DATA-DRIVEN STRATEGY FOR IMPROVING ENERGY EFFICIENCY IN RETAIL BANKS

by

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ABSTRACT

EVAN NEELY. Data-Driven Strategy for Improving Energy Efficiency in Retail Banks. (Under the direction of DR. ROBERT COX)

This thesis explores a data-driven strategy approach to curtailing HVAC energy consumption in a large retail portfolio. Energy building simulation software was utilized to predict setpoint related energy savings potential across all United States climate zones. An extensive field study was conducted using building automation data of current setpoints, setpoint scheduling, various programmable features, and general building operations during the cooling season in Phoenix, Arizona. Experiments were conducted during the cooling season in Phoenix, Arizona, in order to verify suggested simulated cooling savings. Extrapolation models were created with building automation data to predict annual site energy reduction to further verify the savings opportunities suggested with simulation models.

ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Robert Cox for all his help throughout the development of this thesis. I would also like to thank Dr. Robert Cox for allowing me to have the opportunity to work with the Sustainable Integrated Buildings and Sites program and for giving me the opportunity to make this thesis a reality. In addition, I would like to thank the entire Wells Fargo Corporate Properties Group for allowing me to work closely with them over the past couple years and for making this thesis possible.

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LIST OF ABBREVIATIONS

DAT An acronym for discharge air temperature

DOE An acronym for The Department of Energy

EIA An acronym for U.S. Energy Information Administration

HVAC An acronym for heating,ventilation, and air conditioning

NREL An acronym for National Renewable Energy Laboratory

RTU An acronym for roof top unit

SIBS An acronym for Sustainable Integrated Buildings and Sites

CHAPTER 1: INTRODUCTION

Space heating, ventilation, and cooling account for roughly about 44% of commercial building energy consumption[3]. Large real-estate portfolio owners have significant incentive to utilize data-driven strategies to reduce energy consumption. For instance, Wells Fargo Corporate Properties Group is responsible for approximately 6,000 retail banking locations in the United States. The average annual energy consumption at each branch is approximately 80,000 kWh; therefore,the approximate energy consumption across their retail portfolio is 480,000 MWh. The average retail home in the United States consumes on average per year of about 10,766 kWh. If Wells Fargo could even see at minimum a 1% reduction to their overall energy retail portfolio, it would be like taking away the energy consumption of 445 homes. Using the 2017 national electricity average of 10.59 cents/kWh, the savings this could generate per year is nearly $508,320.

This thesis focuses on using building automation system data to determine potential savings opportunities in a large retail portfolio. Specifically, the focus is on determining optimal setpoint schedules for building operation. A data driven approach to each specific building would likely be the ideal approach to building setpoint optimization. However, Wells Fargo did not show any interest in such an approach due to cost concerns. In addition, we also explore the impacts of improper maintenance and other practical issues that make achieving an optimal solution somewhat difficult.

To clarify the thesis agenda further, lets examine the diagram in figure 1.1 of a typical setpoint schedule for a retail zone. Typically, HVAC energy can be represented through 3 main user control variables.Those variables being setpoint scheduling, unoccupied setpoints, and occupied setpoints. Let us define those there variables as the user input variables. It is important to note that this is assuming ideal conditions, which is often not the case in many real world applications. We'll discuss that further in the subsequent section.

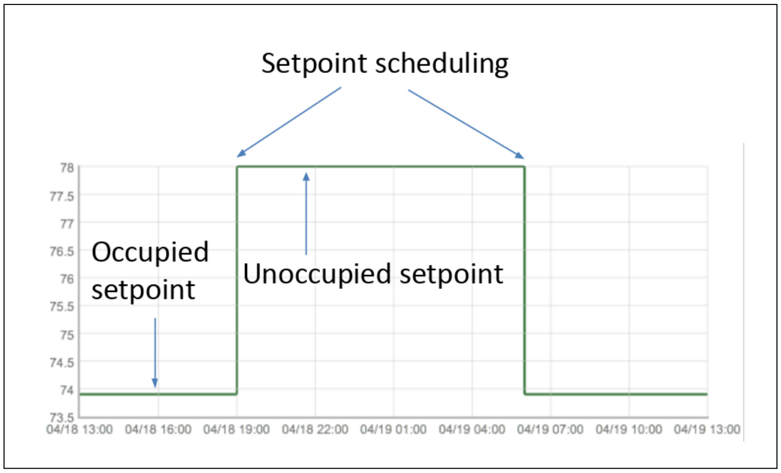

Figure 1.1: Savings variables

Let us now define each setting in figure 1.1 a variable as follows: X_1=setpoint scheduling, X_2=unoccupied setpoint, and X_3=occupied setpoint. What would be the optimal mix of these variables that would lead to minimized energy consumption? We can visualize this question by expressing it mathematically. Equation 1.1 shows the mathematical expression for minimized building HVAC energy J, with the associated defined input variables. This thesis will aim to explore strategies Wells Fargo Corporate Properties Group might explore to minimize their building HVAC energy consumption J.

$$J = min(E(X_1, X_2, X_3) \tag{1.1}$$

1.1 Improper Equipment Usage

A field study in 2004 discovered 72% of 4,168 air conditioners in service had refrigerant levels below manufacture specifications[4]. It has been reported that nearly 50-67% of all air conditioners suffer from improper refrigerate charge or air flow problems causing systems to run up to 20% less efficiently[5]. Building automation data explored throughout this research would show that some sites had problematic behavior that could possibly be attributed to low refrigerant charge or level. Figure 1.2 shows two plots—one on the top with the compressor on-off state—and another on the bottom with the discharge air temperature, zone temperature, and zone temperature setpoint. This particular zone is showing an extremely high DAT and the zone doesn't seem to be properly cooling. The inability of the zone to cool is causing the compressor to continuously run throughout the day and never reach its setpoint. It appears that only a small percentage of the sites on the building automation system actually utilize alarm systems that notify building operators of troublesome behavior. Also, there are inefficiencies in some zones causing others zone compressors to overcompensate and run more than they would otherwise to mask system inefficiencies. In addition to spiking energy consumption, these type of building inefficiencies make the task of constructing data driven models from actual site automation data a challenging process.

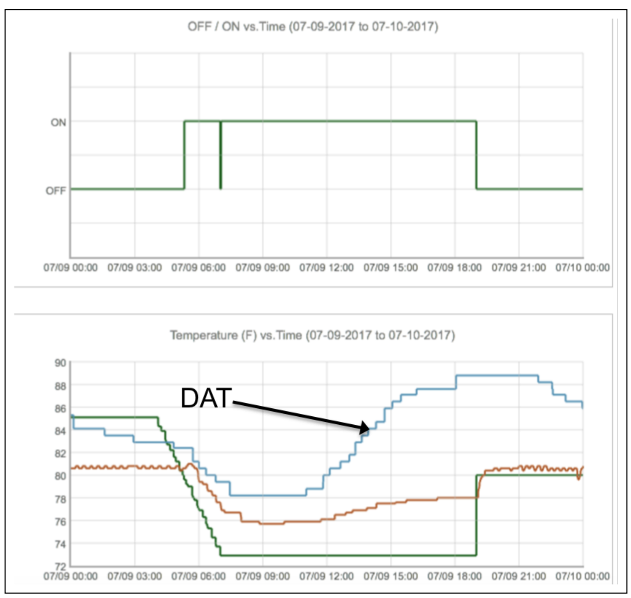

Figure 1.2: Problematic zone behavior

1.2 Thesis Approach

The thesis approach ended up being broken down into three separate parts. Figure 1.3 represents the flow of the thesis approach that will be outlined in detail in the subsequent chapters.

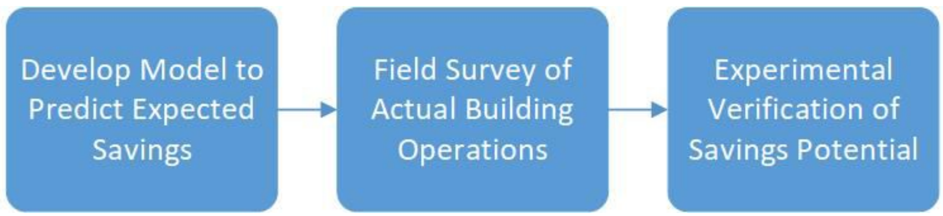

Figure 1.3: Thesis approach diagram

EnergyPlus is the software tool used to build predictive building energy models.This simulation tool allows users to input specific building parameters into building templates in order to customize simulations to fit particular building types. Simulations were ran across each climate zone in the United States in order to explore the potential of setpoint optimization energy savings.

An extensive field study of building automation data was then conducted in order to examine current building operations and behavior. Current setpoints, schedules, discharge air temperatures, and other various programmable features were explored. In addition, building zone temperature behavior and compressor functionality were examined in order to determine if sites seem to be working optimally.

The final stage of this thesis was experimental verification.Setpoints and schedules were manipulated during the cooling season at retail buildings in Phoenix, Arizona. Analysis was conducted by comparing experimental day consumption with the consumption of a recent similar benchmark day. In addition, data-driven energy extrapolation models were developed using experimental results and historical building data.

1.3 Summary

The remaining chapters of this thesis describe the complete approach mentioned in Section 1.2. Chapter 2 begins by providing the theoretical underpinnings of the proposed scheme and energy predictions using model building simulation software. Chapter 3 presents a summary of field findings documenting the current challenges associated with implementing improvements across a large portfolio. Finally, Chapter 4 explains the experimental procedure, results, and data-driven extrapolation model development using real building automation system data.

In conclusion, the full scale of the savings potential will be explored with data supported strategies. Challenges that exist for setpoint optimization, building efficiency, and data-driven modeling approaches will be discussed in detail as well.

CHAPTER 2: MODEL DEVELOPMENT AND PREDICTIONS

If the thermodynamic properties of a building can be understood in a theoretical sense, it becomes possible to build useful and practical predictive energy models. There is one specific phenomenon intrinsic to all buildings that this chapter will aim to address. The natural heating and cooling phenomenon in buildings is a complicated process, but capturing that behavior is certainly possible. Modern technological advancements have aided our ability in capturing these processes, but what is the theory behind these software tools? That is the first topic addressed in this chapter.

In addition to taking a dive into the theoretical background behind modern building energy modeling, an existing simulation software tool used to build models in this thesis will be explored. EnergyPlus is a free public access software that was utilized during this research. Energy prediction models were created using this software and ran across various climate zones. This modeling would lay the foundation for constructing further change-point regression models with actual experimental data.This entire process will be explored in more detail towards the end of this chapter.

2.1 Theoretical Building Modeling

There are many different variables that contribute to a buildings natural ability to heat up or cool down. The thermostat control of building zone temperature is not so ambiguous. When the temperatures rise above a specified cooling setpoint range, the HVAC system will operate to cool the zone temperatures. And Likewise, when the temperatures dip below the specified heating setpoint range,the HVAC system will operate to warm the zone temperatures. Saving on energy consumption by setting a thermostat during the day higher during the summer might seem intuitive. However, managing setpoints in commercial buildings during unoccupied hours is slightly more complex. If a building is utilizing unoccupied setbacks, there often is an extended period of time the system stays off. Figure 2.1 shows the zone temperature following its occupied setpoint throughout the day and a setpoint change as it goes unoccupied. But how does the zone temperature heat up and work its way towards the higher setpoint during this time period? This phenomenon plays a key role in the savings associated with unoccupied setbacks. In order to explore this question further, various building thermodynamic properties need to be considered.

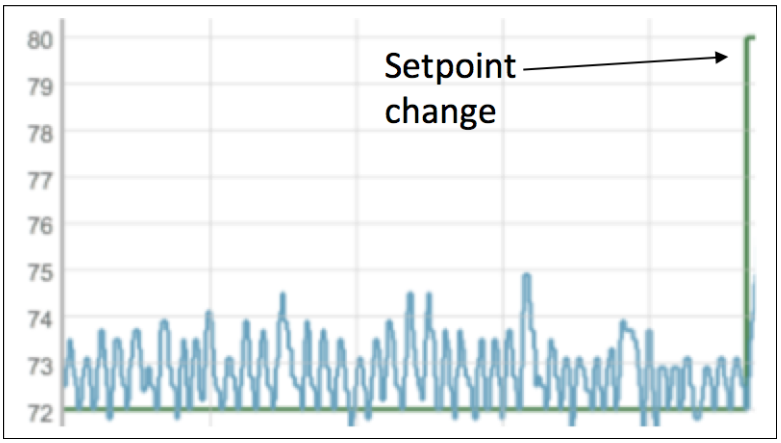

Figure 2.1: Zone setpoint change

Figure 2.2 is a diagram of building wall surfaces with their associated thermal nodes. T_o is the outside air node, T_1 is the node on the outside wall, T_2 is the node on the inner wall, and T_i is the node associated with the inside of the building. There is an associated resistance between each node, based on the building physical parameters. There is an energy storage capacitance associated with T_1 and T_2. These two capacitance play an integral role in how the zone in figure 2.1 will naturally warm up and trend towards its new programmed setpoint.

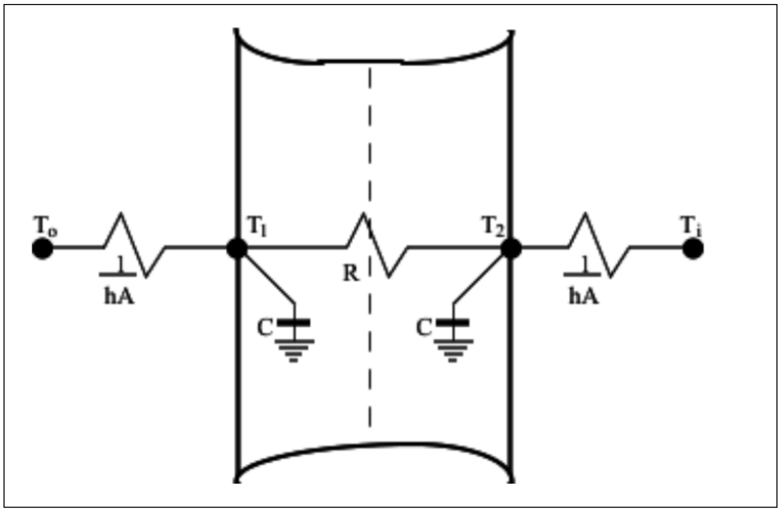

Figure 2.2: Surface circuit modeling[1]

Outdoor air temperature has a contribution to the overall stored energy in the wall surfaces. However, there are other variables in play that contribute to this energy storage. Let us examine the diagram in figure 2.3. The sun is contributing shortwave radiation to the outside of the wall—while longwave radiation is being generated from the inside environment. The convective heat exchange with the outside air is also highlighted in the diagram. All of these processes are contributing to the stored energy in the wall capacitance—energy that eventually dissipates into the interior system of the building during the cooling season.

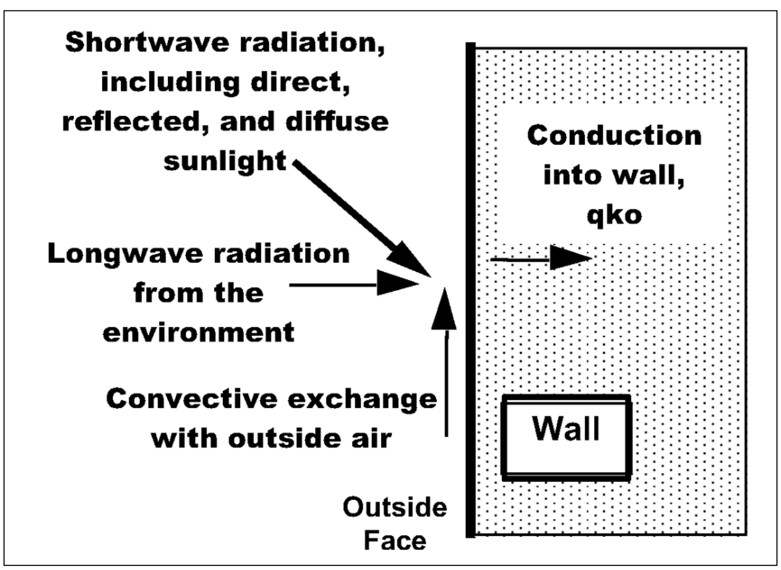

Figure 2.3: Radiation surface modeling[1]

During certain periods of the year, an inverse relationship can be observed with zone temperature and outdoor air temperature during the overnight hours. For example, zone temperature might rise and trend towards a higher setpoint, while the outdoor air temperature trends down and eventually below the zone temperature. Figure 2.4 highlights this behavior during a fall month in Phoenix, Arizona. The temperature rises towards the setpoint of 80°F, while the OAT temperature continues to drop. This phenomenon highlights the energy exchange taking place between the building walls and the zone temperature of the buildings.

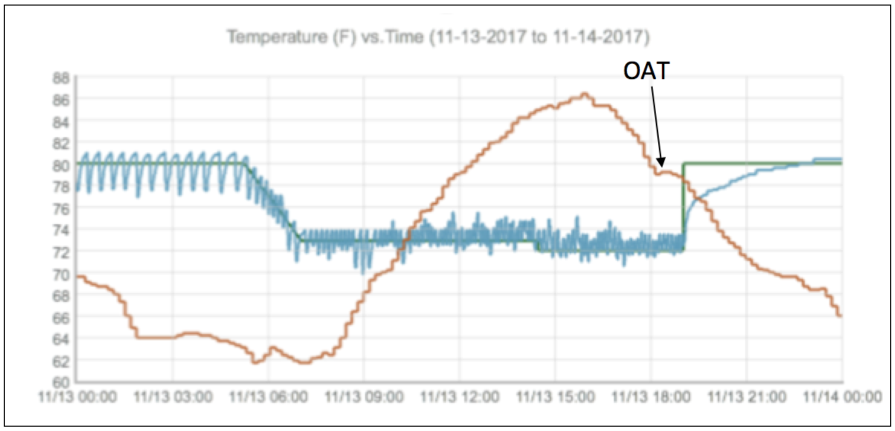

Figure 2.4: OAT and zone temperature

The exact nature of the process in which an accumulation of energy storage dissipates into an interior is a complicated process. Fortunately, the process can be simplified and theoretically modeled with an RC circuit at a high level. The concept in figure 2.2 and figure 2.3 can be expanded upon with additional inputs being added to the system.

