accepted international thermal comfort standards for mechanically conditioned buildings, including ASHRAE Standard 55 (ASHRAE 2010), International Standards Organization (ISO) 7730 (ISO 2005), and EN 15251 (EN 2006). These standards define acceptable ranges of the environmental factors in the indoor environment. The polygons in Figure 31 represent the typical thermal comfort zones (TCZs) for cooling and heating seasons according to ASHRAE 55 (ASHRAE 2010). Changes in assumed level of clothing (clo) and metabolic rate (met) may be adjusted, resulting in a different location and size of the thermal comfort zone.

Methodologies for defining the level and severity of thermal comfort/discomfort over a period of time have been proposed by a number of authors. The Percentage Outside Range (Carlucci and Pagliano 2012), Hourly Performance Index (Hensen and Lamberts 2012), and Hours of Exceedance (Olesen and Brager 2004) methodologies, discussed in Standard ISO7730 (ISO 2005), count the number of hours inside and outside the TCZ, represented as a fraction of the total number of hours evaluated.

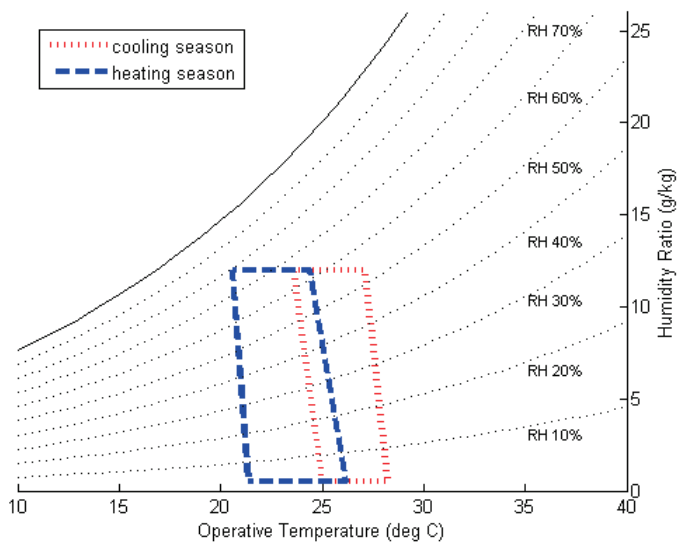


Figure 31: Psychometric chart showing thermal comfort zones (TCZs) for cooling and heating seasons according to ASHRAE 55 (2010).

The ability to achieve a comfortable indoor environment for occupants is influenced by changes to a building, its systems, and its external environment. Many of these are summarized in Table 16. Particularly in the United States, thermal comfort is typically achieved, in part, through mechanical heating, ventilation and air conditioning (HVAC) systems, which are designed to meet the internal cooling and heating loads of a building.

In the United States, 83% residential, and 78% of commercial buildings utilize HVAC systems, including more than 94 million housing units (RECS 2009), and 3.6 million commercial buildings (CBECS 2003). Worldwide, demand for HVAC in buildings is predicted to increase by 5.7% annually from 2014 to 2018 (Freedonia Group 2014). The operation and maintenance of building HVAC systems affect indoor thermal comfort. This includes intentional changes in operational strategies such as changes to indoor thermostat set-points and ventilation rates, and changes motivated by a need to reduce peak electricity loads (Sinato 2014; Gymfi et al 2013). Building performance is also affected by lack of maintenance of HVAC equipment that can cause equipment faults and inefficiencies or failures (SCE 2013; Cetin and Novoselac 2014).

Table 16: Common design variables influencing thermal comfort in mechanically conditioned buildings

Characteristics	Variables	Effects on Building Interior Conditions when Variable Increased
Operational	Cooling Set-point (°C) Deadband of Thermostat (°C) HVAC Cooling Capacity (kW)	Increase interior temperature; Increase allowable temperature variation above/below set-point; Increase HVAC ability to remove heat from interior;
Building Envelope	Air Exchange Rate (1/h) Windows/Doors, Walls, Roof, Ground U-value (W/m^2-°C) Window Area, Interior Shading (%) Thermal Mass (W/m^2-°C)	Increase in unconditioned outdoor air entering building interior; Increase in heat transfer between interior and exterior conditions; Increase and reduce, respectively, effect of solar heat gains (temperature) to interior; Slow the effect of exterior conditions on interior conditions;
Internal Loads	Large Appliances (W) Occupants (W) Electronics (W) Hot Water Heater (W) Lighting (W)	Increase in internal heat (temperature) and/or moisture (humidity) gains;
Climatic Conditions	Outdoor Temperature (°C) Outdoor Humidity (%) Solar Radiation (Wh/m^2)	Increase internal heat gains (temperature); Increase internal moisture gains (humidity); Increase internal heat gains (temperature) ;

In addition, buildings are one of the largest consumers of energy (US EIA 2013); thus, there is often a desire to build and retrofit existing buildings to be more energy-efficient. Among other measures, this includes intentional physical changes to exterior wall construction and fenestrations (Pacheco et al 2012) which change a building's thermal properties. These changes all can affect the indoor environment, particularly if temporary modifications are made to HVAC operations for energy savings or peak electricity load reduction events, as they affect the thermal response of the building when the HVAC use is limited or off.

To quantify the effect of these influences on indoor environmental performance, including thermal comfort, building energy modeling (BEM) is often used. BEM refers to the use of computer-based tools for developing a model of a building and its systems, and simulating its performance at a design location and over a defined period of time. Its use is becoming increasingly common as a tool for making building design decisions. However, carrying out a large number of BEM simulations to evaluate different scenarios is time-consuming, particularly if the goal is to take into account the uncertainties of the input variables used to evaluate building performance. Various techniques to simplify the evaluation of BEM have been proposed. Eisenhower et al (2012) developed a simplified normative model and calibrated it to BEM, based on the techniques discussed in other works (ISO 2007; EN 2005). Reduced-order models have also been developed for the purpose of building control strategies (Goya and Barooah 2012; Dewson et al 1993). Cole et al. (2013) developed a simplified building energy model for building control by fitting a reduced-order model to BEM data for energy consumption evaluation. Artificial Neural Networks (ANN) have also been used to develop models to predict building energy use and thermal comfort (Yuce et al 2014, Chang et al 2015, Ashtiani et al 2014).

The Response Surface Methodology (RSM) is another technique for the study of the relationship between a measured response and a set of design (input) variables (Box and Wilson 1951). The use of RSM has several advantages. Between the upper and lower bounds of each variable considered, RSM includes a large amount of information from a limited number of controlled experiments. It can be used in reducing the computational cost of expensive analysis methods such as finite element analysis (Guan and Melchers 2001, Reh et al 2006, Ren and Chen 2010) and computational fluid dynamics (Khalajzadeh et al 2011, Madsen et al 2000, Gel et all 2013). One advantage of using response surfaces is that it results in a function that can be used as input into uncertainty analysis, such as Monte Carlo simulation. In addition after its initial development, obtaining a model response is extremely fast. The use of RSM has been extended to many applications, including modeling naturally ventilated buildings (Shen et al 2012, 2013), predicting the air diffusion performance of displacement-ventilations offices, and determine effects of parameters on heat exchangers (Khalajzadeh et al 2011), and complex structural evaluation application of buildings (Kang et al 2010; Leira et al 2005).

The response function is developed from a set of experimental or simulated results that are used to estimate the coefficients appearing in the response surface definition. This is achieved using regression analysis, minimizing the sum of the squares of the residuals between model predictions and data (Box and Draper 1987). There are several techniques proposed for the selection of specific experimental results needed as inputs to the RSM development. For first-order models, 2^n factorial design is often used (Ratkoe et al 1981). For each design variable, two extremes, a high and low value, are considered. The Plackett-Burman (Plackett and Burman 1946) and Simplex (Box 1952) methodologies are better suited for situations where the number of design variables is large, making the 2^n response evaluations less practical. The most common methodologies for second-order models include the 3^n factorial design (Hoke 1974) and the Box-Behnken design (1960). For the 3^n model, in addition to two high and low extreme values, a third middle (mean) value is also used. To reduce the number of design points, the Box-Behnken design uses a subset of the 3^n design, as described in Box and Behnken (1960), Box and Draper (2007), Khuri and Cornell (1996), and Myers and Montgomery (2009).

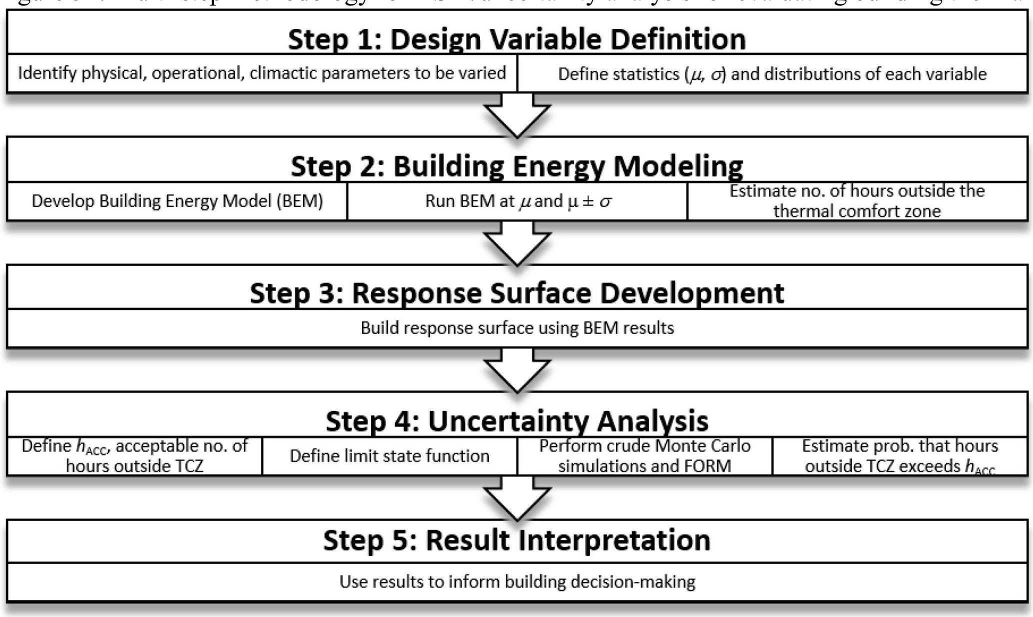
Uncertainty analysis is widely used in many engineering fields to aid in decision-making. Monte Carlo simulation is a well-established tool for this analysis. In BEM, previous studies have assessed the uncertainty in the design parameters and assumptions. De Wit (de Wit 2001; de Wit 2002) studied uncertainties in building parameters and established ranges of building characteristics that may be considered for use in building energy simulation. Building thermal comfort has also been evaluated using uncertainty analysis (Parys et al 2012; Hopfe and Hensen 2011; Breesche and Janssens 2010; Heo et al 2012; Hopfe et al 2007; Encina and De Herde 2013). The findings from these previous studies related to the uncertainty are helpful where choices of design variable probability distribution functions and associated statistics are needed.

This study applies the RSM and uncertainty analysis to building thermal comfort modeling. Ultimately, for a given set of design conditions, the main objective is to provide a measure of how likely it is that a building's thermal performance will meet the thermal comfort requirements needed to satisfy the occupants. A five-step methodology is proposed and discussed. This is followed by a case study applying the proposed methodology to a real-world application. The proposed methodology may be implemented for a mechanically conditioned building as a tool to evaluate thermal comfort for any user-defined range of a set of design values. This methodology may be applied both in the design phase of a building when evaluating energy savings strategies versus the risk of discomfort, and for existing buildings in which operational or physical changes to the buildings are being evaluated for use in building energy use or peak electricity use reductions.

Methodology

A multi-step methodology is proposed to evaluate building thermal comfort; it is presented schematically in Figure 32. It is divided into five main steps: (1) design variable definition, (2) building energy modeling (BEM), (3) response surface development, (4) uncertainty analysis, and (5) result interpretation. Each of these steps is outlined in detail below.

Figure 32: Multi-step methodology for RSM/uncertainty analysis for evaluating building thermal comfort



Step 1: Variable Definition for Response Surface Model Development

In evaluating options for construction or operational changes of a building, different design variables are considered. These design variables are used as inputs to build and define the response surface. These design variables can include physical building characteristics such as window area and wall construction, operational characteristics such as thermostat set-points and fan schedules, or climatic characteristics such as the location of the building and potentially even future climate change scenarios. Building, operational, and climatic characteristics that may affect thermal comfort in buildings are included in Table 16. To develop a response surface for use in this study, the design variable vector, $\mathbf{X} = \{X_1, X_2, \dots X_n\}$ of size n must be chosen. The greater the number of variables, n, the greater will be the computational effort required to evaluate all possible combinations of the design variable values employed to construct the response function.

A larger number of design variables allows definition of a more generalized response surface to describe the response of the building.

Each design variable, X_i, is defined by its mean value, μ_i, a standard deviation, σ_i, and a probabilistic distribution function. Commonly, upper and lower bounds are chosen for each design variable. Following Wong (1985) and Faravelli (1989), $x_{i,high}$ and $x_{i,low}$ are selected as upper and lower bounds (r_i standard deviations above and below the mean, respectively) for design variable, X_i, to be evaluated in the RSM (Equation 1a and 1b).

$$x_{i,high} = \mu_i + r_i\sigma_i \tag{1a}$$

$$x_{i,low} = \mu_i - r_i\sigma_i \tag{1b}$$

Caution should be exercised if the RSM is used in uncertainty analysis, to evaluate the system response outside of the upper and lower bounds of each design variable, as doing so may provide an inaccurate assessment of the response function, S. Values for μ_i, σ_i, and the probabilistic distribution function for each design variable, X_i, may be selected based on documented studies of building characteristics as well as operational and climatic considerations (Persily 1998; Persily 1999; ATTMA 2010; CIBSE 2010; Offermann 2009; ASHRAE 2004; Persily et al 2010; Parker 1990; Roberts and Lay 2013). They may also be chosen following a data collection effort or by using engineering judgment. For example, if a set of existing homes is being considered for energy-efficient retrofit strategies and one of the design variables is the window area (measured in m^2), the window area may be measured for each of the buildings considered and a mean, standard deviation, and distribution function may be derived directly from the data. The choice of r_i in Equations 1a and 1b could be selected as the upper and lower bounds on window area that the RSM may be assumed to be valid for, while also considering the largest and smallest window areas in the data. As an example of the use of engineering judgment, if indoor temperature is a variable, previous studies that reported average indoor temperatures, such as those summarized by Roberts and Lay (Hammersley et al 1964). These could be related to the study for which the response surface model is being developed, to define design variable ranges, statistics, and distributions.

Step 2: Building Energy Modeling (BEM) simulations

In the present study, to establish the desired response surface, input data on the thermal comfort performance of the subject building are needed. Such data include consistent time-interval data of, typically hourly, the indoor operative temperature (ºC), or both the dry bulb temperature (ºC) and the mean radiative temperature (ºC). Data indicating relative humidity (%) or humidity ratio (g/kg) of the indoor air could also be included. The required data may be obtained using results from building energy modeling or from field-collected building performance studies. The use of building energy simulation results is the more cost-effective methodology as field testing is expensive and takes far more time and effort than simulations. In the present study, BEM is used to produce the indoor temperature and humidity data; it is assumed that air speed criteria (ASHRAE 2010; Gyamfi et al 2013) for thermal comfort are met in the analyses.

In additional to a consistent time interval for measurements or simulated values, both the design period of evaluation over the calendar year and the design time of day must be chosen. In reporting the results of the methodology employed in this study, all the assumptions, including those discussed here, should be explicitly stated so that the results are not misinterpreted, as discussed by Carlucci and Pagliano (2012).

A design period is defined by a start day, d_{start} and an end day, d_{end}. Thus, the day of simulation, d, is such that $d_{start} \leq d \leq d_{end}$, and the total number of days evaluated is d_{tot}. One year ($d_{start} = 1; d_{end} = 365, d_{tot} = 365$) may be used to capture the behavior of the building accounting for all seasons of the year, a single year is a typical period of time used in BEM studies. If a year-long period is used, since there are different thermal comfort zone criteria for heating and cooling seasons, a reasonable division of the year into heating and cooling seasons may be made consistently for all the BEM simulations considered. Portions of the year representing a cooling season or a heating season may each be evaluated, provided the same period of time of the year is considered for each season in all the BEM simulations carried out.

Heating and cooling only occur during certain months of the year. These seasons and can be determined using monthly average temperatures (MATs) and typical meteorological year (TMY3) data (Wilcox and Marion 2008), or the 99% annual winter and summer and design temperatures as defined by ASHRAE (ASHRAE 2009). All months where the MAT or 99% design temperature is less than 18.9°C are defined as the heating season, and all months where the MAT is greater than 18.9°C are defined as the cooling season. Additional information on this methodology is included in the Building America House Simulation Protocols (Wilson et al 2014) used for building energy simulation.

Design times of day must also be chosen for evaluation; the time interval representing the time of simulation each day, h_d, is such that $h_{d,start} < h_d < h_{d,end}$, where $h_{d,start}$ and $h_{d,end}$ represent the starting hour and the ending hour of each daily simulation. The total number of time interval data each day is $h_{d,tot}$, and the total for the design period is $h_{tot} = h_{d,tot}d$, where d is the number of days in the design period. If a building is occupied all day, and hourly time interval data are used, then $h_{d,start} = 1, h_{d,end} = 24,\ h_{tot} = 24d$. If the building is only occupied at specific times during the day, such as is the case for an office building, then we may have, for example, $h_{d,start} = 8, h_{d,end} = 17, h_{tot} = 9d$. Note that design times of day for evaluating thermal comfort may only consider occupied time periods since thermal comfort may not be of interest when there are no people in the building.

