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Exploring Energy, Comfort, and Building Health Impacts of Deep Setback and Normal Occupancy Smart Thermostat Implementation

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Exploring Energy, Comfort, and Building Health Impacts of Deep Setback and Normal
Occupancy Smart Thermostat Implementation

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Mechanical Engineering

by

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The University of Iowa
Bachelor of Science in Engineering in Mechanical Engineering, 2010

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This thesis is approved for recommendation to the Graduate Council.

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Abstract

As smart thermostat adoption rates continue to increase, it becomes worthwhile to explore what unanticipated outcomes may result in their use. Specific attention was paid to smart thermostat impacts to deep setback and normal occupancy states in a variety of conditions while complying with the ventilation and temperature requirements of ASHRAE 90.2-2013. Custom weather models and occupancy schedules were generated to efficiently explore a combination of weather conditions, building constructions, and occupancy states. The custom modeling approach was combined with previous experimental data within the Openstudio graphics interface to the EnergyPlus building modeling engine. Results indicate smart thermostats add the most value to winter deep setback conditions while complying with ASHRAE 90.2. Major potential humidity issues were identified when complying with ASHRAE 90.2 during cooling season. It also appears smart thermostats add little value to occupants when complying with ASHRAE 90.2 during cooling season across multiple climates and building constructions. Further exploration into humidity issues identified are required, as well as refining the energy model and moving towards real-world validation.

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Dedication

This master's thesis is dedicated to my wife, Shannon Alderman, for her constant support, motivation, and humorous high candor feedback throughout the development of this thesis. It is also dedicated to my parents, Heather and Stephen Alderman, for continually instilling an attitude of curiosity, and my brother, Jacob Alderman, for continually showing me what can result from hard work and self-motivated knowledge cultivation.

Table of Contents

1 – Introduction	1
2 – Justification of Research	2
3– Background and Literature Review	4
3.1– Background	4
3.1.1– Human Reactive Control	4
3.1.2 – Physical Control	5
3.1.3 – Electrical and DDC Digital Control.....	5
3.1.4 – Building Environmental Control Today	6
3.1.5 – Residential Environmental Control Demands	7
3.2 – Literature Review.....	7
3.2.1 – Building Thermal Mass.....	7
3.2.2 – Control Algorithms and Associated Thermostat Performance.....	11
3.2.3 – Computational Building Simulation Modeling.....	15
3.2.4 – Current Smart Thermostat Market Information	21
3.2.5 – Deep Setback	23
4 – Methodology	26
4.1 – Software Package Selection	26
4.2 – Setpoint Selection Basis	27
4.3 – Custom Weather File Creation.....	32
4.4 – Floorplan Selection Basis and Creation	33
4.5 – Internal Loads and Scheduling	34
4.6 – Data Outputs	36
5 – Experimental Results and Discussion	36
5.1 – Moisture Issues	36
5.2 – Deep Setback.....	38
5.2.1 – Heating and Cooling Recovery Results	38
5.2.2 – Energy and Comfort Discussion	48
5.3 – Normal Occupancy	51
5.3.1 – Heating and Cooling Recovery Results	51
5.3.2 – Energy and Comfort Discussion	53
6 – Conclusions and Recommendations for Future Work.....	54
6.1 – Future Work.....	54
6.2 – Conclusions.....	56
References	58

1 – Introduction

A smart thermostat can be defined as “a thermostat or measuring device that is enabled by Wi-Fi or another (home area network) communications protocol to gather and transmit in-home temperature data in a two-way format that can be accessed remotely via a web portal or mobile application...with a robust backend platform and enhanced data gathering and analytics functionality that optimizes HVAC settings for efficient and automated energy consumption” [1]. The basic goal of a smart thermostat is to improve energy savings by using “enhanced data gathering and analytics” to reduce energy consumption, and improve user comfort compared to other environmental control approaches. Examples of smart thermostats currently on the market include offerings from Nest Labs, Honeywell, EnergyHub, Ecobee, and Schneider Electric. Although smart thermostats (which will henceforth be referred to simply as ST’s) have been in the market since the turn of the millennium, their usage has exploded in the last three years. Research predicts a global market annual revenue expansion from \$143.6 in 2014 to \$2.3 billion in 2023 with the largest growth occurring in the US and Asia/Pacific markets [1].

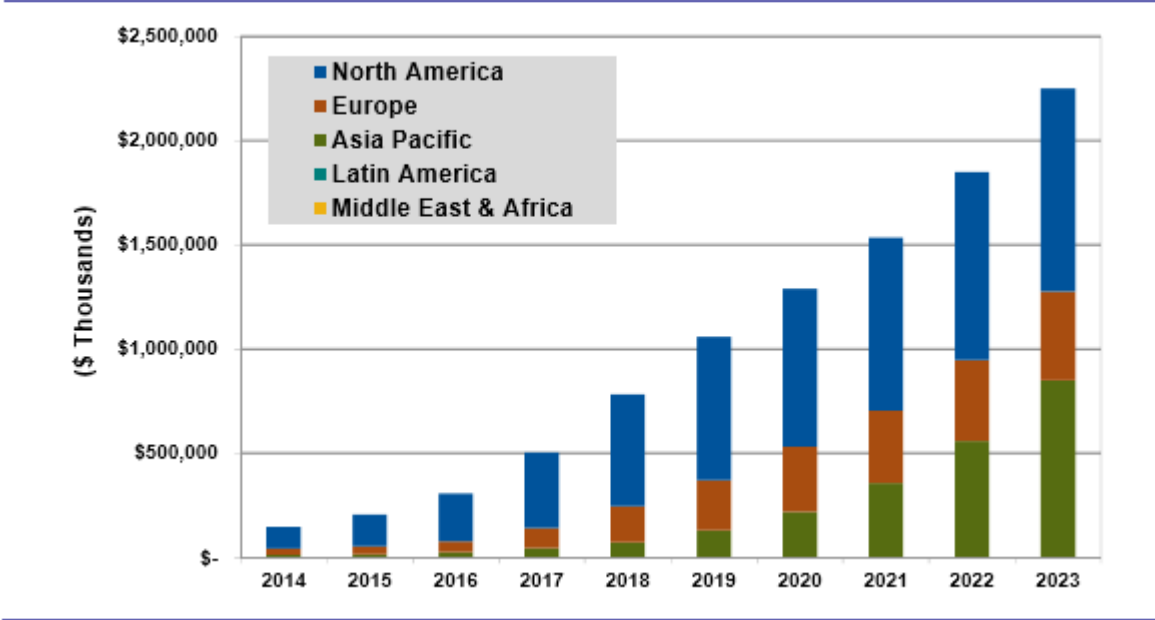


Figure 1.1: Communicating/Smart Thermostat Devices Revenue by Region, World

Figure 1.1 highlights the market breakdown by region, and indicates North America and the Asia Pacific regions are expected to see the greatest growth of the ST market. The bulk of this growth is expected to be driven by residential adoption of ST's and associated services [1].

Focusing on the United States, the primary factors driving market growth include utilities, state and federal regulations, and an aggressive marketing approach by market leaders. Several utilities have implemented subsidies and other incentives to encourage consumers to implement ST's.

2 – Justification of Research

In 2014 the United States consumed 98.4 quadrillion BTU of energy. Figure 2.1 shows how US energy consumption was distributed to various uses in 2014.

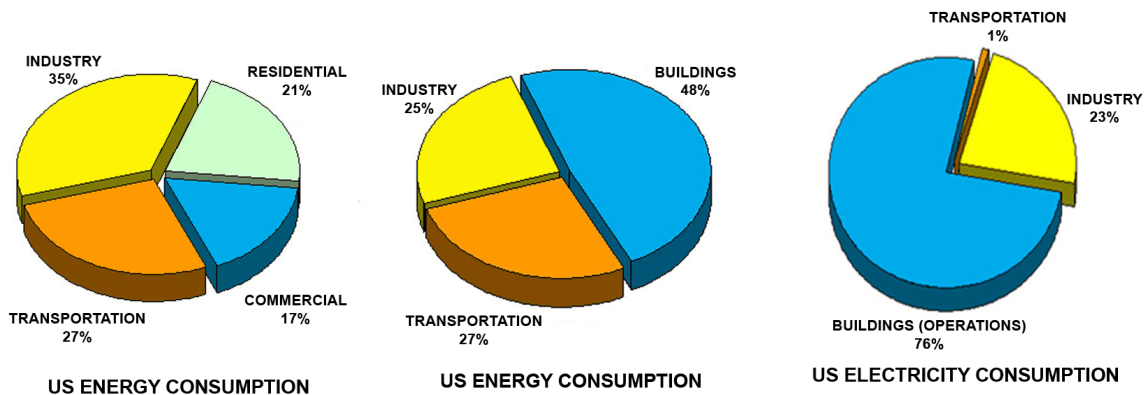


Figure 2.1: US Energy Consumption Breakdown

Considering buildings consume 48% of all energy and 76% of all electricity in the US, reducing building energy use would go a long way towards increasing energy independence, reducing greenhouse gas generation, and lightening the load on aging and increasingly stressed energy infrastructure. An additional factor not accounted for in the above figure is the fact most of those 98.4 quad are lost as waste heat.

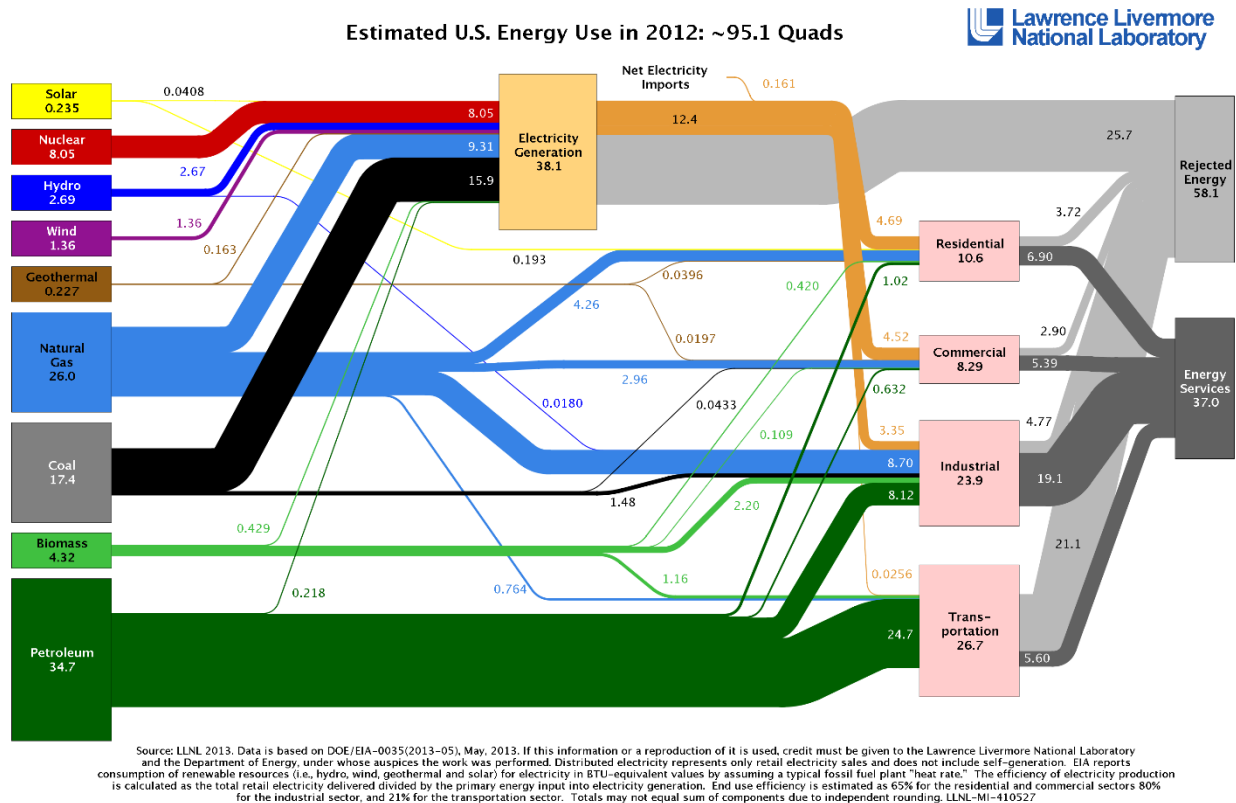


Figure 2.2: 2012 US Energy Use and Waste Tracking

In 2012, when US use was approximately 95.1 quad, over 58.1 quad was eventually rejected and wasted as shown by 2.2 above. Of particular interest within the scope of ST research is the 3.72 quad of wasted energy from residential energy consumption. Assuming consumption to waste ratios still hold true, nearly 35% of energy still is wasted in the residential market. While improved building materials and increasingly efficient HVAC systems have an opportunity to contribute to reducing waste, HVAC controls will also play a major part.

Based on reported benefits from manufacturer research, energy savings due to implementing an ST can be as much as 31% less than a baseline thermostat, with documented average annual savings in the 10-15% range for most Nest users based on a February 2015 white paper released from the manufacturer [2]. 10-15% savings could translate to 30-50% of the wasted residential energy being saved. Additionally, the majority of reports by the individuals participating in the Nest studies indicated that comfort was also increased with the

implementation of an ST [2]. Therefore, it appears there is mounting evidence to support the case for smart thermostat utilization.

There are however outstanding questions about the outer limits of Smart Thermostat use, and what kinds of unexpected impacts may result from the adoption of ST's across a wide variety of climates, building constructions, and HVAC equipment pairings when used for aggressive energy savings. What are the deepest setback temperatures allowed when factors such as infiltration, ventilation and energy code fore a variety of climate and building construction combinations? Answering these questions and developing a series of recommendations will be the primary objective of this thesis.

3– Background and Literature Review

Before the actual literature is discussed it is critical to have a general understanding of the history of building environmental control. Building environmental control can be broken up into four primary phases. These phases are primarily chronological; however all phases are in current use across the world today.

3.1– Background

3.1.1– Human Reactive Control

The first phase of building environmental control is human reactive control. Simply put, human reactive control is humans controlling their built environment by reacting to its current state. An individual engages in physical activity to change the temperature in their space to suit their comfort. This can be as simple as opening a window, stoking a fire, or putting on a coat. To a degree human reactive control is not in fact building environmental control at all, but simply people doing what people always do, just inside.

3.1.2 – Physical Control

Physical control is based on manipulating various physical phenomena in an engineered manner to dictate a specified output. Physical control focusing on building environmental comfort can date back as far as the 17th century when Cornelius Drebbel invented a device that contained mercury as a temperature sensor which actuated a lever arm to control the draft to a furnace for heating (REF). The majority of automated physical control systems prior to the early 20th century dealt with pressure, temperature, and rotational speed in mechanical systems, and were not directly utilized in a building environmental control application.

The next major innovation to physical control was the definition of PID control in 1911 by Elmer Sperry. PID control involves proportional control, integral control, and derivative control. Proportional control is actuating the control mechanism based on the actual current position of the mechanism compared to the desired position. Integral control is the amount of reset required to correct an amount of error. Derivative control is an attempt to look at how far a set point has historically been from the desired point in anticipating what correction will need to be made in the future. With the foundations of the modern PID loop defined scientists and engineers could then move forward in advancing control mechanisms to include electrical systems.

3.1.3 – Electrical and DDC Digital Control

As electronic relays began to become more commercially available throughout the 20th century electronic sensors were more frequently tied into physical control systems to give a more complete PID loop. Initially, with simple on-off relays only binary control was available, where the systems were either on or off. As modern circuitry advanced, electronic automatic controls became readily usable with much of the research being spurred on through weapons and instrumentation development during World War II. At this point however, electrical controls were still directly tied to specific mechanical systems. For example, a thermostat would be

directly tied back to mechanical actuators on the furnace it was controlling. With the advent of increased computing power and reduced costs through the availability of semiconductor-based systems, direct digital control came to the fore. Direct digital control programs interface a physical sensor, a (often user customizable) computer logic controller, and analog and digital outputs to control the transport medium (liquid, gas, etc.). Today, nearly all new and existing commercial building environmental control equipment is based on some level of DDC control. DDC control is not limited however to just one to one ratio of control. Rather, it is a hierarchy where the DDC system can be multi-tiered. It can control one system, or monitor parallel systems and control them. It can also control a source plant (heating, cooling, ventilation, water, etc.) as well as the parallel systems the source plant supplies.

3.1.4 – Building Environmental Control Today

Today building environmental control systems take three primary forms; single set point control, multi-point set point control, and adaptive control. Single set point control takes a single physical variable and reports that value back to the control system moderating the HVAC system. The physical variable can be a temperature, humidity, airflow, or pressure set point. Typically, it is a temperature set point and the mechanical system is modulated in an on-off fashion, or with some sort of PID loop to try reach and maintain the set temperature.