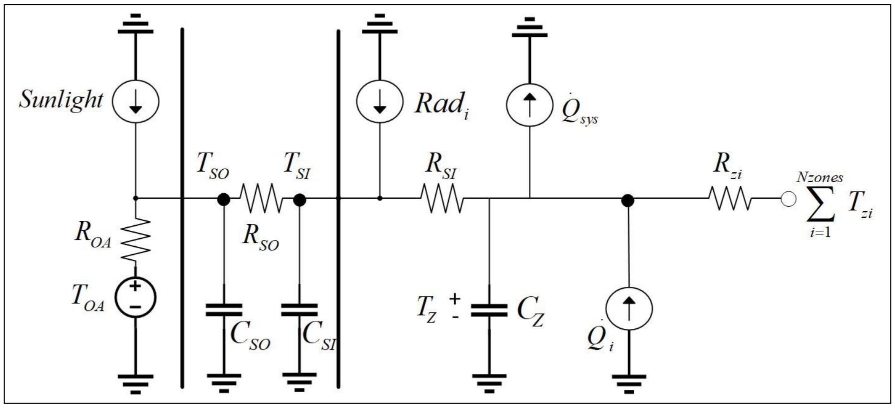

Figure 2.5: Full building circuit model

Figure 2.4 shows a circuit model of an entire building zone air system, T_Z.The variables in the circuit are defined as such:

T_{OA}=outside air temperature

T_{SO}=outside wall convective node

T_{Si}=inside wall convective node

Rad_i=internal radiation

$\dot{Q}_i$=internal load

$\dot{Q}_{sys}$=cooling system output

$\sum_{n=1}^{Nzones} T_{zi}$=separate zone air

C_{SO}=energy stored in outside wall

C_{Si}=energy stored in inside wall

C_Z= energy stored in zone air

The capacitance at node T_{OA} is getting much of its energy storage from the sunlight and the outdoor air temperature.The capacitance at node T_{Si} gets a good bit of its energy storage from internal radiation within the building. Figure 2.5 shows the building model when it goes into its unoccupied mode at night when the sun goes down. Internal radiation has become negligible for any further energy contributions at this point. Also, since the building has switched to its unoccupied mode, this means the building has either no occupants or very few; therefore, the internal load $\dot{Q}_i$ is said to be negligible. In addition, the system $\dot{Q}_{sys}$ has turned off until the zone temperature reaches its new thermal equilibrium or its desired setpoint. Let us assume this is the circuit model for the building in figure 2.1, when the setpoint changes and the building can start to naturally warm.

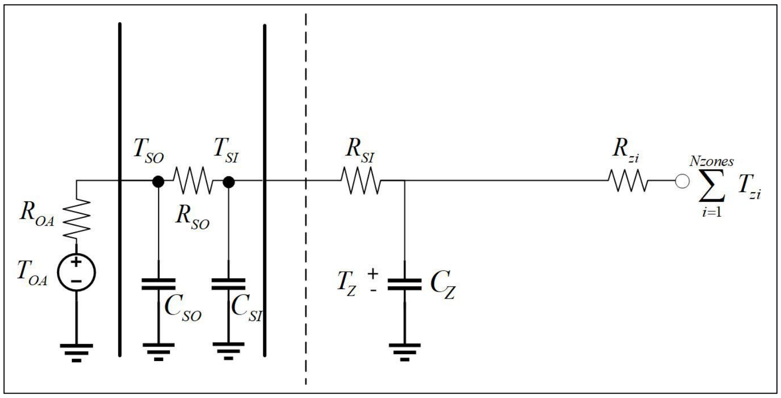

Figure 2.6: Unoccupied overnight building circuit model

In order to get the circuit in 2.5 in a more simplistic form, we use Thevenin's theorem to create a thevenin network. The circuit is broken on the left side of the dotted line; thus, the Thevenin source can be defined as T_{Si}. One final assumption is used for the zone air temperature interactions, $\sum_{n=1}^{Nzones} T_{zi}$. The zone temperatures are said to be approximately equal; therefore, we have $T_Z \approx \sum_{n=1}^{Nzones} T_{zi}$ and we can ignore the contributions from T_{zi} in this specific model.

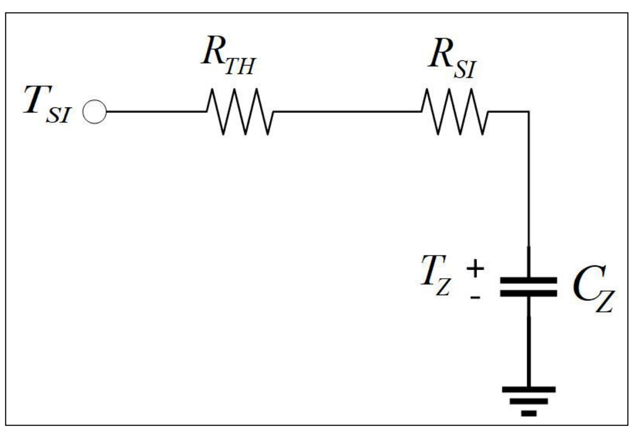

Figure 2.7: Simplified building circuit model

Figure 2.7 shows the simplified building model. A first order ordinary differential equation can be derived easily using this model. Equation 2.1 shows the differential equation for the circuit in figure 2.7.

$$RC_Z \frac{dT_Z}{dt} + T_Z = T_{SI} \tag{2.1}$$

where R is defined as $R_{TH} + R_{SI}$

The solution and waveform for the temperature T_Z is then defined in equation 2.2 as follows:

$$T_Z(t) = (T_{SI}(t = 0+) - T_{SI})e^{-\frac{t}{\tau}} \tag{2.2}$$

where τ is defned as RC_Z

The time constant τ controls the rate at which the temperature rises. Figure 2.8 shows the plot of equation 2 as a function of time. $T_{Z(t)}$ rises to a natural equilibrium state with a max of T_{SI}. If this model is actually an accurate high level representation, there should be a similar behavior with zone temperatures as they rise towards their natural peak.

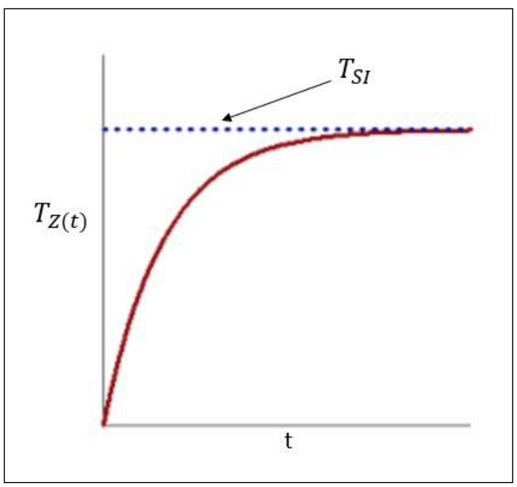

Figure 2.8: Theoretical $T_Z(t)$ plot[2]

As it turns out, that is exactly the type of behavior seen when the real data is examined. Figure 2.8 shows the rising zone temperature in one specific zone at a retail branch in Phoenix, AZ. The behavior is exactly as expected. Each building would have a specific τ associated with it, and its zone temperature would rise at that rate until it hits its natural peak. In other words, the energy storage associated with the rest of the wall surfaces will dissipate its energy into the zone capacitance and it will rise according to its specific τ.

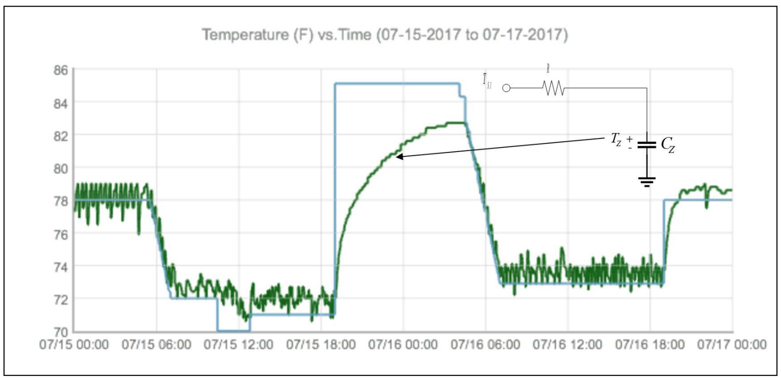

Figure 2.9: Actual $T_Z(t)$ plot

If the τ behavior of a building can be captured, predictive energy modeling becomes possible. It becomes possible to create models that give energy usage predictions based on particular building parameters. In theory, the impact of setpoint, setback, and schedule adjustments on HVAC energy consumption could all be estimated if the buildings natural heating and cooling ability is understood. Fortunately, there is existing software that uses this theoretical concept, albeit in a much more detailed manner. That software will be examined in the subsequent subsection.

2.2 EnergyPlus Modeling

The DOE has funded the development of a software called EnergyPlus that utilizes the building τ concept discussed in Section 2.1, but at a much more detailed level. EnergyPlus allows users to run building simulations that can output total building energy consumption. The software allows users to use building templates and adjust their physical parameters and technical equipment to fit specific "builds". In addition, the user has the ability to vary lighting loads, scheduling, setpoints, setbacks, and building occupancy.

The main goal of the EnergyPlus modeling process was to gain insight concerning how building cooling and heating energy is impacted by setpoint changes. Wells Fargo seemingly had a fairly "loose" setpoint policy and seemed somewhat interested in moving towards a stricter policy if data proved to support significant savings potential. The UNCC team worked with the Wells Fargo team with the aid of building automation data to determine a base case occupancy schedule and temperature settings.The occupancy schedules were held constant and temperature settings would be varied in simulations.Table 2.1 shows the base case setpoints settings used for occupied and unoccupied periods.

Table 2.1: Base Case Setpoints for occupied/unoccupied periods

Setpoints	
Occupied cooling	72°F
Unoccupied cooling	78°F
Occupied heating	70°F
Unoccupied heating	67°F

Like the determination of the base case settings, the new setpoints to be used in simulations were determined in collaboration with the Wells Fargo team. Table 2.2 shows the new range of occupied setpoints and unoccupied setpoints that will be simulated and compared to the base case.

Table 2.2: New programmed setpoints and setbacks

<table>
<tr><th colspan="6">New setpoints and setbacks</th></tr>
<tr><td>Occupied cooling</td><td colspan="5">74°F</td></tr>
<tr><td>Unoccupied cooling</td><td>80°F</td><td>81°F</td><td>82°F</td><td>84°F</td><td>85°F</td></tr>
<tr><td>Occupied heating</td><td colspan="5">70°F</td></tr>
<tr><td>Unoccupied heating</td><td>62°F</td><td>63°F</td><td>64°F</td><td colspan="2"></td></tr>
</table>

A template was created by the SIBS research team during a prior project that modeled a typical Wells Fargo retail branch building. This template was used to simulate new temperature setpoints and setbacks. The EnergyPlus software is able to simulate typical daily weather within a specific climate zone, which includes daylighting effects and temperature patterns. For example, figure 2.10 shows the energy plus simulation interface where the user loads a specific weather file. This particular simulation is using historical weather data from Chicago O'Hare International Airport, Chicago, Illinois.

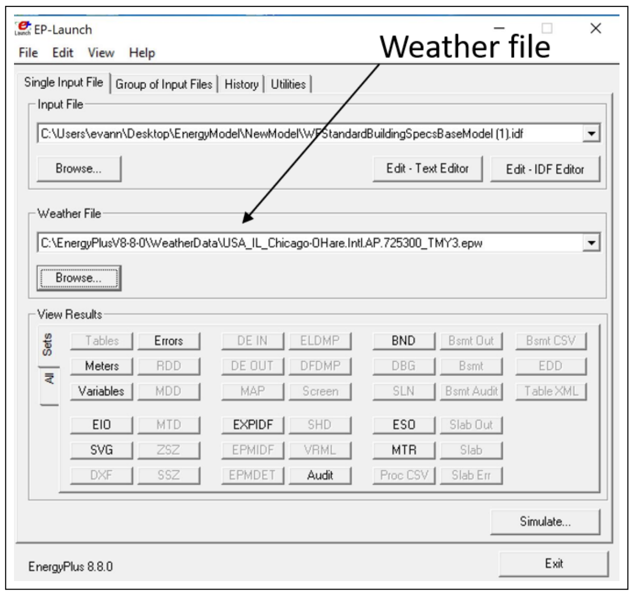

Figure 2.10: EnergyPlus user interface

The simulation outputs can be specified within the building template as well. For example, if outputs for hourly electric energy, hourly outdoor air temperature, hourly day type, and hourly zone mean air are wanted they would be programmed at the beginning of the building template. Day type is useful as it specifies whether the system was in a cooling or heating mode for that specific day. Figure 2.11 shows the programming scheme for the specified output variables.

```
Output:Variable,*,Zone Packaged Terminal Air Conditioner Electric Energy,hourly;

Output:Variable,*,Site Outdoor Air Drybulb Temperature,hourly;

Output:Variable,*,Site Day Type Index,hourly;

Output:Variable,*,Zone Mean Air Temperature,hourly;
```

Figure 2.11: Simulation outputs

The initial simulations were ran over the range of unoccupied hours for only weekdays(Monday AM- Friday PM)throughout the year.The actual experiments ran at buildings during this research would only address unoccupied weekday energy savings; therefore, creating an initial base case model was essential. Why the experiments only addressed unoccupied weekday energy consumption will be discussed further in Chapter 4. The EnergyPlus software produces output summary PDF files and CSV raw data files.The summary files are great for cumulative high level analysis, but obviously lack the fine detail found within the raw data files. The raw data files were used to create detailed comparisons with the base case models.

Figure 2.12 shows the weeknight energy consumption over an entire year vs average daily outdoor air temperature. This particular simulation was ran in the Phoenix, Arizona climate zone. Blue represents the base case setback of 78°F and orange represents the a new setback of 85°F. The plot shows a pretty distinct difference in energy consumption between the two difference setbacks. Interestingly, they seem to diverge at an outdoor air temperature of approximately 80°F. This turns out to be a fairly significant divergence, and will play a key role in the development of the extrapolations models built with experimental data. The point at which the divergence takes place is defined as the change-point. Above this change-point is where the higher temperature setbacks start making a difference in energy consumption.

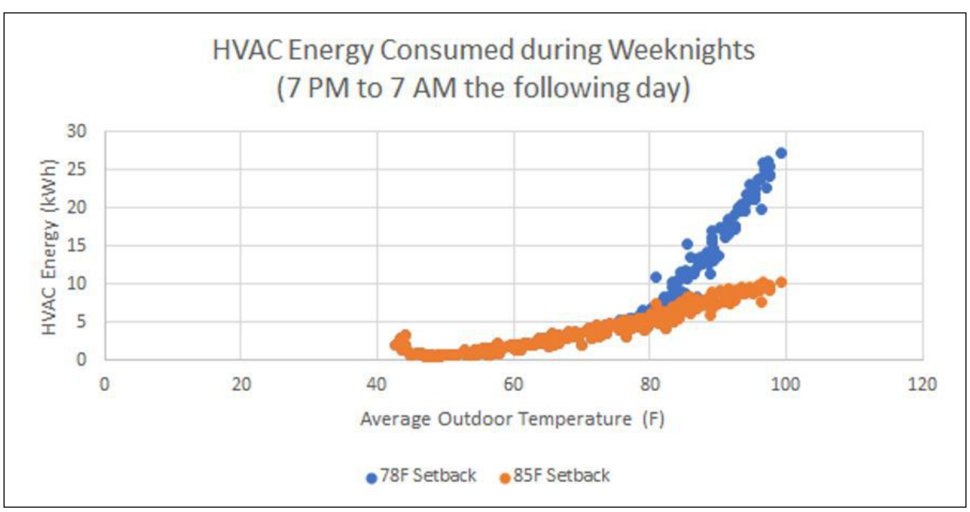

Figure 2.12: EneryPlus change-point model

This distinct change-point where there is a divergence of energy consumption sort of makes sense when the theoretical models in Section 2.1 are considered. It seems somewhat intuitive to think that when the average outdoor air temperature is lower there would be less overall energy to charge the surface capacitance in the building walls. In such conditions, buildings can maintain lower setbacks with minimal compressor activity during the overnight unoccupied hours. However, when the average outdoor air temperature trends up, the walls in the building become charged with more energy. This excess of energy eventually dissipates into the building during the overnight hours; hence, the zone air capacitance charges to a higher peak—ultimately leading to higher indoor temperatures. If the zone allows the temperatures to rise higher without activating the system, minimal compressor activity is still possible—which is the scenario you get with the orange curve in figure 2.1. On the other hand, the blue curve represents a system that has to cycle much more during its unoccupied hours in order to maintain a lower space temperature. Simulations were ran to include weekends in order to do a complete comprehensive analysis of setback savings potential. One specific example of the cooling energy savings in the Phoenix area will be highlighted in this chapter, as well as a total climate zone summary for all setpoint adjustments. Figure 2.13 shows simulated building cooling energy for the Phoenix climate zone with the base case settings and all new setpoint adjustments. The savings is at its max percentage at 85°F. It is important to note that the savings with the 85°F setback is 2,773 kWh. That will be key in comparing what we find in Chapter 4. Table 2.3 shows the energy kWh and percent reduction for each setpoint adjustment.

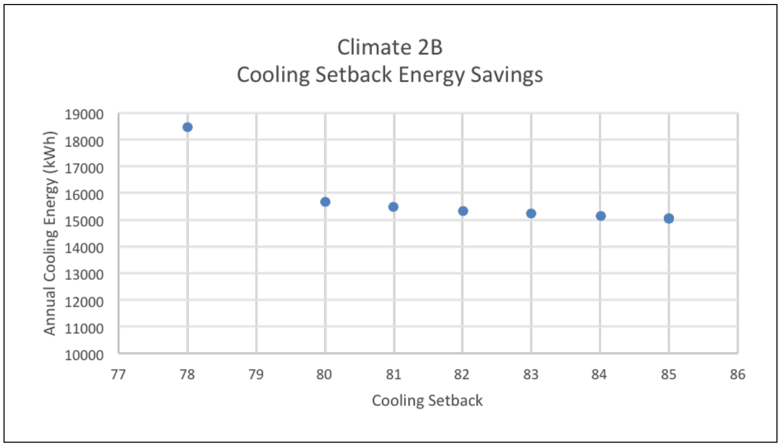

Figure 2.13: Climate zone 2A & 6A energy consumption

Table 2.3: Climate Zone B simulated energy & reduction

Setpoint°F	kWh	% reduction
78	18460.9	0
80	15687.66	15.1
81	15486.3	16.1
82	15335.26	16.9
83	15224.96	17.5
84	15136.87	18
85	15065.99	18.4

The high end of the initial Wells Fargo setback standard was at 85°F. The EnergyPlus model seemed to suggest significant savings potential at that temperature. Lets look at the cooling savings potential with climate zone 2B compared with climate zone 6A in figure 2.14.The cooling savings opportunity is going to be much greater in warmer climates like Phoenix because there is just considerable more consumption going on. For example, the savings at the 85°F case for climate zone B is 3,394 kWh and the savings in climate zone 6A is 1,195 kWh. Climate zone B has roughly 35% more than climate zone A. To explore the cost difference, let us use the national average for commercial energy pricing at 10.59 cents/kWh and compute the savings for both 85°F cases. The savings in Phoenix is approximately $359, while the savings in Minneapolis is only $126.