A nonlinear response surface is constructed using 3^n BEM simulations. This includes a simulation at each combination of the n design variables (X_i; i = 1 to n) at three design points, $x_{i,high}$, $x_{i,low}$ and μ_i. Once the BEM simulation results are generated, the percent of time inside and outside the thermal comfort zone must be computed from each simulation. With a defined thermal comfort zone, such as in Figure 31, each simulated time interval data point for the selected design time period is plotted on the psychometric chart to determine its location relative to the thermal comfort zone for that season. The percent of simulated data points that lie outside the thermal comfort zone, $S_{k,data}$, where k = 1 to 3^n, is computed using Equations 2a and 2b, where a value of 1 for each time interval data point indicates that the simulated point is outside the thermal comfort zone while a value of 0 indicates it is inside the thermal comfort zone.

$$S_{k,data} = \left(\frac{\sum_{d=1}^{d_{tot}} \left(\sum_{h=h_{d,start}}^{h_{d,end}} c_{d,h} \right)}{d_{tot} * h_{tot}} \right)_k \tag{2a}$$

$$c_{d,h} = \begin{cases} 1 \leftarrow (\text{outside thermal comfort zone}) \\ 0 \leftarrow (\text{inside thermal comfort zone}) \end{cases} \tag{2b}$$

If a large number of design variables are being evaluated, the number of simulations needed (3^n) for the Full Factorial Design may become computationally expensive. In this case, methodologies such as the Fractional Factorial design (Gunst and Mason 2009), Box-Behnken design (Box and Behnken 1960) or D-optimal design (Silvey 1960) may be used to reduce the number of BEM simulations needed. These designs are desirable when the extreme points are expensive or impossible to test, or when the Full Factorial Design requires too many runs for the amount of resources or time available.

Step 3: Response Surface Development

The third step in the methodology adopted involves development of the response surface. RSM generally assumes the use of a low-order polynomial response function, S, which is an approximation of the measured response of the system under consideration. This response function may be defined using a set of linear and/or nonlinear terms made up of n design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ and including a set of model coefficients, b_i (i = 1 to n) for linear variation and b_{ij} (i,j = 1 to n) for quadratic variation, along with a random experimental error term, ϵ. Simpler response functions are often of first-order (Equation 3a) or second-order (Equation 3b) forms (Khuri and Mukhopadhyay 2010).

$$S(\mathbf{X}) = b_o + \sum_{i=1}^{n} b_i X_i + \epsilon \tag{3a}$$

$$S(\mathbf{X}) = b_o + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} X_i X_j + \epsilon \tag{3b}$$

Additional information on response surface creation is discussed in previous works (Meyer et al 2011, Khuri and Mukhopadhyay 2010, Meyer et al 1989). Least-squares regression is used with the selected design variables (Step 1) and the BEM simulations (Step 2) to build the response surface. To evaluate the goodness of fit of the regression model to the data the R^2 (coefficient of determination) value is used. A good fit of the response surface to the data is indicated by an R^2 value close to unity. Evaluation of goodness of fit should be conducted on both in-sample data used to develop the response surface as well as on out-of-sample data that were not used to develop the response surface, but are within the range of the upper and lower bounds of the design variables considered in the study.

Step 4: Uncertainty Analysis

The response surface model developed following BEM simulations is an approximate representation of a real-world based situation based on assumptions and approximations. To address uncertainty in the underlying design variables, **X**, a limit state function (Equation 4), $g(\mathbf{X}; T_{acc})$, is used to quantify the probability of exceeding the acceptable percent of time, T_{acc}, outside the thermal comfort zone. Note that $S(\mathbf{X})$ represents the predicted number of hours outside the thermal comfort zone based on the response surface defined by Equation (3b), which is built using the design variables. We assume that all the design variables, X_i (i = 1 to n), can be treated as independent random variables.

$$g(\mathbf{X};\, T_{acc}) = T_{acc} - S(\mathbf{X}) \tag{4}$$

To achieve compliance with generally accepted standards (ASHRAE 2010), as a part of the design of a building, the maximum allowable percent of time outside the thermal comfort zone must be stated. Monte Carlo simulations (Hammersley et al 1964) can be used with assumed distributions for all the design variables (**X**) and with the developed response surface, $S(\mathbf{X})$, and the specified value of T_{acc}. A "failure" in a single Monte Carlo simulation is defined to have occurred when $S(\mathbf{X})$ exceeds T_{acc} or, effectively, when $g(\mathbf{X};\, T_{acc})$ is less than zero. Crude Monte Carlo (CMC) simulation, i.e., Monte Carlo simulation without any additional variance-reduction refinement, is used in this manner to estimate the failure probability, P_f, which is the probability of exceeding the allowing percent of time outside the thermal comfort zone. An alternative procedure referred to as the First-Order Reliability Method (FORM) can also be used to estimate P_f ; in this procedure, the notion of a limit state function (here, $g(\mathbf{X};\, T_{acc})$) is used along with the design variable vector definition to estimate P_f more efficiently than with CMC simulations. The accuracy in P_f estimates based on CMC simulations increases with the number of simulations.

Step 5: Result Interpretation

The methodology presented in the preceding four steps provides a means of evaluating a range of physical, operational, and environmental characteristics of a building as well as its proposed environment from the point of view of thermal comfort. The results of Steps 1 to 3 provide the response surface function (a polynomial built using BEM simulations) that defines the number of hours outside the thermal comfort zone based on *n* design variables. Multiple sets of CMC simulations allow the systematic study of the design variables and their importance. An example of the overall analysis and interpretation of the results is provided in the illustrative case study presented next.

Case Study

There are many different applications of the proposed methodology that can benefit from understanding building occupants' risk of exceeding a specified number of hours outside the thermal comfort zone. A case study is presented to describe the effect on thermal comfort of executing a single hour of air conditioner-based demand response during the summer months for homes in Austin, Texas. This involves turning off the air conditioner of homes during times when there is greatest load on the electric grid. According to historical data from ERCOT (Electric Reliability Council of Texas), this often occurs at around 5:00 pm during the summer (ERCOT 2013).

In this case study, we assume that the air conditioner is shut off for one hour from 5:00 pm to 6:00 pm. The characteristic home used in this study is a single-family detached home (114m^2, 3 bedroom, 2 bathroom home), located in Austin, Texas. Building physical and system characteristics as well as internal loads follow those recommended by the Building America guidelines for homes of this size (Hendron and Engebrecht 2010). Two design variables (n = 2) are chosen as a case study; these include the average indoor cooling set-point temperature (ºC), assuming a single zone model, and the whole-home air exchange rate (ACH, 1/hr).

Set point temperature determines the target indoor temperature of the building under consideration and directly affects the indoor thermal comfort. The upper and lower bounds of the set point temperatures were chosen to be within the upper and lower limits of the thermal comfort zone. The air exchange rate (ACH) affects the amount of unconditioned exterior air that is exchanged with conditioned interior air. A higher ACH means that when there is a difference between the outdoor and indoor conditions, the indoor conditions follow outdoor conditions closely, such that the HVAC system must work longer to meet the desired indoor conditions. ACH can vary significantly across residential buildings, with newer homes with tighter building construction having a lower ACH, and older, leakier homes having a higher ACH. The upper and lower bounds were chosen to cover a range of values common in newer buildings, or older buildings in which weatherization measures have been installed. Details related to these design variables are presented in Table 17. Only the summer, i.e., the cooling season, is evaluated such that $d_{start} = 121, d_{end} = 273, d_{tot} = 153$. All data are in hourly intervals and all hours of the day are included in the analysis such that

$h_{d,start} = 1$; $h_{d,end} = 24$; $h_{tot} = 24d_{tot}$ = 3,672 hours. Since there are two design variables, 3^2 or 9 simulations are carried out to construct the response surface.

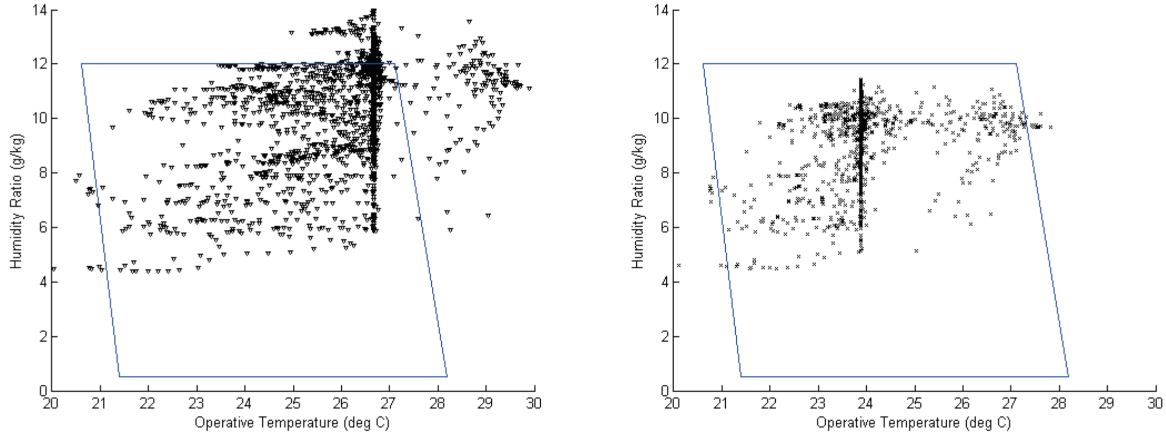
Table 17: Design variables in case study

Property	Design Variable	μ_n	σ_n	r_n	Probability Distribution	$x_{n,high}$	$x_{n,low}$
Set-point Temperature (°C)	x_1	23.9	0.93	3	Normal	26.7	21.1
Air Flow (ACH, 1/hr)	x_2	0.26	0.07	3	Normal	0.47	0.05

Building Energy Modeling (BEM) simulations were run using the EnergyPlus software (US DOE 2007) and available weather data for Austin, TX (Wilcox and Marion 2008). The thermal comfort zone assumed clothing insulation of 0.5-1 clo and a metabolic rate of 1.1 met. The resulting number of hours outside the thermal comfort zone for each BEM simulation is shown in Table 18. Plots of the extreme cases of 20 hours (0.5%) and 695 hours (18.9%), Simulation nos. 5 and 9 in Table 3, are shown in Figure 33a and 33b.

Table 18: Building Energy Modeling simulation results

#	x_1, Set-point Temperature (°C)	x_2, Air Flow, ACH (1/h)	Hours Outside Thermal Comfort Zone	% Outside Thermal Comfort Zone
1	21.1	0.26	34	0.9%
2	23.9	0.26	23	0.6%
3	26.7	0.26	470	12.8%
4	21.1	0.05	30	0.8%
5	23.9	0.05	20	0.5%
6	26.7	0.05	403	11.0%
7	21.1	0.47	45	1.2%
8	23.9	0.47	31	0.8%
9	26.7	0.47	695	18.9%



(a) (b)

Figure 33: Building energy model (BEM) hourly data results for specific simulations with (a) the largest number of hours (x_1 = 26.7°C, x_2 = 0.47 1/h), and (b) the smallest number hours (x_1 = 23.9°C, x_2 = 0.05 1/h) outside the thermal comfort zone (shown in blue).

Least-squares regression is carried out to develop the nonlinear response surface function, $S(\mathbf{X})$ (Equation 5). The estimated R^2 is 0.982. A comparison of the predicted (RSM) and simulated (data) indicating the time outside the thermal comfort zone is shown in Figure 34a. To verify the accuracy of the RSM, a set of eight randomly selected values for X_1 and X_2 are chosen within the upper and lower bounds from Table 17. BEM simulation was conducted using these values and evaluated against the predicted values from the RSM. These are shown in Figure 34b with an R^2 is 0.965.

$$S(\mathbf{X}) = 4.73 - 0.41x_1 - 0.80x_2 + 0.032x_1x_2 + 0.0089{x_1}^2 + 0.176\,{x_2}^2 + \epsilon \tag{5}$$

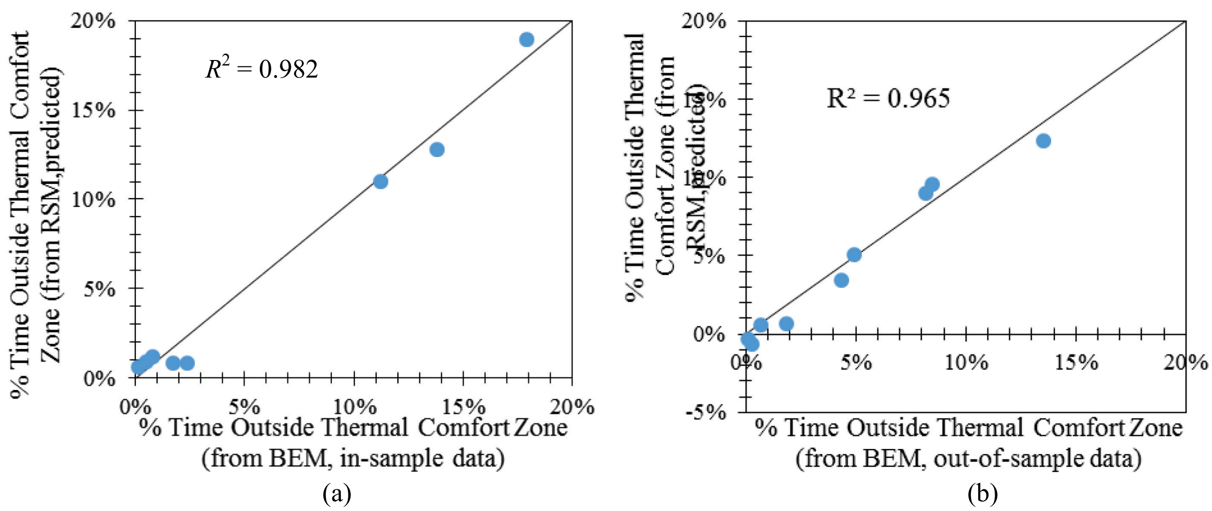


Figure 34: Comparison of the percent (%) of time outside the Thermal Comfort Zone based on the (a) in-sample and (b) out-of-sample Building Energy Model (BEM) simulations and the Response Surface prediction

For this case study, three values of T_{acc} are considered corresponding to 5%, 7% and 10% of the time when it is acceptable to be outside the thermal comfort zone. The limit state function, $g(\mathbf{X}; T_{acc})$, is evaluated for each of these values of T_{acc} to estimate the probability that each of these design allowable percentages of time outside the thermal comfort zone is exceeded. A total of 10,000 CMC simulations are run using the design variable characteristics given in Table 17. Since the RSM was developed using energy simulations out to $\pm 3\sigma$ for each variable, the polynomial function is valid for all values within this range of each design variable.

Figures 35a to 35e summarize the results of this simulation. Figures 35a, 35c, and 35e show the estimated probability of exceeding the maximum allowed percent of time, T_{acc}, outside the thermal comfort zone as a function of air exchange rate for fixed set-point temperatures, for Tacc equal to 5%, 7%, and 10%, respectively. Similarly, Figures 35b, 5d, and 5f show estimated of the probability of exceeding the maximum allowed percent of time, T_{acc}, outside the thermal comfort zone as a function of set-point temperature for fixed air exchange rates, for T_{acc} equal to 5%, 7%, and 10%, respectively. By choosing a single fixed set-point temperature (as in Figures 35a, 35c, and 35e), or a single fixed air exchange rate (as in Figures 35b, 35d, and 35f), trends in how sensitive the probability of exceeding T_{acc}, is to the other varying parameter are evident.

In Figure 36a, the variation in probability of exceeding the maximum allowed percent of time, T_{acc}, outside the thermal comfort as a function of air exchange rate is studied for a single indoor set-point temperature fixed at its mean value (23.9°C) and for three different values of T_{acc} (5%, 7%, and 10%). Similarly, in Figure 36b, the variation in probability of exceeding the maximum allowed percent of time, T_{acc}, outside the thermal comfort as a function of set-point temperature is studied for a fixed single air exchange rate fixed at its mean value (0.26 ACH (1/h)) and for three different values of T_{acc} (5%, 7%, and 10%).