Multi point set point control can take one of two forms, and the two forms are in fact capable of being used at the same time. The first form (MP-I) takes multiple inputs of various parameters and tries to meet all or most of them based on a schedule of priorities. Multi point control is what allows an air handler to separately modulate humidity, airflow rate, and temperature of an airstream. The second form of multi point control is scheduled control (MP-II). In this approach, the user inputs set points (either a single or multiple points per time period) across discrete time intervals for the system to try and meet during different parts of the day.

The third form of environmental control available is adaptive control. Based on a variety of user inputs and environmental sensors an adaptive control mechanism utilizes a combination of PID loop as well as other algorithms to create and schedule its own set points without active user input. Nest Smart thermostats are an example of adaptive control mechanisms.

3.1.5 – Residential Environmental Control Demands

Residential space have unique requirements in providing satisfactory indoor environmental control. Residential spaces are utilized in a wide variety of occupancy patterns ranging from morning evening use, to constant use, to sporadic use throughout the day. Additionally, residential spaces have traditionally been served by a single thermostat placed in the middle of a home, and are served by single zone air-conditioning system. This reality necessitates the entire occupied space be conditioned to meet the needs of even a single occupant in a small space. It is important to note the bulk of residential HVAC systems are controlled by (and has equipment designed to handle) indoor dry bulb temperature set point, with limited to no concern for humidity or outside air effects.

3.2 – Literature Review

3.2.1 – Building Thermal Mass

Building thermal mass is the heat energy stored and released by the structure of the building itself. The source of energy stored in building thermal mass can be mechanical (pre-cooling), or natural (radiant loads). Building thermal capacitance, the quantity of, and rate of absorption/release of thermal energy is dependent on construction materials, and building geometry. The concept of utilizing the thermal mass of the building to offset the cooling loads was first explored in detail by Ruud in 1990 [3]. Utilizing a live building experiment on the Independent Life Insurance building in Jacksonville, Florida, Ruud found it was possible that by pre-cooling the entire building during the weekend and at night, cooling energy could be reduced by up to 18%. Building on Ruud's research and moving into the computational arena

Balaras identified various parameters affecting the performance of building thermal mass including material properties, thermal mass location and distribution, and the role of ventilation and occupancy patterns [4]. Balaras also tabulated parameters for describing thermal mass, and a selection of those definitions is shown below.

Table 3.1: Thermal Mass Contributing Factors

Parameter	Physical Meaning
Admittance Factor	Represents the extent to which heat enters the surface of materials in a 24h cycle of temperature variation
Capacitance	Accounts for the ability of the external and internal materials to store heat
Comprehensive transfer functions	Describes heat flows in building elements, combining individual wall transfer functions for an enclosure
Conduction transfer functions	Expresses decay of temperature throughout the material
Cooling load temperature difference	Includes the effect of time lag in the propagation of heat through the material, due to thermal storage.
Diurnal heat capacity	Measures the effectiveness of the material for heat storage during a continuous 24h cycle
Effective heat capacity	Accounts for the effects of the building's materials' thermal properties and design factors on the long term energy performance
Effective heat storage	Accounts for the effects of thermal transmittance of the material along with heat transfer rate due to infiltration
Heat Capacity	Introduces the effect of heat storage
Thermal Capacity	Determines the heat flow in unit time by conduction through unit thickness of a unit area material, across a unit temperature gradient, defined as the product of density by specific heat
Thermal Effusivity	Accounts for the response of a surface temperature to a change of the heat flow density at the surface
Total Thermal Time Constant	The heat stored in a whole enclosure per unit of heat transmitted to or from the outside through the elements surrounding the enclosure and by ventilation

Additional research followed in 2003 from two different labs. In a joint experiment between the University of Nebraska-Lincoln, and the technical University of Dresden Henze et. al. explored optimal building control for both active and passive building thermal storage [5]. The study highlighted a major determining factor of utility cost savings based on time-of-use rate differentials is highly accurate weather forecasting for effective predictive control. At the same time Braun was also exploring load control utilizing thermal mass [6]. The model was developed to optimize zone temperature set points based on utility rates, load profile, equipment characteristics, building storage characteristics, and the weather. Modeling was performed both

in field studies as well as in controlled experimental conditions at the National Institute of Standards and Technology test facility. Important features for optimal building control based on thermal mass included a networked digital thermostat system for large buildings, easy global configuration of thermostats, and site-specific control technology for each given building [6]. Braun and Lee followed up this research in 2006 working on demand limiting control using building thermal mass and identified methods not only to reduce energy consumption but specifically target peak demand periods and how to avoid them using set point control [7]. The steps to do so are listed in Table 3.2 below

Table 3.2: Steps for Demand-Limiting Control with Buildings Thermal Mass [7].

Step	Description
1. Enable demand-limiting control	Demand-limiting control is enabled three hours prior to occupancy on days when critical peak pricing is expected. Some utilities are experimenting with automatically sending CPP signals at midnight of the day on which they will be invoked. If this information is not available, then it would be necessary to anticipate the occurrence of CPP through forecasting.
2. Precooling	Precooling should begin about three hours prior to occupancy at around 70°F to provide an appropriate balance between comfort and peak load reduction potential. This setpoint should be maintained until the onset of CPP (critical peak pricing) rates.
3. Demand limiting	The zone temperature setpoints should be adjusted upward from the precooling temperature (70°F) to an upper limit dictated by a balance between comfort and demand-reduction potential (e.g. 78°F). The setpoint trajectory during this period should be designed to achieve maximum demand reduction for the air-conditioning equipment.
4. Setpoint return	At the end of the demand-limiting period, the setpoint can be returned to a normal value. If the end of the demand-limiting period corresponds to the end of occupancy, then the setpoint can be set to a higher value

Based on this approach Braun was able to realize “between a 30 and 100% reduction in baseline peak air-conditioning power depending primarily on the climate” [7].

While work discussed above added value to the field by establishing baseline building data and knowledge, it was not directly applicable to the residential environment. That changed in 2006 when Katipamula and Lu explored similar demand response control strategies in a residential environment [8]. Multiple residential HVAC control approaches were explored, and

results indicated while curtailment control provided the most demand relief it also caused a reduction in comfort. Compared to curtailment control pre-cooling appeared to reduce demand costs nearly as much, but consumed more energy, and cost more overall although it did not see the same comfort loss that curtailment did. It is also important to note that unlike in commercial settings, residential utility rate schedules in most of the United States typically have a fixed demand charge, and do not vary the usage charge rate throughout the day. This is changing in some locales however, particularly during peak cooling season during the peak cooling hours of the day.

Further work by Yang and Li in 2008 explored using thermal mass and night ventilation to reduce cooling loads in air-conditioned office buildings [9]. Their work indicates there is a balance between thermal mass quantity, environmental factors (shading, urban density, trees, etc.), climate, and internal loads which is required for precooling thermal mass to be truly effective as a control mechanism for energy (or cost) reduction. In 2010 Yin et. al. explored precooling strategies specifically in hot California climate zones, and utilized a building simulation tool and a variety of field test buildings to show that accuracy of simulation models has the potential to be greatly enhanced by calibrating them with measured data, and once calibrated the models can be used to accurately predict load reductions on automatic demand response days [10]. This research would indicate the value of a “self-learning” thermostat that can calibrate its initial model based on environmental responses, and shows an ST has the potential to have a major impact energy and cost reduction. However, when paired with the work of Yang and Li, it is possible that in residential environments there is an imbalance between the envelope, building thermal mass, and internal loads to such a degree that precooling may not be effective. This is particularly possible in buildings with high ratios of envelope to internal/occupancy driven loads – as many residential buildings are.

3.2.2 – Control Algorithms and Associated Thermostat Performance

Equally important to understanding how building thermal mass contributes to environmental conditions within a building is the performance of thermostat control algorithms. As early as 2001 Maheshwari et. al identified the value of programmable thermostat settings in an effort to provide energy savings [11]. While focusing on hot air in countries such as Kuwait they identified the importance of time of day control for energy conservation in three distinct occupational environments (a kindergarten, polyclinic, and a mosque). The results indicated what is now recognized fact; scheduled temperature setbacks based on known occupancy profiles are an easy and effective manner for reducing energy consumption.

Another approach previously mentioned while discussing building thermal mass is demand control response. The work of Motegi et. al. highlights commercial building control strategies for demand response [12]. At a high level demand response is controlling building temperature set points and load utilization based on utility demand rates to minimize peak demand and costs, as well as energy consumption. Methods for demand response and HVAC systems include global temperature adjustment, passive thermal energy storage (building thermal mass), increasing supply air temperatures, and increasing chilled water temperatures [12].

Because thermal comfort in buildings is not determined purely based on temperature but also other factors such as on humidity and air velocity, one control algorithm proposed in 2007 by Donaisky et.al. is the use of a Predictive Mean Vote [13]. A PMV model takes a broader array of inputs of what “matters” to the occupants and then produces a control signal for the HVAC system based on those inputs as well as terminal constraints. While PMV may do a better job of increasing occupant comfort it does not necessarily also focus on energy reduction. Freire et. al. also did PMV research at the same time as Donaisky but with two different focuses [14]. They developed one algorithm with the intent of optimizing comfort, and a second that

includes energy consumption minimization while still satisfying indoor thermal comfort needs. The most important conclusions from their study were PMV controllers are most successful when there is at least an approximation of occupants in the space available, temperature set points are highly related to thermal comfort sensation, and it is possible to either increase or maintain occupant comfort while reducing energy consumption.

Work by Moon and Han published in 2010 focusing on thermostat strategies energy consumption in residential spaces demonstrated the impact that three parameters (setback period, set point, setback temperature) have on energy consumption in both cold and hot-humid climate zones [15]. The results indicate in both climate extremes energy savings can be realized by modifying control strategies. The research indicates cold climates are particularly suitable to gaining energy savings with proper thermostat control. As discussed previously occupancy control is an important part in determining internal loads and modulating temperature set points accordingly. Additional residential thermostat research was conducted by Surles and Henze exploring automatic thermostat control based on residential time of use utility tariffs. This is similar to demand response control in large commercial buildings but applied in a residential setting [16]. Again, total savings were highly dependent on both the climate and home location.

Benzeth et. al explored a different manner of occupancy detection from the typical ultrasonic or infrared sensors most commonly used [17]. They developed a visual sensing algorithm combined with video cameras which attempt to more effectively "count" the actual number of occupants in a space while avoiding "ghosting issues" when occupants sit still in a single position for a long period of time. The NEST thermostat line does have the ability to integrate with other NEST products including a security system, so the opportunity to integrate video occupancy recognition is on the horizon.

Most recently, NEST has released a series of white papers as well as partnered studies detailing the savings their smart thermostat is capable of providing. A 2013 study on seasonal

savings indicated using the Seasonal Savings feature in NEST thermostats allowed users to use 5 to 10% less heating and cooling on average when compared to the standard NEST control algorithm [18]. Seasonal Savings were determined by the smart thermostat by automatically “adjusting temperatures in the setback and set point schedule over a period of several weeks based on the thermostat learning each customers’ preferences and occupancy patterns” [18]. NEST reported 80% of people kept the new changes, and only 9% reported a decrease in comfort. Heating energy savings were realized by reducing runtime of heating equipment by 5 to 10.4% depending on the climate, and 6.1 to 12.1% for cooling equipment runtime. These values included users readjusting the schedules after the thermostat created, and these user driven set point adjustments contributed to a 24% reduction in energy savings compared to allowing the thermostat to govern itself.

In 2014 NEST released the Enhanced Auto-Schedule control algorithm for its thermostat. The primary difference between the new control algorithm and the old one is an increased level of attention to user inputs and lack of user inputs. The thermostat not only pays attention to occupancy throughout the week at a more detailed level, but also “consider(s) lack of interactions (indicating satisfaction with the current temperature)” which provides “a more holistic view of user preference and was considered previously” [19]. Based on in-house simulations the new scheduling system appears to be capable of providing a 5.6 to 6.1% increase in savings over the original NEST algorithm. Additionally it appears to provide more satisfied users, based on a reduction in user generated temperature adjustments. NEST does acknowledge at the end of the report that “actual savings will vary with a number of factors, including weather, energy use, utility rates and plan” which does indicate there are other parameters to consider including in future control algorithms and predictive modeling simulations.

NEST's February 2015 white paper delves further into these other contributing factors and identifies conditions and behavior with smaller or larger savings potentials. Table 3.3 below highlights these factors which appear to match commentary made in other building thermal mass and controls papers discussed already.

Table 3.3: Factors Associated with Higher or Lower Thermostat Savings [2]

Larger Savings Potential	Behavior / Characteristic	Smaller Savings Potential
Rarely or never used setback, but willing to	Nighttime setback: before installing Nest	Always used setback
Often away during the day but didn't use setback	Daytime occupancy / prior setback	Home during the day or already used setback regularly
Often go away for days or weekends or vacations and forget to turn down heat; vacation homes	Vacations and other away periods	Never go away or always remember to turn down heat when away
Keep nest features enabled: auto-schedule, auto-away; set heat pump balance to max savings	Nest settings	Disable energy saving features; select less efficient settings (heat pump balance max comfort)
Colder climates (but % savings may be less)	Climate	Milder climates (but % savings may be greater)
Heat pumps with typical or excess auxiliary heat use	HVAC type	Heat pumps with little auxiliary heat use, heat pumps due to limits on setbacks from aux. Heat requirements; condensing boilers if often running in condensing mode
Leakier, less insulated homes lose heat faster during setback, save more	Building shell efficiency	Tighter, better insulated homes lose heat slowly and save less from setback
Low mass homes cool down more quickly and save more from setback	Building mass	High mass homes (e.g., Masonry) cool down more slowly and save less from setback

3.2.3 – Computational Building Simulation Modeling

In the last 15 years building simulation modeling has progressed greatly in level of detail and complexity. In 1999 Medina developed a quasi-steady a balance model for residential walls [20]. He looked at steady-state models for estimating total energy transfer, and transient models for incorporating energy storage, building structures, and moisture transfer. These would become recognized as the major forces that needed to be dealt with in the future building simulation modeling. The model accounted for shape factors, radiation coefficients, convection coefficients, convective heat transfer, forced convection coefficients, solar radiation and then it overall heat balance equation. Conclusions of the research indicated the model was validated using a test house in the South United States. Recommendations were made to further develop transient models, including improving the characterization of windows, moisture, and desorption components for higher level of accuracy [20].

In 2001 Mendes et. al. released the first paper on using Matlab/Simulink the model building thermal performance. This first paper focused on creating a dynamic model for heating mode only. It is highly simplified and had two distinct advantages over previous simulation research. First Matlab/Simulink is widely available, user friendly, and very fast to implement. Secondly even with the relatively uncomplicated multimodal capacitive nonlinear model, nonlinear phenomena such as radiation exchange is able to be analyzed, and as computational power would grow the level of complexity available to end-users would increase dramatically [21].

Mendes et. al. followed up this research in 2003 by exploring specific control strategies using the Matlab model they already created and refined. Another advantage of the Matlab system is the ability to create a block-based structure and then tying them together within the software package. Blocks can include the building, an HVAC system, a sensor, weather, and internal loads. Simple energy consumption models and runtime reports can be developed for

each of the five control methods (on-off control, PID, robust control, adaptive control, and intelligent control), and research noted that while the models were effective and relatively accurate the addition of hygrothermal exchange would likely increase the accuracy in the future [22].

In 2004 Weitzman's dissertation explored modeling two types of heat transfer equipment in a residential simulation in both a 1D and two-dimensional model [23]. Of particular interest from his research was the indication that a simple RC-thermal network model yielded results very similar to the significantly more complicated two dimensional model, which may indicate that if sufficient accounting of the primary contributed factors is able to be accomplished via an RC network, more complex models may not necessarily be required for high-level energy consumption investigations.

In 2005 El Khoury et. al built on the research of the Mendes group and utilized Matlab as well as the SIMBAD building HVAC toolbox within Simulink to attempt to create a multi-zone building model. The model included components for air zones, walls, windows (component missing from previous models), infrared heat exchange, and solar radiation [24]. Simplified model structure of both the internal model as well as the building envelope are shown below in Figure 3.1.