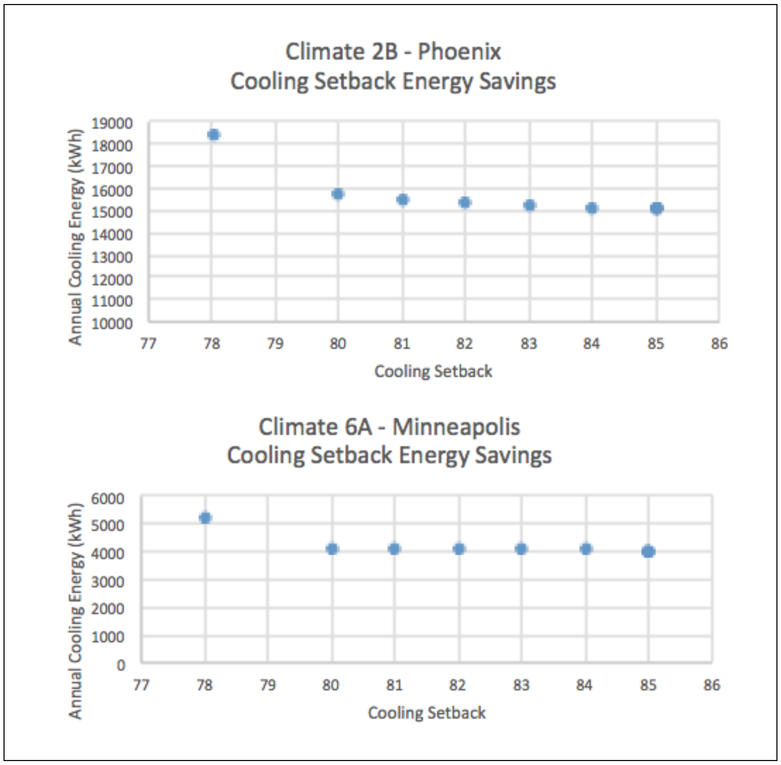

Figure 2.14: Climate zone 2A & 6A energy consumption

Estimating heating savings in some parts of the country might be a bit more difficult than cooling savings due to the use of natural gas. Simulations were ran to predict heating savings, but obviously this would only be valid where electric heating actually took place. It is important to note that heating potential could not be verified in the experimental process associated with this thesis.

The SIBS team had many discussions with Wells Fargo concerning what setpoints and setbacks should actually be. Although the most effective approach might be on a per climate zone basis, Wells Fargo eventually determined that a hard standard might at least initially be most effective. Initial discussions lead the SIBS research team to believe the setpoints in table 2.4 would be the standard implemented across their retail portfolio. However, that would be an ongoing process of adjustment due to some concerns with building recovery. This will be addressed in further throughout chapter 4.

Simulations for heating and cooling across each climate zone were ran under the

Table 2.4: Initial proposed setpoint standard

Proposed setbacks	
Occupied cooling	74°F
Unoccupied cooling	85°F
Occupied heating	70°F
Unoccupied heating	64°F

setpoints in table 2.4 and compared to the conditions in the base case specified in table 2.1. Fan energy was included in this analysis as well. Figure 2.15 shows the energy consumption comparison by climate zone for each case. The average savings across all of the climate zones was about 4.9%.

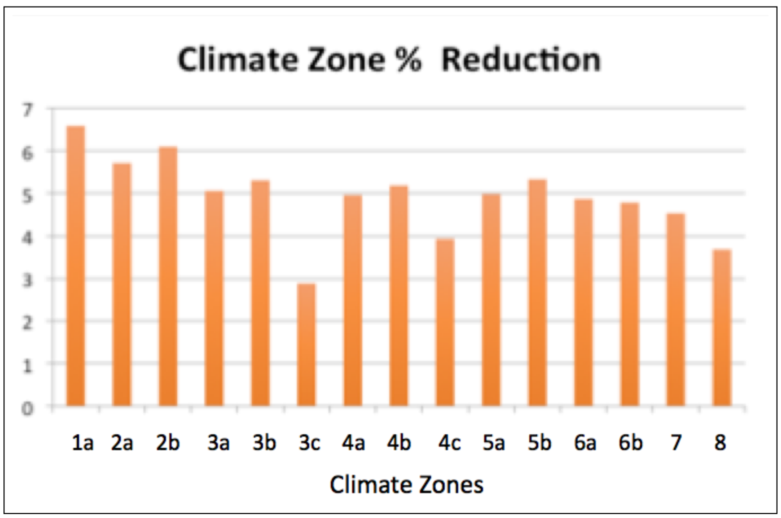

Figure 2.15: Energy comparison old and and new standards

CHAPTER 3: EXAMINING THE REAL DATA

The branches examined in the Phoenix metro area were all connected to a building automation system contracted out by Wells Fargo. Building operators can adjust occupancy scheduling, temperatures, or other various operational settings through its online interface. Various operational nodes were deployed in order to track different aspects of the HVAC performance. For example, compressor on/off time, discharge air temperature, and zone air temperature were all tracked. The building automation system had easy data trending capability; therefore, various different aspects of building performance could be visually inspected. In addition, data could easily be extracted out of the system in CSV format for further extensive analysis with data tools such as Matlab.

Diving into the real time data would provide a sense of how schedules and setpoints might be further optimized to create more energy efficiency. The first settings explored were the existing occupancy scheduling and occupied/unoccupied set points. Other system behaviors such as discharge air temperature, compressor-run time, and system recovery would be explored.

3.1 Occupancy Scheduling, Setpoints, User Adjust Capability

The branch occupancy schedules are relative to specific branch hours. All 24 of the Phoenix sites chosen for experimentation were utilizing the occupancy scheduling feature in the building automation system. However,branch hours are not listed anywhere on the building management site, so it could not be determined if schedules were being optimized with specific branch hours by using the data in the building automation site alone. Fortunately, Wells Fargo has a public access data base online that lists all of their retail branch hours.

Since a major emphasis of the experiments in this study will be on overnight unoccupied setpoints and system recovery, it seemed reasonable to take a deep dive into the current times the branches were switching to their occupied modes during the morning hours. Occupancy schedules in 24 buildings were explored and the time they each went occupied in relation to its opening hours was documented. Figure 3.1 is a bar chart highlighting those findings.

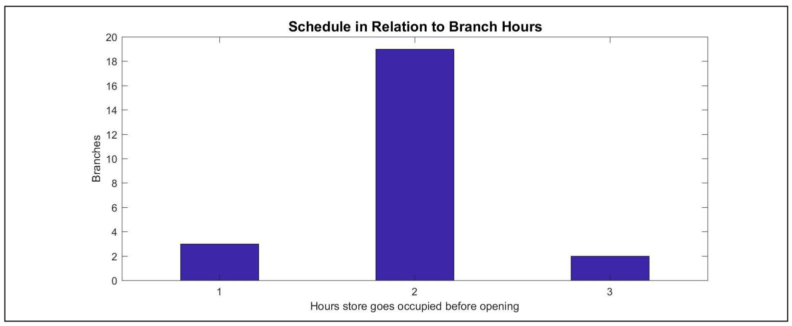

Figure 3.1: Occupancy in relation to branch Hours

The overwhelming majority of branches go occupied approximately 2 hours before the store opens. With the system smart recovery being activated in all of the branches examined, it is questionable whether or not it's necessary to bring the branch to its occupied temperatures so early. It is true that some employees do arrive earlier than the stores open, but there still seems to be some room to play with the occupancy time without risking occupancy comfort.

The next settings examined during the data dive was the occupied and unoccupied zone setpoints. Wells Fargo had a preliminary temperature standard for occupied temperature of 72-74°F that was enforced very loosely. Out of the 96 zones examined, most occupied set points fell around 74°F-which is the high end of the standard. Figure 3.2 shows the distribution of setpoints in all the zones across the 24 sites.

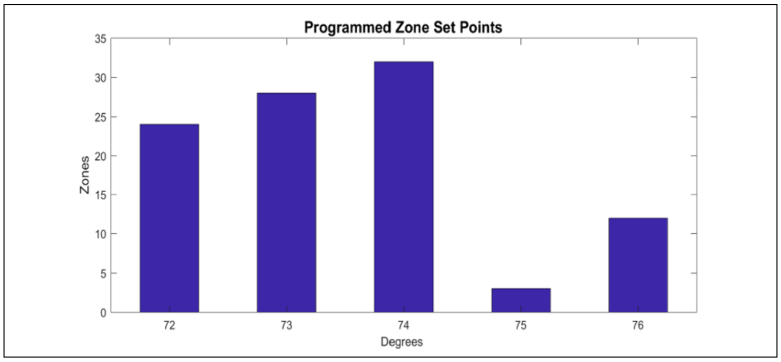

Figure 3.2: Occupied Setpoints

Wells Fargo also had a preliminary standard being used for the unoccupied setpoints of 83-85°F. The unoccupied temperature distribution across the 96 zones is shown in figure 3.3. Unlike the current occupied temperature settings, an overwhelming majority of the unoccupied setpoints were outside of the standard range and around 80°F. Pushing the unoccupied set points to the high end of the standard could create opportunity for energy savings by shaving off compressor run time. However, recovery time might have to be examined if temperatures are allowed to float higher during the unoccupied hours. Wells Fargo has stated repeatedly how important it is that zones be able to recover properly if pushed to the high end of the current standard.

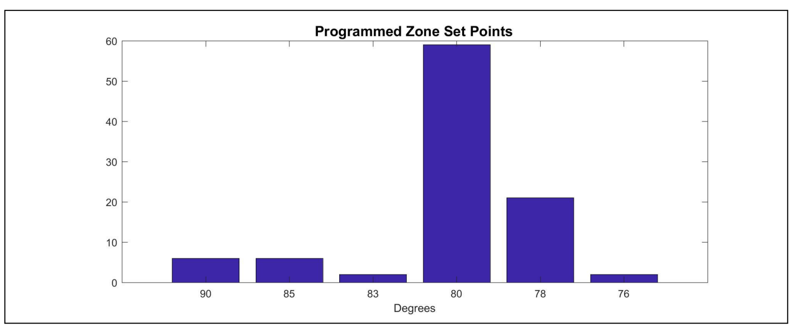

Figure 3.3: Unoccupied setpoints

Most of the thermostats being utilized throughout the Wells Fargo retail portfolio allow a programmable range of temperature user adjust capability for occupants to utilize. Wells Fargo has stated that this range should not exceed +/- 2°F, but such a standard lacks any real traction. If occupants have too much control of thermostat settings it could be detrimental to building performance and hinder any conservation strategies implemented; therefore, it seemed reasonable to explore the current programmed user adjust settings across a sample size of retail branches. The results were not entirely consistent with what Wells Fargo had loosely implemented as a standard. Although most of the user adjust ranges were programmed to be controlled in the specified range of+/- 2°F, some were found to be as high as +/- 5°F, and even one zone as high as +/- 7°F. Figure 3.4 shows the distribution of user adjust settings of 150 zones in the Phoenix area.

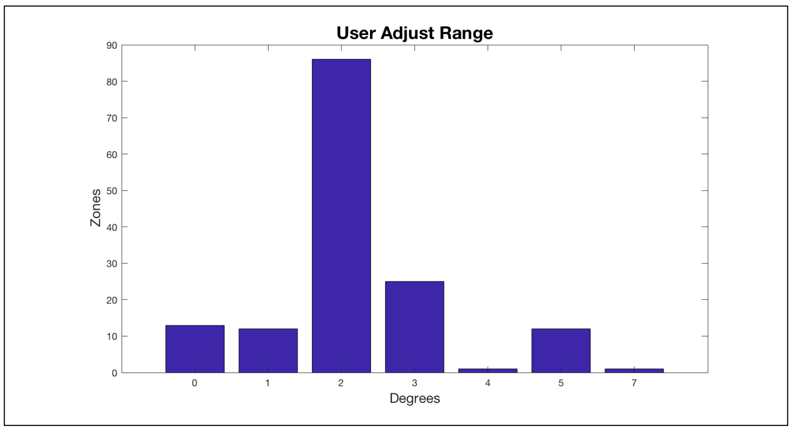

Figure 3.4: User adjust temperature range

3.2 Smart Recovery & Zone Temperature Recovery

As already discussed, Wells Fargo Corporate Properties Group has shown great concern in the ability of zones to recover by morning operational hours. But what exactly do we mean by recover? This means that a zone can properly recover from its unoccupied setpoint to its occupied setpoint by the time the time employees and customers show up at the branch. This is a valid concern since Wells Fargo is a service orientated business. Fortunately—at least in a majority of the sites examined throughout this research—many zones seem to be utilizing thermostats with a control feature called "Smart Recovery". This control feature takes building load into consideration and ramps the setpoint slowly when going from its unoccupied mode to occupied mode[6]. When a specific zone switches to its occupied mode, in theory the

"Smart Recovery"control should already have the zone at its occupied temperature.

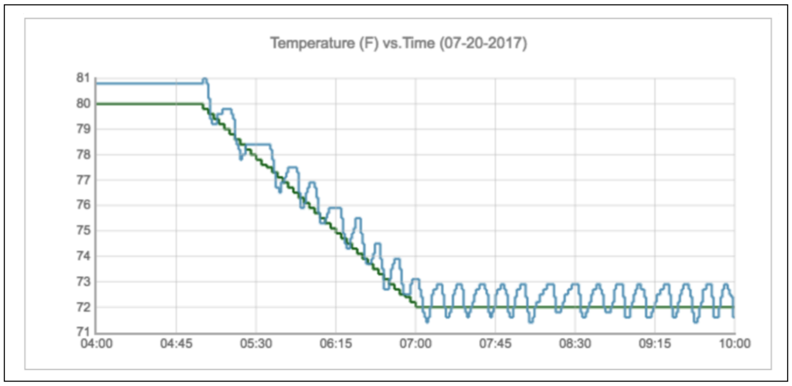

Figure 3.5: Morning cool down with smart recovery activated

The "System Recovery" is a particularly important feature that Wells Fargo should properly utilize. If the "Smart Recovery" is properly working, zone temperatures should be at their occupied temperatures well before the time the store actually opens. However, examining the recovery capability of "x" amount of zones might lead to misleading results. As already mentioned in Chapter 1, some zones never seem to show the capability of maintaining or even reaching certain setpoints. Table 4.1 breaks down the zone recovery of 96 zones utilizing "Smart Recovery" and gives the time relation to their specific store hours (30 minutes or 60 minutes before the store opens) for 3 different scenarios.

Table 3.1: Zone Recovery

Zone Parameter	74°F		75°F	
	30(min)	60(min)	30(min)	60(min)
97 Total zones	87%	78%	93%	89%
92 Total zones capable of hitting 75°F	N/A		96%	91%
94 Total zones capable of hitting 74°F	91%	83%	N/A	

All of the zones in the analysis actually had a programmed setpoint of 73°F, but the analysis was when they were in a +1 or +2 °F range of setpoint. This analysis was actually done on the actual experimental day, which will be discussed in more detail in Chapter 4. Moreover, at first glance the analysis seems to suggest that zones do not seem to all be optimally recovering. But when troublesome zones that never seem to reach their setpoints consistently are taken into consideration the numbers of recovered zone start looking much better.

3.3 System Anomalies & Struggling Zones

The building automation system has an alarm system set up for a small minority of retail sites. However, some zone issues are not necessarily even detected by existing alarm protocols in place. Figure 3.6 shows some odd zone behavior in one of the Phoenix retail building zones. The zone temperature is the blue- line that is following the green setpoint. The temperature seems to quickly drop when the store goes into its unoccupied state. This could possibly be due to some sort of signal inversion. These types of behaviors might lead to faulty data models and more importantly energy inefficiencies. Regardless, temperature sensors and data points relaying these type of signals should be examined to ensure proper functionality. These type of issues might be easily spotted when looking directly at the data, but they might slip through the cracks of less robust automated alarm systems.

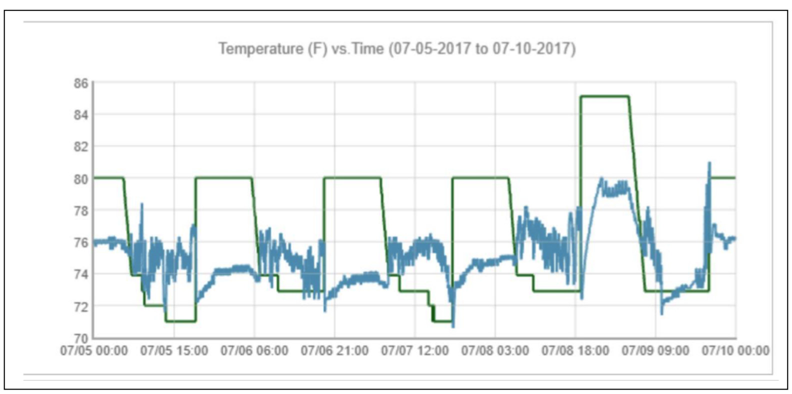

Figure 3.6: Odd zone temperature behavior

In addition to system anomalies, some of the zones examined showed an inability to maintain or even reach occupied setpoints at all. Figure 3.7 shows a Phoenix branch zone struggle to reach its occupied setpoints. The system does actually hit the setpoint eventually —albeit only momentarily. The system looks like it tried to ramp down during "System recovery", but after touching the occupied temperature 2 hours after the zone went occupied—the zone temperature just floats back up and doesn't maintain setpoint throughout the day. This seems to be a common occurrence in this particular zone. Factors such as undersized units, low or undercharged refrigerate might be responsible for these type of system faults. The faults discussed throughout this research did not have any sort of fault detection in place through the automation system.

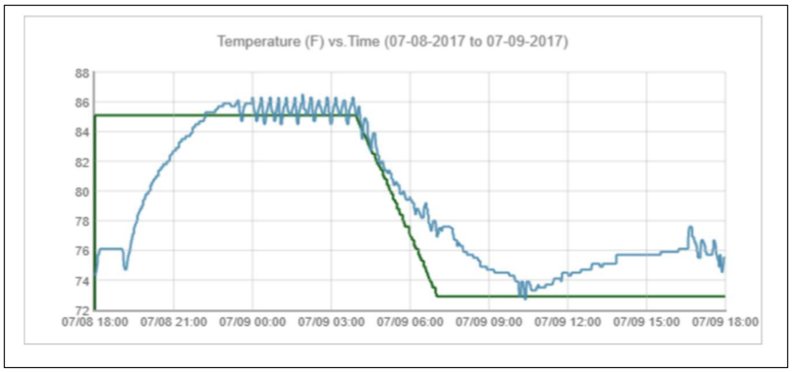

Figure 3.7: Setpoint issues

Zones that seem to never hit their setpoint or rarely ever hit it seemed to be an issue as well. Figure 3.7 shows one of the branch zones that never rarely seemed to hit its occupied setpoint. The plot in figure 3.7 is temperature (blue-line) following setpoint (green-line) over an entire week. There were some days towards the end of the week where it never came close to hitting its programmed setpoint. It is worth mentioning that the last day on this plot is the day the branch was actually the experimental day associated with this research. However, the day before it experienced similar issues maintaining its occupied setpoint. That is an important note when it comes to examining the zone behavior when overnight setbacks were pushed back to 85°F.