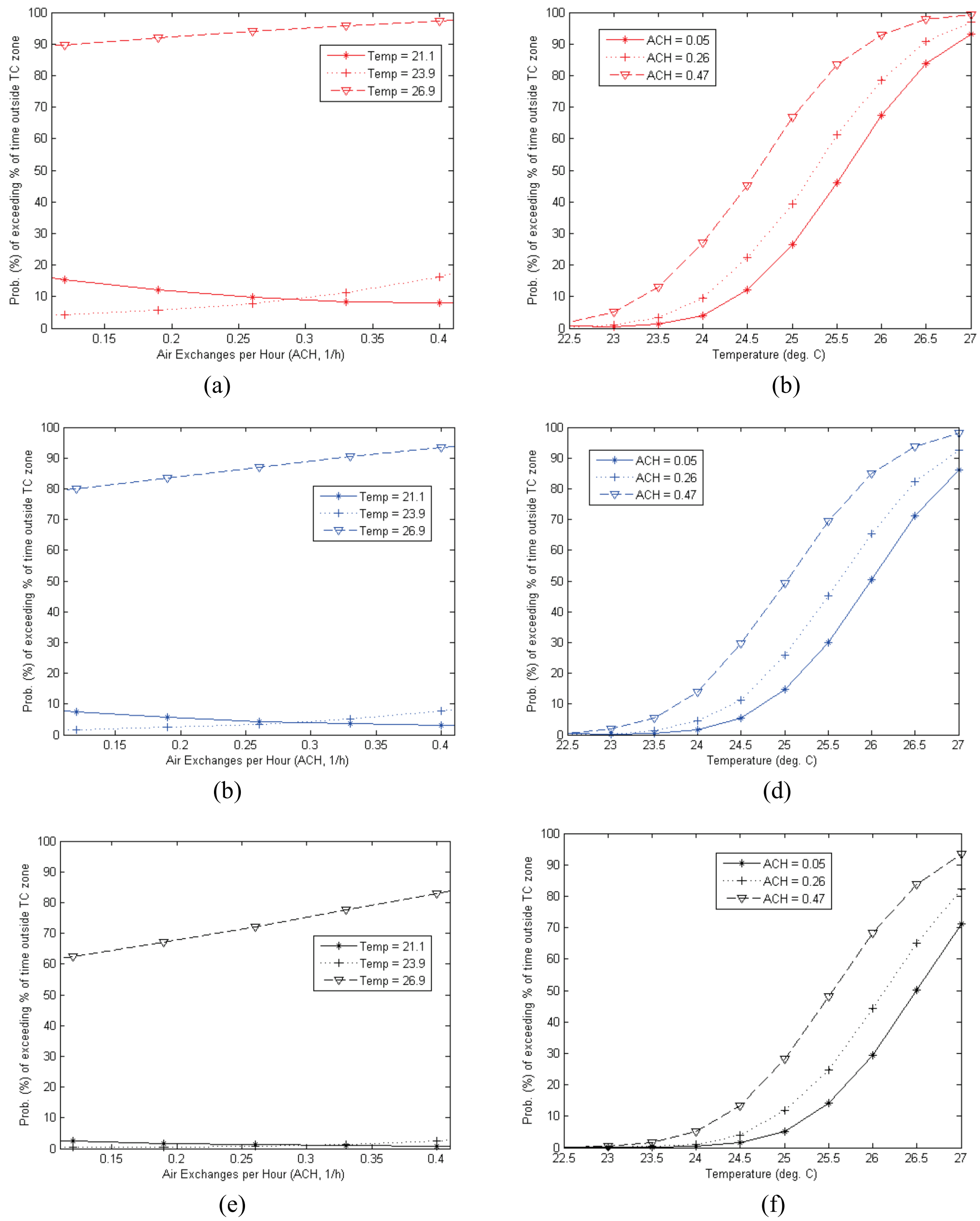
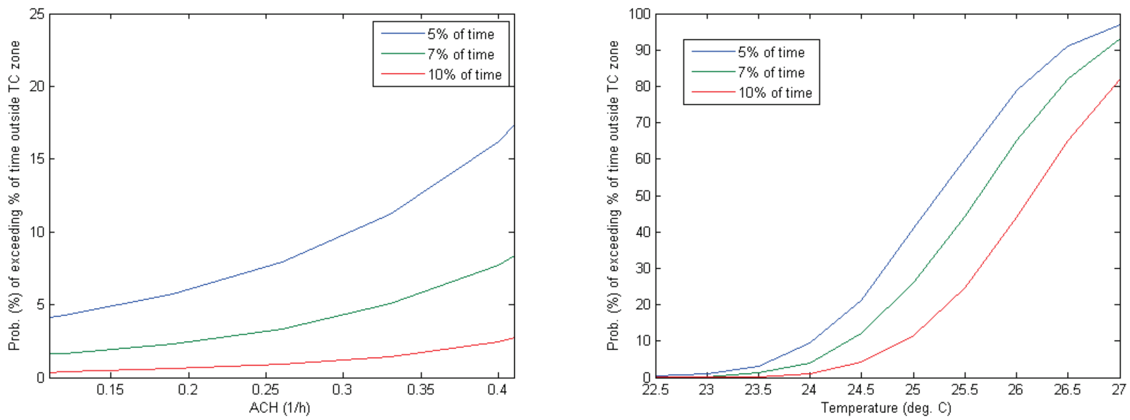


Figure 35: Probability of exceeding the maximum allowable percent of time, T_{acc}, outside the thermal comfort zone: (a) variation with air exchange rate for different set-point temperatures, T_{acc} = 5%; (b) variation with temperature for different air exchange rates, T_{acc} = 5%; (c) variation with air exchange rate for different set-point temperatures, T_{acc} = 7%; (d) variation with temperature for different air exchange rates, T_{acc} = 7%; (e) variation with air exchange rate for different setpoint temperatures, T_{acc} = 10%; (f) variation with temperature for different air exchange rates, T_{acc} = 10%



(a) (b)

Figure 36: Probability of exceeding the maximum allowed percent of time, T_{acc}, outside the thermal comfort for situations where (a) the indoor set-point temperature is fixed at its mean value (x_1=23.9°C), and (b) the air exchange rate is fixed at its mean value (x_2=0.26 ACH (1/h)).

Discussion

The value of the use of the response surface and uncertainty analysis is that by using the response surface developed, a continuous range of values for any design variable may be evaluated easily without carrying out any BEM simulations beyond what were run to construct the response surface. The results of this case study show that with increasing values of T_{acc}, the probability of exceeding this allowed percentage of time outside the thermal comfort zone decreases; this is not unexpected. If occupants are more tolerant of a greater amount of time outside the thermal comfort zone, the risk of exceeding that threshold will naturally be reduced. Comparing the influence of the indoor set-point temperature (°C) and that of the air exchange rate (ACH, 1/h), we find that a change in set-point temperature has a greater effect on the probability of exceeding T_{acc} than does the air exchange rate. By changing the indoor set-point temperature from a lower value (22.5°C) to a higher one (26.5 °C), the probability of exceeding any selected T_{acc} value increases by 70 to 100% in all cases (Figures 35b, 35d, and 35f). On the other hand, changing the air exchange rate from a lower value (0.15 ACH (1/h)) to a higher one (0.4 ACH (1/h)) leads to a change in the probability of exceeding T_{acc} by between 3 and 20% (Figures 35a, 35c, and 35e). The influence on changes to the probability of exceeding T_{acc} for the range of values of T_{acc} studied (5-10%) is greatest at high air exchange rates (above 0.35 ACH (1/h)) and at higher set-point temperatures (25-26 °C) (Figures 36a and 36b).

For the single family home evaluated in this case study, the results of the response surface model development and the uncertainty analysis provide combinations of the design variables that will meet specified thermal comfort requirements of the occupants. The results of the uncertainty analysis quantify the likelihood that these specified comfort requirements are met. For example, if an occupant of the considered building wants to have 90% confidence (i.e., Pf = 10%) that he/she will be outside the thermal comfort zone only 5% of the time, the indoor set-point temperature can be set as high as 24.5°C as long as the air exchange rate is extremely low. At a higher air exchange rate (around 0.5 ACH), typical of an older home, the set-point temperature must be set to 23.3°C, more than a degree lower. The graph presented in Figure 37 shows upper bounds of acceptable parameters for the case study home covering various situations where the 90% confidence and 95% confidence curves correspond to Pf values of 10% and 5% of the time outside the thermal comfort zone (when $Tacc$ is set at two different values).

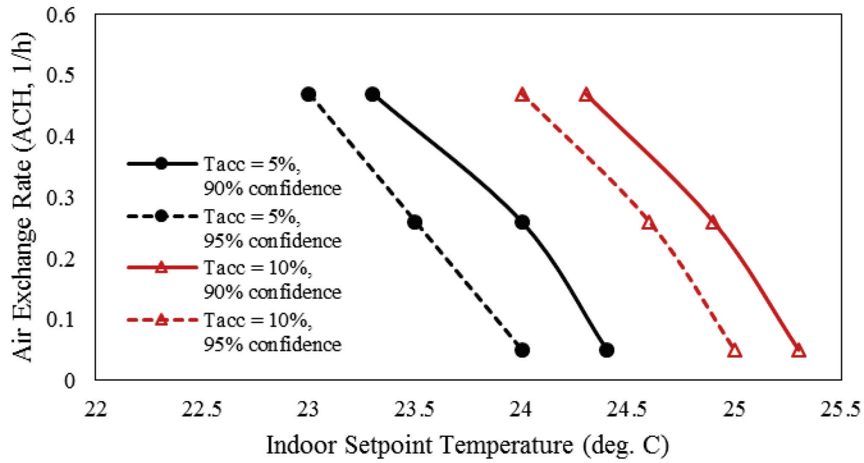


Figure 37: Acceptable combinations of indoor set-point temperature (°C) and air exchange rate (ACH, 1/h) for specified values of T_{acc} that guarantee desired levels of confidence (1-P_f) in meeting thermal comfort requirements of occupants

Note that the results in Figure 37 show how the uncertainty analysis with Monte Carlo simulation can be used to address specific "design" requirements where one is interested in combinations of the design variables (set-point temperature and air exchange rate, here) to meet desired thermal comfort zone levels with a target level of confidence. An alternative and more efficient approach to Monte Carlo simulations is to use "inverse reliability" approaches where the target level of confidence is the starting point and candidate values of the design variables are directly derived using information on the underlying random variables (Winterstein et al 1993; Saranyasoontorn and Manuel 2004a; Saranyasoontorn and Manuel 2004b; Saranyasoontorn and Manuel 2006).

Limitations

There are several limitations of the present study. The main one is related to the sources of possible error in the results that arise from each of the five steps in the methodology. The results are limited by the uncertainty in the statistics and probability distributions of the design variables. In some cases, required statistics and distributions may not be readily available. One solution then is to use expert engineering judgment in selecting suitable statistics (de Wit and Augenbroe 2002). BEM, as it employed in this study, relies on many simplifying assumptions; also, not all the various design variables are considered in the response surface methodology. Assumptions both in the BEM and response surface methodology need to be recognized and should provide context and bounds for situations the end results can be applied to, when the methodology presented here is applied.

In the development of the response surface for this study, three values for each design variable were considered in developing the response surface; thus, 3^n BEM simulations were used. Additional points beyond the upper and lower bounds and the mean value for each design variable would improve the accuracy of the response surface. This would also increase the computational time needed to develop the response surface from the BEM simulations. When compared to both in-sample and out-of-sample BEM simulations, the response surface provides a good fit with 1.8% and 3.5% errors, respectively. However, particularly in cases where the amount of time outside the thermal comfort zone is low, the response surface can predict values even below zero. However, these cases near zero percent of time outside the thermal comfort zone are less likely to represent situations in which the occupant thermal comfort is significantly affected. Crude Monte Carlo (CMC) simulation studies also have limitations. CMC probability estimates have uncertainty associated with them; this is only reduced when a large number of simulations are carried out.

The methodology proposed here can benefit from additional analysis and development beyond that dealt with in the limited scope of this study. The case study considered a single-zone building energy model evaluation and used one indoor set-point temperature. If a larger and more complex building is evaluated, an average or weighted average of multiple indoor parameters at different locations of the building may need to be considered. The proposed methodology may also be applied to other building performance characteristics that are affected by changes to the building's physical and operational properties as well as to other environmental parameters. In the present study, we only took into account the amount of time outside the thermal comfort zone; in general, it may be of interest to consider the severity of the indoor environmental conditions (relative, say, to ideal indoor conditions). For instance, instead of weighting all the data points with temperatures between 28°C and 32°C equally as not meeting thermal comfort requirements, one could consider a greater weight for the higher (around 32°C) temperatures, as they bring more severe thermal discomfort. These are all subjects of ongoing and future work.

Conclusions and Applications

This research study proposes a five-step methodology to assess the thermal comfort of a building based on building energy simulations over ranges of selected multiple design variables. Using the results from these simulations, a response surface describing the percent of time outside the building occupants' thermal comfort zone is constructed. This response surface provides an empirically derived polynomial function that relates building thermal comfort performance to the design variables. Uncertainty analysis is then carried out by defining a limit state function that incorporates the response surface and a user-defined limit or threshold for acceptable thermal comfort conditions. The results provide bounds on design variable values, such as the air exchange rate and set-point temperature, that will meet the design needs with a specified level of confidence (e.g., one can arrive at combinations of design values that can guarantee with 95% probability that the percent of time spent outside the thermal comfort zone will not exceed some specified value, say 10%). This methodology is applied to a case study to demonstrate the overall procedure and result interpretation.

There are many potential applications of the proposed methodology beyond the case study. It is our belief that the use of uncertainty analysis and response surface development is the first of its kind that has been applied to such studies related to building energy and occupant comfort. Today, building energy modeling is used mostly for the development of buildings, such as to achieve desired green building energy ratings; this study suggests that the same building energy model may also be used to conduct a thermal comfort analysis to assess the effects of proposed design strategies on thermal comfort. This may prove valuable in balancing the risk of discomfort against energy savings. It is easy to envision an extension of the methodology presented here to consider complex multi-variable comfort "zones" beyond the single one used here.

Finally, for utility companies that target customers for demand response, tiered electricity rate structures and other load reduction and load shedding techniques, the results of the proposed methodology may prove valuable in identifying the best customers to target and in making recommendations to residential customers to aid in load shedding while assuming low risks of thermal discomfort.

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Appendix D

Paper 4: Evaluation of the Effect of Technology-Enabled Time-of-Use Energy Pricing on Thermal Comfort and Energy Use in Mechanically-Conditioned Residential Buildings in Cooling Dominated Climates

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(In preparation for submission to Building and Environment)

Abstract

The effects of automatic setbacks using smart thermostats in response to time-of-use (TOU) pricing on occupant thermal comfort are evaluated for representative single family residential buildings located in 3 climate zones with dominant cooling loads. Building energy models (BEM) of single family homes are evaluated using a full factorial experimental design to create a response surface which provides a continuous function to evaluate the impact of four design variables on long-term thermal comfort indices, including Average Percent of People Dissatisfied (Average PPD), and Percentage Outside Thermal Comfort Zone (POS). These design variables include indoor set point temperature, TOU degrees of setback temperature, thermal mass, and air exchange rate for each climate zones. These are compared to the relative energy savings resulting from TOU thermostat setbacks while considering other design variables. A second-order response surface is found to provide a reasonable fit to BEM simulation in- and out-of-sample data. The set point temperature is the most influential of the variable studied in

decreasing long-term thermal comfort, while improving HVAC energy efficiency. The thermostat setback has the strongest influence on thermal comfort in a hot-dry climate, while the most HVAC energy savings is achieved in the mixed-humid climate zone. The results are tabulated for weighing the costs and benefits of TOU rates for homes with different characteristics, in climate zones with air conditioning-dominate energy consumption.

Keywords: building energy modeling, response surface methodology, thermal comfort, time-of-use pricing

Introduction

In residential buildings, in which people spend on average 63% of their time, it is important to maintain a comfortable indoor environment. The properties of this indoor environment, including thermal comfort, have been linked to the health and productivity of occupants (Schellen et al 2010, Akimoto et al 2010). In mechanically-conditioned residential buildings which represent 83% of all residential buildings in the United States, the indoor environment is highly dependent on the operation of the heating, ventilation and air conditioning (HVAC) system. This is particularly important in the extreme warm and cold seasons in which the desired indoor conditions are much different than the outdoor weather conditions.

As a result, in part, of the high penetration and use of residential HVAC systems, particularly in warmer climate zones, the electric grid in these locations experiences large fluctuations in the electricity demand (MW) during the summer months. A graph of a summer demand profile (MW) is shown in Figure 38a for electric grids in the hot-humid climate, zone 3a as defined by the ASHRAE climate zones regions (ERCOT 2014). The hot-dry (2b), and warm-humid (4a) climate zones experience similar peak load in the summer (cooling) season. A significant portion of the peak loads in these areas is due to residential energy use, including HVAC systems. In ERCOT (Electric Reliability Council of Texas), for example, over 50% of summer peak electricity loads (Figure 38b) can be attributed to residential buildings (ERCOT 2012).

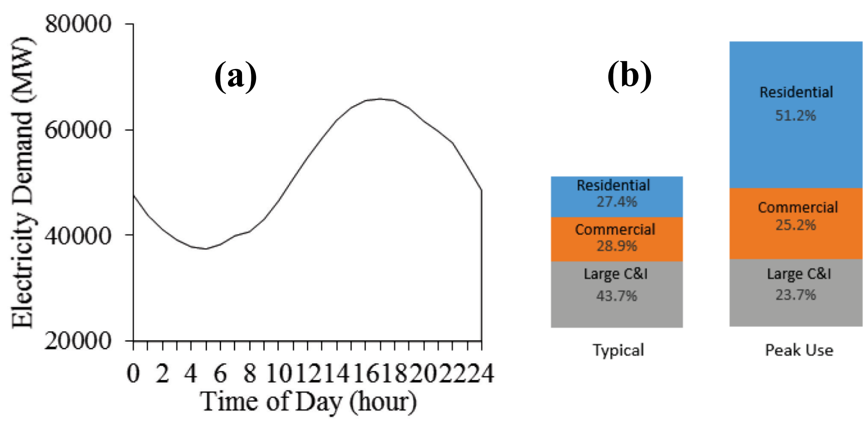


Figure 38: (a) Example of hourly fluctuation in electricity demand in the ASHRAE climate zone 3a (hot-humid) for a typical summer (cooling) season day (data: ERCOT 2014); (b) Comparison of a typical electricity demand (MW) in ERCOT (Electric Reliability Council of Texas) for a typical day, and a summer day (left) during a peak-use time (right), indicating over 50% of peak demand is from residential buildings (data: ERCOT 2011).

To address the variability in electricity demand, many electric utility companies have piloted or offer time-of-use electricity pricing (TOU) strategies (OpenEI 2014). Historically electricity rates schedules for residential buildings have not varied by time of use, but rather may be a constant rate, or tiered by the amount of total electricity used throughout a one month period. TOU rates vary based on the time of day in which the electricity is used. These pricing structures include a lower “off-peak”, and a higher “on-peak” rate ($/kWh), with some utilities also offering “mid” level rates between the off- and on-peak times. The TOU pricing trials that have achieved the highest energy savings and peak load reduction have been with homes that have “enabling technology,” or technology that automatically reduces electricity use when sent a pricing signal (Newsham and Bowker 2010). A common enabling technology is a smart thermostat, which is a programmable thermostat that communicates via two-way radio such that at on-peak times, the thermostat automatically introduces a setback in the set point temperature of the thermostat. Additional enabling technology includes smart appliances, which also reduce or defer electricity demand by altering their time-of-use of operation (Cetin et al. 2014). Since the change in HVAC system operation has a direct effect on indoor thermal comfort this research is focused on smart thermostat-enabled HVAC operational changes.

For the adoption of TOU pricing structures, it is important that energy and/or cost savings are achieved to obtain participation from residential customers. However, it is also important to consider the effects these changes have on occupant comfort. In changing thermostat set point temperatures, thus changing the operation of the HVAC system, this also alters indoor environmental conditions. This includes both the indoor temperature and humidity, which affect occupant comfort (ASHRAE 2010). The thermal comfort of occupants is a measure of occupant satisfaction with the indoor environmental conditions. A commonly used and widely accepted mathematical model of thermal comfort was developed by Fanger (Fanger 1967; 1970; 1972). It is a function of dry-bulb air temperature (ºC), mean radiant temperature (ºC), air speed (m/s), and humidity (%), metabolic rate (met), and clothing insulation (clo) (ISO 2005; ASHRAE 2010). This model uses these input parameters to predict the predicted mean vote (PMV) and the percent of people dissatisfied (PPD), with an acceptable PMV between -0.5 to 0.5 of a scale of -3 to 3, and a maximum acceptable PPD of 10%. Outside of these conditions is considered outside of the thermal comfort zone. This model, however, only evaluates the thermal comfort a single point in time.