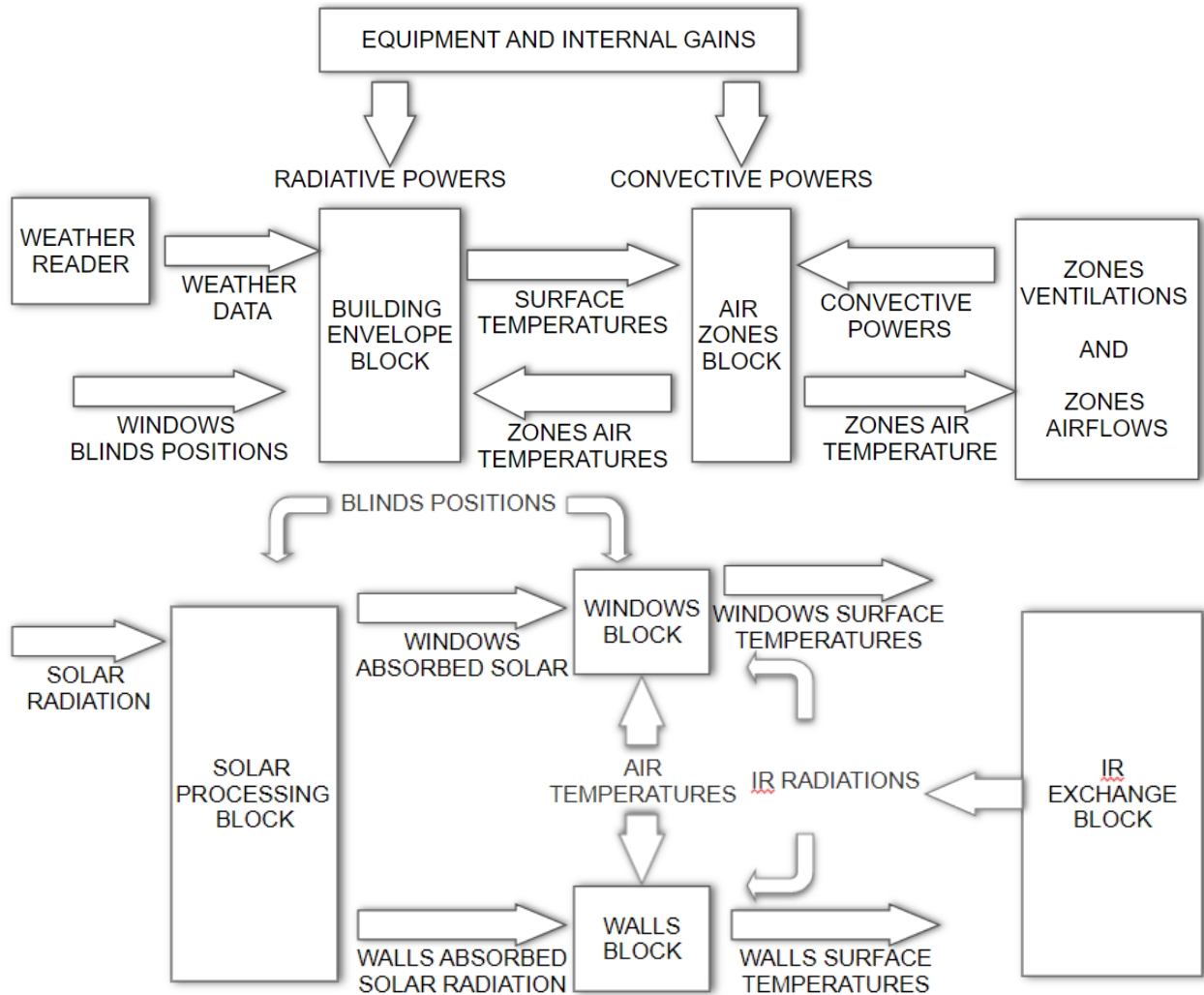


Figure 3.1: Matlab/SIMULINK Internal and Building Envelope Block Diagrams [24]

A main problem that many building simulation models had and continue to suffer is a lack of highly dynamic reporting because their time steps are typically limited to the order of an hour or greater. To explore control strategies a finer level of resolution is desired, and in 2005 Schijndel and Steskens proposed the utilization of the system identification approach within Matlab to reduce computation time and improve sample frequency rate [25]. Unfortunately the method is limited in practical applications, and is only truly possible and effective in modeling continuous free-floating indoor air temperatures.

Another component to building simulation models which had been considered but not yet implemented was the use of the moisture transport hygrothermal model. Barbosa and Mendes continue their progress in building simulation modeling in 2006 by releasing an updated building model that included hygrothermal considerations of vapor and liquid transfer [26]. The model was based on a chilled water loop and included HVAC systems for a chiller, cooling tower, pump, mixing box, cooling and dehumidification coil, humidifier, and fan. Although this level of complexity is greater than what is needed for residential modeling it was interesting to see the conclusion that disregarding moisture transport has the potential to cause up to a 13% over size of an HVAC system to satisfy loads, and up to 4% underestimate in energy consumption [26]. Zhong made further explorations into hygrothermal modeling in his dissertation in 2008. Of note his research was focused primarily on residential buildings, although the motivation was not necessarily energy savings but rather indoor relative humidity from an occupant safety and comfort standpoint [27]. His research moved simulation modeling forward by integrating “1) weather data treatment including wind driven rain and solar radiation, 2) air infiltration and inter-zonal air flow, 3) indoor heat and moisture generation, 4) heat transfer through slab-on-ground floors, 5) indoor moisture storage within furnishings and other soft materials, and 6) HVAC equipment” [27].

Although results regarding energy savings and thermostat control were not directly discussed this is a useful model for exploring the inclusion of more complex factors to yield more detailed output reports.

While developing exploring new simulation models and approaches it is also important to standards with which to validate the effectiveness of known software packages. In 2007 Szewczuk and Conradie published a comparison of 12 different commercial or research-based simulation packages against ASHRAE 140-2007 [28]. The standard based on a test matrix that evaluates whether or not simulation software is capable of handling a variety of building thermal

mass conditions as well as shading and orientation. Table 3.4 below shows evaluation matrix utilized.

Table 3.4: ASHRAE 140-2007 evaluation matrix [28]

Low mass building		High Mass Building	
Annual heating energy – MWh		Annual heating energy – MWh	
Annual cooling energy – MWh		Annual cooling energy – MWh	
Peak heating loads – kW		Peak heating loads – kW	
Peak cooling loads – kW		Peak cooling loads – kW	
Case 600	Base Case	Case 900	Base Case
Case 610	As case 600, South shading	Case 910	As case 900, South shading
Case 620	As case 600, East/West wind orientation	Case 920	As case 900, East/West wind orientation
Case 630	As case 600, East/East shading	Case 930	As case 900, East/East shading

The researchers found that three software packages fully satisfy the standard, and one was found to have substantial differences in high mass modeling while also being incapable of modeling low mass buildings.

In 2011 Hensen published a summary report highlighting current tools for HVAC design analysis, as well as known issues and proposed solutions. A major opportunity posed in examining existing software packages was co-simulation. Co-Simulation is simply coupling multiple existing software packages and align them to communicate in a manner which best leverages each packages strengths diminishing the weaknesses each would have by being used individually. As Hensen puts it:

“It facilitates reuse of state of the art BPS tools by taking advantages of existing models...allows combining heterogeneous solvers and modelling environments of specialized

tools...It enables fast model prototyping of new technologies...facilitates collaborative model design and development process...(and) makes immediate access to new model developments” [29].

Of particular note with regard to co-simulation is the potential for using an advanced building simulation model that is well-vetted such as EnergyPlus or TRYNSYS in conjunction with the development of a control algorithm in a Matlab environment which would allow a much more advanced control algorithm and more detailed reporting interval to be developed than EnergyPlus is capable of its own.

Bernal et. al took the idea of co-simulating using a Matlab toolbox and EnergyPlus as the motivation for creating MLE+. MLE+ is a Matlab toolbox which pairs with EnergyPlus to leverage the strengths of both models. MLE+ uses a Simulink based block workflow to interface with EnergyPlus which is outlined in Figure 3.2 below.

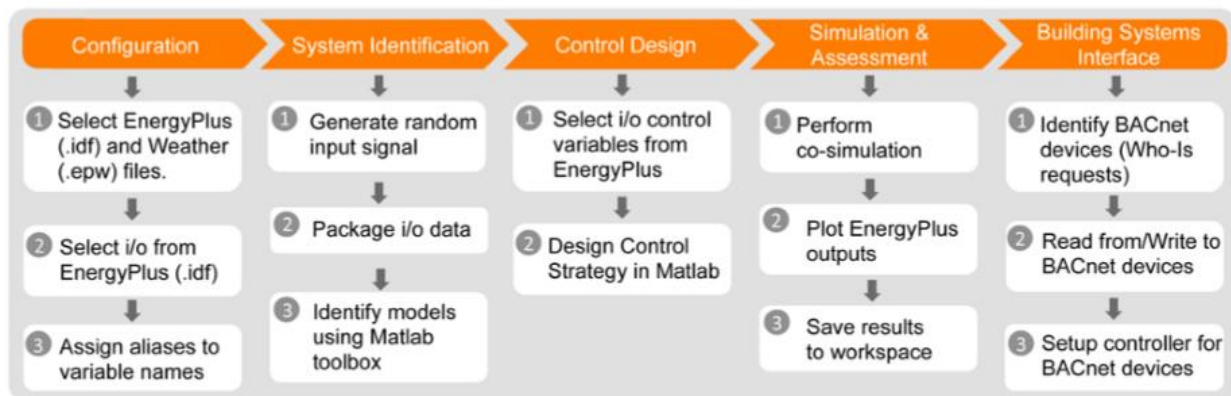


Figure 3.2: MLE+ Workflow [30]

An additional benefit of MLE+ is the ability to integrate with BACnet communication devices to test actual building control models in real life environment. This allows a control algorithm to be tested in simulation, and then immediately rolled into a building space if the simulation outputs indicate positive results. Additionally, it shortens the calibration loop between simulated control algorithm, and actual results.

One critically important component of building simulation is the utilization of real world experimentation to calibrate and validate the computational model. Lu et. al. did so in 2010 when developing a smart thermostat based on occupancy sensors in a home [31]. The research team developed a control method based on public smart home occupancy data, as well as data from 8 sample houses, and a survey of 41 homes. After implementing the control method in EnergyPlus they built two model homes to calibrate and validate the simulation they were using to develop their results. Doing so builds to confidence in the resulting data, and provides a baseline from which future models can be developed. Similar approaches have been taken by researchers at NREL and other DOE sponsored programs. Simulation approaches and previously experimentally validated building constructions, equipment models, and thermal models will be the basis of all simulations conducted as a part of this study. Attention will also be paid to meeting the necessary energy, construction, and ventilation codes such as ASHRAE 90.2, ASHRAE 60.2 and IBC codes.

3.2.4 – Current Smart Thermostat Market Information

While an academic literature review in its own right, before moving on to the most recent research and fleshing out a specific thesis question it is important to understand the current capabilities of smart thermostats that are on the market today. Present smart thermostats are available with the wide range of capabilities. The table below identifies the leading competitors in the smart thermostat market as well as the various sensing, control, and adaptation abilities each possess.

Table 3.5: Current Smart Thermostat Market Overview

Thermostat Name	Features	Approximate Cost
Ecobee3	Multiple temperature/occupant sensors for single thermostat Home/Away overrides “Smart Recovery” develops time to temp model Free cooling mode Humidity Control (when available) AC overcool to dehumidify Performance alerts/monitors Fan dissipation for max cooling gain Multi-stage heating and cooling Mobile app	\$249.99- \$313.00
Emerson Sensi	C-wire not required in most cases, allows for broader installation with existing HVAC equipment Mobile app for schedule control 7 independent schedule days 9 preset schedules to choose from and customize Does not have a smart or learning mode, 100% user designed	\$129.99
Nest	Auto Schedule learns user preferences and occupancy and then programs itself Seasonal Savings slowly shifts temp schedules up or down seasonally to reduce energy consumption while adjusting user comfort zone Auto away turns down when no occupants detected Mobile app to control temp Nest Leaf shows user instant feedback when they set an energy saving temperature. Integration with Nest Camera	\$249.99
Ecobee Smart Si	Same as the Ecobee3, minus: - free cooling capability - remote sensors - tsat proximity sensors - Smart home/Away over rides -touchscreen control	\$179
Honeywell Wi-Fi Smart Thermostat	Seven day programmable schedule Energy Saving mode Smart Response learning mode Remote Access through mobile app	\$229.99
Honeywell Lyric	Geofencing allows the ST to know when user is returning based on smart phone GPS location Intelligent temperature control based on humidity and OAT Mobile app remote access/geofencing Ties to a water freeze and leak detector for added confidence in home integrity while away Also links to Apple Homekit for added mobile/IOT connectivity	\$249.99

Again, it must be noted that while some of the units have the capability to sense parameters other than temperature, the HVAC equipment it is tied to may not be designed for the operating intervals that controlling for other parameters may generate. Issues such as frozen cooling coils, or short-cycling equipment may result.

3.2.5 – Deep Setback

Based on a combination of building simulation research, an understanding of the functionality of building thermal mass and controls method investigations, the concept of deep setback has been presented as an ideal method of conserving energy via a smart thermostat. Lu et first discussed the concept in their 2010 paper proposing a smart thermostat controlled by an array of occupancy sensors to compete against reactive and traditional thermostats. Conclusions based on their simulations included the assertion that

“deeper setbacks have a larger impact on energy savings than longer setback periods; a five degree increase in setback temperature has the same effect as an additional five hours of setback time that uses the normal setback temperature, even in a moderate climate like Washington, D.C.. Since the smart thermostat is designed to preheat the home or quickly respond to occupant arrivals, it can exploit the large energy savings made possible by deep setbacks without sacrificing occupant comfort” [31]

The statement regarding a five degree increase in setback for an hour saving the same energy as five hours at typical setback was not provided with any data or qualifying specific situation to back it up. While certainly possible, the advantage a deep setback has over a standard setback is dependent on climate, building thermal mass, capacity and efficiency of the HVAC system, and the total load in the building and what its sources are. It is therefore an indefensible statement in its current form and raises interesting questions about what the true value of deep setback in various situations. That being said, the experimentally validated results of the research did show the energy saving potential of deep setbacks (50F heating mode and

104F cooling mode in Charlottesville, VA climate, an ASHRAE climate Zone 4A city) when used in combination with an occupancy sensor driven smart thermostat controller paired to a multi-stage heat pump HVAC system. Deep setback was shown to be able to save 8.6% more energy than the shallow setback smart thermostat control, and 27% more than a standard manual home thermostat. However, no mention was made of the potential issues that could arise from using such deep setbacks in a home, other than to state that they “are safe temperatures which do not cause damage to a house in real life.”

The same research group continued to explore methods of saving energy and maintaining occupant comfort, and in 2013 Whitehouse et. al. published a discussion of new approaches to operating buildings. The driving concept which they recognized is that the existing residential (and some commercial) building and HVAC controls/equipment stock is based on the design paradigm of steady state operation [32]. That is to say residential buildings and the equipment/controls we select to condition them are inherently designed to go to a set point temperature and just operate in an effort to maintain that set point constantly. We know that paradigm is directly in conflict with the current move towards energy savings while maintaining occupant comfort. The new paradigm requires a building and its equipment to be able to react quickly to changes in occupancy, while also doing so in an efficient manner which best uses available energy. Whitehouse titles this approach “dynamic response” to occupancy. It is an integrated approach which in the long term entails a paradigm shift about the way buildings are designed, controlled, and equipped. In the short term it includes methods such as smart zoning, dynamically responsive (variable volume/variable load) equipment, and smart thermostat control.

While dynamically responsive HVAC equipment, systems, and design approaches are commonplace for medium to large commercial HVAC systems they have not yet made serious inroads into the residential market. Doing so will be expensive with long payback periods, so for

the time being a reasonable assumption is that the best way to move towards an occupancy-driven dynamic building approach is to (relatively) inexpensively retrofit with smart thermostats paired to buildings and HVAC equipment originally designed for steady state operation.

In an effort to test this approach further, Pisharoty et.al. continued the Whitehouse group's work by comparing the energy saving potential of a manual thermostat, a NEST smart thermostat, and an updated software-based thermostat system based on the 2010 smart thermostat model proposed by Lu et. al. The software package-called ThermoCoach-uses a combination of occupancy monitoring as well as energy consumption reports from a connected NEST thermostat to make recommendations to the homeowner via email about modifications they could make to their set point schedule based on comfort, balancing comfort and energy, for targeting exclusively energy savings. Three groups were established for the study; homes used a NEST thermostat with all scheduling capabilities disabled to represent a manual thermostat, a NEST thermostat left to operate as intended, or a NEST thermostat with automatic control disabled but schedule control enabled to allow the homeowner to use ThermoCoach to set the set point schedules. All three user groups received weekly energy use reports generated by their NEST thermostats and the manual group and ThermoCoach groups made changes based on these reports while the standard NEST group simply ran their homes. The results at the end of the test indicated ThermoCoach homes saved an average of 4.7% more energy than homes manually changing their schedules, and 12.7% more energy than homes with a NEST operating on it's own.