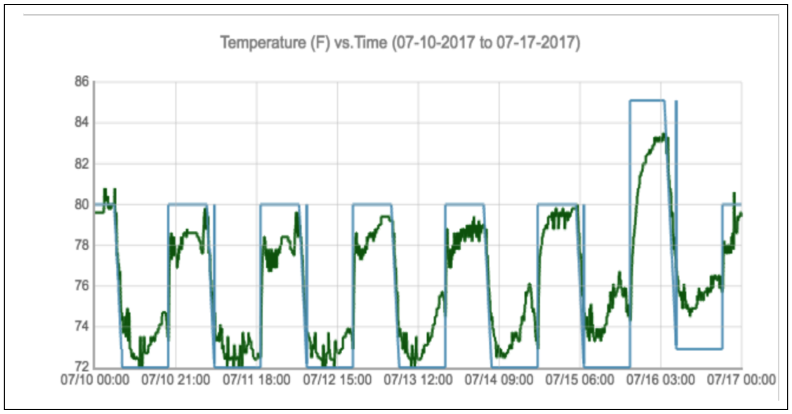

Figure 3.8: More setpoint issues

Figure 3.9 shows a snapshot of one of many excel spreadsheets created to highlight some zone statistics in the retail branches in Phoenix. There are some interesting statistics highlighted. For example, AVG DAT is the average discharge air temperature while the compressor is running. Most of the zones are reading an AVG DAT in the 60s—which seems reasonable according to Pacific Northwest National Laboratory[7]for occupied hours. However, the south platform zone is reading an AVG DAT temperature in the high 80s and that seems problematic. Another interesting statistic in figure 3.9 is the integral. In this context the value of the integral is defined as a numerical value that is strictly the measure of the area between the zone setpoint and the actual zone temperature. For example, the integral value is consistently reading above 800 for the South Platform/Office zone. Zones like BR/RR have normal setpoint and zone temperature behavior and its corresponding integral value is consistently around 200-300. Anything above 500 seems to suggest problems maintaining zone setpoint. The South Platform has an extremely high integral value on 7/9 at about 2834. This zone had extreme issues on that day maintaining its setpoint.

OCCUPIED ANALYSIS 7/5/17-7/9/17

Temperature/Zone	Statistic	Wend	Thurs	Fri	Sat	Sun
OAT	Avg OAT	107.45	108	112	108	103
	Max OAT	116.2	117	122	118	114
	Min OAT	88.9	89	90.7	93.7	86.5
BR/RR	Max Run Tim	16	7	7	8	5
	Total Run Tir	554	167	184	127	153
	Setpoint	73.9	73.9	73.9	73.9	72.9
	Max Differer	1.6	1.2	1.6	1.8	1.2
	AVG DAT	60.1	63.9	63.7	63.4	64.7
	Integral	335	197	269	316	198
South Platform/Office	Max Run Tim	525	592	666	225	717
	Total Run Tir	554	592	666	490	717
	Setpoint	72	72	72	72.9	72.9
	Max Differer	2.1	3.1	2.9	2	3.6
	AVG DAT	60.8	61.2	61.6	62.1	61.4
	Integral	849	971	1304	566	1540
South Platform	Max Run Tim	230	252	399	120	718
	Total Run Tir	230	252	399	120	718
	Setpoint	72.9	72.9	72.9	72.9	72.9
	Max Differer	1.8	2	2.8	3.6	5.1
	AVG DAT	87.1	88.6	87.5	86.7	82.6
	Integral	335	427	797	548	2834
Teller Line & Lobby	Max Run Tim	8	9	28	13	12
	Total Run Tir	231	249	456	287	361
	Setpoint	72	72	72	72	72.9
	Max Differer	1	1.5	2	1.9	1.8
	AVG DAT	64.2	64.7	61	65.5	65.8
	Integral	343	364	561	404	473

Figure 3.9: Zone statistics

CHAPTER 4: EXPERIMENTAL VALIDATION

Experiments were ran in the summer months during the cooling season in one of the more extreme climates in Phoenix,Arizona. The big question heading into the experimental aspect of this thesis was pretty much summed up as follows: will pushing the overnight setback result in energy savings, without risking occupant comfort? To answer this question, the overnight compressor cycling and morning warm-up became key areas of interest. Many of the current setbacks were around 78-80°F, which fell short of current Wells Fargo standard of 83-85°. After discussions between the Wells Fargo and UNCC team, it was decided that those overnight unoccupied setpoints would be pushed to 85°F in all the building zones during experiments.

Figure 4.1 highlights the overnight cycling of a single compressor during an unoccupied period. The top plot with the green binary signal shows the on-off signal for a single compressor unit. The bottom plot shows the space temperature (blue-line) and the set-point (green-line). When the space temperature reaches the setpoint, the compressor unit begins to cycle. If the temperatures are allowed to float slightly higher, there might be some inherit risk for the system to actually consume more energy trying to cool back down, or even losing its ability to properly recover; hence, risking occupant comfort.

Since this study was aimed at retail branches rather than administration buildings, occupant comfort was a major concern during the duration of this study. If temperatures in branches are pushed to a level where it makes their recovery troublesome than pushing unoccupied temperatures higher might not be advisable.

Figure 4.1: Compressor unoccupied activity

There were originally 32 retail buildings identified as ideal experimental sites within a 20 mile radius of Phoenix, Arizona. It was determined that all test sites should be stand alone sites. Stand alone in this context means they are not connected to any other spaces that might have separate controlled HVAC systems; this would ensure the test site could be properly controlled.

4.1 Experimental Setup

To avoid any potential conflicts during branch operational hours, it was determined that all experiments would be conducted during the branches official unoccupied hours over the weekend. Figure 4.2 shows the scheduling setup used during the experimental process. The idea was to use a Sunday as a hypothetical workday. In order to do so, the occupancy schedule for Saturday was adjusted at each branch to make its unoccupied period start where it would typically go unoccupied Monday-Thursday. The Sunday occupancy schedule was also adjusted to each stores typical Monday-Thursday hours. Unoccupied setpoints at each branch were adjusted during the day on Saturday before the branches went unoccupied and set to 85 °F. Occupied setpoints for Sunday were set to 73 °F after the stores went unoccupied on Saturday. The experimental setpoint for the occupied period was initially set to 73 °F, but it was determined at a later date that 74 °F would be ideal. This detail would be taken into consideration during the analysis of the experimental data. During the day on Sunday, all unoccupied setpoints were returned to their usual settings. When the stores went unoccupied Sunday evening, all scheduling and occupied setpoints were to returned to their usual settings. All programmed setpoints and schedule changes were implemented using remote write access on the building automation system.

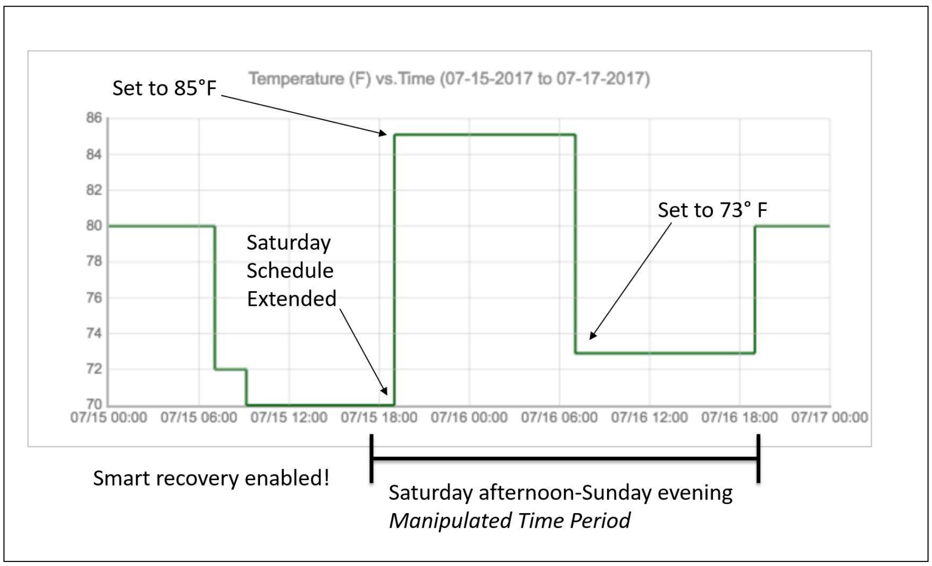

Figure 4.2: Experimental day scheduling

The experimental process was broken up into 2 separate weekends during July. Half of the sites would be reprogrammed over one weekend to operate at new occupied and unoccupied setpoints and the other half the following weekend. This was to ensure that changes could be made in an efficient manner and without complications. The "Smart Recovery" option was left on for all the zones during the experimental process.

4.2 Experimental Results

After the experiments were ran and the data was processed, a benchmark day was needed to conduct a preliminary analysis. Since its rare that any two days are exactly the same, the most similar recent day was found to make energy comparisons with. The temperature profile for the unoccupied overnight period for the experimental and benchmark days used is shown in figure 4.3 The red-lines represent the experimental days and the blue-lines represent the benchmark days.

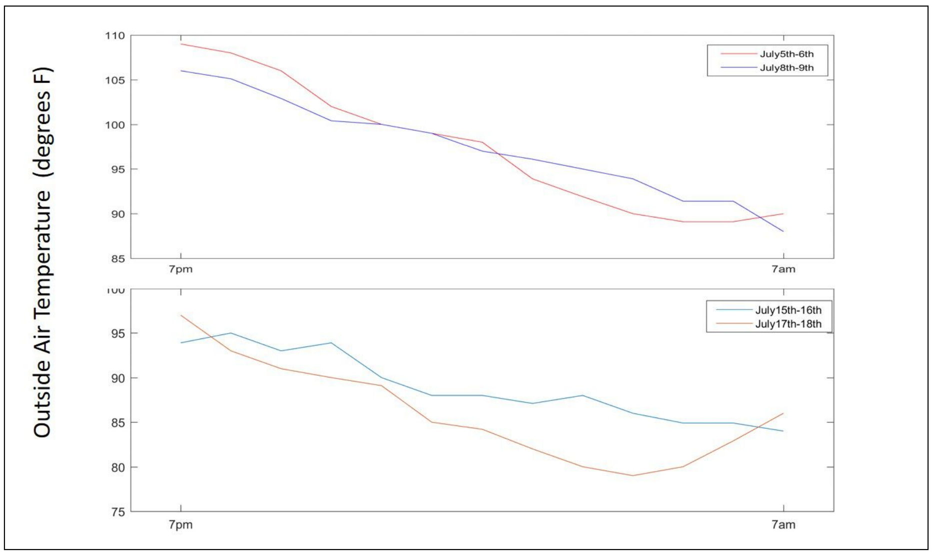

Figure 4.3: Temperature profiles

Figure 4.4 is a scatter plot of percent reduction in energy for experimental week 1. All of the sites saw an overall reduction in energy consumption. It is important to note that this is only taking into account the compressor energy. The building automation site used to collect data in this experiment was not tracking any actual building energy consumption. After discussions with the Wells Fargo team, the energy analysis was done assuming 3-ton packaged roof top units and using a COP of 3. Details of how this calculation was made is shown in Appendix C. Fan energy was also not taken into account in this analysis.

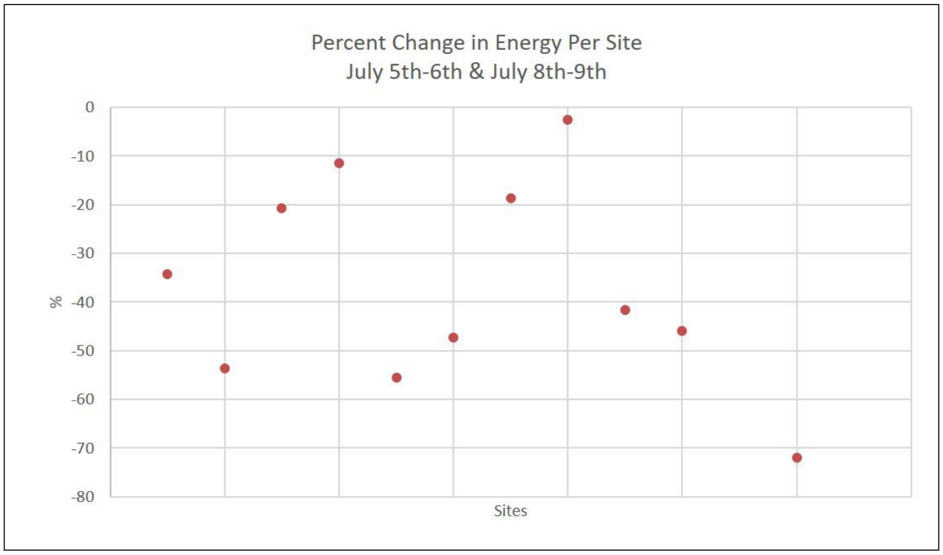

Figure 4.4: Experimental week 1 -% energy change

There is one extreme case where the savings came back over 70%. This was due to one of the zones that stayed unoccupied and never experienced a morning cool down. Figure 4.5 shows the zone temperature and temperature setpoint plot. The zone never responded to the occupancy changes made on 7/9; therefore, the compressor never needed to run to cool the branch, resulting energy savings that were somewhat exaggerating for this particular branch.

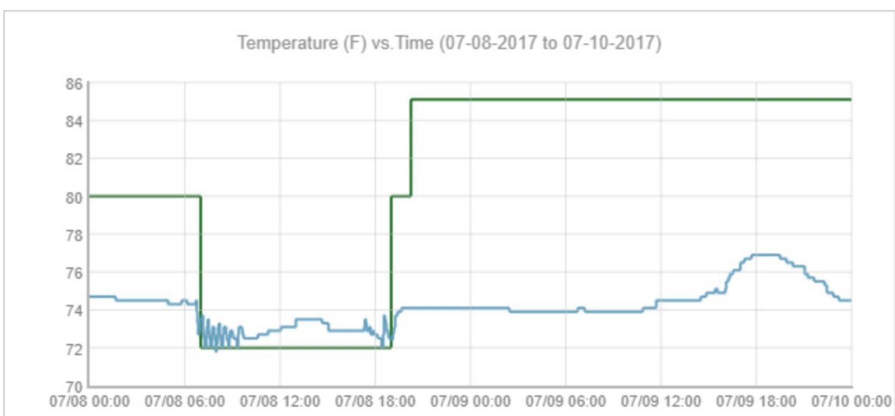

Figure 4.5: Desert F. setpoint(green) & zone temperature(blue)

Figure 4.6 is a scatter plot of percent reduction in energy for experimental week 2. Although most branches saw an overall reduction in energy, there were a couple that did not. One of the sites had some unusual zone temperate issues that made the compressors at this branch run continuously. The issues at this branch extended to days beyond the experimental day and seemed to be somewhat of a common theme. The other branch that saw an increase was a branch that actually had overnight setbacks as high as 90°F and they were brought to 85°F. That will be discussed in more detail shortly.

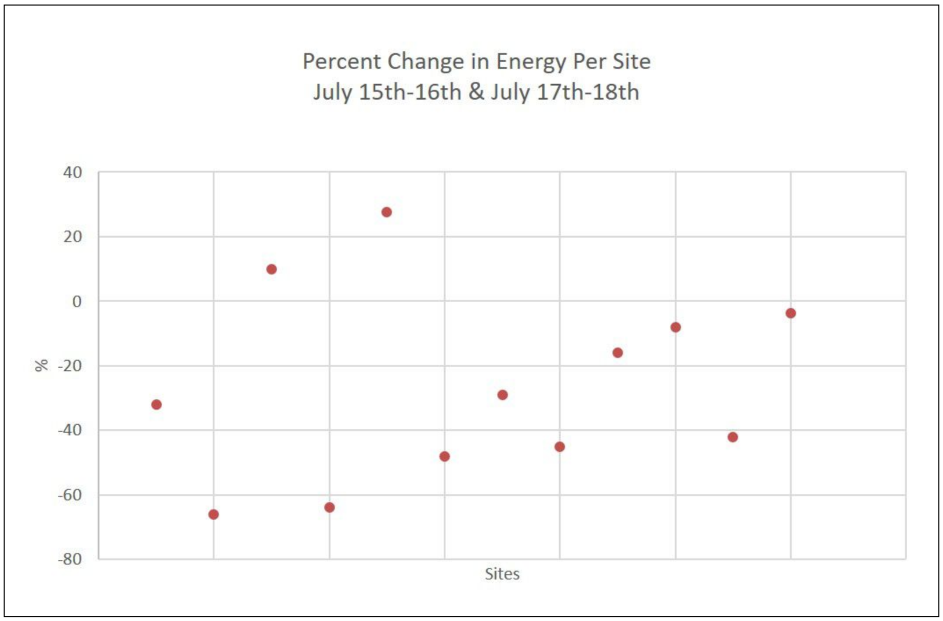

Figure 4.6: Experimental week 2 -% energy change

Figure 4.7 shows a zone that had a fairly dramatic decrease in overnight compressor cycling. The plot on the left side shows the comparison day zone temperature (blue) following its set point (green). The bottom plot on the left is the compressor on/off signal for the comparison day. When compared to the experimental day plots on the right side of figure 4.7, its obvious that compressor run time dramatically decreased.

Figure 4.7: Zone decrease in run time

Figure 4.8 shows a zone that had a fairly dramatic increase in overnight compressor cycling. This entire branch saw an increase in energy consumption in experimental week 2. This was due to the temperature being taken from 85 °F to 90°F

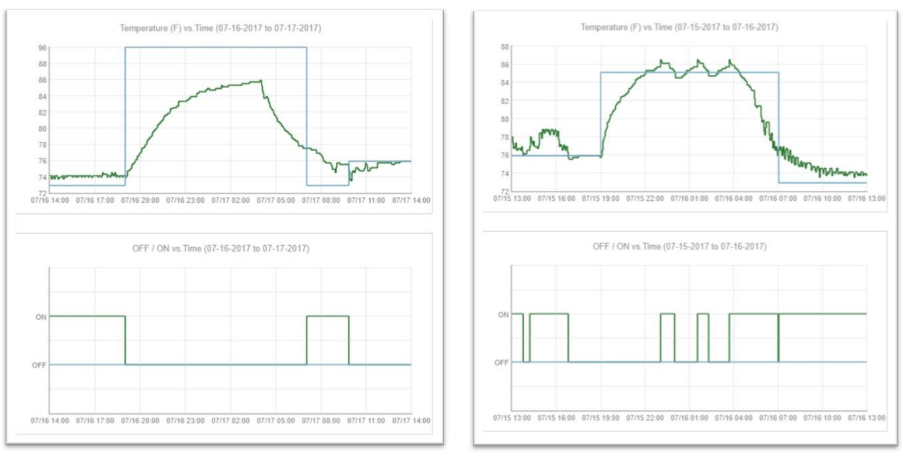

Figure 4.8: Zone increase in run time

4.3 Extrapolation Model & Annual Predictions

While the cooling saving results in Section 2.1 are encouraging, they needed to be investigated in the field, given the various problems observed in the field. There was a question about whether the expected savings could be achieved. The EnergyPlus change-point model discussed in Chapter 2 would serve as a useful guide in how to create predictive models for the experimental buildings and extrapolate potential annual energy savings. If a potential change-point can be identified in a set of buildings in a specific region, then such a point can serve as an divergence point for two distinct setpoints. Figure 4.9 shows an overview of the construction of a change-point regression model for one of the experimental sites in Phoenix, Arizona. The x-axis is weekday unoccupied average outdoor air temperature and the y-axis is energy consumption. The original building automation data does not give a reading for cooling energy. It gives a binary signal for the compressor being on or off. Since the signal is sent in minute intervals—each 1 is assumed as a minute of compressor run time. As noted earlier in Section 4.2,compressor run time can be easily turned into energy by making assumptions of the typical branch compressor units and efficiency. Since the experimental data only addresses weekday energy savings—extrapolation models will only address weekday energy savings.