Methodologies for defining the level and severity of thermal comfort/discomfort over a period of time have been proposed by a number of authors, many of which are summarized by Carlucci et al (2012). These include indices that evaluate the percentage outside a threshold comfort range (e.g. Carlucci and Pagliano 2012, Hensen and Lamberts 2012, Olesen and Brager 2004, ISO 2005, Cetin et al. 2015), cumulative indices (e.g. ISO 2005, Borgeson and Brager 2010) in which thermal comfort values are added up over time, and averaging indices (e.g. Nicol et al. 2005) which calculate an average metric over a period of time.

Each long-term evaluation methodology has advantages and disadvantages. The Percent Outside Thermal Comfort Zone (POS) methodology is able to capture upper and lower exceedances from the thermal comfort ranges; however, it suffers from the discontinuity occurring at the proposed thermal comfort zone limits. This implies an abrupt change in comfort perception which is inconsistent with reality. This methodology also does not measure the severity of discomfort, only its occurrence. However, this methodology has been used significantly in previous studies (e.g. Sage-Lauck and Sailor 2014, Carlucci and Pagliano 2012, Hensen and Lamberts 2012, Olesen and Brager 2004, Cetin et al. 2015). Cumulative indices such as Accumulated PPD (ISO 2005), do not have a discontinuity at the thermal comfort zone boundary. However, the value requires defining a reference cumulative value of what is an acceptable level of comfort over the given period of time. Average PPD also does not have a discontinuity at the thermal comfort zone boundary and can be compared to the existing ASHRAE 55 (2010)-defined recommended limit for acceptable PPD. It is calculated by averaging the all of the measured PPD values over the time evaluated. Based on these advantages and disadvantages, for comparison to previous studies, POS is used in this research, and because Average PPD can be compared to current recommended thermal comfort limits, Average PPD is also utilized. The PPD can be related to the PMV using the equations defined by the Fanger model (1972). No known additional relationship between the different indices, however, are known to have been developed.

To evaluate the effect of changes of building operations on thermal comfort, Cetin et al (2015) proposed a methodology that uses building energy modeling simulations to develop a response surface (RSM) (Box and Wilson 1951) that models the change in the POS of a residential building due to operational and physical changes as a continuous function. In this study this methodology was applied to assess a building's POS due to a one-hour demand response event in which the HVAC system is turned off. This study found that the RSM provided a reasonable fit to in-sample and out-of-sample BEM simulation data. The lower-order RSM function provided a model that enabled a quick evaluation of thermal comfort response of a building within a range of values of each of the design variables. Compared to running a building energy model simulation for every possible combination of variables desired to be studied, this methodology provides a way to quickly evaluate the effect of the change in a design variable of the building rather than running additional BEM simulations. Additionally the function is used to take into account the inherent uncertainty in the design variables, by using Monte Carlo simulation to evaluate the probability that a given situation will exceed a given threshold values of acceptable thermal discomfort. This study, however, only applied the proposed methodology to one-hour demand response event and merits further investigation in other thermal comfort evaluations. Additionally, Cetin et al (2015) could be improved by evaluating the energy savings of the demand response event in comparison to the effect on occupant comfort.

Various techniques, including the RSM, have been proposed to simplify the evaluation of BEM by defining the relationship between a measured response and a set of design (input) variables. Specifically, the response surface methodology has been used in recent studies for the modeling of buildings and their components (e.g. Khalajzadeh et al 2011, Kang et al 2010; Leira et al 2005). Other methodologies include a simplified normative model (Eisenhower et al. 2012), reduced order models (Goya and Barooah 2012, Dewson et al. 1993, Cole et al. 2013), and artificial neural networks (Yuce et al. 2014, Chang et al. 2015, Ashtiani et al. 2014). The response surface results in a function that can easily be used as input into probabilistic modeling, such as Monte Carlo simulation. In addition after its initial development, obtaining a model response is extremely fast. Also it has previously been shown to provide good agreement with in and out of sample data in building applications. For these reasons this methodology is used in this research in the evaluation of TOU pricing on different building types in different climate zones, on thermal comfort.

There are three main objectives of this study. The first main objective is to further evaluate the use of the RSM constructed from BEM simulation data to determine long-term thermal comfort effects on a residential building. In this research methodology is applied to determine the effect of TOU pricing on thermal comfort in the cooling season (summer) for a range of climate regions, and building and operational characteristics. As a long-term thermal comfort index, this study uses the Average PPD index, and also, it compares this to the POS index. Second, this study seeks to utilize the results of the RSM and probabilistic analysis to understand the influential design variables and RSM terms of those studied, on long-term occupant thermal comfort. Third, this study compares the thermal comfort levels resulting from TOU pricing to the energy savings that results from this change in operations. The results of this research are intended to be used for evaluating the costs (thermal discomfort) and benefits (energy savings) due to TOU pricing for residential buildings with the flexibility of a model that provides a continuous function to evaluate thermal comfort changes due to operational and physical property changes within a specified range.

Methodology

To evaluate the effects of TOU on thermal comfort in different climate zones a building with same geometry was modeled while considering specifics of each climate. The five-step methodology includes: (1) design variable definition, (2) building energy modeling (BEM), (3) response surface development, (4) probabilistic evaluation using the response surface, and (5) result interpretation; each are discussed in order below.

Three climate zones are evaluated, including ASHRAE climate zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry) (ASHRAE 2010). A representative location was chosen within each of these climate zones for evaluation. These climates zones represent a significant portion of the residential buildings in the U.S. in warm and hot climate zones, totaling 63.3 million U.S. residential households. A summary of the descriptive characteristics of these locations is included in Table 19. The average number of cooling degree days (CCD) and average outdoor relative humidity in these climate zones throughout the year and in the summer period was determined based on Typical Meteorological Year (TMY) datasets developed using Class I weather station data (NCDC 2015). This weather data source is commonly used for building energy modeling (2010).

Table 19: Climate Zones Characteristics and U.S. Residential Buildings

Climate Zone	ASHRAE Climate Zone[1]	Single Family Homes (millions)[2]	Multi-Family Households (millions)[2]	Location of Study in Climate Zone	Annual CCD (10°C)[3]	Summer[4] CCD (10°C)[3]	Summer[4] Average RH (%)[5]
Mixed-Humid	4a	24.4	8.6	Baltimore, MD	2169	1870	70
Hot-Humid	3a	13.0	4.0	Austin, TX	3046	2537	71
Hot-Dry	2b	9.5	3.8	Phoenix, AZ	4064	3368	27

[1] *As defined by ASHRAE 90.1-2013*
[2] *From Residential Energy Consumption Survey (2009)*
[3]*CCD = Cooling Degree-Days with a reference temperature of 10°C*
[4]*Summer is defined as May 1 to September 30*
[5] *From Typical Meteorological Year (TMY3) weather data (NSRDB 2005)*
[5]*RH = Relative Humidity (%)*

To represent a typical building, a single-story 204 m^2 single family home with a centralized air conditioning system was used to evaluate the effects of HVAC operational changes on thermal comfort. This size is equal to the average size of a U.S. single family home based on the Residential Energy Consumption Database (2009) for the three studied climate zones.

In the development of a building energy model, the building envelope properties, HVAC system specifications, and internal loads and schedules need to be defined. The properties of the building envelope were defined using the International Energy Conservation Code (IECC) (2010), and include the insulation values for the walls, ceiling, and fenestrations, and the solar heat gain coefficient of the windows. These characteristics represent the minimum prescriptive values required by the IECC, thus the building model represents the characteristics common to newer buildings. Additional building properties were defined based on the Building America House Simulation Protocol (2010) for new buildings. Previous research has also cited the need to adjust the moisture absorption capacity assumption of building energy modeling, particularly when evaluating indoor thermal comfort. Based on this research a value of 15 was used in the building model (Fang et al 2011, Woods et al 2013, EPA 2001, Hendron and Engerecht 2010). The building systems include a single-stage residential HVAC system with external compressor and condenser unit and indoor air handling unit, with an air distribution system and duct system in the attic space. Cooling and heating are is electric-based from a heat pump. Since the building is a single story house, the HVAC control is a single zone with standard on/off compressor and air handling unit fan (Hendron and Engerecht 2010). The size of the HVAC system was fixed based on Manuel J (2010) sizing calculations for each of the studied climate zones assuming a constant cooling set point and the mean values of the properties of the studied variables listed in Table 20. Internal loads are based on typical occupancy and internal load schedules for residential buildings from Building America (2010). These building envelope and system properties are summarized in Table 20.

Table 20: Residential Building Construction and System Properties by Climate Zone

Climate Zone (#)	Ceiling[1]	Wall[1]	Window[1]	SHGC[1]	Exterior Boundary Conditions	Window Area (%)[2]	HVAC size (kW)[3]	SEER[4]
Mixed-Humid (4a)	R-38	R-13	U-0.35	--	All exterior walls	15%	12.3	13
Hot-Humid (3a)	R-30	R-13	U-0.50	0.30			15.8	
Hot-Dry (2b)	R-30	R-13	U-0.65	0.30			19.3	

[1]*Minimum building construction properties per residential prescriptive requirements in International Energy Conservation Code 2009*
[2]*Percentage of total exterior wall surfaces*
[3]*HVAC is sized according to Manual J calculations by climate zone (ACCA 2011)*
[4]*SEER rating is the minimum value for a residential system per ASHRAE 90.1 (2013)*

To define the Time-Of-Use rate schedule, data from TOU times and pricings was surveyed (OpenEI 2015). Since time of use rates are implemented with the purpose of incentivizing peak load reduction, only cooling period of the year when TOU is applied.

Based on the studied TOU pricing trials, the length of study was limited to May 1st to September 30th for the cooling season (summer), paralleling the TOU rate schedule periods for the cooling season (summer) in the studied areas. A two tier rate structure was used, such that the peak use rate occurs between 2:00 pm and 8:00 pm and the off-peak rate occurs between 8:00 pm and 2:00 pm. The time-of-use rate versus the standard rates used are shown in Table 21.

(1) Design Variable Definition: Building Operations Variables

To develop a response surface several design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ are considered, including the degrees of setback during on-peak times. These design variables are used as inputs to build and define the response surface. It is desired that the model allow for adjustments for a range of occupant controlled parameters, as these parameters are adjustable without making modifications to the building structure. These parameters include the thermostat cooling (summer), set point temperature (ºC), the degrees of setback temperature (ºC) during on-peak times, and the air exchange rate (hr^{-1}). The set point temperature and degrees of setback temperature can be adjusted by changing the thermostat; the air exchange rate varies based on the natural and mechanical ventilation and the weatherization of a home. The thermal mass of the home is the fourth design variable. Thermal mass can vary depending on the type of building construction and the amount and thickness of the interior partition walls; variations in the thermal mass of a building can affect how quickly a building's indoor environmental conditions respond to set point temperature changes, and thus are important to also include in this study.

Each design variable requires an upper and lower bounds of which the variable is evaluated and the model is valid for in the developed response surface. The upper $x_{i,high}$ and lower $x_{i,low}$ bounds of the set point temperatures were chosen to be within the limits of the summer thermal comfort zone. The degrees of setback temperature was chosen to represent the extreme minimum (no setback), to maximum setback from demand response and time-of-use rate trials (Siemann 2013). The upper and lower bounds of the air exchange rate were chosen to cover a range of values common in newer buildings (Offerman 2009). Thermal mass varies depending on the amount of interior walls and furniture inside a residential building. The values used are measured in kJ/°C-m^2 and include interior drywall used for the external and internal walls and ceiling. The lower bound of the thermal mass equates to 13 mm drywall on the interior side of the exterior walls, on the ceilings and on the interior partition walls. These variables are summarized in Table 22.

Table 22: Design variables used to create thermal comfort response surface model

Type	Variable	Lower bound $x_{i,low}$	Upper bounds $x_{i,high}$	(Geometric) Mean μ_i	(Geometric) Standard Deviation	Distribution
Operational	Summer (Cooling) Set Point Temp. (ºC)[1]	21.1	29.4	25.1	1.7	Normal
	Setback Temp (ºC)[2]	0	4.5	1.8	1.3	Normal
	Air Exchange Rate (ACH) (1/hr)[1,3]	0.10	1.0	(0.26)	(1.04)	Lognormal
Structural	Internal Thermal Capacitance (kJ/°C-m^2) [4]	26.4	39.3	35.1	4	Normal

[1] *Pecan Street Research Institute; Dataset on building energy audits and survey performed in 2013 and 2014 on residential buildings in Texas*
[2]*Siemann 2014*
[3]*Offermann, F. J. (2009). Ventilation and indoor air quality in new homes, California Air Resources Board and California Energy Commission, PIER Energy-Related Environmental Research Program. Collaborative Report. CEC-500-2009-085.*
[4]*Building America Building Simulation Protocol (2010)*

(2) Building Energy Modeling (BEM)

Using BEM software EnergyPlus version 8.1 (2014), the response of the studied building was evaluated using a 3^n full factorial experimental design for the four sets of design variables. For each climate zone, this amounts to 81 trials, or a total of 243 BEM simulations. This includes a simulation at each combination of the n design variables (X_i; i = 1 to n) at three design points, $\boldsymbol{x_{i,high}}$, $\boldsymbol{x_{i,low}}$ and a center point. The output variables of BEM, including indoor temperature, $\boldsymbol{T_a}$ (°C), mean radiative temperature, $\boldsymbol{T_{MR}}$ (°C), operative temperature $\boldsymbol{T_o}$, (°C) and humidity ratio HR (%) are used to evaluate the values of Average PPD (Equation 1a) and the POS (Equation 1b-c) for all simulations. In these equations k is the climate zone, h is the hour being evaluated, and $\boldsymbol{h_{tot}}$ is the total number of hours. Within the thermal comfort zone (c_h = 0) is defined as a PPD value of less than 10 or a PMV between -0.5 and 0.5 per ASHRAE 55 (2010). PPD, a function of the input variables, was based on the equations in by ASHRAE 55 in Appendix D (2010). The output of the BEMs was combined and a MATLAB code was developed to calculate Average PPD and POS for each trial.

$$Average\ PPD_k = \left(\frac{\sum_1^{h_{tot}} PPD(T_a, T_{MR}, T_o, HR)_h}{h_{tot}}\right)_k \quad (1a)$$

$$POS_k = \left(\frac{\sum_1^n c_h}{h_{tot}}\right)_k \quad (1b)$$

$$c_h = \begin{cases} 1 \leftarrow (\text{outside thermal comfort zone}) \\ 0 \leftarrow (\text{inside thermal comfort zone}) \end{cases} \quad (1c)$$

(3) Response Surface Development

Based on the results of the building energy modeling simulations, a response surface $\boldsymbol{S}(\mathbf{X})$ (Equation 2) is created. This response function is defined using linear and nonlinear terms made up of the n design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ listed in Table 23, and a set of coefficients, b_i (i = 1 to n) for linear variation and b_{ij} (i,j = 1 to n) for quadratic variation. These are discussed in Meyer et al (2011), Khuri and Mukhopadhyay (2010), and Meyer et al (1989). Least-squares regression is used with the selected design variables and the results of the BEM simulations to develop the nonlinear, second-order response surface function. To evaluate the goodness of fit of the model, the R^2 (coefficient of determination) value is used. Evaluation of goodness of fit was conducted on both in-sample and out-of-sample data which are within the range of the upper and lower bounds of the design variables considered. Out-of-sample data was developed using a random number generator to create values for each of the design variables between the upper and lower bounds, $\boldsymbol{x_{i,high}}$, and $\boldsymbol{x_{i,low}}$, then BEM was evaluated for each of these trials and compared to the model-predicted values.

Terms in $\boldsymbol{S}(\mathbf{X})$ that have a significant influence on the response surface are defined as those in which the p-value is less than 0.0005.

$$S(\mathbf{X}) = b_o + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} X_i X_j \qquad (2)$$

.

(4) Probabilistic Evaluation Using the Response Surface

The response surface model developed following BEM simulations is an approximate representation of a real-world based situation based on assumptions and approximations. To address uncertainty in the design variables, Monte Carlo simulation (Hammersley et al 1964) is used with the distributions of the design variables specified in Table 22 to determine the *Average PPD* for each of the three climate zones for the typical home studied. The distribution parameters for each of the design variables were determined based on data collected from previous studies, as summarized in Table 22. An Anderson-Darling test was performed to determine the best distribution fit for the data for each of the design variables based on the collected data. This is compared to a threshold acceptable level of PPD, $\boldsymbol{PPD_{acc}}$ to determine the probability that the *Average PPD* will exceed this threshold value (Equation 3), where $\boldsymbol{S}(\mathbf{X})$ is the response surface function developed in Step 3. In this evaluation it is assumed that all the design variables are independent random variables. The $\boldsymbol{PPD_{acc}}$ is evaluated as 5%, 10% and 15%. The accuracy in P_f estimates based on MC simulations increases with the number of simulations, which was set at a maximum of 100,000 simulation.

$$P_{f,PPD} = PPD_{acc} - S(\mathbf{X}) \tag{3}$$

Results and Discussion

The results of research are divided into three different sections to specifically address each of the three objectives. The first section addresses the evaluation of the RSM to create a continuous function that represents the long-term thermal comfort performance of a building due to changes in the considered design variables. The second section utilizes the resulting model and probabilistic analysis to evaluate the influence of the design variables and the terms in the RSM model on long-term thermal comfort. The third section compares HVAC energy use with the long-term thermal comfort indices.