While the results are certainly encouraging from a standpoint of furthering the case for deep setback, they did have some limitations and issues worth noting. First, all the homes were confined to one geographic location, and data acquisition was limited to one three-month seasonal period. Additional locations and seasonal ranges need to be considered. Also, two story homes with bedrooms on the second floor had the lowest adoption rate and energy

savings of the ThermoCoach homes. This supports the 2016 report released by the DOE's NREL assessment indicating that when attempting to maintain uniform temperature across an entire house, two story homes (and especially two story homes with a basement) are nearly impossible to control in such a manner with a single HVAC zone and thermal stratification of the house is almost certain to occur. Additionally, two households had their cooling coils freeze over after the NEST thermostats were installed and could not be included in the final results.

These results add real-world credence to the question of what are the unintended consequences of the implementation of smart thermostats seeking deep setbacks with the goal of energy savings. How deep of a setback can we sensibly recommend or allow in heating and cooling conditions? What is the impact of local climate and weather fluctuation on these setback points? What are the impacts of building tightness? How do current ventilation, construction, and energy codes impact the ability to reach deep setback points? These are the questions we hope to answer, and in doing so hope to provide recommendations on setback limitations and best practices regarding smart thermostat use for a variety of residential occupancy combinations.

4 – Methodology

4.1 – Software Package Selection

Modeling was conducted using the OpenStudio platform. Openstudio (OS) is an open-source, highly developed GUI for the DOE's EnergyPlus energy modeling engine. OS permits users to generate building geometry using the widely available Google Sketchup software package. It then imports and converts the 3D model into a gbxml file and allows the user to define a wide array of physical envelope conditions, weather conditions, HVAC systems, HVAC control approaches, scheduled internal and external loads. The user then determines which modeling packages in EnergyPlus are to be run, what outputs are required, and then OS translates all of that information into an EnergyPlus model. This is similar to the co-simulation

described by Hensen [29]. After internally running the model in E+, OS reports the requested results in both an SQL file, as well as specific data streams as .csv files if configured to do so.

4.2 – Setpoint Selection Basis

The three major factors explored were comfort, energy savings, and building integrity. These factors were assessed while varying representative ST accuracy and unoccupied setback depth of a dry-bulb-based smart thermostat. Both short and long term unoccupied cycles were modeled. Table 4.1 describes in matrix format the factors explored, variables and metrics used to explore those factors, and the questions to answer based on the results.

Table 4.1 – Study Design Matrix

Factors to Consider	Transient Variables/Metrics	General Questions to Answer
Building Integrity	Indoor Wet Bulb/Dry Bulb Temperatures	Deep Setback Temp Setpoints in heating and cooling season?
	Outdoor Wet Bulb/Dry Bulb Temperatures	Impacts of geography?
	Infiltration and Exfiltration Rates	Impacts of Building Construction?
Energy	Moisture generation sources and rates	Impacts of Ventilation Requirements?
	HVAC Equipment Run Time	What limitations must be considered?
	“Unmet Hours”	What operational best practices may be recommended?
Occupant Comfort	Building envelop insulation ratings	What issues may arise that require future exploration and consideration?
	Building envelope infiltration tightness	

Since Openstudio does not have an integrated smart thermostat function one had to be designed. A smart thermostat is no more than a programmable thermostat which has some advanced logic to determine when to change the setpoint based on anticipated knowledge of occupancy. The easiest way to replicate that logic in Openstudio was to create a standard

occupancy schedule which demonstrated the various absence intervals and occupancy rates which we wanted to explore, and then simply set heating and cooling setpoint schedules around those occupancy schedules which replicated a high performing, ideally performing, and poorly performing smart thermostat. Figure 4.1 through Figure 4.34.3 below show the difference in ST accuracy predicting occupancy on the standard occupancy schedule which was used for the majority of the test.

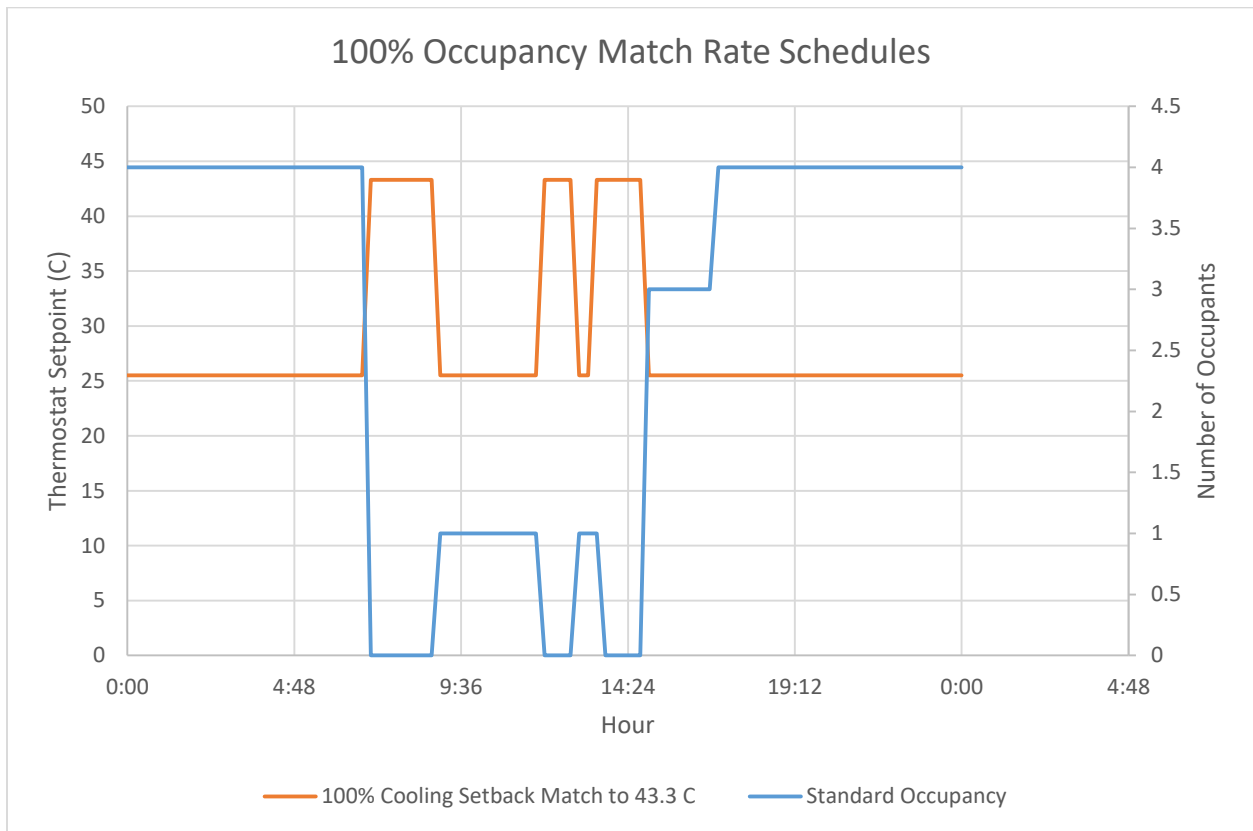


Figure 4.1: 100% Occupancy Match Setback Schedule

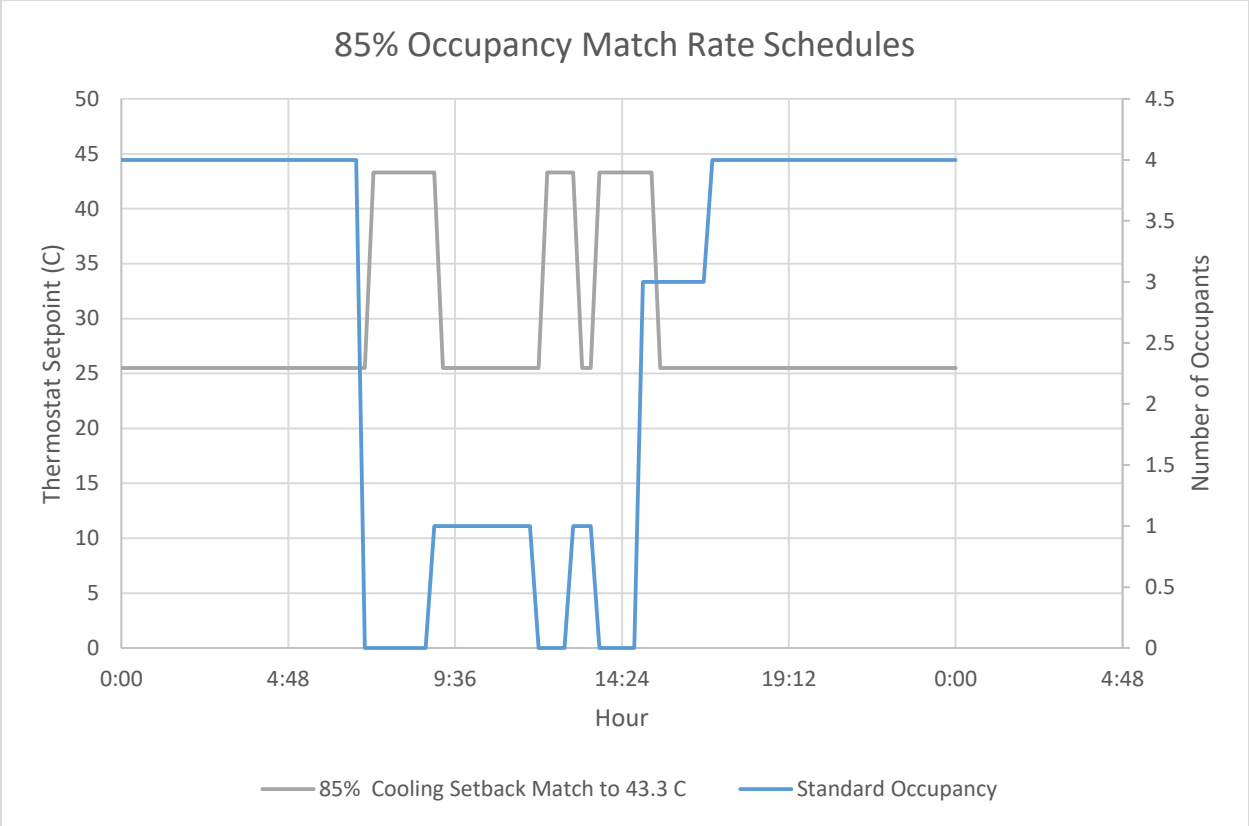


Figure 4.2: 85% Occupancy Match Setback Schedule

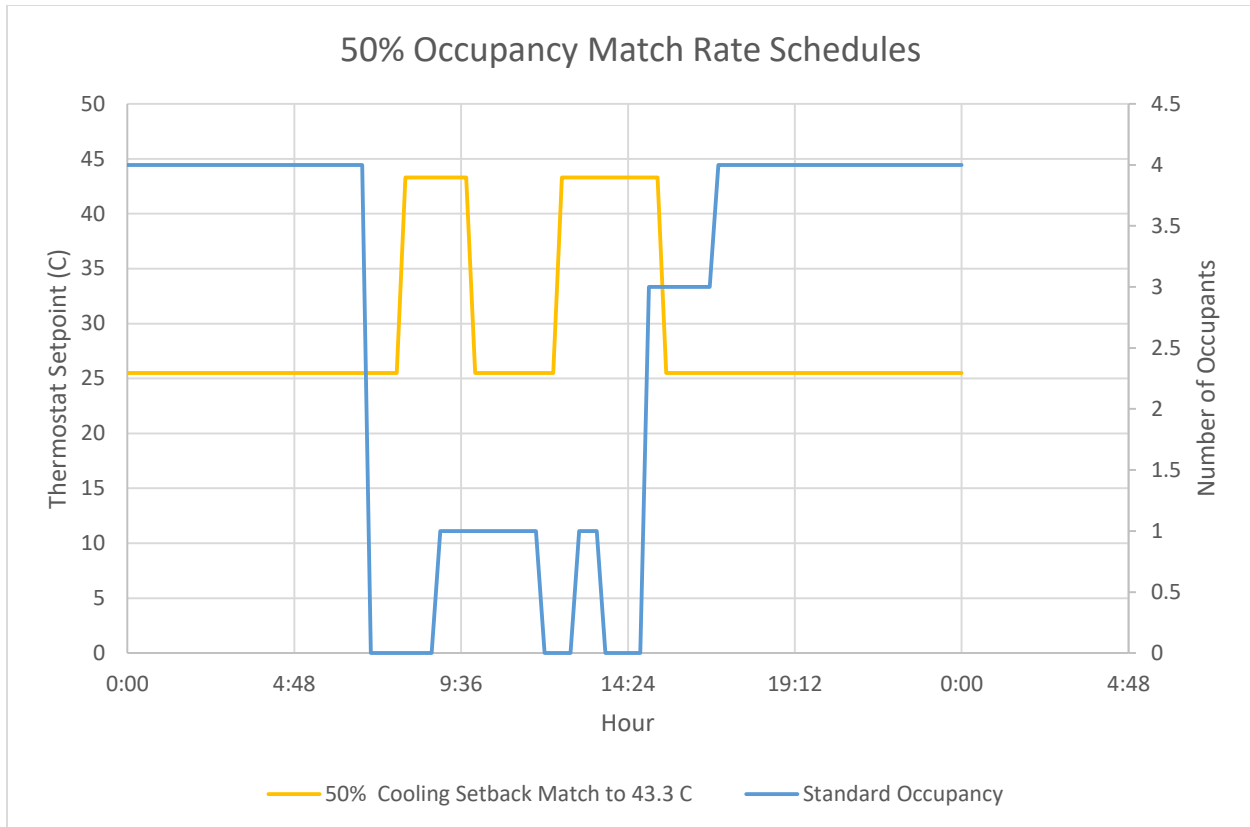


Figure 4.3: 50% Occupancy Match Setback Schedule

The intent of the above approach was to explore relationships between setpoint, occupancy state, and weather. It did not need to match any specific ST algorithm because that is not the goal. Rather, we wanted to understand the conditions which would make implementing such an algorithm either useful, or potentially problematic.

In addition to modeling various levels of accuracy the weekly thermostat schedules also needed to reflect increasing levels of thermostat setback temperature during unoccupied mode to determine the deepest setback a given combination of building construction, infiltration, and location could reach in either a short term or extended absence scenario. Based on the paper by Yang and Li it was stated a house could be allowed to reach anywhere between 35 and 114 degrees Fahrenheit in setback mode and be recoverable [9]. Therefore the deepest setbacks allowed in this model were 35F in heating and 110F in cooling seasons, respectively. Table 4.2 below outlines a week by week schedule over the entire year of the heating and cooling setback

schedules, paired with different occupancy profiles every model used to run its simulations. It should be noted there are weekly gaps during normal occupancy mode. This was done to allow the space to recover after each run, and let it start from the same point without creating a stacking effect of the model conditions running back to back.

Table 4.2: Annual Thermostat Setpoint Schedule

Heating Mode		Cooling Mode	
Weeks	Setpoint	Weeks	Setpoint
1-2	35 F	27-28	110 F
3	ASHRAE 90.2 Recovery	29	ASHRAE 90.2 Recovery + Dehumidification
4	100% Setback match to 65F	30	100% Setback match to 85F
6	85% Setback match to 65F	32	85% Setback match to 85F
8	50% Setback match to 65F	34	50% Setback match to 85F
10	100% Setback match to 55F	36	100% Setback match to 95F
12	85% Setback match to 55F	38	85% Setback match to 95F
14	50% Setback match to 55F	40	50% Setback match to 95F
16	100% Setback match to 45F	42	100% Setback match to 105F
18	85% Setback match to 45F	44	85% Setback match to 105F
20	50% Setback match to 45F	46	50% Setback match to 105F
22	100% Setback match to 35F	48	100% Setback match to 110F
24	85% Setback match to 35F	50	85% Setback match to 110F
26	50% Setback match to 35F	52	50% Setback match to 110F

With the above approach a model can explore a total of 24 discrete setback and occupancy match behaviors during normal occupancy mode as well as a two week period during each season to see what would happen if the house were allowed to drift as high or low as possible given zero occupancy in the space and no temperature control as long as it remains within the highest and lowest bounds listed above (35-110F). During heating season the

recovery week setpoints were compliant with ASHRAE 90.2-2014 (60F 0000-0600, 68F 0600-2300, 60F 2300-2400), and during cooling season the recovery weeks were set to 74F (below the ASHRAE recommended 78F) and controlled for humidity as well with a target RH of 40%. This was done to ensure each cooling season test week would see the same opportunity for a cool and dry initial space condition.