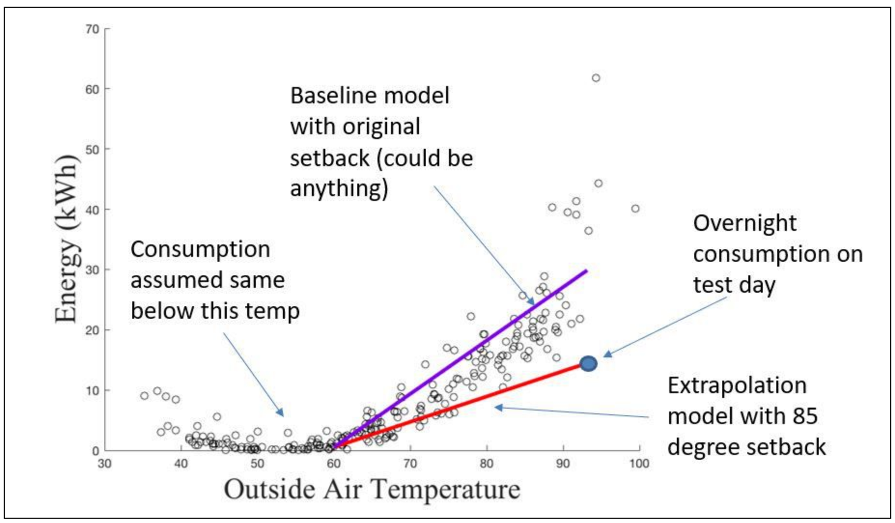

Figure 4.9: Overview of extrapolation model

The baseline consumption model is marked with the blue regression line. This represents the regression model for the ordinary cooling setbacks throughout the year.The red line represents an extrapolation line for the test day with the newly implemented setback. The point where outdoor air temperature seems to start impacting cooling consumption for the phoenix area seemed to be around 60°F. This is the point chosen to represent the change-point for the Phoenix metro area.

The idea behind the extrapolation process is to create two linear regression models—one with all the days above the chosen change-point of 60°F at the old setback, and another with the test day data with the new setback. The daily average outdoor air temperature for each day above the change-point was then taken and passed through both models as inputs. The difference in the two model outputs is the predicted energy reduction between prior and the newly implemented setback on the test day. To make this procedure clearer, the three main steps of the model development will be explained in more detail. Figure 4.10 shows a scatter plot for one of the experimental sites in Phoenix, Arizona. Like the plot in figure 4.13, the x-axis is the average weekday unoccupied outdoor temperature and the y-axis is energy consumption.

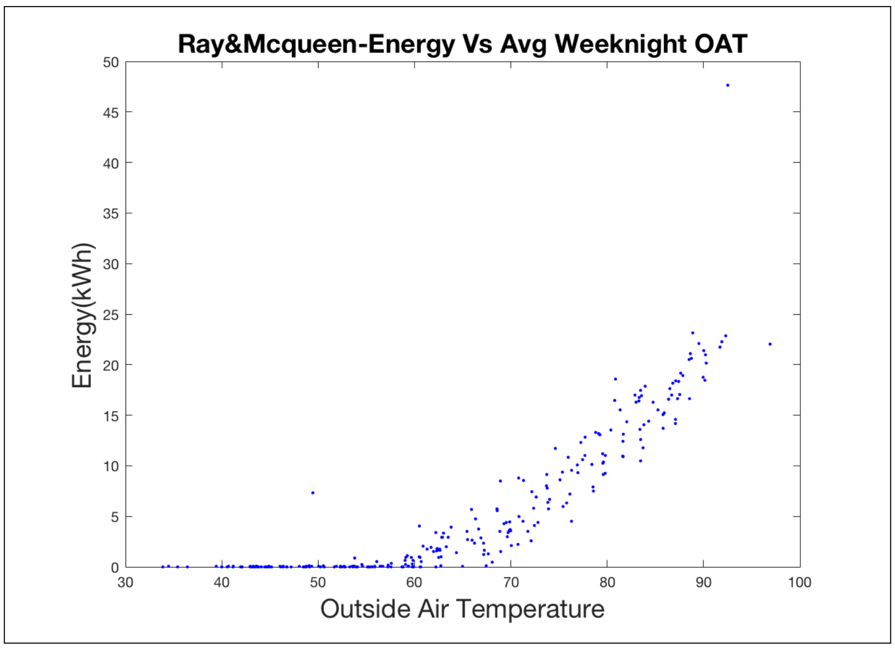

Figure 4.10: Ray & McQueen yearly scatter plot model

Since the change-point has already been defined at the point of 60°F, a linear regression model can be constructed for every overnight period after that point. You can see clear linear behavior for each day past 60°F. Figure 4.11 shows the adjusted regression model.The form of this is obviously linear and the equation for the model is shown in equation 4.2

$$y_o = a_0 x_o + b_0 \tag{4.1}$$

where y_o is the compressor energy output for days after change-point unoccupied outdoor air temperature and under old setbacks; x_o is the average unoccupied outdoor air temperature input for the days after the change-point.

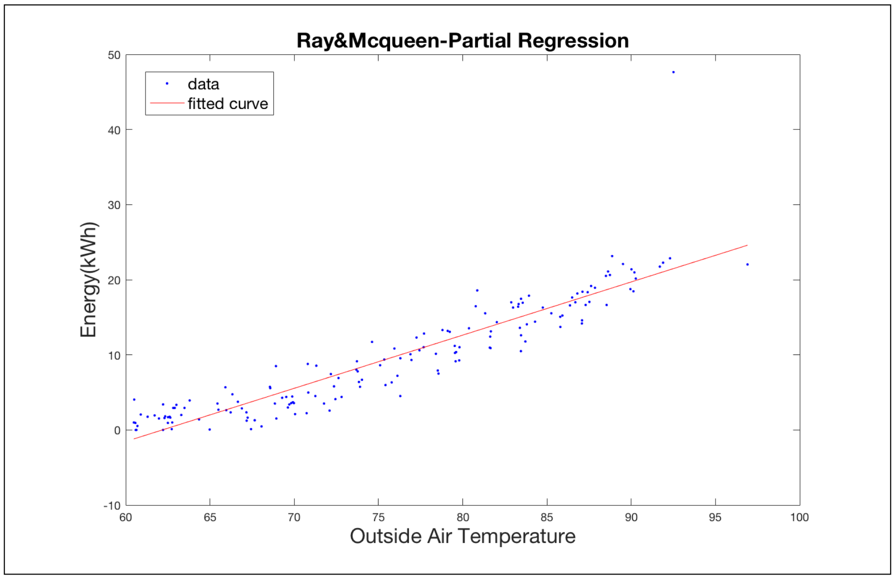

Figure 4.11: Ray & McQueen change-point regression model

The test day extrapolation is then determined by fitting a linear line from the point on the y-axis where the point at which the change-point to the test day run time. Figure 4.12 shows the linear fit for the test day. The form of this model is clearly just linear and is shown in equation 4.2:

$$y_e = a_e x_e + b_e \tag{4.2}$$

where y_e is the compressor energy output for days after change-point unoccupied outdoor air temperature and under new setback; x_e is the average unoccupied outdoor air temperature input for the days after the change-point.

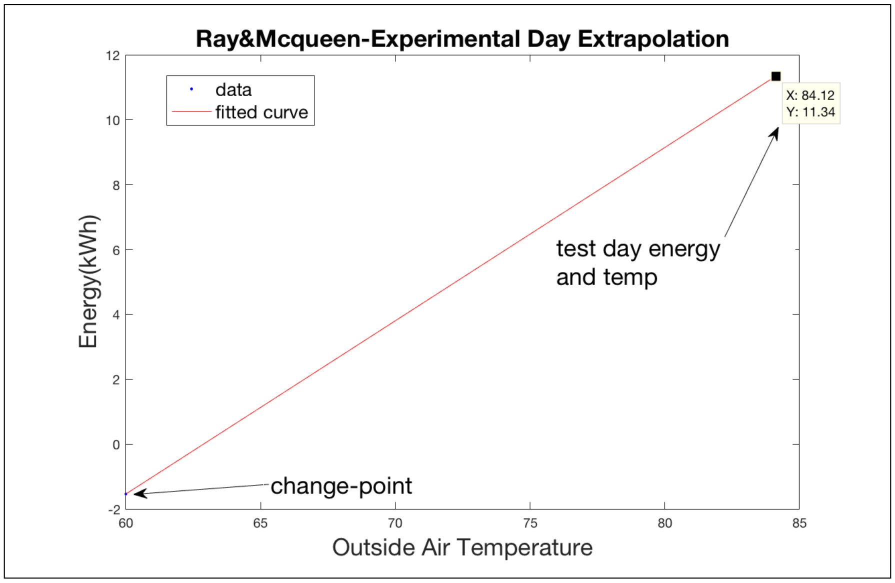

Figure 4.12: Ray & McQueen experimental day extrapolation model

With the two models now constructed—calculations can be made to get the energy reduction predictions. Equation 4.3 represents the equation used to calculate the energy reduction.

$$y_{rr} = y_o - yi = a_0 x_o + b_0 - a_e x_e + b_e \tag{4.3}$$

where y_{rr} is the compressor energy reduction; x_o and x_e are the days the average unoccupied temperature is greater than specified change-point temperature. The full extrapolation model for this example is shown in figure 4.13

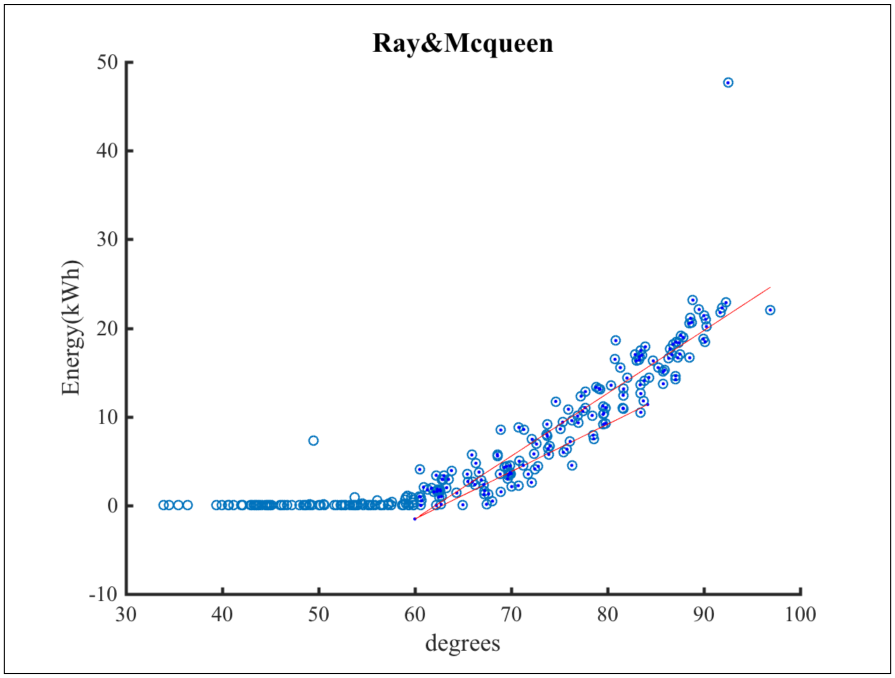

Figure 4.13: Ray & McQueen experimental day extrapolation model

Unfortunately, some of the sites are not so easy to construct models with, due to questionable data at some of the sites. Figure 4.14 shows a regression model at one of the branches in Phoenix. This is a site that is most likely experiencing some faults that cause the cooling system to run inconsistently. Sites like this make the extrapolation model building quite challenging.

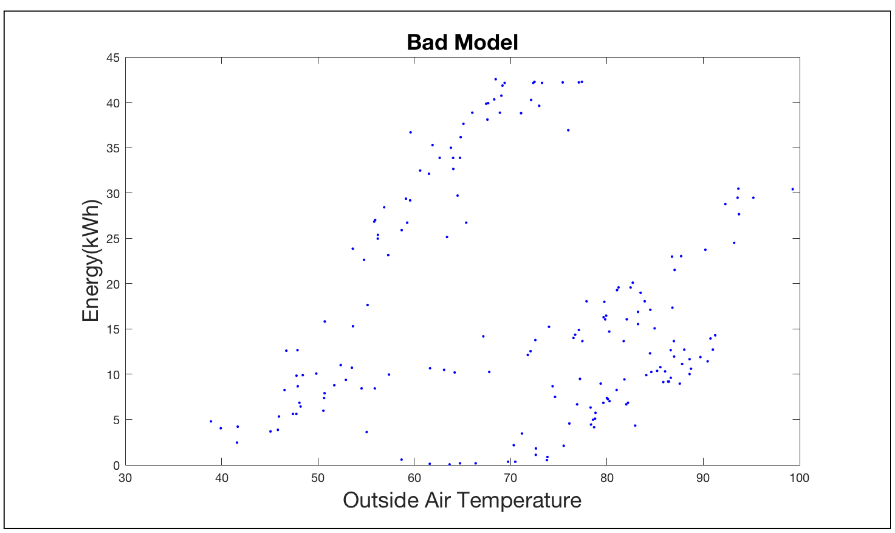

Figure 4.14: Problematic site data

Figure 4.15 shows the energy reduction across 19 of the experimental Phoenix sites. Extrapolation regression models for some of the experimental buildings did not get constructed due to fault issues similar to the model shown in figure 4.14. Two of the sites had negative reduction—which means the site actually was predicted to consume more energy. However, the one of those sites is the branch discussed in earlier that moved from 90° to 85° setbacks. For most locations, predicted energy was positive—which means there was potential for cooling energy reduction.

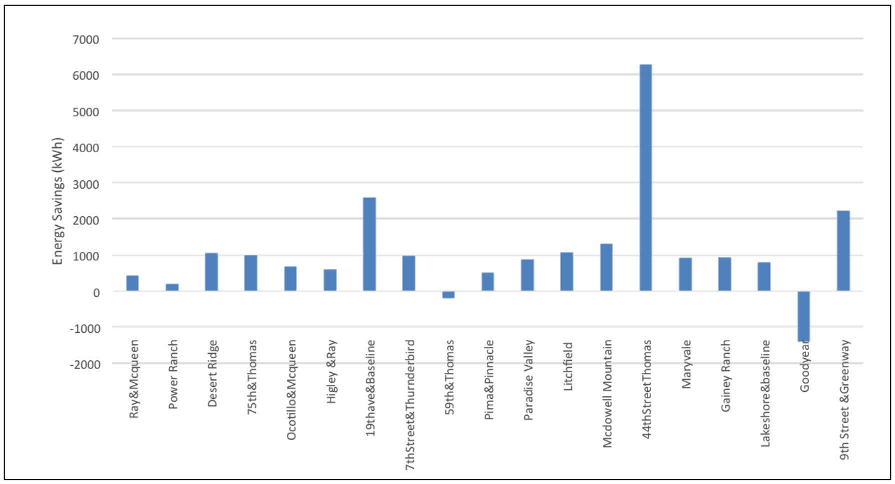

Figure 4.15: Experimental energy reduction

Historical building energy data was attained from Wells Fargo in order to do an analysis of total site energy reduction potential. Figure 4.16 shows the percent reduction of total building energy throughout the 19 experimental buildings with models. There was an average of 0.85 % reduction of total building energy. It is important to remember this number only reflects Monday-Friday weeknight savings and does not include the weekends—where there is quite a bit of savings potential as well. It also does not include any sort of fan energy independent of the compressor.

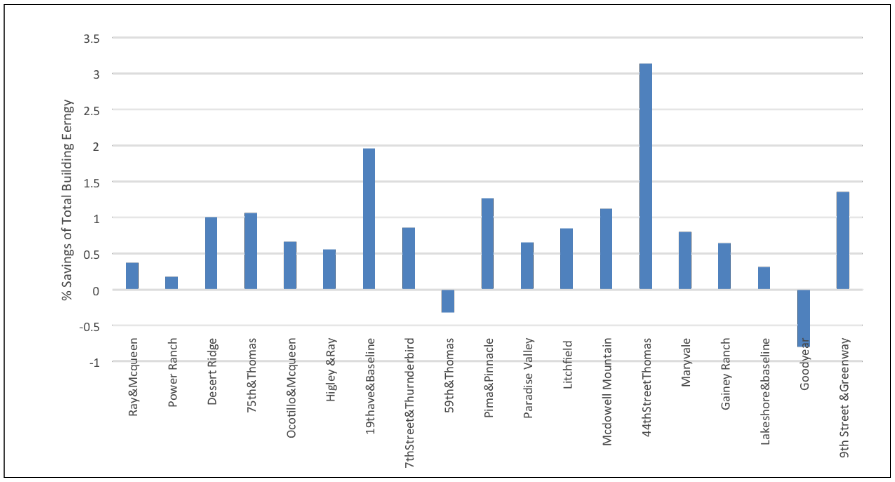

Figure 4.16: Experimental percent of total building energy

CHAPTER 5: CONCLUSIONS

Even if the site savings of total building reduction was simply only 0.85% like the experiments ran in Phoenix, Arizona, suggested, Wells Fargo Corporate Properties group would still have quite a bit of incentive to realize this potential due to their large retail portfolio. Using the analogy in Chapter 1, an 0.85% savings would be like taking 379 homes off the grid—potentially saving $432,072 dollars per year. This is a reminder that with large numbers even small percentages can make quite a bit of difference. Table 5.1 shows the average site reduction per site in Climate Zone B and the simulation reduction at the experimental setpoints.