Model Evaluation to Predict Thermal Comfort

The coefficients for the response surfaces built for each of the studied climate zones is include in Table 19. The second order response surface model shows a stronger fit than a first order model, with a coefficient of determination (R^2) value of 0.995 to 0.997 for in-sample data fitting in each of the studied climate zones. Table 23 shows the coefficients and p-values for each of the terms for each of the three locations of study for both the *Average PPD* and the *POS*

.Table 23: Average PPD[1] and POS[2] coefficients and p-values of the second-order response surface model

	Climate	Intercept	T_{SP} (°C)	T_{SB} (°C)	TM (kJ/°C-m²)	ACH (1/hr)	T_{SP}*T_{SB}	T_{SP}*TM	T_{SP}*ACH	T_{SB}*TM	T_{SB}*ACH	TM*ACH	T_{SP}^2	T_{SB}^2	TM^2	ACH^2
Average Percent of People Dissatisfied (PPD)																
Coefficient	2b	452.72	-40.10	-1.514	-0.501	3.421	0.110	-0.001	0.161	0.006	-0.342	0.063	0.912	-0.051	0.005	1.732
	3a	291.4	-27.4	-0.122	-0.718	11.034	0.010	-0.003	0.005	0.015	-0.528	0.038	0.662	-0.003	0.009	0.027
	4a	78.995	-8.640	0.521	-0.020	26.248	-1.4E-04	-0.002	-1.312	0.001	0.018	-0.004	0.245	-0.051	0.000	2.944
P-value[3]	2b	0.000	0.000	0.081	0.409	0.434	0.000	0.929	0.477	0.449	0.006	0.401	0.000	0.430	0.559	0.278
	3a	0.000	0.000	0.904	0.317	0.000	0.725	0.858	0.968	0.116	0.000	0.398	0.000	0.971	0.376	0.957
	4a	0.000	0.000	0.442	0.967	0.000	0.994	0.848	0.000	0.932	0.919	0.944	0.000	0.320	0.981	0.021
Percent of Time Outside Thermal Comfort Zone (POS)																
Coefficient	2b	-18.85	1.442	0.093	0.003	0.014	-0.004	-7.8E-06	0.005	-3.7E-05	-0.002	-3.4E-04	-0.026	0.005	-3.6E-05	0.002
	3a	-19.14	1.502	-0.002	-0.024	0.074	1.2E-04	-2.0E-05	1E-04	-0.001	-0.005	0.001	-0.027	-4E-05	0.001	0.009
	4a	-14.13	1.081	0.032	0.329	-0.001	-0.001	0.000	-0.020	2.9E-05	0.002	0.000	-0.019	0.001	3.5E-06	0.081
P-value[3]	2b	0.000	0.000	0.000	0.815	0.894	0.000	0.983	0.403	0.848	0.465	0.849	0.000	0.001	0.864	0.952
	3a	0.000	0.000	0.909	0.070	0.123	0.815	0.952	0.963	0.000	0.000	0.458	0.000	0.976	0.000	0.293
	4a	0.000	0.000	0.010	0.000	0.925	0.000	0.785	0.000	0.799	0.500	0.926	0.000	0.165	0.977	0.001

[1]*Percent of People Dissatisfied*
[2]*Percent of time Outside Thermal Comfort Zone*
T_{SP} =Set point temperature, T_{SB} =Setback temperature, TM = thermal mass, ACH = air exchange rate
2b = Hot-dry (Phoenix, AZ), 3a= hot-humid (Austin, TX), 4a = mixed-humid (Baltimore, MD)
[3]*If less than 0.0005, the p-value is shown as a zero value*

In predicting the *Average PPD* and the *POS*, the response surface provides a strong fit to in-sample data (Figure 39a,c). For out-of-sample data, a set of values for the design variables was created using a random number generator within the range of the minimum ($x_{i,low}$) and maximum ($x_{i,high}$) limits of the experimental design and compared to the predicted values using the response surface. This also shows the strong fit between the model-predicted and the actual values. Parity plots showing the fit of out-of-sample data are shown in Figure 39b, d. For the out-of-sample data, the *Average PPD* models show a strong fit, with the model for Climate Zone 2a and 4b over-estimating the value of *Average PPD* slightly (1% and 3% respectively). The out-of-sample data for the *POS* generally fits the predicted the values, however it generally is shown to under-predict POS values greater than 20%.

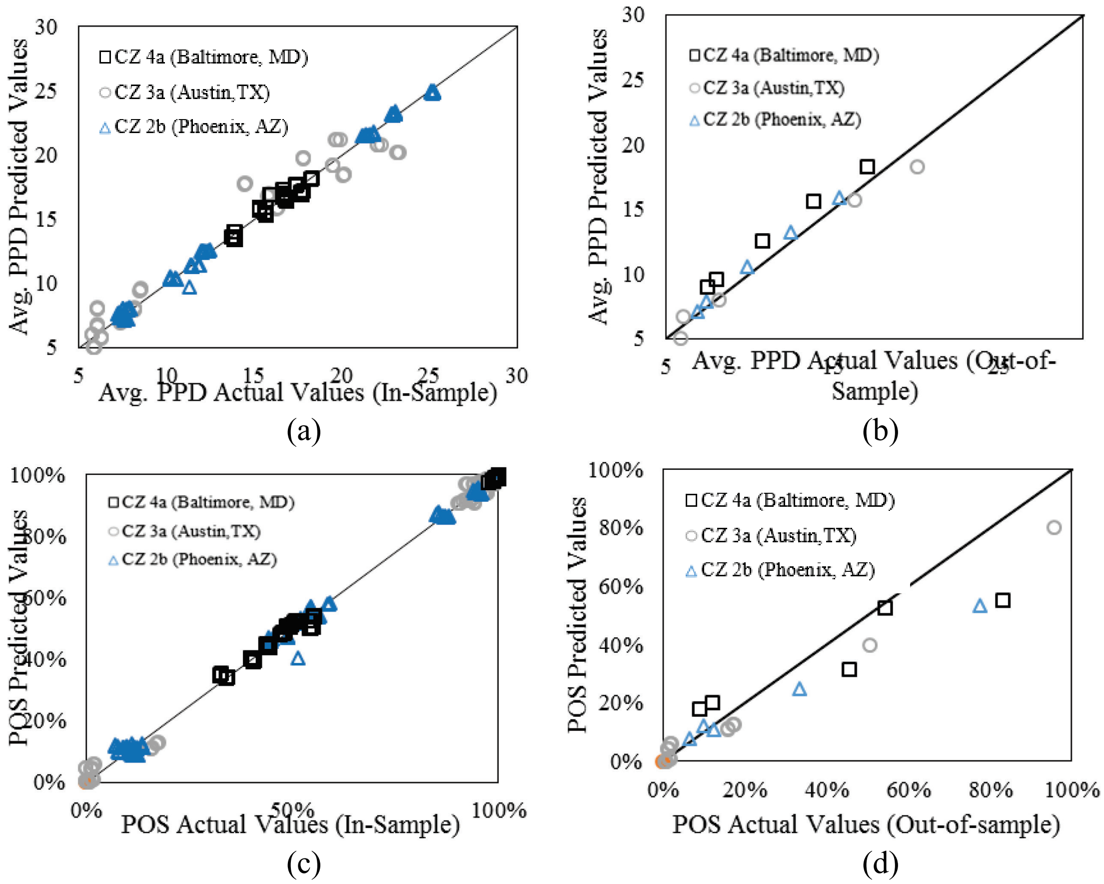


Figure 39: Parity plots comparing the model-predicted values of the Average PPD and POS for in-sample (a and c) and out-of-sample (b and d) data. Note: CZ = climate zone, PPD = Percent of people dissatisfied, POS = percent outside the thermal comfort zone.

Influential Variables and RSM Terms on Thermal Comfort

In all of the studied climate zones, increases set point temperature and increases in setback temperature also increase the *PPD* and *POS*. Increased discomfort due to increased set point temperatures is consistent with ASHRAE 55 (2010), in which the percent of people dissatisfied increases with increasing indoor temperatures. Similarly, in all of the studied climate zones, an increase in thermal mass has very little effect on the *PPD* and *POS*. A home with a larger thermal mass can reduce indoor temperature increase rates because a higher thermal mass introduces a thermal lag or time delay in the flow of heat from exterior to interior. Thus if the thermostat is set back it can take more time for a higher thermal mass building to increase in temperature to where the occupants are uncomfortable. However, the thermal mass in the modeled buildings represents the typical thermal mass of a newly built home. This thermal mass and variation in thermal mass is small in comparison to what has been used to effectively affect thermal comfort in residential buildings in previous studies (e.g. Balaras 1996, La Roche and Milne 2004, Ogoli 2003). In all of the studied climate zones an increase in air exchange rate, increases the *PPD* and *POS*. This is consistent with previous findings (e.g. Berardi et al 1991, Rijal et al 2007). If an increased amount of unconditioned outdoor air enters into the indoor environment due to a higher air exchange rate, this can increase indoor temperatures faster, resulting in a longer period of time at a higher temperature.

The most significant second-order RSM terms vary by the climate zone in which the building is located. Terms in the response surface with significant influence (p-value less than 0.0005) on the thermal comfort indices are shown to have a p-value of 0.000 in Table 23. The set point temperatures and squared set point temperature were significant influences for both *Average PPD* and *POS* in all of the studied climate zones. The degree of setback term was significant for the *POS* in climate zone 4a (mixed-humid), and thermal mass term in climate zone 2b (hot-dry). Air exchange rate has the most influence in Climate Zones 3a and 2b. Additionally several of the reaction terms were significant.

Degrees of Setback and Set Point Temperature Influence on Thermal Comfort

In evaluating the influence of the degrees of setback on thermal comfort, the *Average PPD* and the *POS* are compared with a constant set point temperature with zero degrees of setback, at each of the different design scenarios. At a degree of setback of zero, this represents a constant set point temperature regardless of the peak pricing. Figure 40 shows that the influence of the number of degrees of setback has small and non-linear influence on the long-term thermal comfort indices. Each of the lines in Figure 40 represents a different set point temperature and is labeled as such.

The degrees of setback during the on-peak times most strongly influences the thermal comfort indices in Climate Zone 2b (hot-dry). A 4 degree setback increases the *Average PPD* by 3.5% to 4.5%, and 5% to 10% for the POS in this climate zone. In a hot climate with the highest number of cooling degree days in comparison to the other studied climates, this is a reasonable result. With a higher outdoor temperature, this will cause the building's indoor temperatures to increase faster during the setback times, as the building absorbs more solar radiation and transfer heat to the interior with a higher interior to exterior temperature gradient. The greatest change in the *Average PPD* is due to changes in the degrees of setback temperature when the set point temperature is lower, while the greatest difference in *POS* occurs at higher set point temperatures. This represents a difference in results that varies based on the long-term thermal comfort index being used, and is discussed further in the comparison of the two thermal comfort indices in the section below.

Changes to the set point temperature have the strongest influence on thermal comfort in the hot climate zones (2b, hot-dry and 3a, hot-humid) (Figure 40). The *Average PPD* varies by approximately 17% across a range of 5°C in set point temperature for Climate Zone 2b (hot-dry), and 19% for 3a (hot-humid). These variations in thermal comfort are 56% and 77% more, respectively, than for Climate Zone 4a (mixed-humid). Similarly, the POS varies by approximately 69% across the evaluated indoor set point temperatures for Climate Zone 2b (hot-dry), and 65% for 3a (hot-humid). These variations are 27% and 20% more, respectively than for Climate Zone 4a (mixed-humid).

This also shows that an indoor set point of 22 to 24°C at varying set back temperatures will generally ensure that the indoor environmental conditions will remain below the threshold value of *Average PPD* of 10%. Thermostat set point temperatures greater than 24°C with varying ranges of degrees of setback temperatures will be over the 10% threshold. Given this information, a 24°C indoor thermostat temperature is a common thermostat set point for the summer (cooling) season for a mechanically-conditioned building.

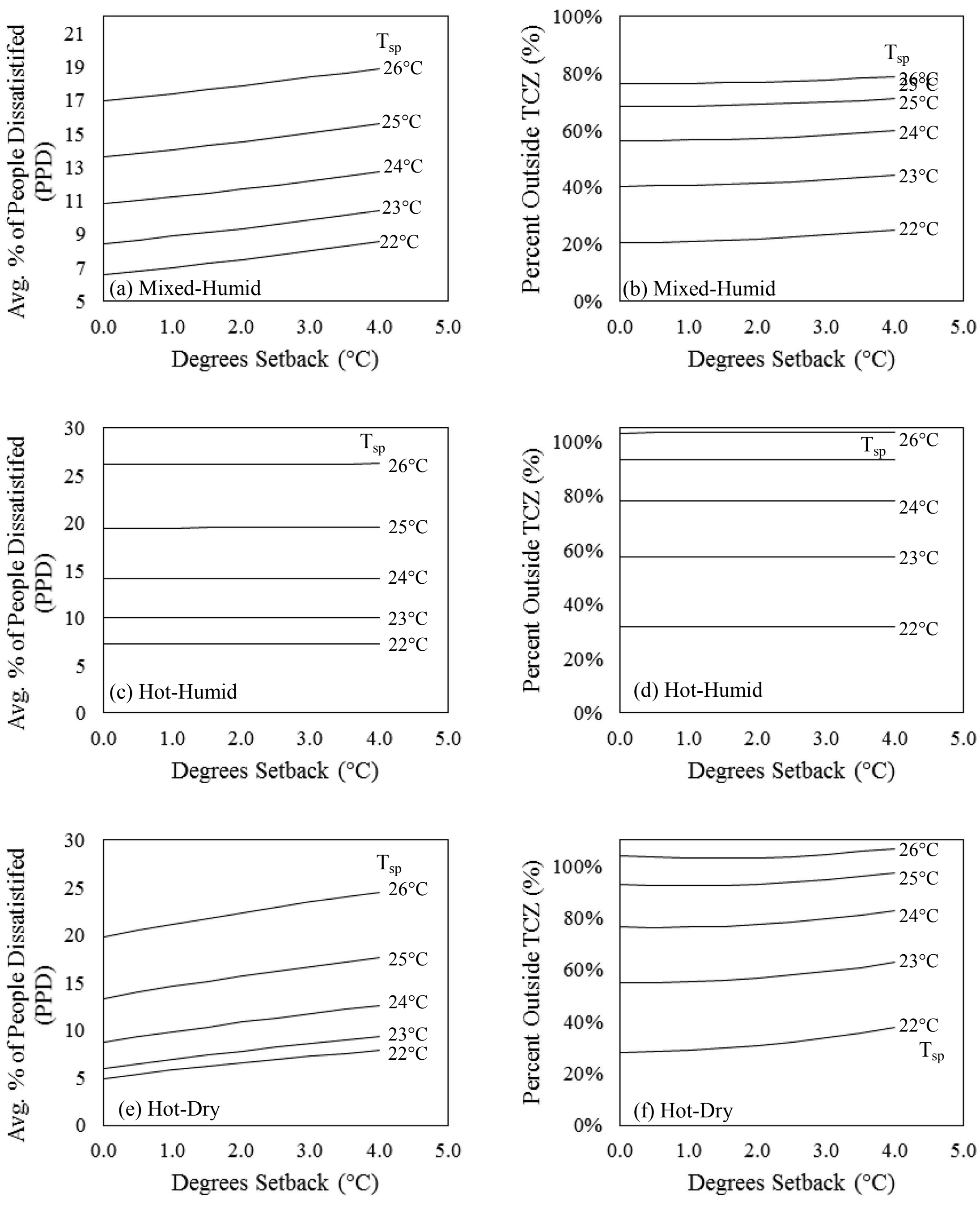


Figure 40: Influence of degrees of setback temperature on the *Average PPD* and *POS* at a range of indoor set point temperatures for Climate Zone 4a (mixed-humid) (a,b), 3a (hot-humid) (c,d), and 2b (hot-dry)(e,f).
Note: Each line represents a set point temperature; a constant value for ACH of 0.4 h^{-1} and thermal capacitance of 35 kJ/°C-m^2 are used in the creation of these graphs.

Probability Analysis: Probability of exceeding threshold acceptable level of discomfort

Looking at the effects of a larger scale implementation of time of use pricing, probabilistic analysis allows for evaluation of the effects on a set of homes with a distribution of setback temperatures. Assuming an adoption rate of the degrees of setback temperature for time of use pricing from Siemenn (2014), and the probability distributions of the design variables specified in Table 20, Monte Carlo simulation the results are shown in Figure 41. For homes in the hot-dry climate zone a lower percentage of the homes meets the suggested maximum 10% PPD as compared to the mixed-humid and mixed-hot climates. For homes in the hot-dry climate zone approximately 35% and 60% of single family homes have an Average PPD of 10% and 15% respectively, where as in the hot-humid and mixed-humid climate zones, 45-65% and 80% of homes have an Average PPD of 10% and 15%. The hot climate zones also have a longer tail of homes at high values of Average PPD than the mixed climate zone.