4.3 – Custom Weather File Creation

The above approach to leveraging Openstudio's control of schedules is only valuable if the user can also look at the same weather conditions cyclically so each test run gets the same weather profile. To create the two week deep setback periods, a three day period of .epw data (centered on the heating or cooling design day) was captured using NREL's System Advisor Model (SAM) weather data viewer package for a given locale. The data was then repeated seven times in MS EXCEL to create a three week period of "worst case scenario" for the given weather station. The first two weeks were used as a long unoccupied test period, and the third a recovery week before the short term testing periods. Next, SAM was used to capture a one week period of .epw data (again centered on the heating or cooling design day) which was then repeated 23 times in MS EXCEL to create the weekly test periods outlined in Table 4.2 above. Once a full "year" of weather cycles was developed, the data was inserted into Elements .epw customization tool, and written as a custom weather file with the necessary header information.

The above process was repeated for the weather stations at; Minneapolis International Airport, Fayetteville Drake Field, and Miami International Airport to provide a varied cross-section of both worst case temperature and humidity conditions across the country. Selecting locations that were not in the dry or marine ASHRAE regions was intentional as exploring the issues surrounding high outdoor humidity was a primary question to be answered, and as discussed in the literature review, there is a significantly greater portion of the US population in this regions of the country represented by the selected weather conditions.

4.4 – Floorplan Selection Basis and Creation

Based on the survey data discussed in the literature review surrounding the makeup of US residential single family homes, it was decided that a single story home with an attached garage, attic, and built on a slab with approximately 1500 square feet of floor area would be a suitable representative model. The same floorplan as Poershke et al used in their research was selected [33]. A floorplan is included in Figure 4.4 below.

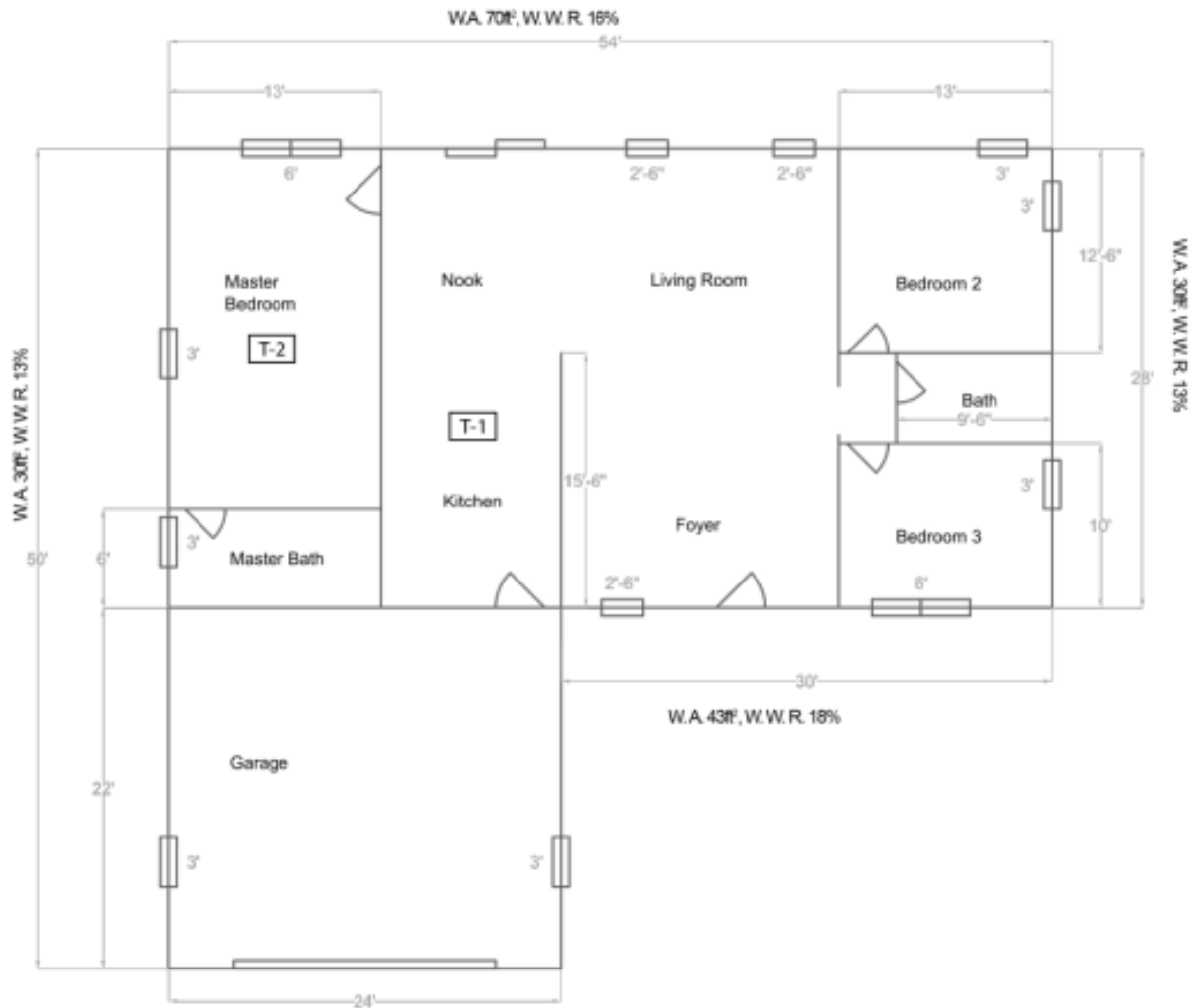


Figure 4.4: House Floorplan

4.5 – Internal Loads and Scheduling

The 2014 Build America house simulation protocols contain a load sizing and scheduling spreadsheet which creates maximum internal (latent and sensible) loads and percentage of total load schedules based on occupancy and equipment tailored to the building profile that it receives as an input. Additionally, it will create custom heating and cooling season hourly lighting schedules based on the variable availability of natural light. Using these tools, schedules and maximum values were input into the Openstudio models where they generated internal load values to run in EnergyPlus. The spreadsheet calculates the likely peak occupancy of the space. This was one variable generated by the spreadsheet which was not used. It was decided the home would have a maximum of four instead of three occupants. This was done to generate additional latent load, and to account for an average American family, rather than a statistical people-per-square foot model.

Based on both the 2014 Build America house simulation protocols, as well as to reflect the NREL work done by Poershke et al. the new construction and renovation construction models were built to have R-values matching the 2009 ICC. The table used to select new construction R-values is shown in Table 4.3 below.

Table 4.3: Insulation Design Values use for New and Renovation Construction Houses

Climate Zone	Ceiling R-Value	Frame Wall R-Value	Floor ^a R-Value	Basement Wall R-Value	Crawlspace Wall R-Value	Slab R-Value, Depth
1	30	13	13	0	0	0
2	30	13	13	0	0	0
3	30	13	19	0 ^b	5	0
4 except Marine	38	13	19	10	10	10, 2 ft
5 and Marine 4	38	13+5 ^c	30	10	10	10, 2 ft
6	49	13+5 ^c	30	15	10	10, 4 ft
7 and 8	49	21 ^d	38	15	10	10, 4 ft

Miami, Fayetteville, and Minneapolis are located in ASHRAE zones 1,4, and 6, respectively, so those are the lines which were used from the table. For old construction

models, per the 2014 Build America house simulation protocols for 1980-1989 construction buildings with 2x4 wall construction and 2x6 Attic cavity insulation Tables 29 and 30 were referenced (shown below in Table 4.4).

Table 4.4: Old Construction Wall and Ceiling Insulations

Table 29. Default R-Values for Framed Wall Cavity Insulation

(based in part on Huang and Gu 2002)

Framed Wall Construction Type	Year of Construction			
	1990+	1980–1989	1950–1979	Pre-1950
2 × 4	13	11	0	0
2 × 6	19	17	0	0

Table 30. Default R-Values for Cathedral Ceilings/Cathedralized Attic Cavity Insulation

Roof Construction Type	Year of Construction				
	1990+	1980–1989	1950–1979	Pre-1950	Pre-1920
2 × 6	13	9	7	0	0
2 × 10	19	15	11	0	0

Because a primary focus of the research was to explore the impacts smart thermostats had on the most prevalent existing building construction and equipment the decision was made to not include any controlled mechanical outdoor air ventilation (outdoor air dampers/coils on the HVAC systems). ASHRAE 90.2 recommends if no constant outdoor air mechanical ventilation is provided in the HVAC system that the minimum natural infiltration rate be no less than 0.35 Air Changes per Hour (ACH). Therefore the new construction and renovation models were specified with 0.35ACH of infiltration. Based on common data and reports, the old construction models were specified with 0.5ACH to reflect a looser, more settled-in home. Additionally, since no latent loads associated with bathing were built into the internal loads, no exhaust fan operations matching such loads were scheduled.

4.6 – Data Outputs

Openstudio contains a set of functions which allows a user to export .csv information at whatever time step they choose for any EnergyPlus output variable they may specify. However for computer stability and total run time it was discovered that at a one minute time step the maximum number of data files that a single model could run was limited to 10. Therefore the nine base models each had to be copied, and both copies run with different reporting outputs. One run focused on air side outputs and the other on energy side outputs. Additionally, each location required a single model run focusing simply on reporting weather data in a minute by minute format since that was the most efficient manner for translating the .epw files into minute by minute (instead of hourly) data for comparison with the rest of the results. Table 4.5 below shows all the initial simulations (numbered) conducted for this experiment.

Table 4.5: Model Number Reference Table

	Minneapolis	Fayetteville	Miami
Weather File	1	8	15
New Air	2	9	16
New Energy	3	10	17
Renovation Air	4	11	18
Renovation Energy	5	12	19
Old Air	6	13	20
Old Energy	7	14	21

Data was then queried directly from the Openstudio SQL Viewer when only a single variable was required, or pulled and processed from the CSV files in MS excel if calculations or transformation of the information was necessary.

5 – Experimental Results and Discussion

5.1 – Moisture Issues

Before the results of either the deep setback or normal occupancy periods of the models are discussed, it is important to note what may be a major issue in all of the models. Even with the humidity and air temperature “reset weeks” discussed in the methodology, all models had

major issues with humidity control during cooling season deep setback and normal occupancy modes. Every model had extended periods of time sustained at 100% RH within the occupied zone. This understandably raised questions.

The first question was could these results be manifesting something other than a properly functioning energy model. First, hand calculations were performed to assess whether indoor and outdoor air conditions matched the moisture loads generated from internal latent loads, and infiltration/exfiltration of moisture with the air. These were conducted at discrete time intervals across several models as a “sanity check”, and came up very close to the internal moisture loads the model results were indicating. Once those results were confirmed to at least be within the realm of possibility, further examination of the capabilities of the computational model itself was conducted. It was realized that the heat transfer model does not account for material moisture transport, particularly absorption / desorption by the building mass. This could play a critical role in dampening moisture load reactivity, similarly to how building thermal mass dampens temperature fluctuations. EnergyPlus has the capability to model buildings using either a Heat and Moisture Transfer (HAMT) or Effective Penetration Depth Model (EPDM) to add building moisture interfacing into consideration. The downside is both models require additional access and parameter definitions within EnergyPlus to sufficiently characterize the building material properties which the Openstudio interface does not natively provide. As noted by both Medina and Mendes, adding moisture factors into the model has the potential to increase the accuracy of the model as a whole.

Given the open ended nature of the moisture issue, consideration was taken that the model was in fact correctly representing the activity taking place, and what that meant from a building systems perspective. These issues match those identified by Zhong in 2008 with hygrothermal factors being considered. As will be discussed further in later sections, the use of the ASHRAE 60.2 cooling season setpoint of 78F led to very little air conditioning run time in all

climates and all constructions. This was magnified in the new construction models versus the old construction models. Because even the best insulated models were limited to a minimum of 0.35ach per hour of infiltration per ASHRAE for naturally ventilated buildings for OA (as most homes do not have dedicated OA control), there was too much moist air infiltrating with not enough load generated to exceed the 78F dry-bulb setpoint and run the AC long enough to effectively pull moisture from the air. Furthermore, higher insulation requirements in northern climate zones designed to combat colder winter conditions led to similar humidity issues that warmer climates saw, but at less extreme summer conditions. That is to say that improving insulation for heating season may have detrimental effects during cooling season if moisture issues are not also considered. It appears once insulation and infiltration is optimized in a residence, humidity control, and not temperature control may become the driving concern in terms of occupant comfort and building integrity, particularly when complying with energy code setpoint and outdoor air rate recommendations with standard residential HVAC equipment.

5.2 – Deep Setback

5.2.1 – Heating and Cooling Recovery Results

This first factor examined in the deep setback results for both heating and cooling seasons was recovery time at the end of each two week setback period. During heating season Minneapolis had the coldest winter design day temperatures, and so it should come as no surprise that the old construction model in that locale took the longest to recover from deep setback mode as shown below in Figure 5.1

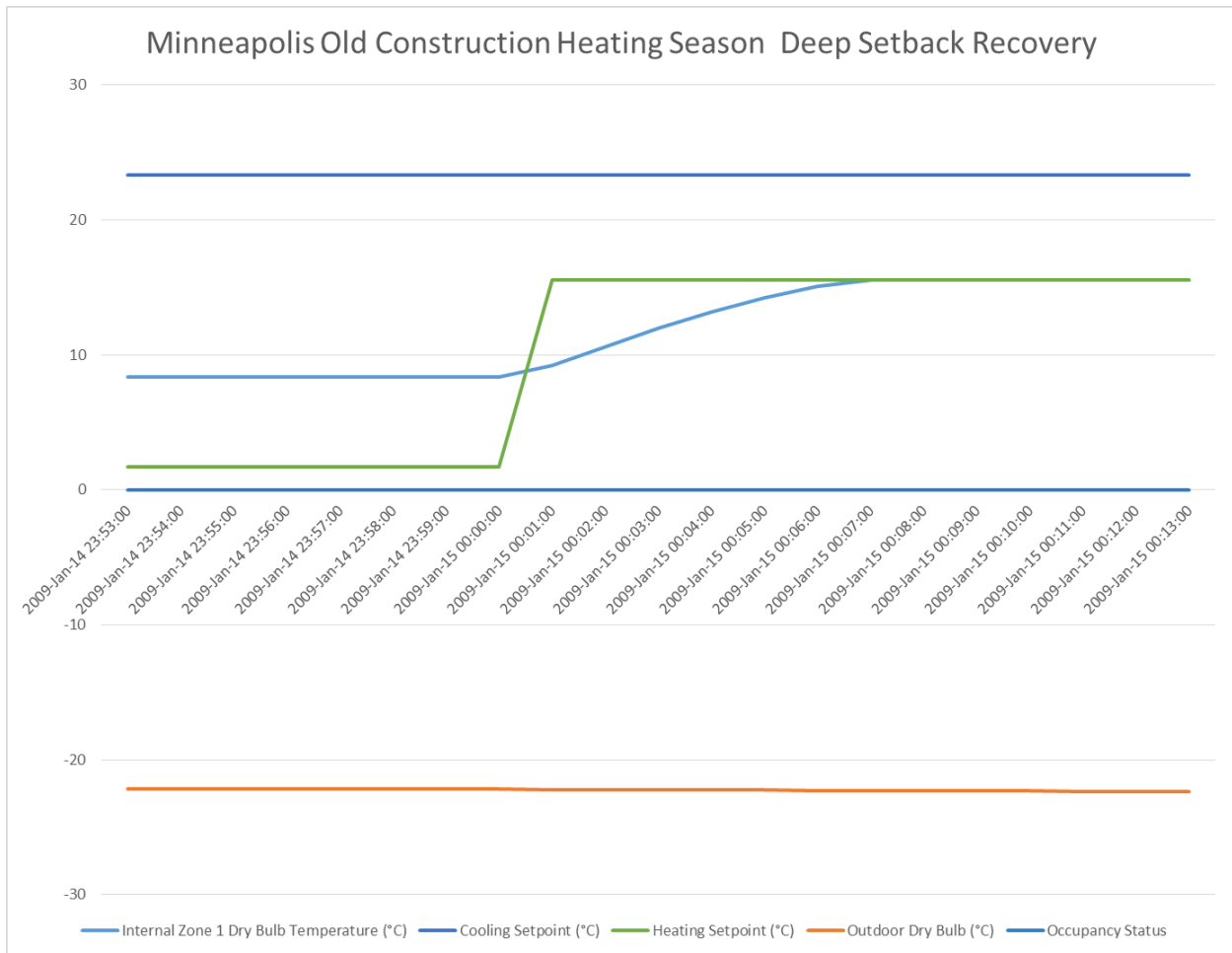


Figure 5.1: Minneapolis Old Construction Heating Season Deep Setback Recovery

We can see the time to recover to the unoccupied non-deep setback mode takes approximately 7 minutes. Similar times were seen in the other Minneapolis Models. Even after two weeks with the lowest quality insulation and the highest infiltration in the coldest climate, the “worst case” house still never got lower than 7C air temp. Daily radiant and equipment loads maintained enough heat to temper the occupied space as shown in Figure 5.2 below