Table 5.1: Climate Zone B simulation and experimental comparison

Climate Zone B (Cooling only)	**kWh/y**
Simulation Site Reduction	2773
Average Site Experimental Reduction	1097

As mentioned in Chapter 4, it is important to remember that the experimental savings only reflects cooling weeknight energy savings potential —while the simulation reduction includes weekend potential. The average simulation total building energy reduction potential across all climate zones with newly implemented cooling and heating setpoints was about 4.8%. There was no way to quantify heating savings during this thesis, as experimental opportunity was minimal and only during the cooling season over the course of a couple weekends.

Modern energy simulation software can be a very useful tool that utilizes basic theoretical framework. However, these tools assume ideal operating conditions—which is often not the case in the field with real systems. Faults in real systems will prevent savings in the field from reaching suggested simulated potential. The field study conducted with this thesis highlighted many problematic issues within a fairly small sample size of the Wells Fargo retail portfolio. Given that Wells Fargo has about 6000 retail sites, the cost for these sort of inefficiencies could start piling up quickly if these sort of issues are as prevalent throughout the rest of their retail portfolio.

Simulation and experimental results do suggest significant savings potential associated with setpoint optimization strategies. Also, the field study suggests that many of the current setpoints, scheduling and other programmable features being used across the Wells Fargo portfolio have room for further optimization. Implementing full fault detection across the retail portfolio would provide significant opportunity for energy savings as well. In addition,ideal setpoint optimization would likely be on a per-site basis using analytics. Buildings can differ so drastically in behavior and what works well in one building might not work very well in another.

Developing data-driven statistical models can often be a challenging task when confronted with the reality of real world systems. Faults in real systems will create large variances that will ultimately lead to wider confidence intervals. In other words, the model accuracy will suffer. Models developed in this thesis did seem to verify the energy savings opportunity associated with setpoint optimization strategies. However, it seems reasonable to question how much savings could actually be realized with setpoint strategies if faults are as common throughout the rest of the Wells Fargo retail portfolio as they were in the sample size of retail stores examined in this thesis.

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[5] K. Woohyun and J.Braun, "Impact of refrigerate charge on air conditioner and heat pump performance," *International Refrigeration and Air Conditioning Conference*, 2010.

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[7] Pacific Northwest National Laboratory, *AHU Discharge Air Temperature Control.* https://buildingretuning.pnnl.gov/documents/84186.pdf.

APPENDIX A: ENERGYPLUS CLIMATE ZONE COOLING & HEATING ENERGY PLOTS

Attached in this appendix are energy plots for all the simulated cooling and heating setpoint adjustments across climate zones.