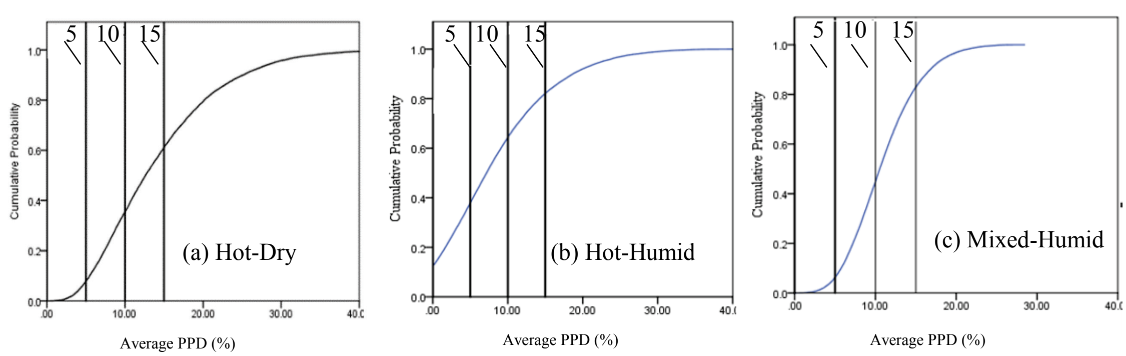
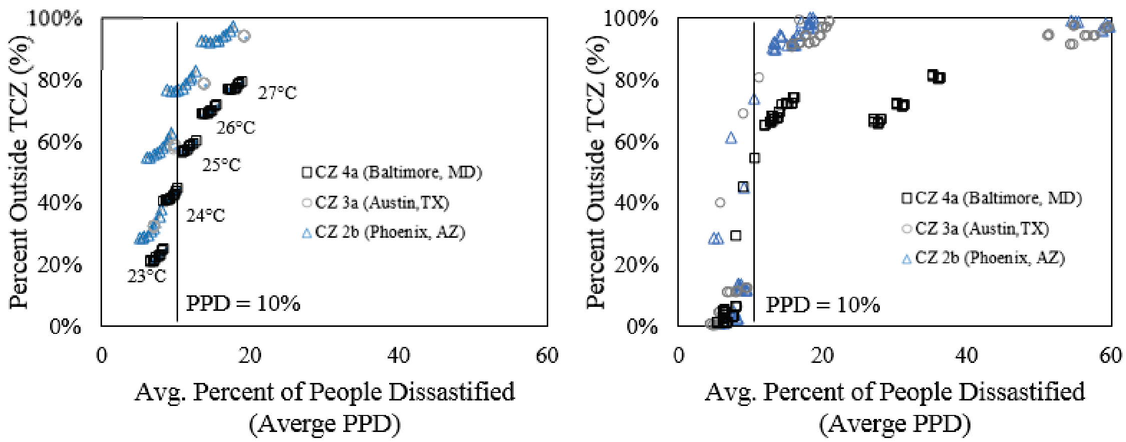


Figure 41: Cumulative probability of the Percent of People Dissatisfied (%) for Climate Zone (a) 2b (hot-dry), (b) 3a (hot-humid), and (c) 4a (mixed-humid) resulting from Monte Carlo Simulation

Comparison of Thermal Comfort Indices

In the development and evaluation of the effect of the considered design variables on *Average PPD* and *POS*, the use of one thermal comfort index versus another is important to consider as the results are different. Figure 42a shows a comparison of the thermal comfort indices at an ACH of 0.4 1/h and a thermal mass of 35 kJ/°C-m^{2,} with variations in set point temperature and degrees of setback. Figure 42b shows the results of the BEM simulations used to create the response surface. The threshold acceptable level of PPD per ASHRAE 55 is equal to 10%, which equates to a *POS* of between approximately 40 and 80% depending on the climate zone and the values of the design variables used. This also shows that the POS evaluation can only evaluate thermal comfort up to the equivalent *Average PPD* of 26-27%. After this level, the POS is nearly 100% or slightly over predicts the 100% value, whereas the *Average PPD* can continue to differentiate the level of thermal comfort at higher ranges of indoor temperature conditions.



(a) (b)

Figure 42: Comparison of Percent of People Dissatisfied (%) and Percent Outside the Thermal Comfort Zone for Climate Zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry) using the RSMs (a), and for all data points used to develop the RSM from building energy modeling

Note: Each cluster of points has a set point temperature as labeled; the variation in the values in the clusters is due to the change in degrees of setback temperature; a constant value for ACH of 0.4 1/h and thermal capacitance of 35 kJ/°C-m² are used.

Comparison of Energy Use and Thermal Comfort:

The energy use of the HVAC system servicing the studied residential building is compared with the two long-term thermal comfort indices for each of the studied climate zones. Similarly using the response surface methodology, HVAC use is related to the studied design variables. The values of these coefficients and p-values are included in Table 24. Similar to the thermal comfort indices, HVAC use is most influenced by the set point temperature in all of the studied climate zones.

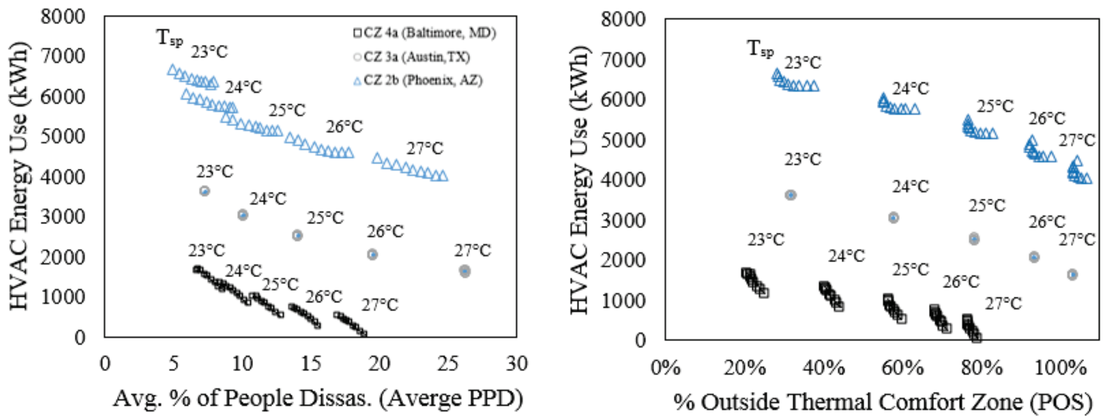
Table 24: HVAC energy use (kWh) coefficients and p-values[1] of the second-order response surface model

	Climate	Intercept	T_{SP} (°C)	T_{SB} (°C)	TM (kJ/°C-m²)	ACH (1/hr)	T_{SP}* T_{SB}	T_{SP}* TM	T_{SP}* ACH	T_{SB}* TM	T_{SB}* ACH	TM* ACH	T_{SP}^2	T_{SB}^2	TM^2	ACH^2
Coeff-icient	4a	21382	-1440	-221.5	2684.2	-2.679	6.228	0.041	-91.89	0.055	-14.99	0.170	24.40	9.77	0.006	-46.82
	3a	32984	-1880	36.9	-201.3	7578	-1.819	-0.441	7.126	2.974	-229.8	-13.198	28.642	2.224	1.717	-205.7
	2b	21647	-965.4	-47.91	14.309	7406	-5.731	0.154	-21.77	-0.293	-231.5	-1.397	10.775	24.941	-0.128	-6.599
P-value	4a	0.000	0.000	0.000	0.000	0.922	0.000	0.952	0.000	0.881	0.148	0.960	0.000	0.001	0.988	0.517
	3a	0.000	0.000	0.705	0.004	0.000	0.507	0.798	0.584	0.002	0.000	0.003	0.000	0.762	0.085	0.000
	2b	0.000	0.000	0.281	0.646	0.000	0.000	0.844	0.065	0.481	0.000	0.719	0.000	0.000	0.775	0.936

T_{SP} =Set point temperature, T_{SB} =Setback temperature, TM = thermal mass, ACH = air exchange rate
2b = Hot-dry (Phoenix, AZ), 3a= hot-humid (Austin, TX), 4a = mixed-humid (Baltimore, MD)
[1]If less than 0.0005, the p-value is shown as a zero value

Figure 43 shows the comparison of the HVAC energy use to the *Average PPD* and *POS* at an ACH of 0.4 h^{-1} and a thermal mass of 35 kJ/°C-m^{2}, with variations in set point temperature and degrees of setback. Each cluster of data points has a set point temperature and are labeled as such. The variation in the values in the clusters is due to the change in degrees of setback temperature (0 - 4°C) with the highest degree of setback being the points with the highest thermal comfort dissatisfaction.

In Climate Zone 2b (hot-dry), the HVAC energy use is highest, followed by Climate Zone 3a (hot-humid) and 4a (mixed-humid). This is consistent with the values of the cooling degree days listed in Table 19. The thermal comfort of occupants decreases as the HVAC use increase, however this trend is not linear and depends on which long-term thermal comfort index is used. As the indoor set point temperature increases, and the degrees of setback increases, the amount of HVAC energy use decreases. An increase in the number of degrees of setback causes the greatest decrease in HVAC energy use in the mixed-humid climate as compared to the other studied climate zones. This is likely due to the less extreme outdoor temperatures and solar radiation in the mixed-humid climate that would not heat the residential building as quickly during the peak use time when the set point temperature is higher. An increase in set point temperature also causes the least increase in occupant dissatisfaction in the mixed-humid climate zone compared to the other studied climate zones.



(a) (b)

Figure 43: HVAC energy use compared to the long-term thermal comfort indices *Average PPD*(a) and *POS* (b) for Climate Zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry).
Note: Each cluster of points has a set point temperature as labeled; the variation in the values in the clusters is due to the change in degrees of setback temperature; a constant value for ACH of 0.4 1/h and thermal capacitance of 35 kJ/°C-m^2 are used.

Study Limitations

There are several limitations to this study. This research is limited to the study of the thermal comfort of mechanically-conditioned, residential buildings. In support of the selected type of buildings, mechanically conditioned residential buildings are most commonly found in the United States, and represent a large majority of the residential building stock (RECS 2009). Air conditioning use is also predicted to increase in use in future years throughout the world (Isaac and Detlef 2009). Naturally ventilated buildings are also common, particularly in European countries, and can be evaluated using the adaptive thermal comfort model. Due to the lack of an HVAC system it is likely that these buildings are more strongly affected by building construction characteristics and climate variations, however, the focus of this study is on the effects of changes in HVAC operations and resulting thermal comfort due to TOU pricing. Since HVAC loads are a significant portion of the peak energy use in the United States (ERCOT 2011) and are often targeted for TOU pricing, focusing on mechanically conditioned buildings is justifiable.

This study is also focused on single family homes rather than multi-family properties. Single family homes were chosen for this research as they are the most common form of the mechanically conditioned residential building stock in the U.S. Differences between single family and multi-family include that multi-family residential buildings do not interface with the exterior on all sides and thus may affect the HVAC performance characteristics (Cetin and Novoselac 2015) and resulting thermal comfort. The single family home size and dimensions are also constant and not varied, as are other variables that are assumed as constant values in this study. The addition of an increasing number of design variables using a full factorial design significantly increases the number of BEM simulations needed to create the response surface. This study is limited in the design variables evaluated, however, the design variables were chosen to represent variables that can have an effect on thermal comfort and vary across the residential building stock. Other factors of the building's construction, systems, and internal loads may also be evaluated as additional design variables in future work.

Additional limitations also arise from the use of building energy modeling, as a building energy model is a simplification of a real-world building. However, significant effort has been done to validate the assumptions in the building energy model (Hendron and Engebrecht 2010). It assumes a single zone HVAC model in which a single temperature represents the temperature of the interior space when this may not necessarily be the case. This does not take into account temperature distributions or stratification which may affect thermal comfort within the studied zone (Zhang et al 2005, Wyon 1994, Olesen at al. 1979, Tanaka et al. 1986). If this methodology is applied to a commercial building or residential building with multiple HVAC systems and zones, multiple zones' thermal comfort would need to be considered. It is also assumed that the velocity of the cooling air provided by the HVAC is within the acceptable range per ASHRAE 55 (2010). It is also assumed that the HVAC system is functioning properly without any faults or inefficiencies and is properly sized using Manual J. An improperly sized HVAC system or an HVAC system with faults may affect the energy use and length of time the HVAC is on (Rhodes et al 2012, Cetin and Novoselac 2014, Braun et al 2012).

The performance of an HVAC system and a building is highly dependent on external conditions. The TMY3 weather files (NSRDB 2010) were used to evaluate the effect of thermal comfort. TMY weather files are the most commonly used form of weather data for energy modeling and were thus deemed appropriate for use in this study. However, TMY weather data does not take into account extreme weather conditions that have been found to be increasingly common occurrence, due to climatic changes (IPCC 2014, World Bank 2011). This may affect that TOU pricing setbacks' influence on thermal comfort.

The thermal comfort model and long-term indices used also have limitations, many of which are discussed in Carlucci et al (2012). The amount of clothing worn by occupants and the level of activity affect the location of the thermal comfort zone and thus the predicted level of comfort experienced by occupants. The thermal comfort indices also evaluates the indoor thermal comfort of the household at all times of the day, regardless of whether or not a building may be occupied. If a building is not occupied during the time that the thermostat set backs are in place any uncomfortable indoor environmental conditions that may results will not affect occupants until the building is occupied. However, additional information and evaluation is needed to further investigate and quantify these potential differences and influences. More recently it has been suggested that other methodologies may be used to evaluate thermal comfort, however, as pointed out in Wong et al 2014, there are limited available models that provide a similar predictor of thermal sensation, thus this research utilized the highly adopted and widely used Fanger model.

Acknowledging the discussed limitations, this research provides information that is valuable in evaluating the effects of TOU pricing on thermal comfort for different climate zones, and homes with different characteristics, and compares these effects to energy use. In addition it expands upon the use of the RSM methodology beyond previously research.

Conclusions

One of the main purposes of time-of-use pricing is to encourage changes in building operations to reduce peak load on the electric grid. This study focuses on residential buildings with smart thermostats that can automatically set back the thermostat of the

HVAC during the on-peak period. This reduces demand on the electric grid and also reduces energy use. The following conclusions can be drawn from this study.

1. A second-order response surface provides a good fit to in-sample and out-of-sample data in predicting the *Average PPD* for a residential building energy model using a 3^n full factorial design. This is consistent across all climate zones studied. For the percent of time outside the thermal comfort zone (*POS*), the second-order response surface provides a good fit to in-sample data, and slightly under-predicts out-of-sample values.

2. The strongest influencing factor on the long-term thermal comfort indices studied is the indoor set point temperature, of the four studied design variables (thermal mass, setback temperature, set point temperature, and air exchange rate). Air exchange rate and thermal mass are less influential on thermal comfort. Increasing the set point temperature by one degree increases the *Average PPD* by 2 to 7 %, and *POS* by 8 to 17%.

3. An increase in the degrees of setback temperature generally decreases the thermal comfort of occupants. This influence is greatest in the hot-dry climate zone (2b). Compared to a constant set point temperature in which the temperature is constant even during on-peak times, the Average PPD increases 2%-4.5%, and the POS increases 5%-10%.

4. Probabilistic analysis demonstrates, based on the distributions of data on new, single family residential buildings, that the mixed climate zone will maintain a threshold 10% *Average PPD* more easily than the hot climate zones in the implementation of TOU pricing.

5. Regarding HVAC use, the set point temperature is an important influencing factor in all climate zones. A one degree increase in set point temperature decreases the HVAC energy use by 300-400 kWh (24-31%), 400-600 kWh (17-19%), and 500-600 kWh (9-10%) in climate zones 4a, 3a and 2b respectively. The decrease in HVAC energy use achieves the greatest energy savings in the hot-dry climate zone, but the largest percent savings in the mixed-humid climate zone.

6. HVAC use is negatively correlated with the *Average PPD* and *POS*, meaning a decrease in HVAC use increases the *Average PPD* and *POS*, negatively affecting occupants. In general the HVAC energy use decreases 100-130 kWh for each degree of increase in *Average PPD*, and 21 to 30 kWh decrease for each additional percent outside the thermal comfort zone (POS). This decrease in energy use per *POS* and *Average PPD* is highest in the hot-dry climate (2b) as compared to the other studied climates.

7. In choosing which thermal comfort index is appropriate for use in evaluating long term thermal comfort of the two studied, the Average PPD can capture a wider range of thermal discomfort as compared to the POS. POS also does not measure severity of

the discomfort. Over an equivalent level of Average PPD of 26%, the POS is at 100%, after which any additional changes to the indoor environment will not be captured by this POS index.

The results of this research are helpful in understanding the influencing factors on occupant comfort for buildings operating under time-of-use pricing, and their relationship to HVAC use. This type of analysis could be used by utility companies to determine what the potential savings would be achieved in implementing smart thermostat-enabled time of use pricing schedule, and the anticipated effect on thermal comfort.

Appendix E

Paper 5: Commissioning of Central Residential HVAC Systems using Energy and Climate Data

Kristen Sara Cetin, Caitlyn Kallus, Atila Novoselac

(In preparation for submission to Energy)

Abstract

This research evaluates the effects of two common faults in the outdoor condensing unit of a split-system central residential HVAC system, including the effect on power draw, energy use, runtime fraction, coefficient of performance and cooling capacity. A no-fault state is compared to up to a 50% fault level, both in short-term near constant-temperature testing and long-term during a summer (cooling season) using a test house with simulated occupancy and internal loads. At higher fault levels, the HVAC system remains on for longer periods of time, with reduced efficiency. For condenser flow faults the power is increase, while with the low refrigerant fault, the power is decreased. An annual whole-home electricity savings of 1.4-3.8% can be avoided by correcting a 10%-25% condenser airflow fault, and 3.8-5.7% savings for the correction of a 10-25% low refrigerant fault.

Key Words: residential buildings, HVAC, fault detection, home energy management systems

Introduction

132 million housing units in the United States are responsible for the consumption of nearly 38% the nation's electricity use (US EIA 2013a). For 83% of homes in the U.S., a heating and air conditioning (HVAC) system is responsible for maintaining an indoor environment that is comfortable for occupants, particularly during the summer (cooling) and winter (heating) seasons. Residential buildings, including the HVAC, particularly in the United States, are responsible for up to 53% electricity demand on the electric grid during peak use times. HVAC is also responsible for a significant percentage of overall residential electricity use (ERCOT 2012).

A fault in an HVAC system is defined as a problem that prevents the system from functioning as designed. Faults in HVAC systems can occur for a variety of reasons, due to aging of equipment, and lack of maintenance on the part of the building owner or occupant. These problems also affect the HVAC operational characteristics, which can have implications for occupants, and the indoor environment, as discussed in Cetin and Novoselac (2015). A survey was conducted on 243 residents of single family homes in Austin, TX, including information on HVAC maintenance. 80% of residents indicated they did not have a regular HVAC schedule for maintenance, and 46% indicated their HVAC system has not been serviced in over 1 year, and 28% had never serviced their system since it was installed.