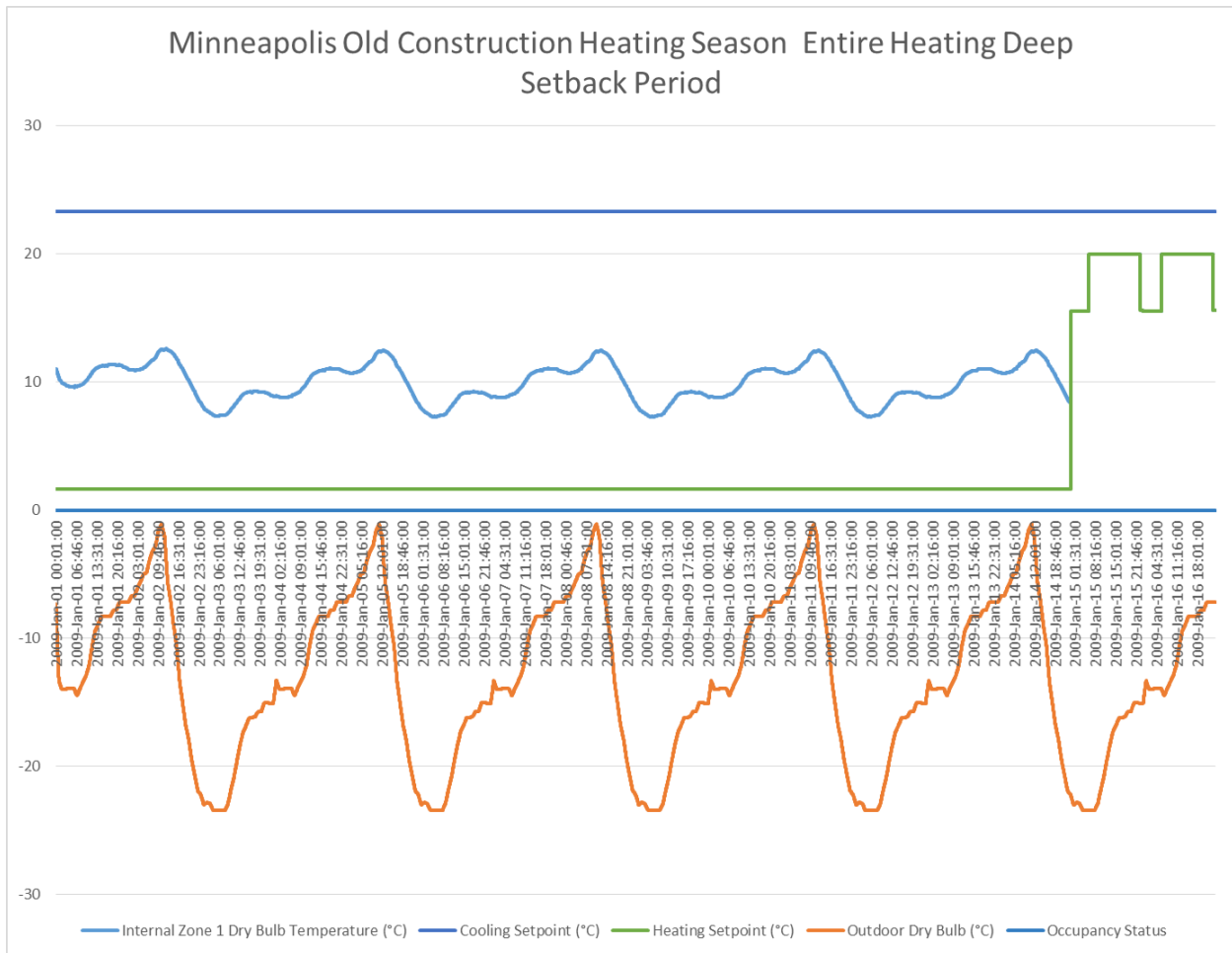


Figure 5.2: Minneapolis Old Construction Heating Season Deep Setback Period

While it is possible uninsulated pipes may have frozen at a 7C air temperature, further data on internal and external wall temps would be needed to determine the risks to building integrity during such a setback.

The Fayetteville models showed most pronounced differences in minimum temperatures seen across construction types as shown in Figures 5.3-5.5 below.

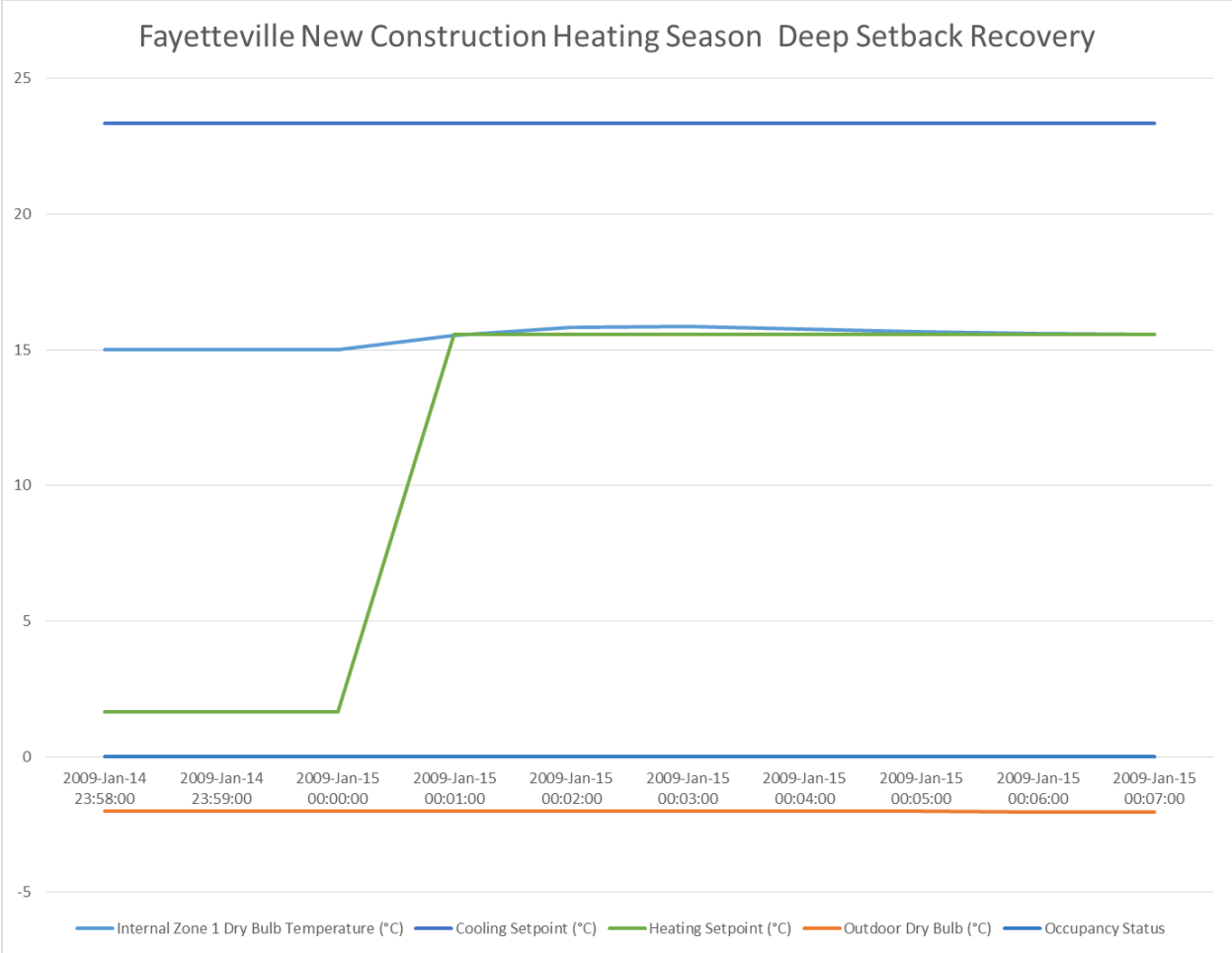


Figure 5.3: Fayetteville New Construction Heating Season Deep Setback Recovery

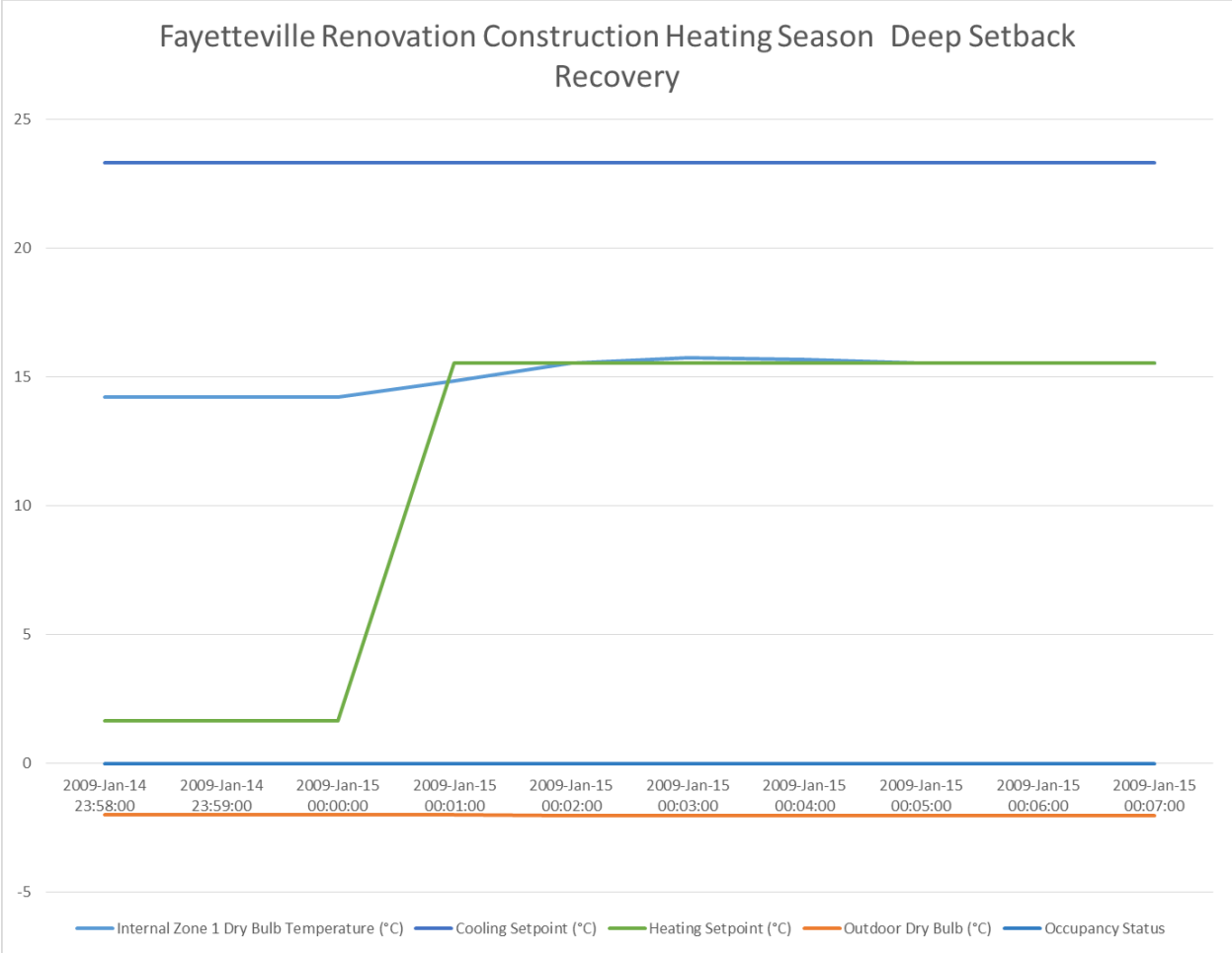


Figure 5.4: Fayetteville Renovation Construction Heating Season Deep Setback Recovery

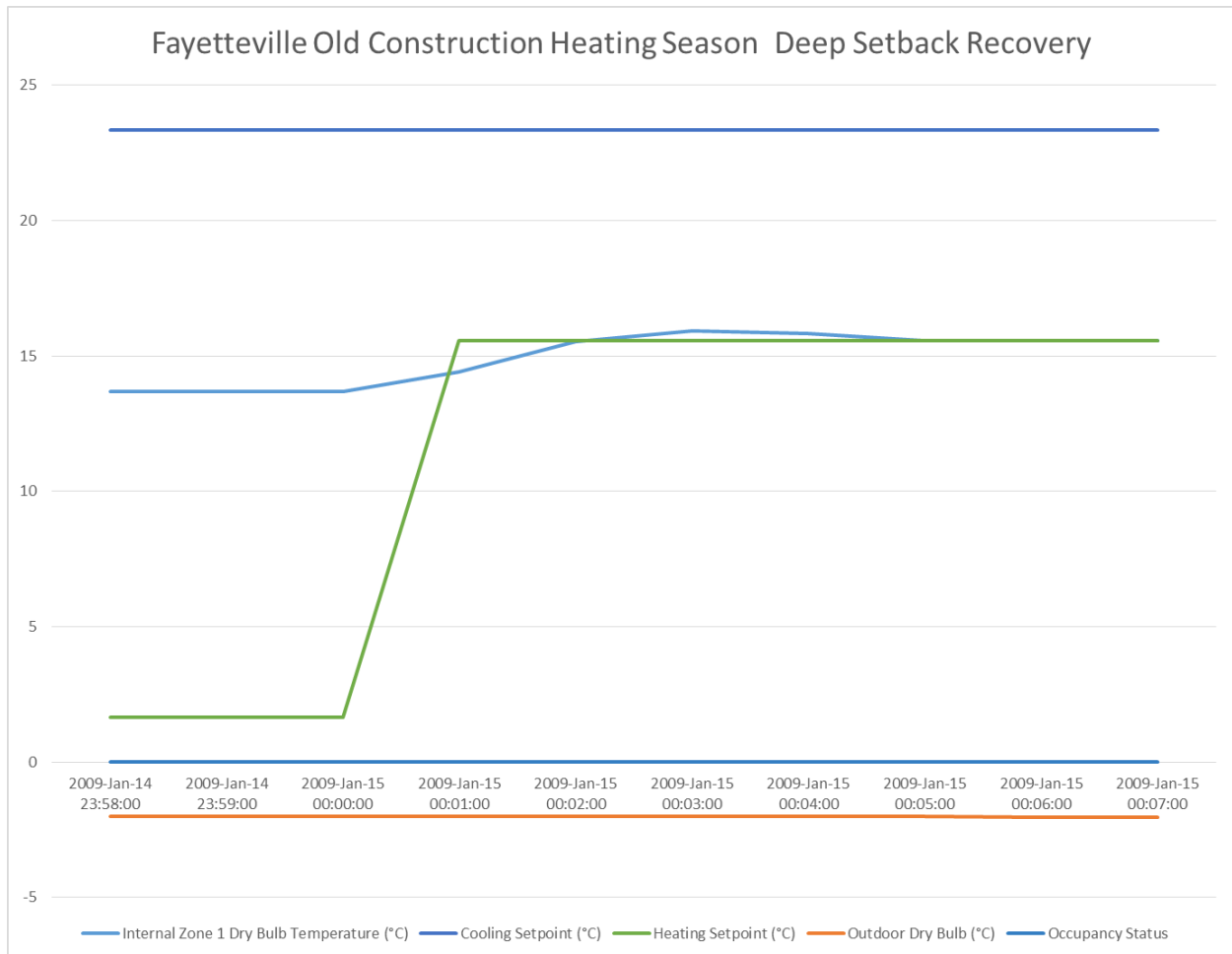


Figure 5.5: Fayetteville Old Construction Heating Season Deep Setback Recovery

Moving from new to old construction reflects a trend of decreasing thermal stability (resistance to temperature change). This matches what is generally accepted; old drafty houses get colder faster than newer tighter houses. That being said, the total difference in minimum temperature reached across the three models was only 1.4C, but said difference was the most noticeable of all locales.

Another point to note during heating season deep setback is that none of the Miami models ever hit the deep setback or normal setback setpoints. This is not particularly surprising given the outdoor air dry bulb (OA DB) temperature was above the heating setpoint the entire time.