A.1 Climate zone cooling energy plots

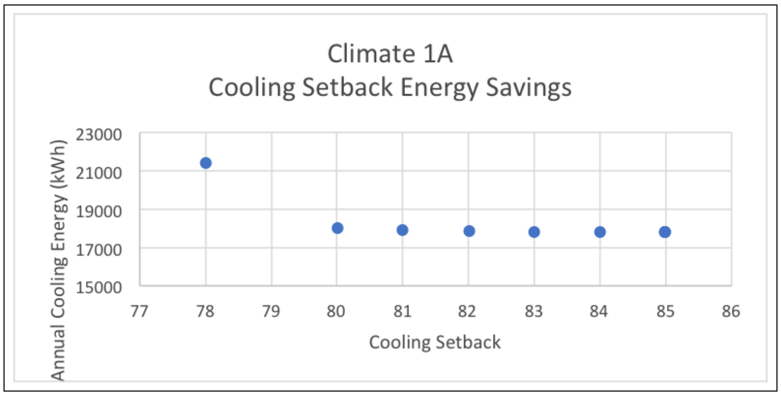

Figure A.1: Climate 1A cooling

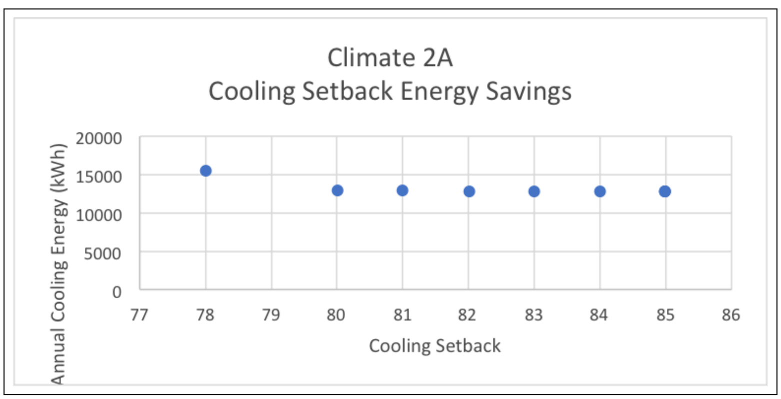

Figure A.2: Climate 2A cooling

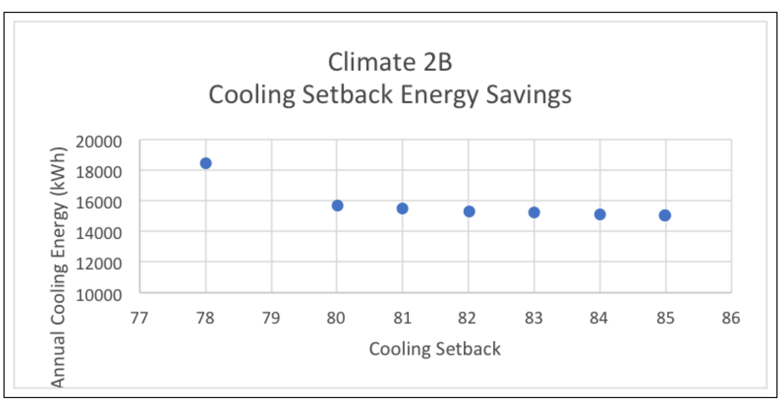

Figure A.3: Climate 2B cooling

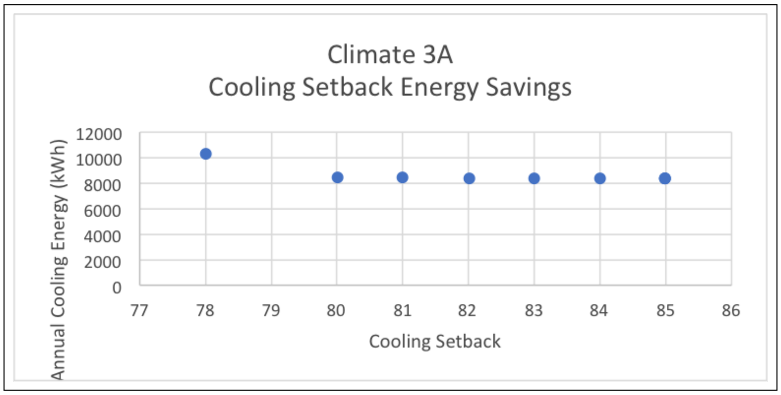

Figure A.4: Climate 3A cooling

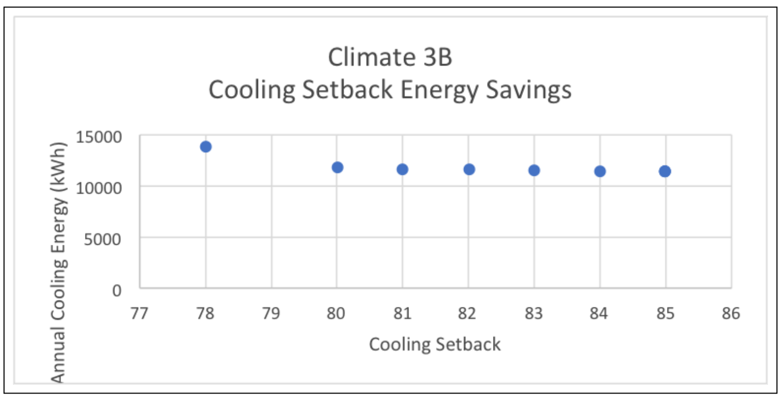

Figure A.5: Climate 3B cooling

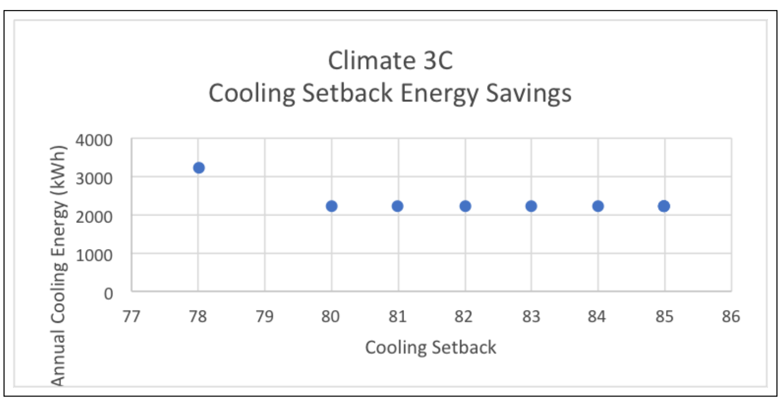

Figure A.6: Climate 3C cooling

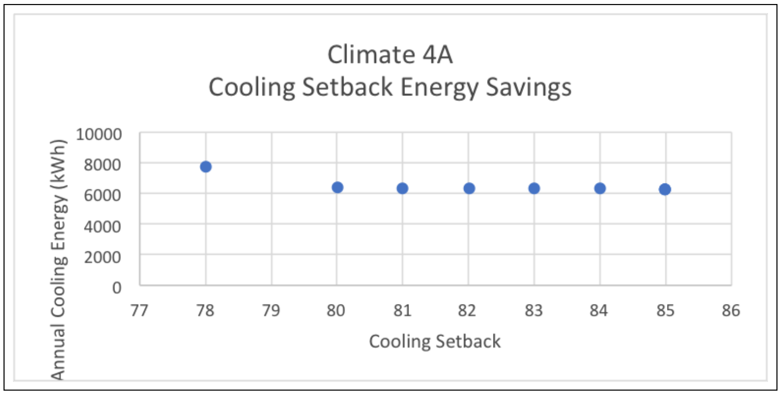

Figure A.7: Climate 4A cooling

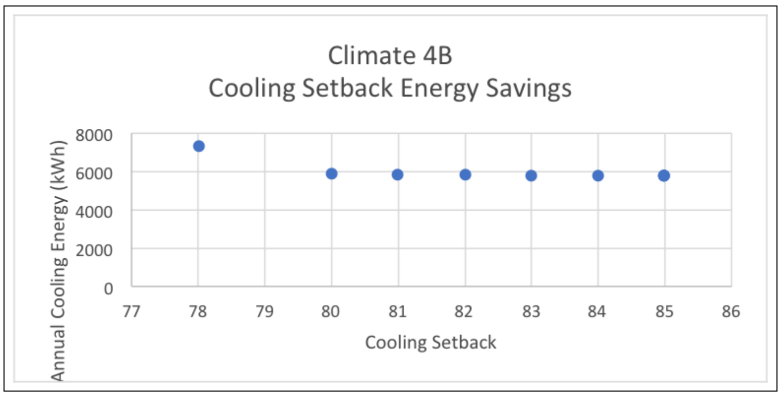

Figure A.8: Climate 4B cooling

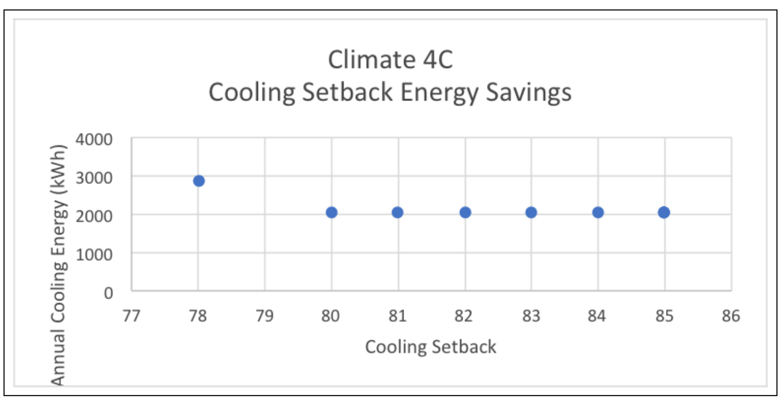

Figure A.9: Climate 4C cooling

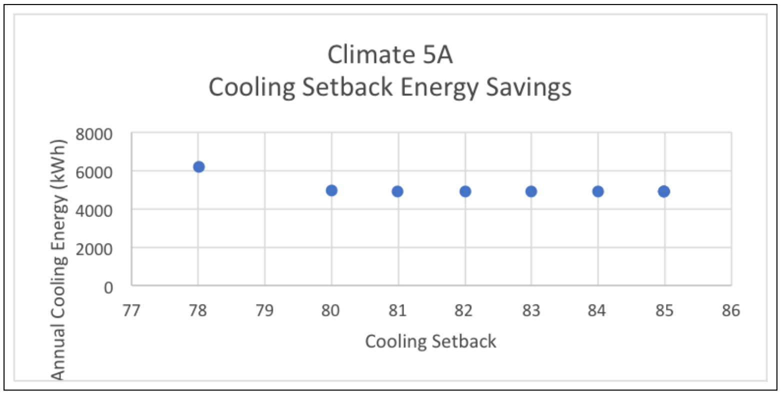

Figure A.10: Climate 5A cooling

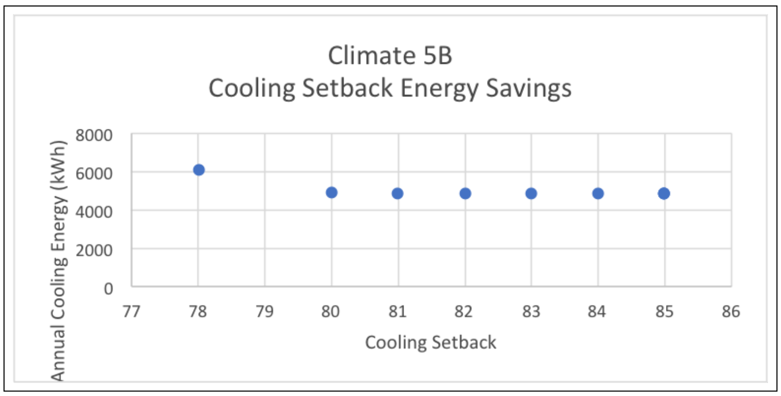

Figure A.11: Climate 5B cooling

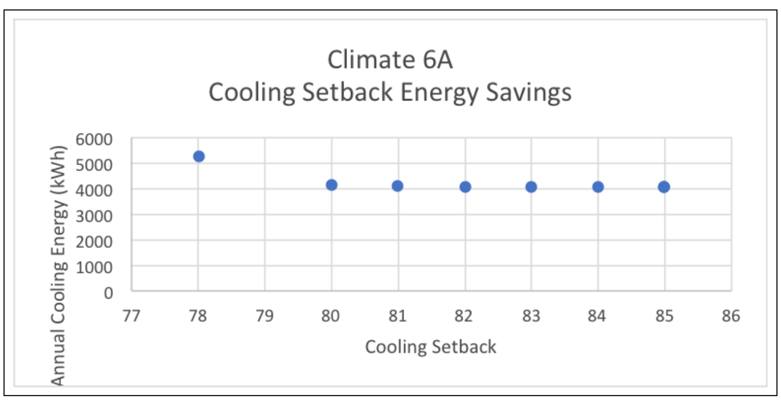

Figure A.12: Climate 6A cooling

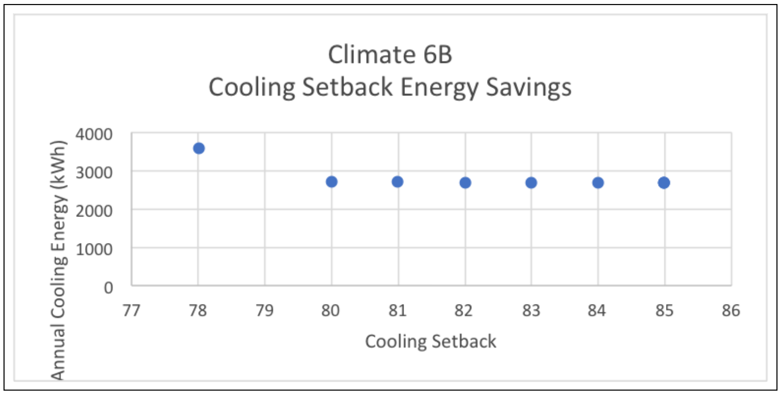

Figure A.13: Climate 6B cooling

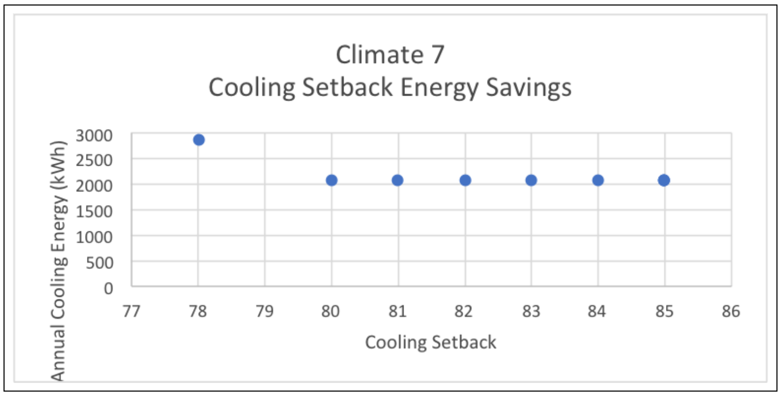

Figure A.14: Cooling 7 cooling

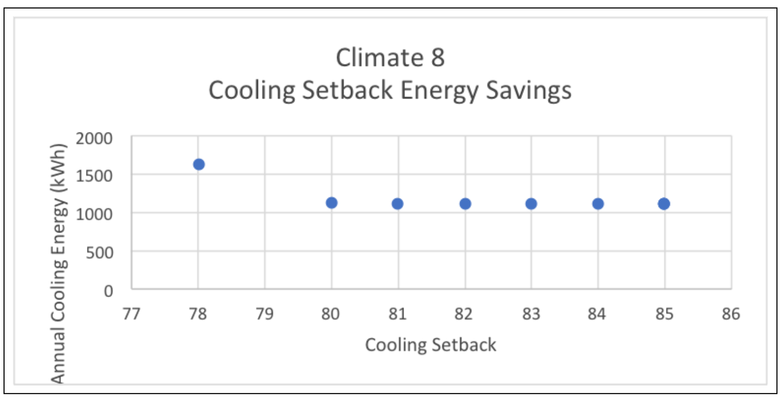

Figure A.15: Cooling 8 cooling

A.2 Climate zone heating energy plots

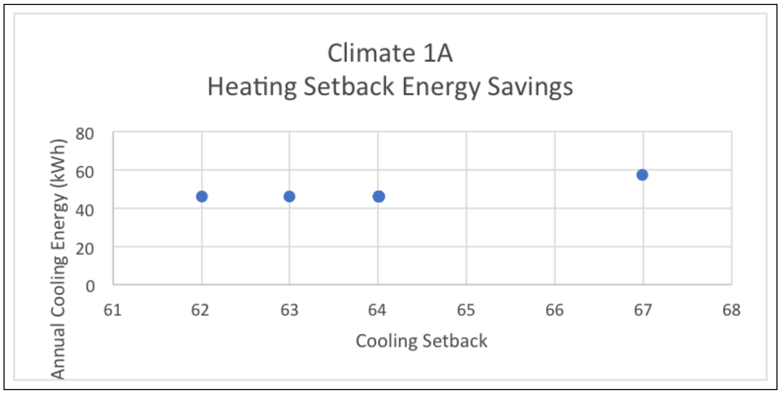

Figure A.16: Climate 1A heating

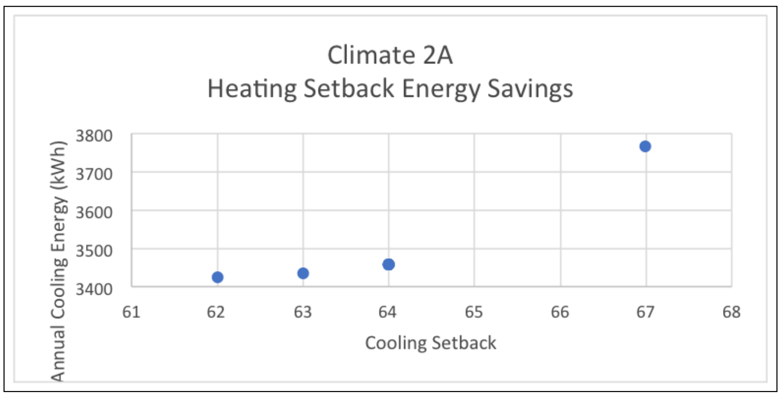

Figure A.17: Climate 2A heating

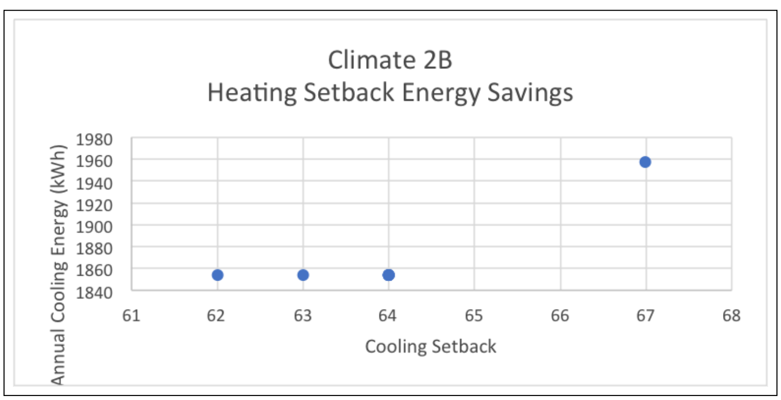

Figure A.18: Climate 2B heating

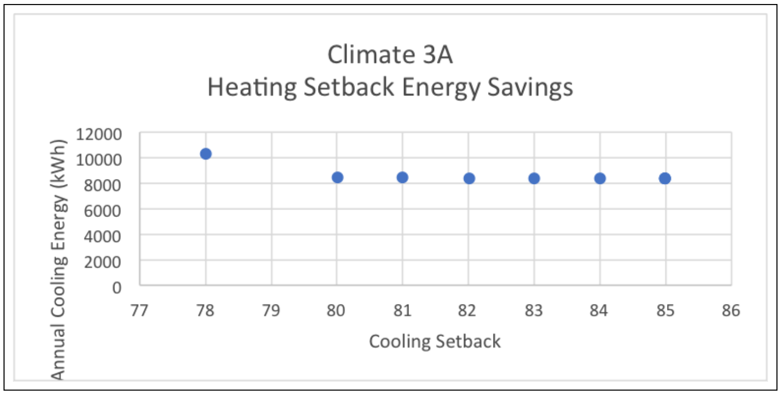

Figure A.19: Climate 3A heating

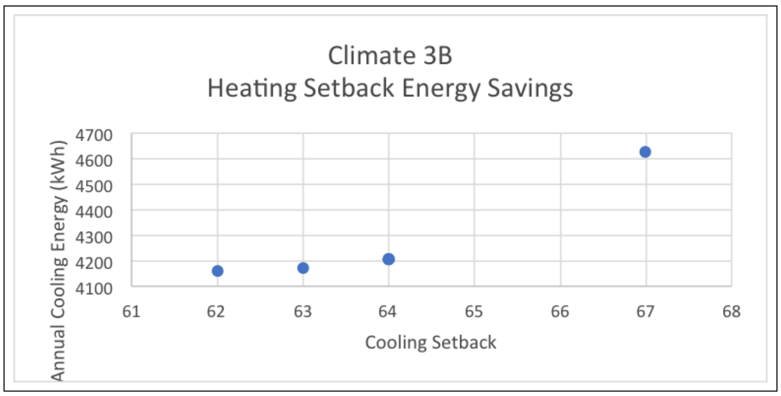

Figure A.20: Climate 3B heating

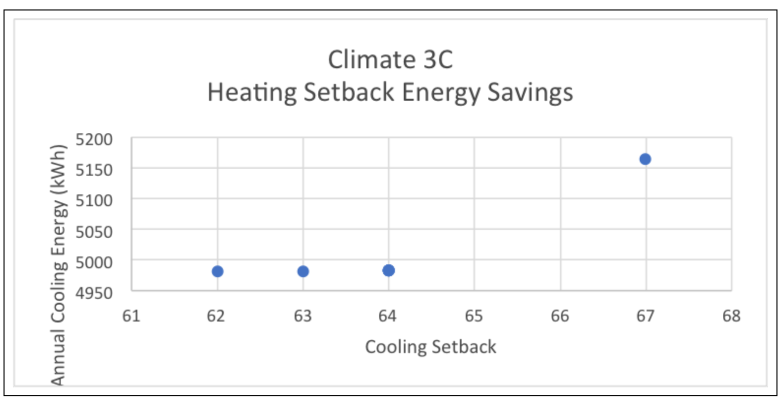

Figure A.21: Climate 3C heating

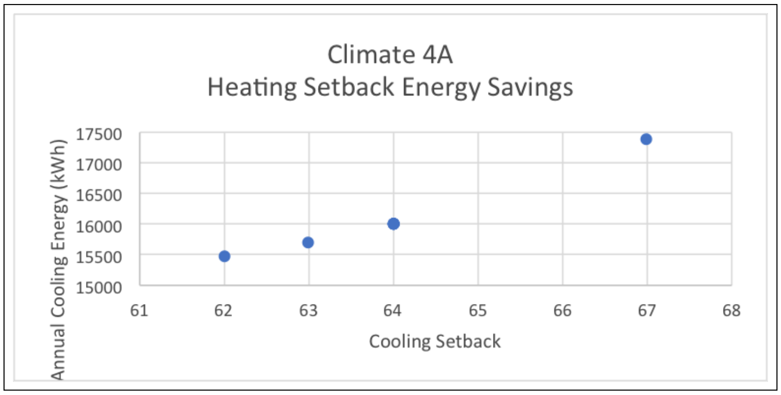

Figure A.22: Climate 4A heating

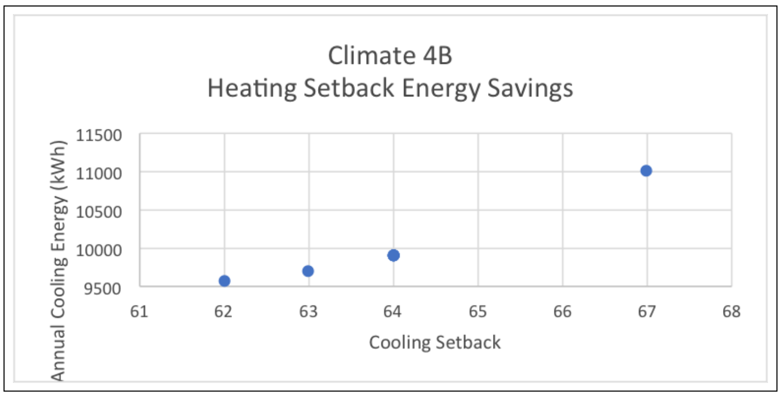

Figure A.23: Climate 4B heating