Less than optimal HVAC performance has consequence for both the electric grid and the building owners or occupants. For the electric grid, HVAC systems are responsible for a large part of the electricity load on the grid, particularly in extreme hot and cold climactic conditions. This is of particular important during the peak use hours of the electric grid. For example, during the hottest days in 2013, total demand on the ERCOT (Electricity Reliability Council of Texas) electrical grid experiences a 63% increase in demand during peak use hours as compared to the rest of the day (ERCOT 2013a). This fluctuation in electricity demand can create spikes in energy prices, transmission congestion on the electric grid, and require the use older, less-efficient "peaker" power plants to meet peak demands. The presence of faults in these systems contributes to this high load on the electric grid. In the face of predicted increased penetration of HVAC systems world-wide (Freedonia Group 2014), and more extreme climactic conditions due to climate change (IPCC 2015) the ability to identify if there is a problem or inefficiency is desired. For the building occupants/owners, faulty HVAC systems may run for an extended period of time, with increased energy bills resulting. If a system fails from an ongoing fault, this can cause indoor occupant discomfort.

Previous research efforts have explored the possibilities of fault detection and diagnostics for packaged unitary systems, which include split systems for residential buildings, and roof top units (RTUs) for small commercial buildings (Farzad and O'Neal 1990, 1991, 1993, Bultman et al 1993, Breuker 1997, Breuker and Braun 1998, Grace et al. 2005, Pak et al 2005, Yang et al 2007a, Yang et al 2007b, Kim et al 2009, Palmiter et al 2011, Yoon et al 2011). Common faults in packaged unitary HVAC systems include: high or low refrigerant charge, refrigerant line restrictions, presence of non-condensables, airflow restrictions to the evaporator and/or condenser, expansion valve failure, short cycling, and sensor failures. However, most of the literature has focused on roof top units for light commercial buildings. A summary of literature published through 2012 is discussed in Braun et al (2012). A limited number have also focused on residential heat pumps and split systems (Kim et al 2009,Yoon 2011, SCE 2012a,b, 2013).

To determine the occurrence of faults, previous studies measured a range of variables, including environmental parameters (e.g. indoor and outdoor air temperature, dew point, relative humidity), and HVAC system dependent parameters (e.g. refrigerant flow rate, pressure, and temperature, power, and air flow rate and pressure). These parameters are measured for use in determining HVAC capacity (kW) and efficiency (%), the two variables commonly used to understand an HVAC's energy use for a given set of conditions. To evaluate and compare the impact of different faults in terms of changes to efficiency or capacity, Braun et al (2012) developed a measure called the Fault Impact Ratio (FIR), which is a ratio of changes in equipment efficiency or capacity.

Of the existing research in HVAC fault detection there has been limited focus in residential building systems. In addition most research has focused on laboratory testing of effects of these problems at constant conditions rather than in realistic conditions similar to that of field testing. This also limits the ability to quantify the energy savings potential resulting from the correction of these faults.

The modernization of the electric grid, also known as the smart grid, is many utilities response to the increasing challenges in maintaining electric grid reliability. This includes, on the residential building level, the installation of smart meters in over 50% of homes in the United States (IEI 2014). Additionally home energy management systems can monitor electricity use on a circuit by circuit basis at a highly granular level. With additional energy use information available, it is advantageous to use this information to quantify the opportunity for energy and peak load reduction, and the cost savings that can result from earlier identification of the need for HVAC servicing due to a detected problem.

This research includes short-term near-constant temperature and long-term multi-day testing of a residential HVAC system servicing a test house building with simulated internal loads of a typical single family home, using a properly functioning system and a system with imposed condenser air flow and low refrigerant faults. This research aims to identify the baseline power and runtime patterns of a properly functioning system and what the affect of different levels of faults are on the energy use signal, including power, runtime and energy use, and on system performance, including coefficient of performance and cooling capacity. This information is used, in combination with previously collected typical HVAC runtime fraction data (Cetin and Novoselac 2015) to determine the whole-home and HVAC energy savings potential. The results of this research can be used by decision makers in determining the energy savings potential of this methodology.

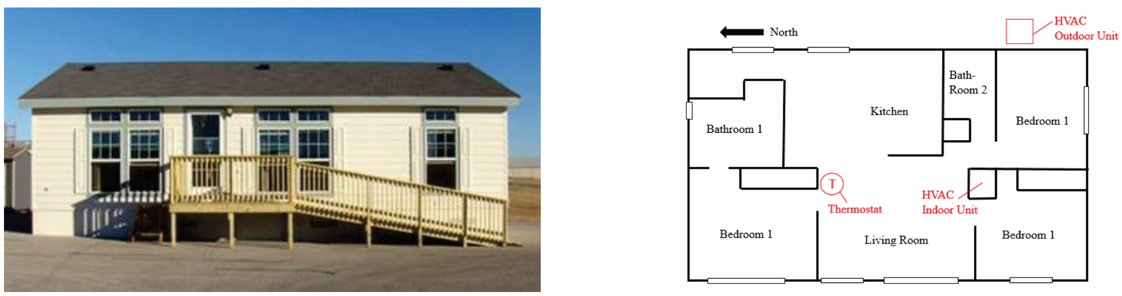
Methodology

This section describes the test methodology used to determine the properties of a baseline, properly functioning residential HVAC system, and measure the changes in the properties of the HVAC system when the (a) condenser airflow is restricted and (b) the refrigerant charge is low. This includes measuring the effects on the electricity signal including runtime, power, and energy use, and the HVAC operational characteristics including the coefficient of performance and cooling capacity. This section also includes a description of the laboratory facilities and test setup, equipment and measurement devices utilized, the schedule of testing, and equations for calculation of the results.

Laboratory Test Facilities

An unoccupied 111 m^2 single family manufactured home was used for this research. A photograph of the exterior and a schematic diagram of the interior are included in Figure 44. This residential building is serviced by an 8.8 kW (2.5 ton) residential HVAC heat pump split-system with 410A refrigerant and a thermostatic expansion valve (TXV). The properties of the HVAC system utilized in this test, including the indoor and outdoor units, are shown in Table 26. Prior to commencing the testing, the HVAC system was serviced by a certified HVAC technician to confirm proper functionality. The HVAC is installed in a downflow configuration, supplying air from floor-level adjustable registers in each room.

The building envelope consists of white vinyl exterior siding, wood framing with fiberglass batt insulation, and interior white-painted interior gypsum board. The fenestrations include double pane vinyl windows, and the roof is sloped grey asphalt shingle roof. All interior doors were open during testing, while all exterior doors and windows were closed.



(a) (b)

Figure 44: Single family manufactured home laboratory facility (a) exterior and (b) schematic diagram of interior space of facility include the location of the indoor and outdoor units of the HVAC and the thermostat.

Table 26: HVAC System Properties[1]

System	Indoor Unit	Outdoor Unit
Size: 2.5 ton (8.8 kW)	Fan: 249 W	Fan: 93 W
Refrigerant: 410A	Volts: 200-230 V	Volts: 200-230 V
SEER: 13	Amps: 2.8 A	Amps: 15 A (min)
Age: 7 years		
Type: Heat Pump		

[1] Properties taken from the manufacturer's data (Trane 2014)

The HVAC system is controlled using a thermostat located in the living room area (Figure 44b). A temperature sensor was placed next to the thermostat for a 24-hour pre-testing period and the thermostat was set to a constant temperature. The deadband width of the thermostat was found to be 0.74°C ± 0.013 at a 95% confidence interval. During testing, the thermostat was manually set to a specific temperature and placed in hold mode to maintain this temperature. The HVAC system was not controlled by humidity. The relative humidity of the space, remained between 40-56%, averaging 45% with a standard deviation of 3.8%.

Simulated Internal Loads & Home Automation

To simulate internal loads associated with occupancy, appliances, lighting, and other electronics present in a typical residential building, the *Field Test Protocol: Standard Internal Load Generation for Unoccupied Homes* was followed (NREL 2011). This test procedure was developed by the National Renewable Energy Laboratory, through the Building America program. The Building America Spreadsheet (Building America 2011) for new residential buildings was utilized to determine, based on the Building America House Simulation Protocol (Hendron and Engebrecht 2010), the hourly profile of internal latent and sensible loads (W) to be generated during testing. These internal loads are those assumed for a new 3-bedroom, 2-bathroom residential building of the same size as that of the test facility used in this research. Additional information on the calculation of these loads is provided in Hendron and Engebrecht (2010). The internal load profile used represents a summer weekday; the BA Spreadsheet contains several internal loads profiles which vary by month of year, and weekday versus weekend. A summer weekday was selected to be most common in residential building during cooling season, and most appropriate to accomplish the goals of this research. The hourly sensible and latent load profiles are described in Table 27. Sensible and latent loads are highest in the mornings and evenings, consistent with higher occupancy outside of normal working hours.

Table 27: Internal Latent and Sensible Load profiles based on the B10 Building America Spreadsheet[1] (Wh)

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Sensible	630	540	500	490	490	570	750	830	680	570	540	520	510	490	520	490	610	800	930	990	1130	1260	1100	870
Latent	140	140	140	140	140	160	200	200	130	110	100	100	90	90	90	80	120	180	220	190	170	180	170	150

[1] Building America 2011

To simulate internal sensible and latent loads, heat lamps and incandescent lightbulbs, and humidifiers respectively were used. In addition to the nameplate power draw of the utilized equipment, the equipment was also tested using a P3 Kill-a-Watt watt meter (0.2% accuracy). Additional information on the type and location of the internal load sources is described in Table 28. The humidifier was refilled with water periodically; each time the total amount of water emitted into the indoor air was recorded. Each of the heat and moisture sources were connected to an X10 building automation system which enabled centralized and remote computer-based programmable control of these internal sources. Following the field test protocol (Building America 2011), the heaters and humidifier were cycled each hour in 15 minute increments to meet the sensible and latent loads of the 24-hour period listed in Table 7.

Table 28: Internal Sensible and Latent Load Generation Equipment

Equipment	Location	Manufacturer/Model	Capacity[1]	Tested Capacity[2]	Electrical
Electric Heat Lamps	Living Room	Utilitec	450 W	425-433 W	120 V
Incandescent Lights	Living Room Kitchen Bedroom	General Electric	60 W	60 W	120 V
Humidifier	Kitchen	Vicks V150SG	5.6 L capacity	7.2 ± 0.29 ml/min (lab tested)	120 V

[1] per manufacturer's data
[2] tested in laboratory

Laboratory Equipment Measurements and Accuracy:

To monitor the electricity use signal of the HVAC system and the effect of the tested faults on HVAC performance, temperature, relative humidity and electricity use sensors and dataloggers were used to record measurements at 1-minute intervals. Additionally periodic measurements, including the airflow across the indoor air handling unit and the outdoor condenser/compressor were measured and recorded. To measure the energy signal, Continental Control Systems (CCS) Wattnode AC true power meters connected to 0–20 A CCS current transducers were used for the indoor air-handler, the outdoor condenser/compressor unit, and whole-home energy use, including the internal loads. The power meters were connected to an Onset HOBO Energy Logger Pro. Indoor temperature and relative humidity sensors were installed before the filter and after the coil, and also next to the thermostat. Outdoor temperature and relative humidity measurements were made with a HOBO U12 datalogger. The HVAC system indoor airflow was measured with an Energy Conservatory TrueFlow metering plate and DG-700 digital manometer. The accuracy of the utilized equipment is shown in Table 29.

Table 29: Measurement Equipment and Accuracy

Measurement	Units	Equipment	Accuracy
Logged Measurements			
	W	Onset Energy Logger Pro	±1.5%
Power[1]	V	CSS Wattnode	±0.45%
	A	CSS Current Transducer	±1%
Temperature	°C	Omega 44000 Precision Thermistor	±0.1°C
Relative Humidity	%	Onset HOBO U12	±2.5%
Periodic Measurements			
Pressure	Pa	Energy Conservatory DG-700	±1%
Air Flow[2]	m^3/s	Energy Conservatory TrueFlow Plate	± 5 %
Refrigerant Charge	g	Acculab VA Series Industrial Bench Scale	± 0.4 g

[1]A value of ±1.5% of uncertainly of the power measurement was determined based on the voltage and amperage uncertainties added in quadrature (±1.2%). This was increased to 1.5% due to unknown uncertainties associated with higher-order harmonics.
[2]Manufacturer's literature reports 7%, however conversations with the manufacturer suggest that a higher accuracy is appropriate for repeated measurements of flow differences, which led to the 5% uncertainty determination used in this work.

Calculated values based on collected data

To understand the effect of the imposed faults on the electricity use signal, the values of power (kW), energy use (kWh), runtime (%), were calculated to determine the operational characteristics of the HVAC system possible in looking at the energy signal. The cooling capacity (kW), and coefficient of performance (COP) were calculated to determine the effect on the HVAC system's performance.

Electricity Use Signal Values: Power, Energy, and Runtime

To determine the values of power, energy use, and runtime, it is necessary to determine what defines when the HVAC system is ON and OFF. To do this, the energy signal was divided into 5 different stages of HVAC operation, as follows. The system state classifications includes (a) OFF, (b) turning ON, (c) ON; transient, (d) ON; steady-state, or (e) turning OFF. These states are also shown in Figure 45. Following the findings of

Cetin and Novoselac (2015), the system is considered to be OFF (a) if the power signal shows a value of less than 0.05 kW. The system is (b) turning ON if the previous value was OFF, and the current value is greater than 0.05 kW. When the system status is set to (b) Turning ON, the timer, $\boldsymbol{l_i}$, which counts the length of time the system has been ON for each cycle, begins. The system is considered to be Turning ON until the current value is within 10% of the previous value and the previous state was (b), at which time the status is switched to ON (c). When the value of the time, $\boldsymbol{l_i}$, is greater than 7 minutes, the status is switched from (d) ON, transient to (e) ON, steady-state. This division is necessary to ensure that in the evaluation of the relationship of the system's power (kW) to the outdoor conditions, only power values recorded in steady-state conditions are considered. The system is Turning OFF (d) when the previous status was (c) or (d), and either the power is less than 0.05 kW or the current value is 10% less than the previous value. The status is set to OFF (d) once the value of the power is less than 0.05 kW for more than 2 minutes.

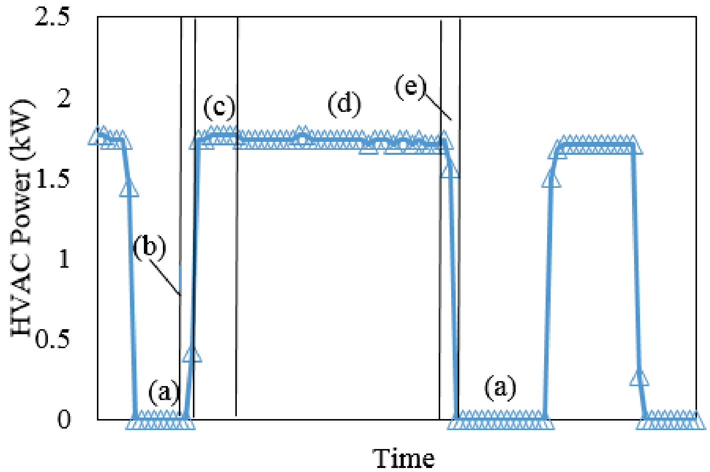


Figure 45: HVAC system state classifications includes (a) OFF (Power < 0.05), (b) Turning ON (previous value = OFF, current value > 0.05 kW, current value = ±10% of previous value), (c) ON; transient (Time ON < 7 min), (d) ON; steady-state (Time ON > 7 min), or (e) Turning OFF (Power < 0.05 kW or current value 10% less than previous).
Note: Timer, l_i*,begins counting when the ON transient state is enabled, and ends when the Turning OFF status is enabled.*

In the determination of the relationship between Power (kW) and outdoor temperature (°C), only power values recorded in HVAC state (d) ON; steady-state, are used.

HVAC energy consumption, E¸ is calculated by summing the outdoor unit and indoor unit power while the system is ON, using the following equation, where division by 60 converts the units of E *from kW-min to kWh*:

$$E = \sum_{j=1}^{j=n} \frac{\sum_{i=1}^{l_{cyc,j}} (P_{out} + P_{in})_{i,j}}{60} \tag{1}$$

Where

$\boldsymbol{P_{out}}$ = Power of the outdoor unit of the HVAC system (kW) for each minute i in cycle j

$\boldsymbol{P_{in}}$ = Power of the indoor unit of the HVAC system (kW) for each minute i in cycle j

$\boldsymbol{l_{cyc}, j}$ = Total number of minutes in cycle j, in HVAC states (c) ON transient, (d) ON steady-state

j = Cycle number

i = Number of minutes since HVAC cycle j started

n = Total number of cycles

To determine the runtime fraction of the HVAC system, the total number of minutes in which the HVAC system is in states (c) ON transient, and (d) ON steady-state, are used, as calculated using the following equation. The runtime fraction was determine for each test and is compared to the cooling degree days (CDD) value during the studied period.

$$Runtime\ (\%) = \left(\sum_{j=1}^{j=n} \frac{\sum_{i=1}^{l_{cyc,j}} 1}{60} \Big/ L_{test} \right) * 100 \qquad (2)$$

Where

$\boldsymbol{l_{cyc}, j}$ = Total number of minutes in cycle j, in HVAC states (c) ON transient, (d) ON steady-state

j = Cycle number

i = Number of minutes since HVAC cycle j started

n = Total number of cycles

$\boldsymbol{L_{test}}$ = Total length of the test

Operational Characteristics: Cooling Capacity and Coefficient of Performance

The performance of an HVAC system can be described by its cooling capacity and its coefficient of performance (efficiency). Both of these values are calculated to determine the effects of the imposed faults on the performance of the HVAC system studied. The cooling capacity, $\boldsymbol{q_t}$, (kW) is calculated using the following equation:

$$q_t = Q_{fan}\rho\left(C\Delta T + \Delta W h_{fg}\right) \tag{3}$$

where

$\boldsymbol{Q_{fan}}$ = volumetric flow rate of air (m3/s) flowing through the cooling coil

$\boldsymbol{\rho}$ = air density, assumed to be constant (1.2 kg/m3)

C = specific heat of air, assumed to be constant (1.005 kJ/(kg-°K))

$\boldsymbol{\Delta T}$ = temperature difference across the cooling coil (°C)

$\boldsymbol{\Delta W}$ = humidity ratio difference across the cooling coil, kg/kg (lb/lb)

$\boldsymbol{h_{fg}}$ = latent heat of vaporization for water, assumed to be constant (2257 kJ/kg)

The coefficient of performance or energy efficiency ratio (EER) is calculated using the value for cooling capacity in the following equation (COP: W/W = dimensionless; EER: (Btu/h)/W).

$$COP\ (EER) = \frac{q_t}{W_{out} + W_{fan}} \tag{4}$$

where

$\boldsymbol{W_{out}}$ = power draw of the outdoor unit of the HVAC, including the compressor (W)

$\boldsymbol{W_{fan}}$ = power draw of indoor unit of the HVAC, including the indoor fan (W)

Testing Schedule and Methodology of Imposing Faults

Two types of tests were conducted to evaluate the effects of the condenser airflow and low refrigerant faults. The first tests was near-constant temperature tests in which the level of fault was varied from 0% to 50% in 20 minute increments, where 0% is the baseline no-fault state. After each fault level test, the HVAC was returned to the baseline no-fault state. The second set of tests were conducted between May 2014 and September 2014. During these tests the level of fault, and the indoor temperature were varied. The level of fault was tested between 0% and 50% fault; the indoor temperatures were evaluated at 21.1°C, 23.8°C and 26.7°C. Each scenario was tested for at least a 48-hour period.