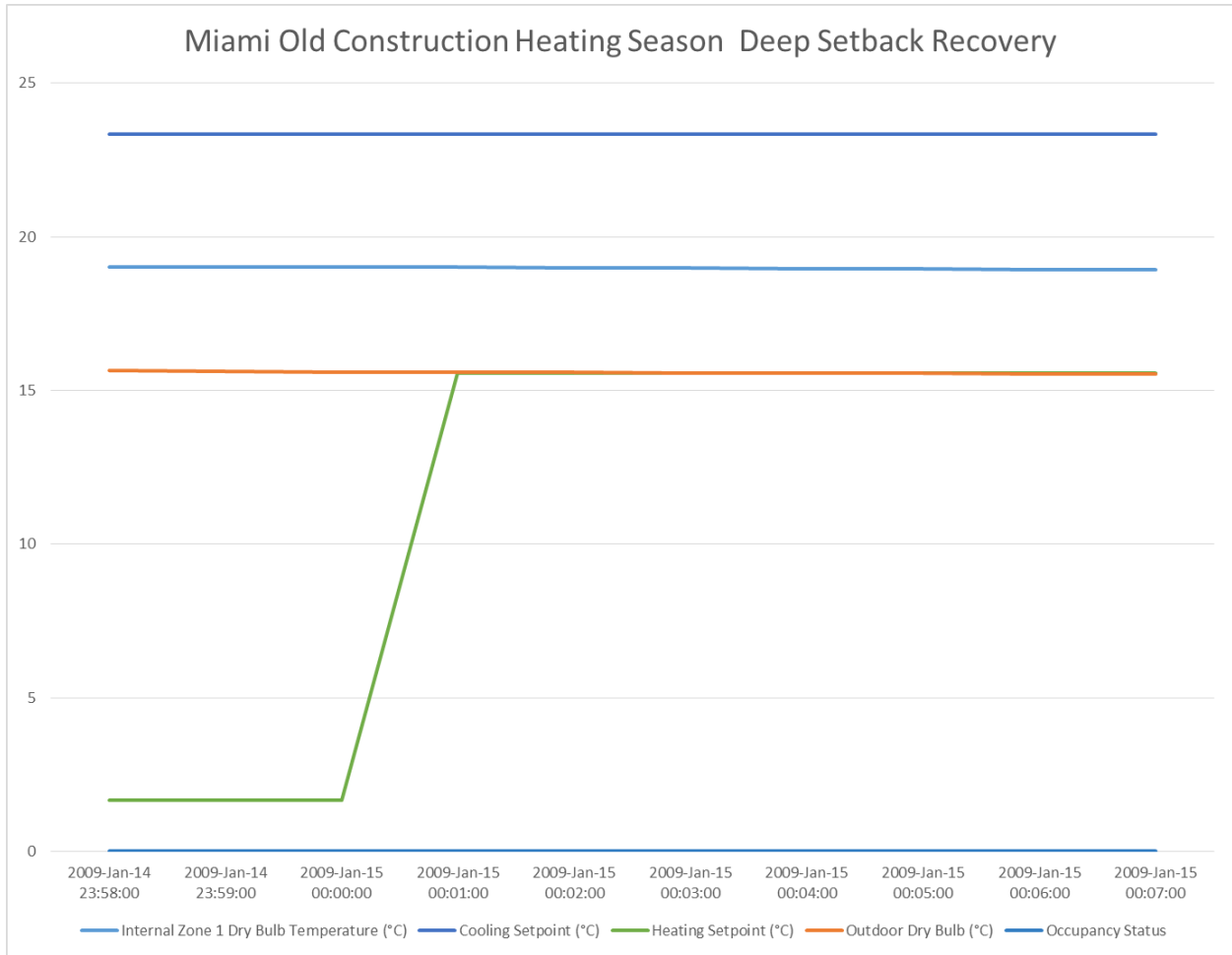


Figure 5.6: Miami Old Construction Heating Season Deep Setback Recovery

Transitioning to examining the deep setback cooling season data, even at the design cooling week the heat was still coming on with an ASHRAE cooling setpoint in all the Minneapolis models during the two week deep setback period at night/early in the morning.

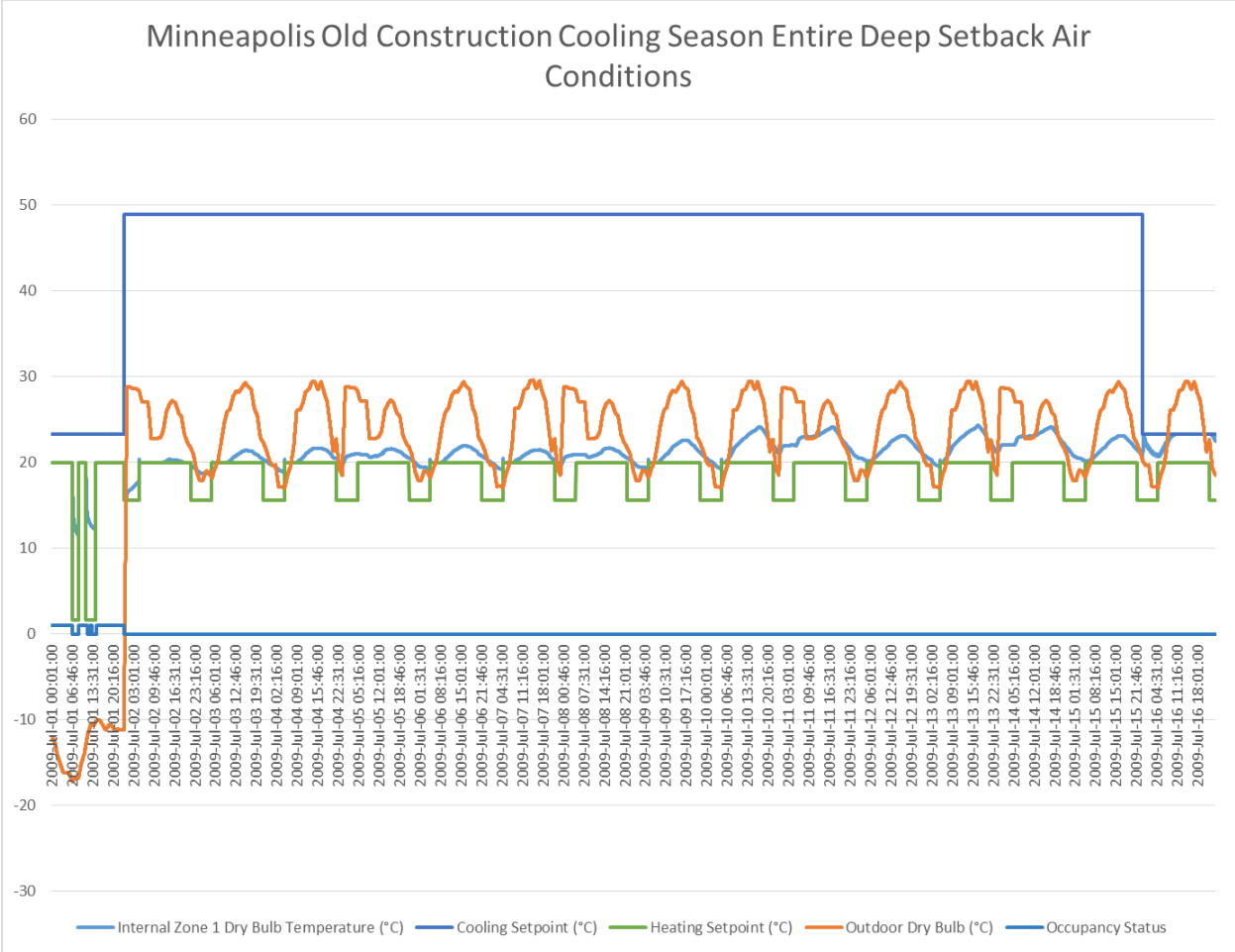


Figure 5.7: Minneapolis Old Construction Cooling Season Deep Setback Air Conditions

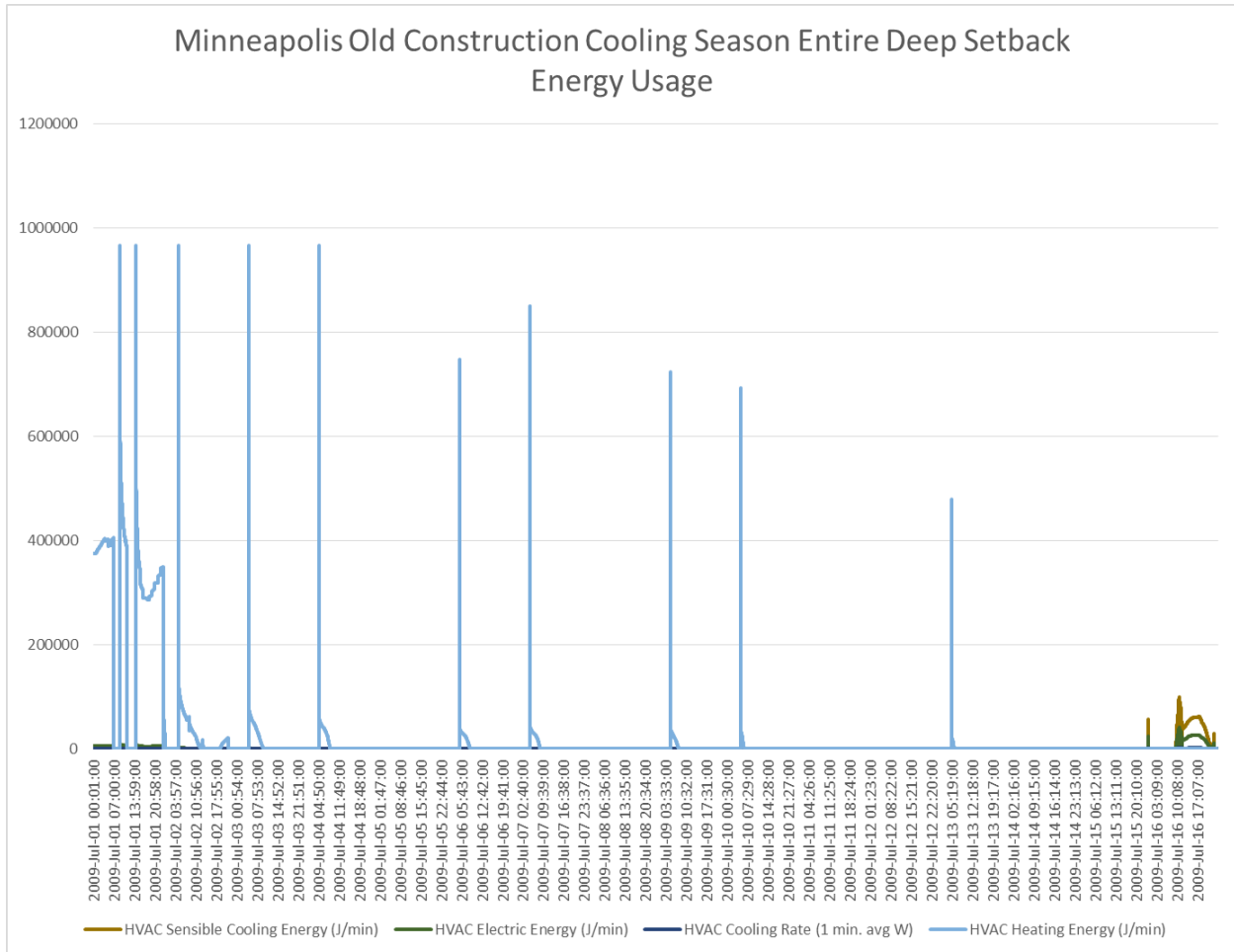


Figure 5.8: Minneapolis Old Construction Cooling Season Entire Deep Setback Energy Usage

In a real house the heat would probably be turned “off” during the summer so even lower daytime temps may be reached than those seen here if the unneeded heating was avoided. The house would have additional potential to act as a thermal sink and reduce energy consumption on during the daytime, also reducing the need for cooling ventilation during deep setback. Also, neither the indoor temperatures in Fayetteville or Miami was ever greater than 25C-still within an ASHRAE 90.2 compliant cooling season setpoint range. This result was independent of construction method in both locales as shown in the figures below.