The test facility is located in Austin, TX, ASHRAE Climate Zone 3a (hot-humid). A psychometric chart of the outdoor conditions and indoor conditions during testing is shown in Figure 46a and Figure 46b respectively. Outdoor temperatures ranged from 15°C to 36°C and the humidity ratio ranged from 0.004 to 0.018. Indoor temperatures are divided into the three tested set point temperatures. Figure 46b also shows the set point temperatures relative to the return temperature, indicating that in general the return temperatures were higher than the set point temperature by 1-2°C.

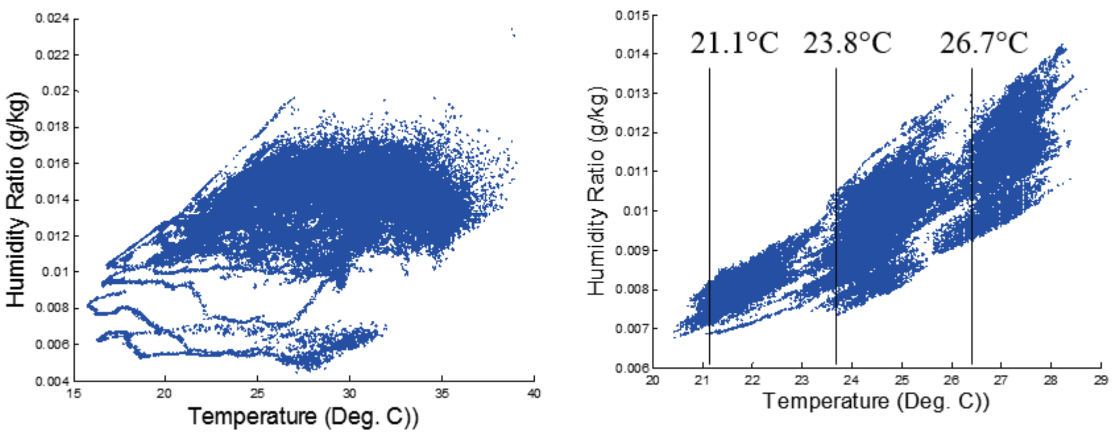


Figure 47: (a) Exterior conditions measured at the test facility location and (b) interior environmental conditions measured before the return air duct during testing; (b) also shows the three tested set point temperatures tested

To introduce condenser airflow faults, portions of the exterior surface of the condenser were covered with polyethalene sheeting and sealed on all edges. For refrigerant faults, a two-valve manifold was connected to the suction (liquid) and discharge (vapor) refrigerant lines using low-loss fittings to minimize refrigerant loss during testing. The HVAC system was turned ON for 15 minutes prior to changing the amount of refrigerant in the system. To remove refrigerant, a refrigerant recovery tank at lower pressure was used to collect the drained refrigerant from the high pressure (vapor) line of the running HVAC system. To add additional refrigerant, a higher pressure tank of new refrigerant was connected to the low pressure (liquid) line. The amount of refrigerant added and removed was measured using a leveled Acculab VA Series Industrial Bench Scale (accuracy ±0.4g).

Results and Discussion

The results section is divided into two main sections, including a discussion of the properties of a properly functioning HVAC system and those characteristics observed when a fault was imposed. The changes to the power, runtime, energy use, cooling capacity and coefficient of performance (COP) are assessed. This is followed by an assessment of the whole home and HVAC energy savings that can be achieved through the correction of these common faults.

The performance of the HVAC system is dependent on the outdoor temperature. During testing period the outdoor temperature ranged from 16°C to 32°C, with an average temperature of 27.6°C. Figure 47a shows the relationship between outdoor temperature and the power of the HVAC system in state (d) ON, steady-state. Linear regression analysis between outdoor temperature is has an R^2 value of 0.908, indicating the outdoor temperature is able to predict approximately 91% of the variability. Variation in the HVAC power is slightly larger at higher temperatures. For an increase of 1°C the power of the HVAC system increases 30.8 W. Figure 47b indicates the relationship between the average 24-hour temperature and cooling degree days (CDD), and the runtime fraction (%). A 24-hour period (12:00 am – 11:59 pm) was used since the automated internal sensible and latent loads simulated during this time are identical.

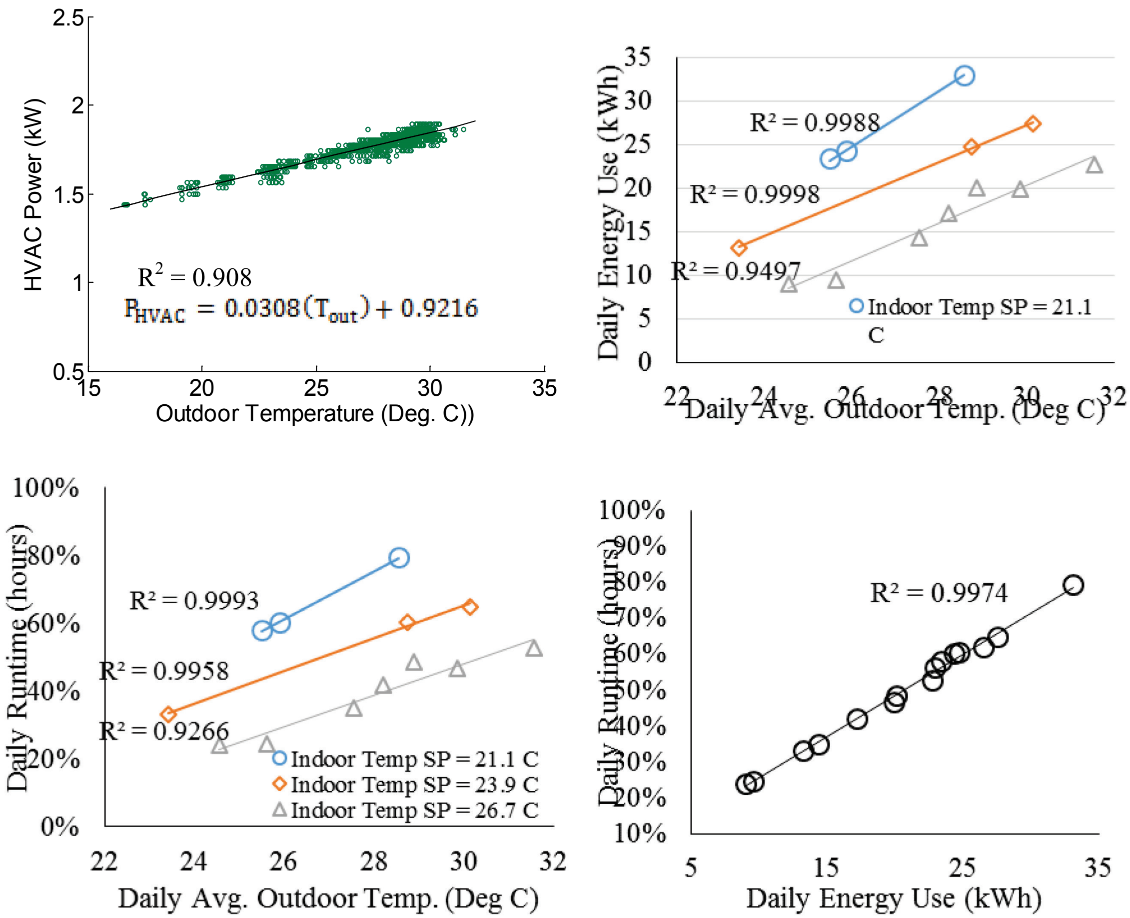


Figure 47: (a) Relationship between outdoor temperature and the instantaneous power draw of the studied HVAC system, (b) relationship between average daily temperature (°C) and the daily energy use (kWh), (c) relationship between average daily temperature (°C) and the runtime fraction (%), (d) relationship between the daily runtime fraction (%) and the daily energy use (kWh)

Figure 47b shows the runtimes for each of the three different indoor temperatures as separate series. An increase in daily average outdoor temperature increases both the daily runtime and daily energy use. When comparing runtime and energy use have a near linear correlation with a high R^2 value. This correlation is significantly higher than found in previous literature (Cetin and Novoselac 2015). This may be expected as the test environment utilized in this research has the same internal loads each 24-hour cycle and does not incorporate the random behaviors of occupants that affect the data and results from Cetin and Novoselac (2015).

To evaluate the impact of the two studied faults, including condenser airflow reduction and low refrigerant charge, two types of tests were conducted, including near-constant temperature tests and long-term tests. Figure 48 shows the impact on power due to low refrigerant (Figure 48a) and reduced air flow (Figure 48b). The power of the outdoor unit of the HVAC system increases up approximately 8% with an increase in the condenser area blocked, and decrease in the air flowrate. For the refrigerant fault a decrease in refrigerant charge decreases rather than increases the power by approximately 12%.

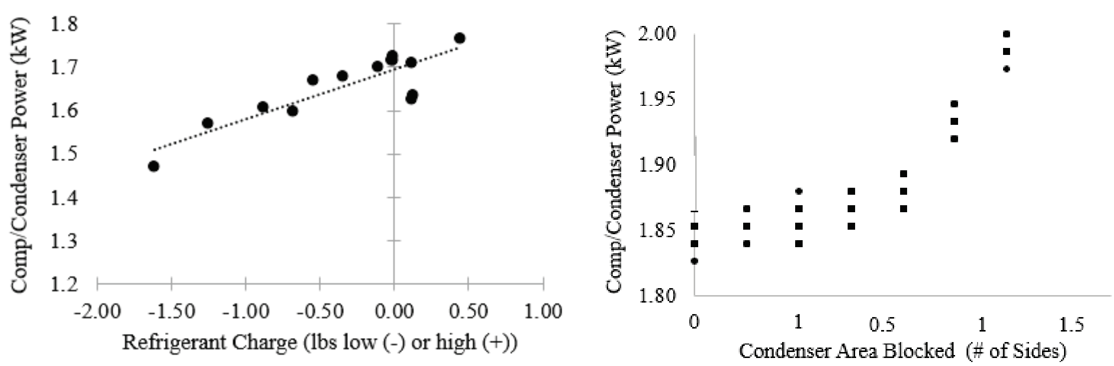


Figure 48: Effect of (a) low refrigerant on HVAC power (kW) and (b) increase in the condenser intake air vent blocked on HVAC power (kW)

Similarly, the long-term tests conducted over a series of days at a range of outdoor temperatures found a similar trend of increase in power with an increase in condenser air flow fault, and decrease in power due to a reduced refrigerant charge. Figure 49 shows this trend for the condenser air flow fault.

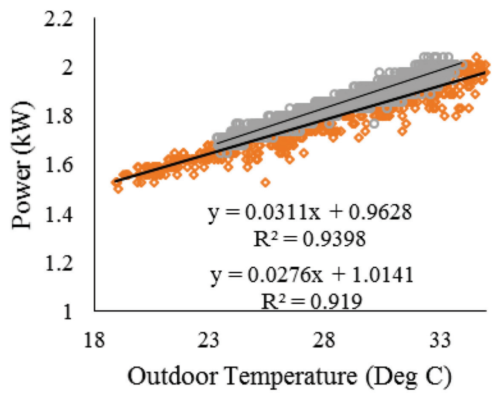


Figure 49: Effect of condenser air flow fault on HVAC power at 10% (orange) and 25% (grey) fault level

Figure 50a and 50b show the runtime and energy use values at a 25% condenser fault level at indoor set point temperatures of 21.1°C, 23.4°C, ad 26.7°C. 7c and 7d show the same changes for refrigerant charge faults. The daily runtime is increased, as is the daily energy use.

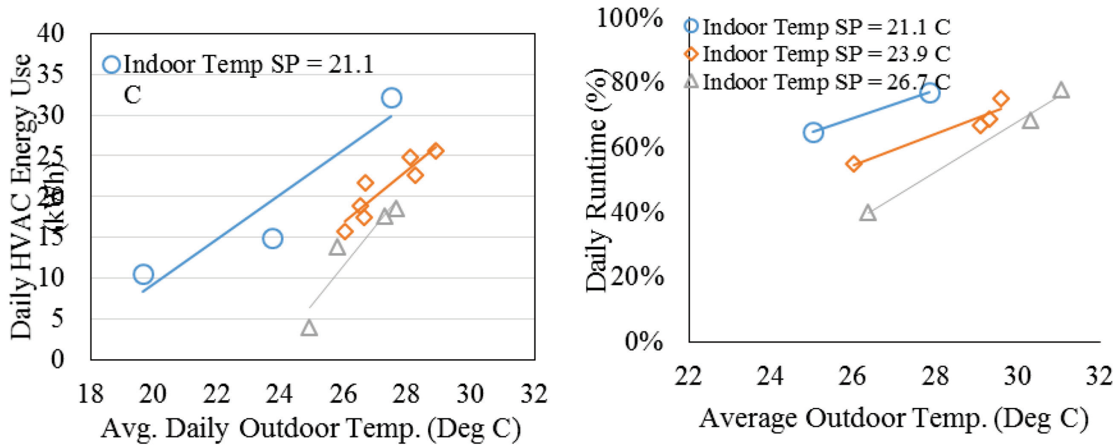


Figure 50: (a) Daily energy use (kWh) and (b) daily runtime (%) at a 25% condenser air flow fault.

The cooling capacity and coefficient of performance were also affected by the HVAC faults. Calculating these values using the equations presented in the Methodology section, the condenser flowrate fault decreases the efficiency by 6% and 12% at a 10% and 25% air flow fault. It similarly decreases the cooling capacity, on average, by 4 and 11% at 10% and 25% air flow fault. The specific data are shown in Figure51.

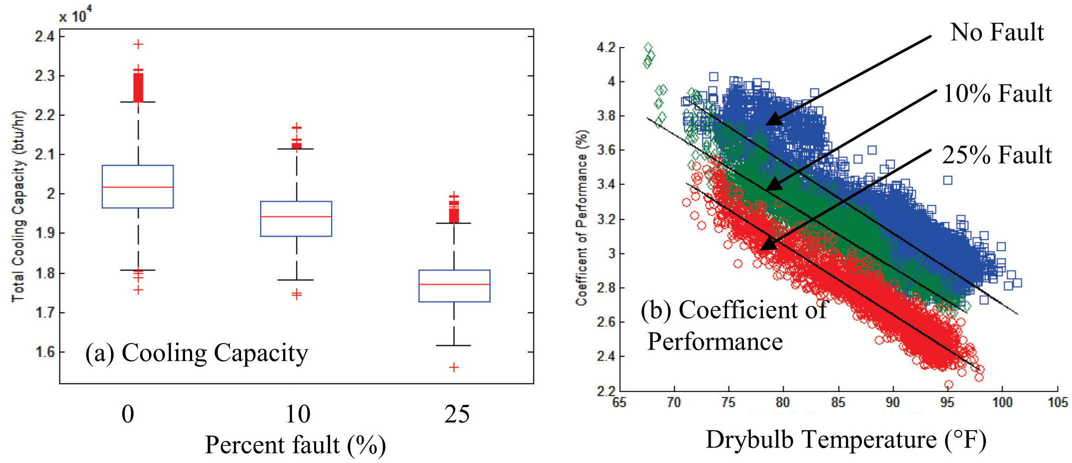


Figure 51: HVAC cooling capacity reduction at a 10% and 25% air flowrate reduction and (b) the coefficient of performance of the HVAC system (%) at the two levels of condenser air flowrate fault

Impact of Earlier Detection of Faults through Real-Time on Energy Savings

Utilizing the changes to the characteristics of the energy signal of the HVAC system studied and the seasonal runtime fractions calculated from Cetin and Novoselac (2015), a 1.4-3.8% can be avoided by correcting a 10%-25% condenser airflow fault, and 3.8-5.7% savings for the correction of a 10-25% low refrigerant fault.

Conclusions

This study evaluated the effects of two faults on HVAC operational characteristics and three aspects of the energy use signal. All of the studied variables, including the power when the system is ON, the runtime fraction, energy use, cooling capacity, and coefficient of performance were found to be affected by two studied faults in a residential HVAC system. Due to a condenser air flow reduction fault, the power is increased, while a refrigerant charge fault decreases the power at a given outdoor temperature. This is a distinguishing feature of two studied faults. With both types of faults, the runtime and energy use increase, and the coefficient of performance and cooling capacity decrease. Utilizing the established relationships between the fault level, outdoor temperature, and the HVAC runtime fraction values presented in previous literature, an annual whole-home electricity savings of 1.4-3.8% can be avoided by correcting a 10%-25% condenser airflow fault, and 3.8-5.7% savings for the correction of a 10-25% low refrigerant fault.

The results of this research are useful for an improved understanding of effects of improperly functioning HVAC systems on the energy use signal of a residential building. If a home energy management system or home energy meter is already installed in a residential building, continuous evaluation of power, runtime, and energy use along with the outdoor temperature conditions, provides a way to continuously monitor the health of a residential HVAC system. The methodology and calculation of energy savings resulting from the correction of the studied faults provides motivation for implementation of measures to reduce faults in HVAC systems.

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