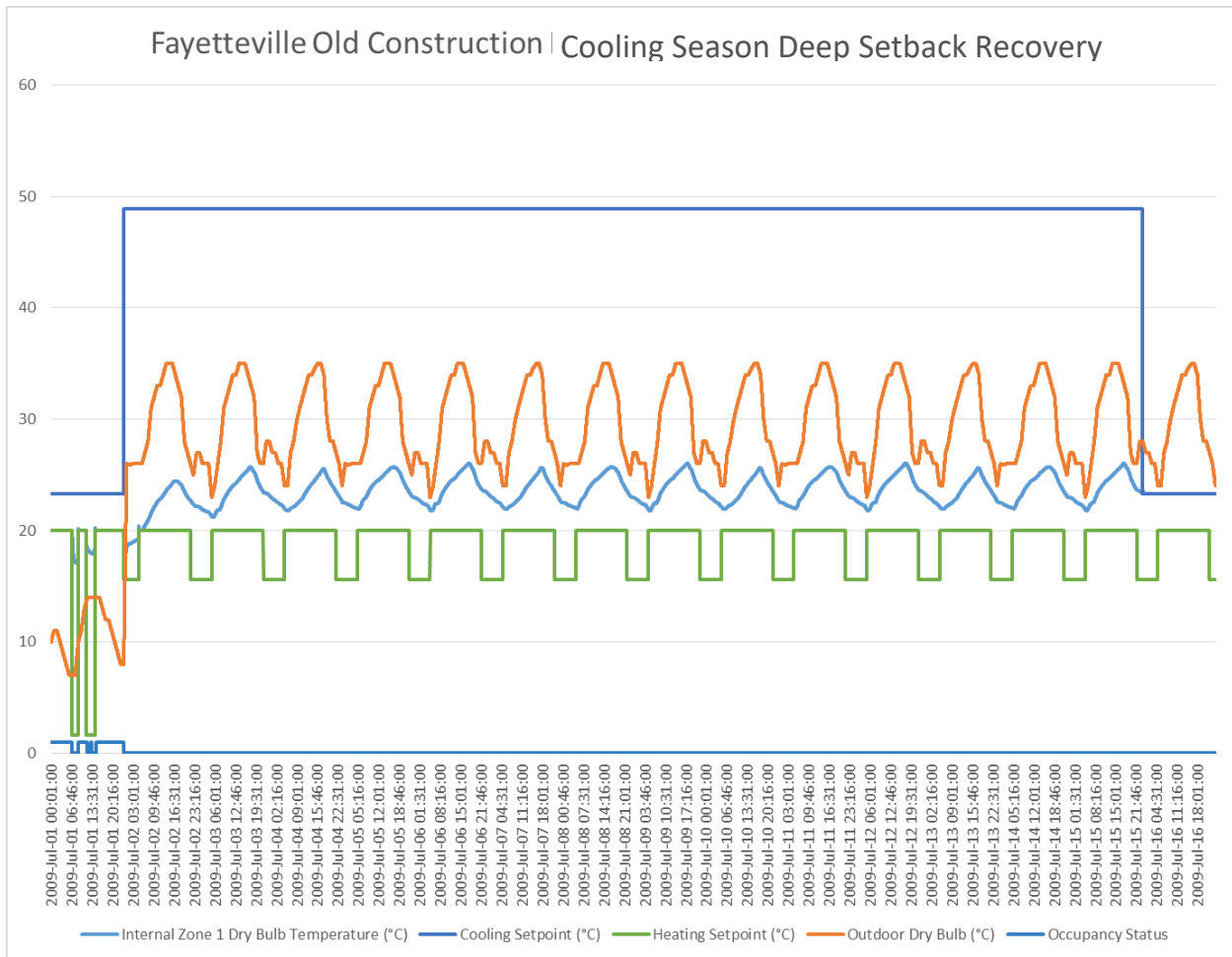


Figure 5.9: Fayetteville Old Construction Heating Season Deep Setback Recovery

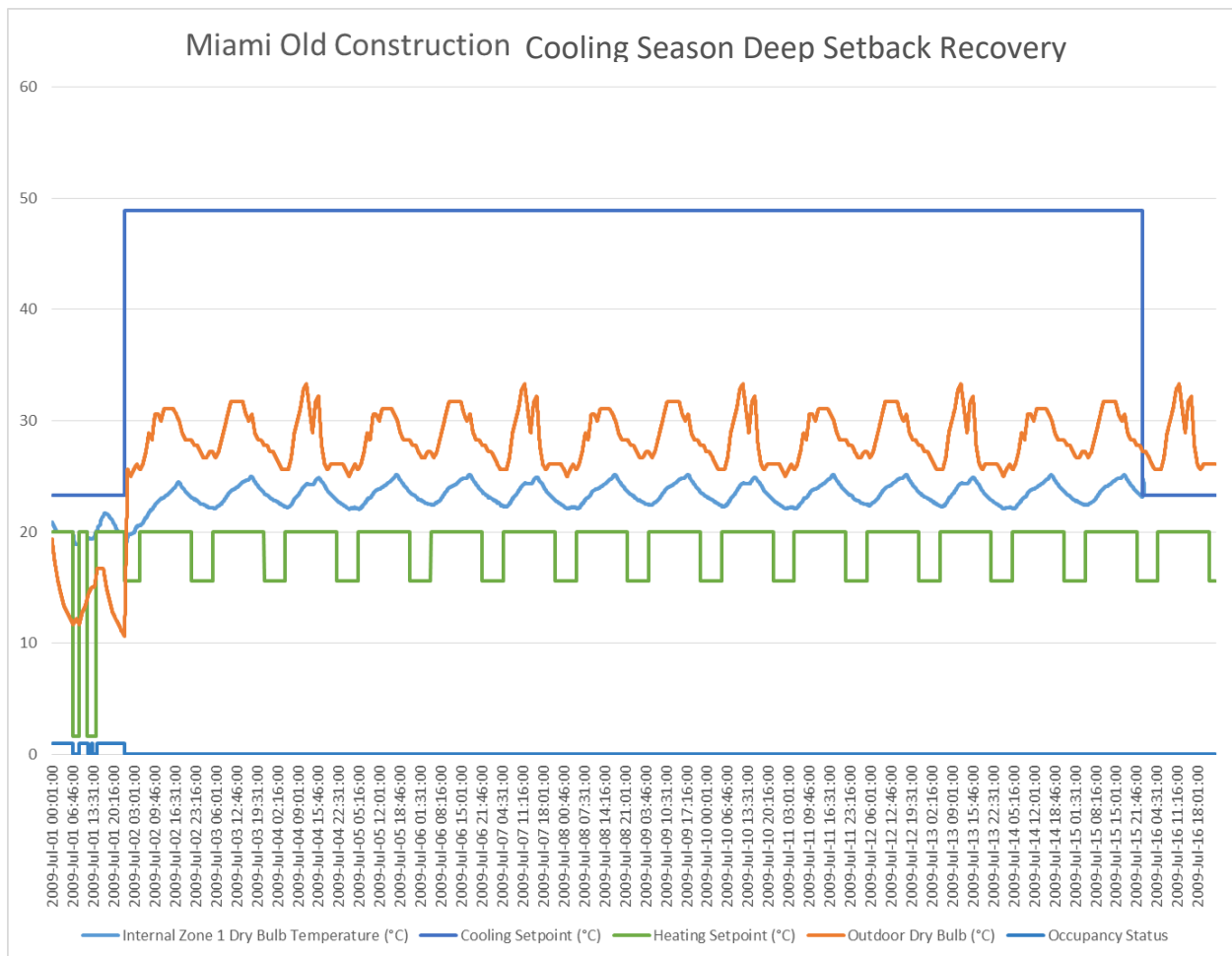


Figure 5.10: Miami Old Construction Heating Season Deep Setback Recovery

While all the construction methods stayed below the ASHRAE setpoint, construction method did align with the magnitude of the dry bulb total range, but even the largest ranging changes were still within the ASHRAE standard occupied limit.

5.2.2 – Energy and Comfort Discussion

A primary concern with the effectiveness of a smart thermostat is balancing energy savings through setbacks with an acceptable recovery rate to a comfortable occupied temperature. The recovery interval will be referred to as “time to temp.” In cooling season, the time to temp was zero for all models, because the indoor temperature was never greater than the occupied mode setpoint while in deep setback mode. Given that fact, the rest of the discussion surrounding deep setback will focus on heating season.

In heating season, the longest time to temp was 7 minutes, predictably in the Minneapolis old construction model. Assuming the ASHRAE 90.2 heating season setpoint is comfortable, 7 minutes does not seem to be an unreasonable time to wait for a space to heat up in pursuit of energy conservation during extended non-occupation. Whether the ASHRAE 90.2 heating season setpoint is in fact comfortable for occupants is not within the scope of this research. Additionally, this time to temp assumes the building furnace is appropriately sized for the building geometry, and the expected heating season design-day conditions. An under-sized furnace or poor quality air distribution within an actual home could significantly impact the real-world time to temp.

The next question arises from an energy conservation and control algorithm perspective. That is, what can be considered a “deep setback” period of time. By defining what constitutes a deep setback interval, smart thermostats can more effectively determine which setpoints to use. Based on the results of this research, deep setback time is primarily climate driven with building envelope playing a secondary role. Even in the Minneapolis old construction model, it took only three days for the building to reach its minimum temperature and a diurnal thermal equilibrium between external conditions, internal loads, and radiant loads. It should also be noted this point of equilibrium was still above the allowed setpoint in the model, so there was no heat ever coming on to temper the space; ie: 100% energy conservation compared to maintaining the occupied setpoint. Therefore, the longest period recommended as a deep setback threshold would be three days. Granted, these results were generated using a custom weather file based on the 0.4% design condition, so often conditions will be milder, and the time to temp (and minimum space temp reached while un-occupied) shorter.

With short time to temps throughout the designed outdoor condition range deep setback mode could effectively be engaged any time the smart thermostat expects the user to be gone long enough that the energy expended to temper the unoccupied space will be greater than the

energy expended to bring the space back to the occupied setpoint from whatever it drifted down to. If the building occupant pays only a usage charge for their energy this strategy will save the user both energy and money. If the occupant pays a demand charge as well then things get more interesting. If the peak usage rate while recovering from deep setback is less than or equal to any other peak usage rate during the billing period the user still saves money. If however peak usage rate during recovery from deep setback is higher than any other peak usage rate the user experiences on their billing cycle, it is possible the increased demand charge would override cost savings earned with a lower setpoint during deep setback. This is where integration of ST's into utility information and tracking, as well as integration with other energy loads in the home may help ST's make more informed control decisions. Traditionally however, demand charges are only incurred by some electric utilities, not gas utilities, and so would only impact those users running an electric furnace or heat pump in their homes.

The next question to answer once a deep setback period is defined is of course what that setpoint should be. A major focus of this research was to explore the limits of what setback temperatures could be used in different climates and with different construction quality/vintage. Based on the results of the models it appears possible to make national recommendations independent of construction style.

Assuming the water piping is properly insulated, and that weather/radiant loads are no more severe than those modeled, past 7.5C indoor Dry Bulb there is no further a house this size will cool even in extended periods of extremely cold weather. Therefore 7.5C could be a heating season deep setback setpoint. Of course radiant loading may vary greatly with different building geometries and external factors, all of which may change the "safe setback" for a given home.

As mentioned above, based on these models, even bad insulation appears "good enough" in most summer conditions to keep homes within the occupied ASHRAE dry bulb limits for extended periods of absence. The air conditioning can be turned off, or to the ASHRAE

setpoint when the occupant departs. The caveat to this statement is the moisture issue with the models discussed in the first section of the results and discussion is still outstanding, and if it is indicative of a real world issue when explored further, then humidity control during cooling season deep setback will be a major concern, the resolution of which has the potential to eat into setback energy and cost savings.

5.3 – Normal Occupancy

5.3.1 – Heating and Cooling Recovery Results

After deep setback normal occupancy mode is the next occupancy behavior where the impacts of a smart thermostat are worth exploring. As an initial method of drilling into the massive amount of data in search of interesting results, the unmet hours (time the space is both occupied, and out of the allowable temperature range) were tallied for each model. A spreadsheet compared the zone dry bulb with the occupancy status, and if the space was occupied, and the zone was outside the allowed temperature range, that minute was tallied to the count. The table below shows the total time, and longest single interval each model did not meet the heating and cooling setpoints while the space was occupied.

Table 5.1: Heating and Cooling Unmet Hours Summary

	City								
	MIA-New	MIA-Reno	MIA-Old	MPLS-New	MPLS-Reno	MPLS-Old	FAY-New	FAY -Reno	FAY - Old
Total Unmet Heating Hours	0	0	0	122.5	122.9	122.6	117.3	118.6	119.4
Longest unmet heating period (minutes)	0	11	18	43	43	43	41	42	42
Total Unmet Cooling Hours	0	0	0	0	0	0	0	0	0
Longest unmet Cooling period (minutes)	0	0	0	0	0	0	0	0	0

It should be noted that across all models, four weeks of heating season and five weeks of cooling season were discovered to be modeled inconsistently with the rest of the data. As such the data for these weeks was discarded. Fortunately the weeks lost were not at the extremes, and so were not the sources of any of the data above. A major point that follows the trends initially noted during deep setback modeling is with an ASHRAE cooling setpoint as the acceptable cutoff, only in old drafting buildings was being outside the cooling setpoint ever an issue while the space was unoccupied. Upon further investigation the intervals that did not meet the setpoint were within the weeks with incorrect schedules discussed above. That is to say that in all the cooling season weeks modeled similarly, the temperature was never above the ASHRAE setpoint when the space transitioned from occupied to unoccupied or vice versa. During heating season the longest “miss time” designed in the occupancy schedule was 45 minutes, which matches with both Fayetteville and Minneapolis longest unmet times. It took several minutes for the space to begin cooling off, after which point the space remained in an unmet comfort state until the occupants “left”.

Similarly to determining the deep setback cutoff temperature, the point at which heating and cooling setback yields no additional “miss time” for each model was examined. During heating season, similar unmet “premature setback” times occurred with all setbacks temperatures, just increasing distance from setpoint was reached up through a 55f setpoint in Fayetteville, 65f setpoint in Miami, and 45F setpoint in Minneapolis. Again matching the deep setback results, the maximum deviation from the setpoint was more driven by weather than building envelope, however the rate at which the setback temperature is reached is driven by building construction. Once again, in cooling season based on this model the ASHRAE 90.2 setpoint of 78F is satisfactory for all climate/construction combinations explored.

When specifically comparing Unmet Hours v. Construction during heating season, the trend in all climates was for increased total unmet hours as construction quality decreased. With

a higher thermal reactivity the buildings are more likely to experience a large enough drop in temperature over the shorter periods of time that add to the total unmet hours.

5.3.2 – Energy and Comfort Discussion

With the ASHRAE setpoints used, heating season weather and occupant behaviors are the driving factors in total energy consumption. It will be interesting to see what role humidity control will play during cooling seasons in reducing the energy savings hoped to be realized by a higher occupied setpoint. Insulation quality appears to have a greater effect on thermal stability than infiltration rate does. Additionally, because tighter/better insulated buildings are more thermally stable, they are less likely to have uncomfortable miss time, and the recovery times will be smaller with than a poorly insulated building with equally sized equipment. So, there will likely be a less significant relationship between smart thermostat accuracy and energy savings as building envelope performance increases. Such relationships have already been identified in Nest white papers. However, the above statement does not consider the impact of humidity control during cooling season in tight buildings, a factor to be assessed in future research.

During cooling season the ASHRAE occupied setpoint all the times appears sufficient. For heating season recovery times in all models are not substantial so setback can be set as far back as the occupant is comfortable walking in to down to 45F. Depending on the occupants' occupation, previous activity prior to entering the house, and what their thermal sensitivity is their heating setback point will vary. Additionally a real house can and will have a different size furnace and time to temp which could impact the decision. Given there is no setback for cooling season, and short recovery times in heating season in all models conducted, setback points can be considered independently of actual ST accuracy in predicting occupancy.

With respect to the impact of climate on setpoints, the coldest weather modeled had a much larger impact than hottest weather modeled. Intuitively this makes sense since the temperature difference between indoor and outdoor conditions is much greater during winter than summer. When factoring construction type into the mix, old construction appears to benefit the most from winter setbacks due to a higher energy loss rate at all times making the “payback period” to reheat from setback v. maintaining the occupied temperature a shorter interval.

6 – Conclusions and Recommendations for Future Work

6.1 – Future Work

While the above results and discussion provide an interesting starting point in exploring the value of smart thermostats as well as the issues that may be generated by them, there is still much left to be explored. The next step is to refine the modeling process and include either a Heat and Moisture Transfer (HAMT) or Effective Penetration Depth Model (EPDM) moisture transport/capacitance model to better understand role of humidity. Given the severity of the issues observed, as well as the supporting hand calculations and previous research by Zhong, Medina, and Mendes, this should prove to be an interesting path to follow. As noted in the 2017 ASHRAE Fundamentals Handbook, moisture management is a prime concern of increasing importance as building envelopes become tighter. Proper vapor barriers and their presence (or absence) in a house’s construction may have a large impact on the latent load and indoor humidity conditions. Follow on research is important because moisture’s impact on comfort increases as cooling coil run times (and therefore moisture removal rates) decrease. Run times decrease when setpoints are based on dry bulb temperature control as ASHRAE compliant setpoints are used.

Another major question is what the changes in the results are when non-ASHRAE 90.2 compliant occupied setpoints are used. It is likely a large number of users would find either the heating setpoint too low or the cooling setpoint too high. If that is the case it would be important

to know what added value a smart thermostat provides or issues that may arise in those conditions. A simple test model conducted with the Fayetteville weather file and renovation construction profile reflected the impact non 90.2-compliant behaviors may have on energy and comfort. Instead of running with the “smart thermostat” model used for all other runs during cooling season, the energy model operated at a fixed 72F cooling setpoint for the entire year. Humidity control was still engaged in “recovery weeks” to be consistent with other models. The result was a total annual cooling energy consumption of 4435.31KWh, compared to 3221.92KWh of cooling energy used by the identical construction/weather file combination operating with the “smart thermostat” setpoint schedule. The difference in consumption reflects a 30% increase in cooling energy compared to a smart thermostat setpoint schedule, which at \$0.15/KWh is over \$180/year in added costs to the homeowner. Put differently, that could be the cost of the thermostat itself. Also of note in the sample test, indoor relative humidity was an average of 20% lower at all times in the 72F run compared to the smart thermostat model. This result appears to confirm the conclusion that lower setpoints increase equipment runtime, thereby increasing dehumidification and lowering indoor humidity levels.

Next, the role of system sizing and its impact on time to temperature should be considered. We assumed properly sized equipment in each zone for each construction based on auto sizing in Openstudio on the design-day conditions in each model. It is possible that with oversized or undersized equipment opposing issues may occur. With undersized cooling equipment, energy costs will increase due to added run times, but it is possible humidity issues will be reduced due to those same increasing run times in cooling season. Conversely, oversized equipment could result in short cycling (impacting equipment performance and operational life), as well as increased humidity issues.

Other factors which may impact both humidity issues and overall energy usage include the impact of the mechanical exhaust and latent heat scheduled from shower/bath use,

modeling natural ventilation through windows (not just infiltration through the building structure), multi zone systems, multi-story homes, and (although they are not yet prevalent in home HVAC installations) the impact of mechanically conditioned outdoor air ventilation and reduced building infiltration. Once more of these questions can be defensibly answered, real world modeling with full or scale-models may be appropriate.

6.2 – Conclusions

An initial investigation into the value added and issues observed with ST's was conducted in single family homes across three climate zones and three construction types using EnergyPlus models developed in the OpenStudio interface. Results suggest ST's have the most potential for savings in cold heating season climates when used for deep setback energy savings with an observed minimum setback temperature of 45F. Given the short recovery time to an ASHRAE 90.2-compliant heating season occupied setpoint, comfort was not considered a major concern. It was also observed that using the ASHRAE cooling season setpoint caused no significant additional increase in space temperature regardless of occupancy status; thus, a ST is not recommended for users who are comfortable during the cooling season at this temperature. However, further work is still required to explore the potential for moisture issues observed while using ASHRAE setpoints during the cooling season.

When considering a ST's value from an energy and comfort perspective in comparison to programmable or single setpoint thermostats, model application yielded varying results when running the recommended ASHRAE 90.2 setpoint. No value was added in cooling mode at a 78F setpoint for the conditions explored in this simulation. A regular single setpoint at 78F will suffice, and the building can be left as is assuming moisture issues are resolved independently. Conversely, possible benefits may be obtained in heating season with a 68F/60F ASHRAE setback schedule. However, this will be dependent on the occupant's tolerance to in-home

temperatures below 68F for a period of time upon returning home. This is not anticipated to vary greatly with ST occupancy prediction accuracy.

If the question is “is installing a smart thermostat the first thing to do from an energy consumption reduction perspective? No. Insulate the house, replace the HVAC equipment with more efficient, potentially smaller sized units, use ASHRAE setback points, and then use an ST for an incremental improvement upon that setup. If the question is what can be done that may save a little energy quickly, and insulating, new equipment, or living an ASHRAE setpoint is not an option then a Smart Thermostat may be a way to save some money/energy each month if the climate and building cooperate. The challenge is, as identified by Whitehouse in 2013, moving through a paradigm shift to focus on a dynamically operating residential structure. Depending on both user behaviors and external conditions, smart thermostats may be a good stepping stone along that path.

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