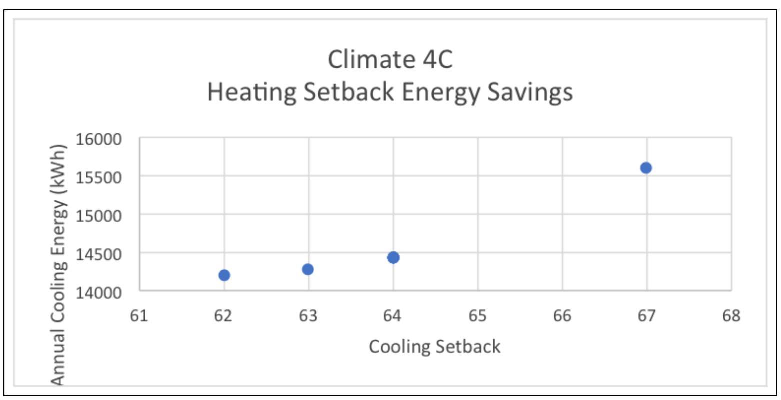

Figure A.24: Climate 4C heating

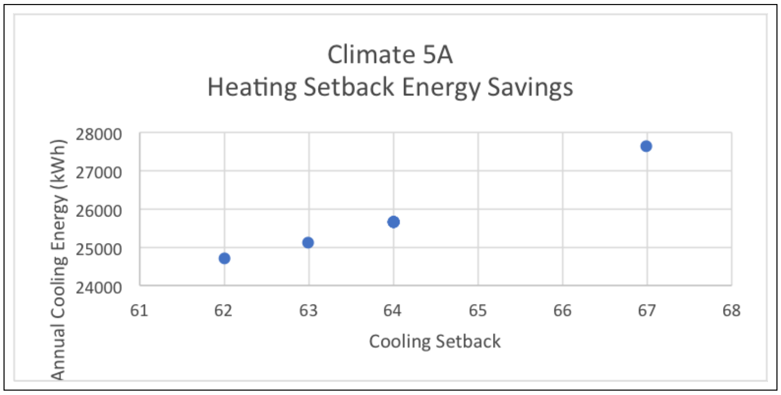

Figure A.25: Climate 5A heating

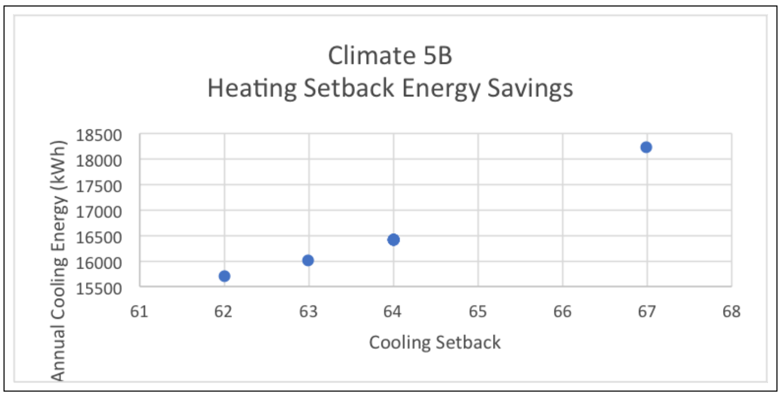

Figure A.26: Climate 5B heating

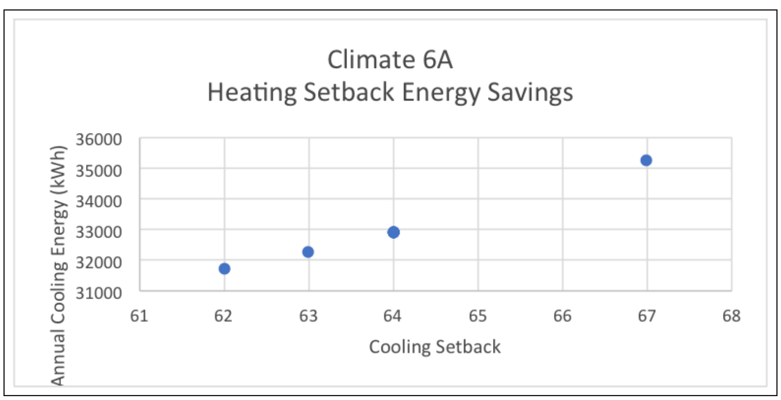

Figure A.27: Climate 6A heating

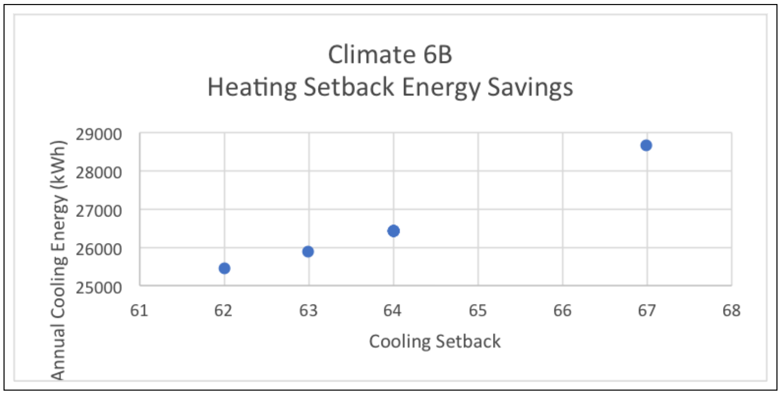

Figure A.28: Climate 6B heating

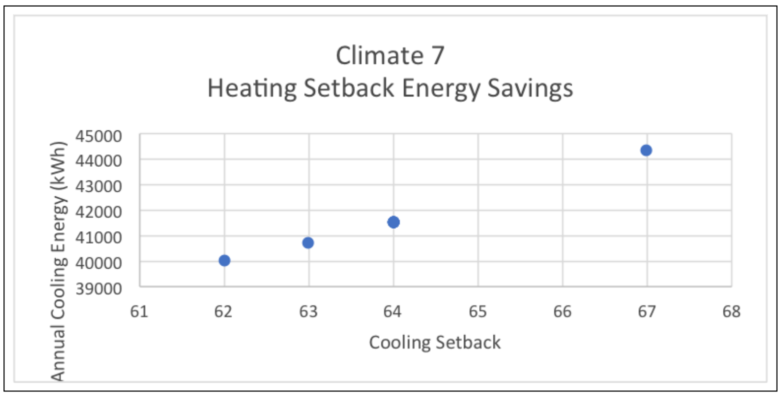

Figure A.29: Cooling 7 heating

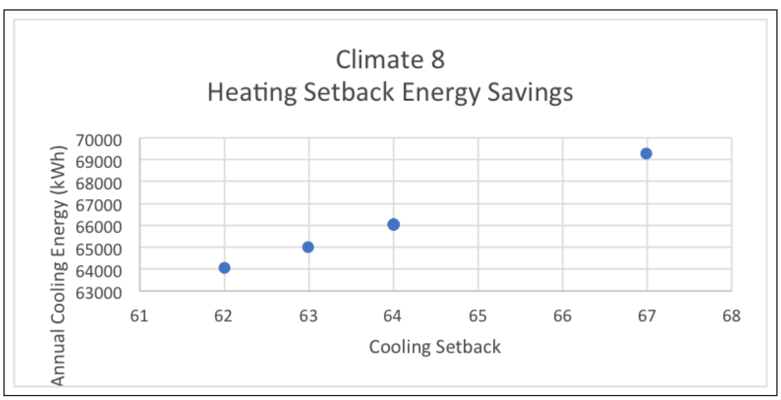

Figure A.30: Cooling 8 heating

APPENDIX B: SITE EXTRAPOLATION MODELS

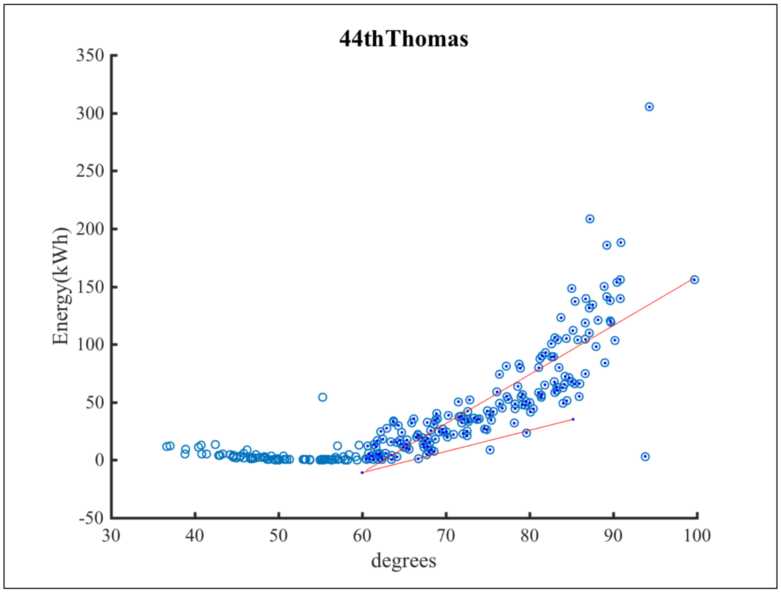

Figure B.1: Extrapolation model 44th Thomas

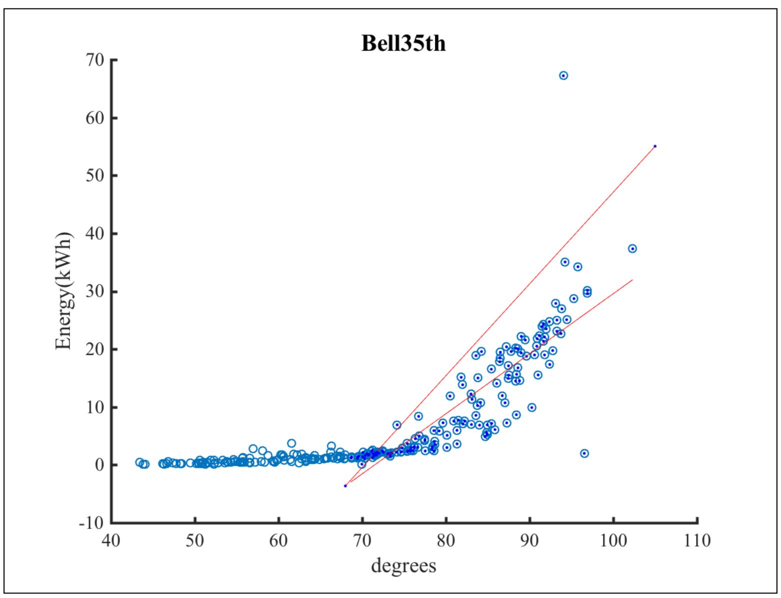

Figure B.2: Extrapolation model Bell 35th

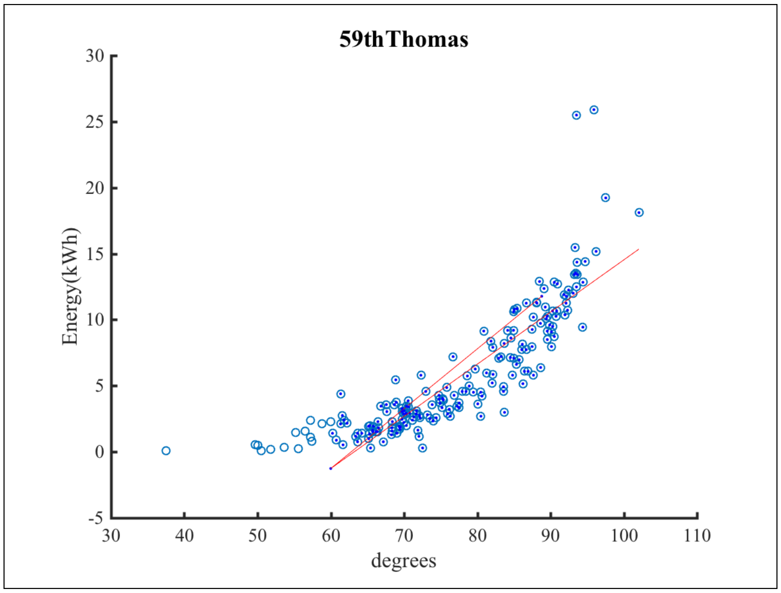

Figure B.3: Extrapolation model 59th Thomas

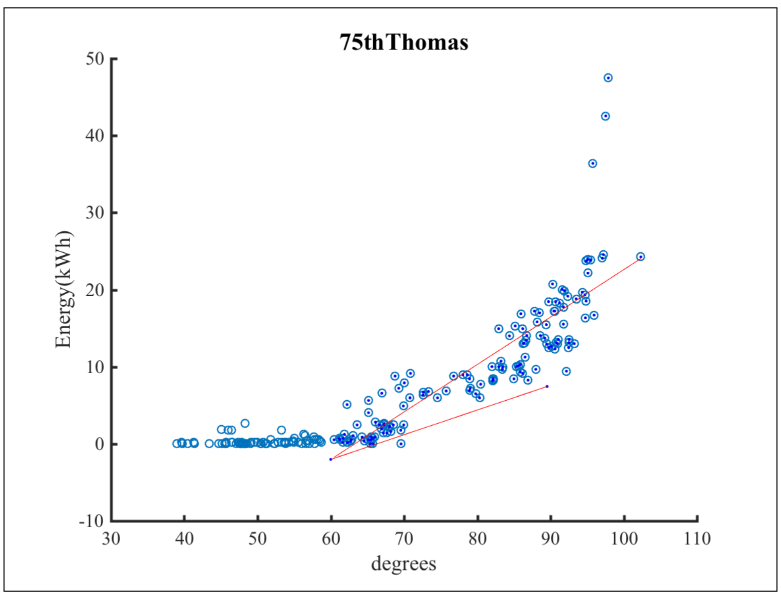

Figure B.4: Extrapolation model 75th Thomas

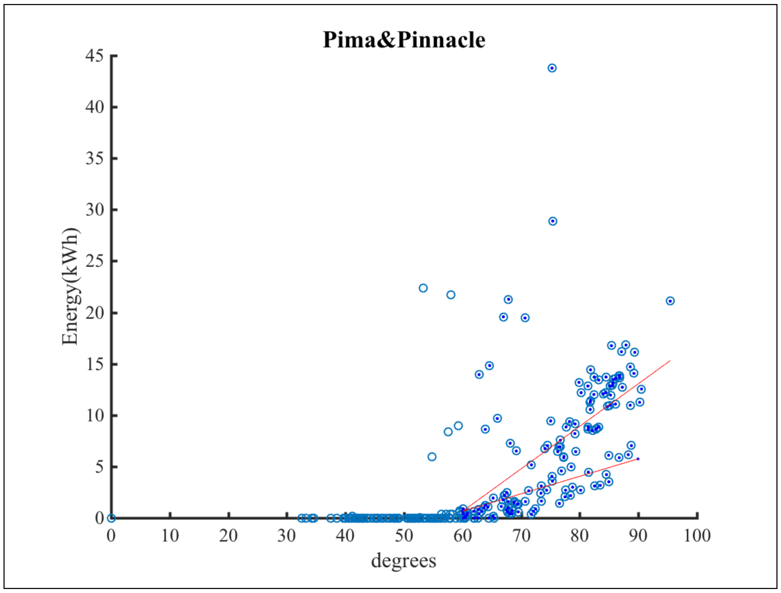

Figure B.5: Extrapolation model Pima Pinnacle

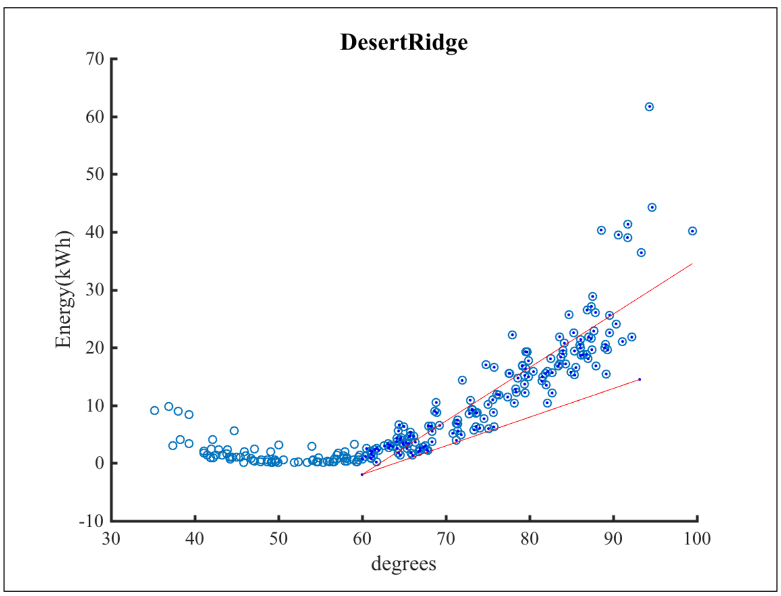

Figure B.6: Extrapolation model Desert Ridge

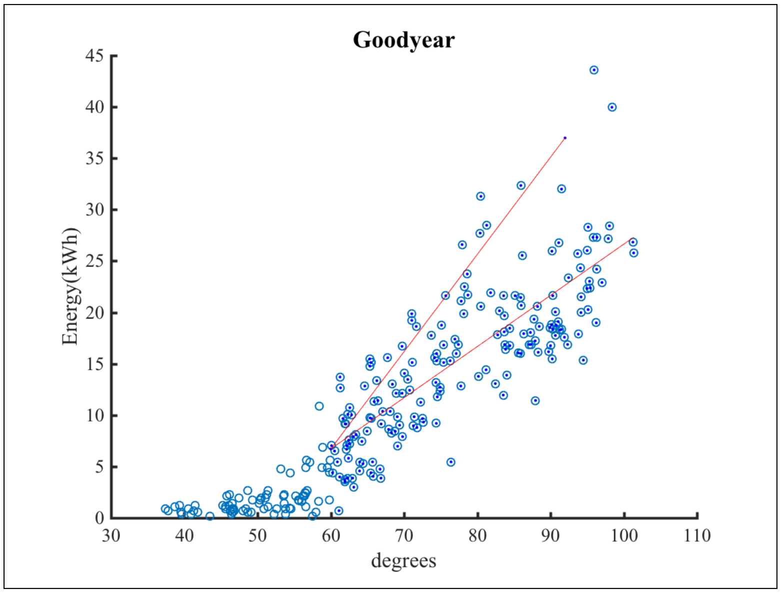

Figure B.7: Extrapolation model Goodyear

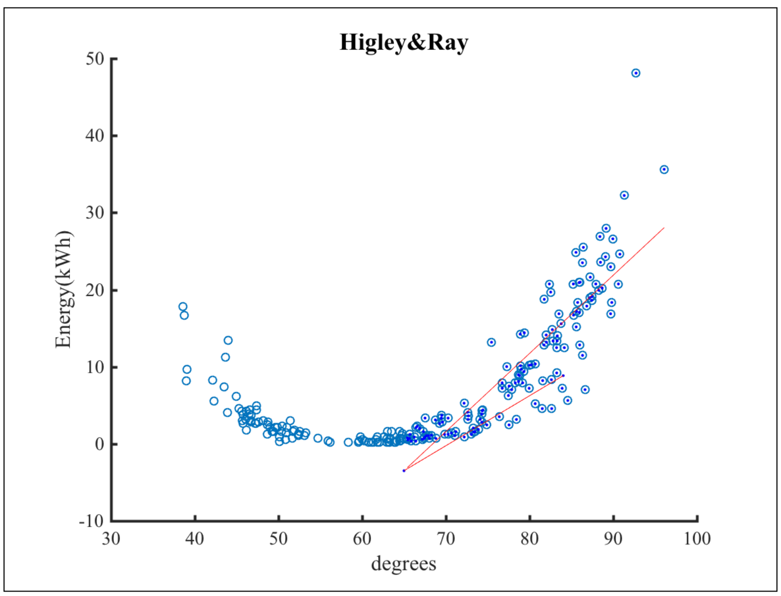

Figure B.8: Extrapolation model Higley & Ray

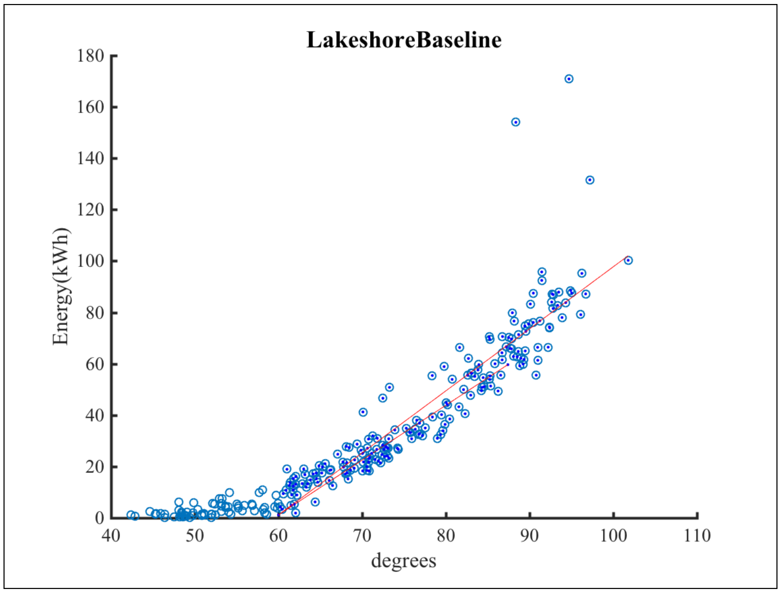

Figure B.9: Extrapolation model Lakeshore Baseline

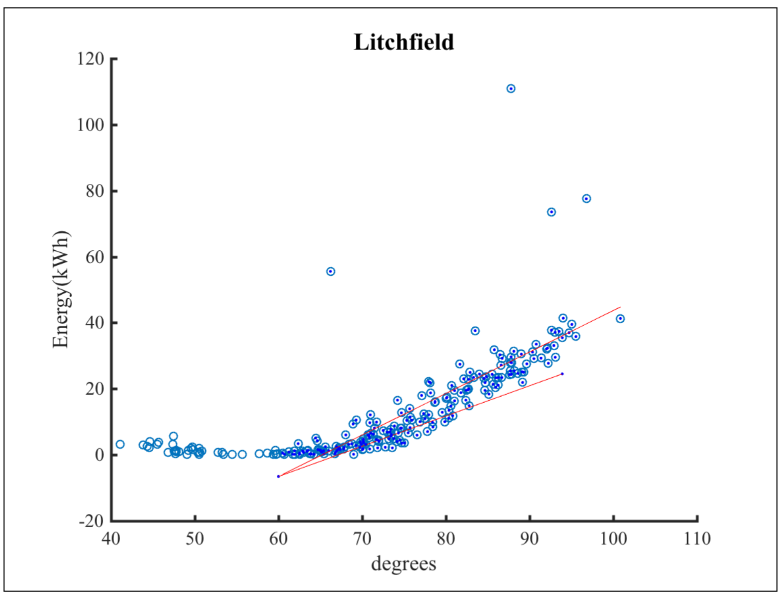

Figure B.10: Extrapolation model Litchfield

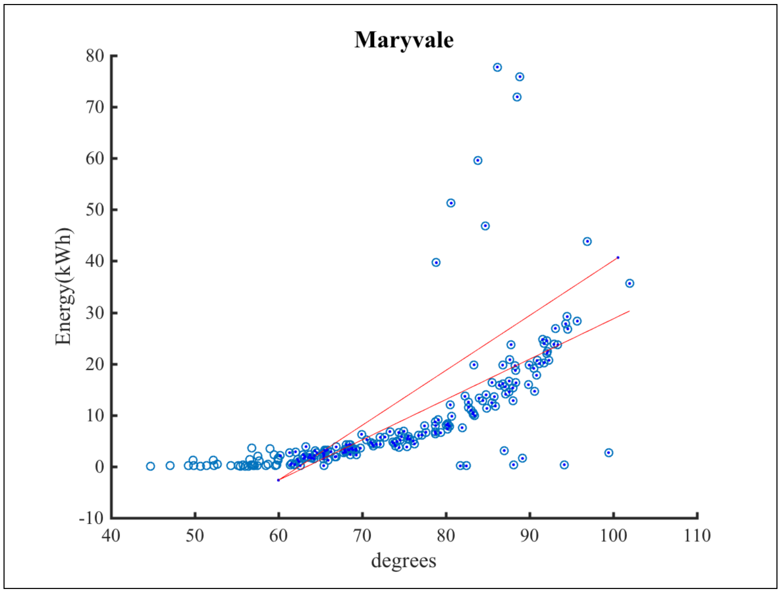

Figure B.11: Extrapolation model Maryvale

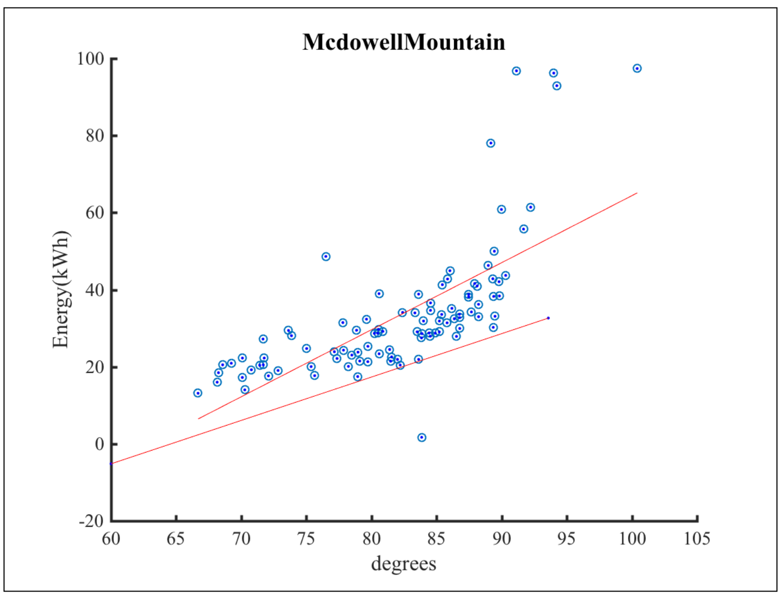

Figure B.12: Extrapolation model Mcdowell Mountain

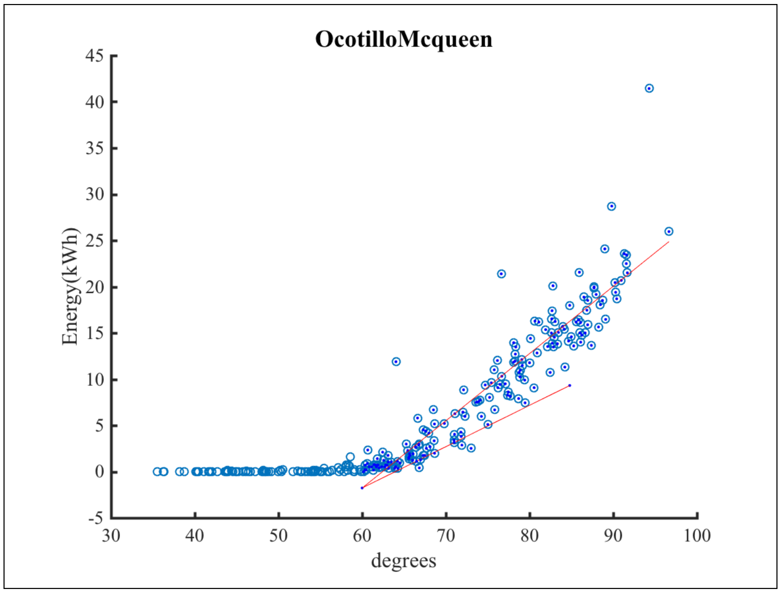

Figure B.13: Extrapolation model Octillo Mcqueen

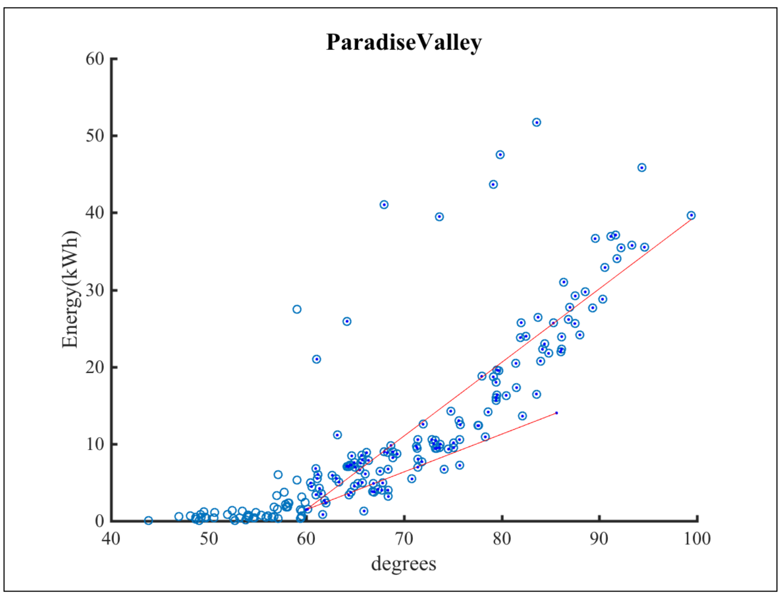

Figure B.14: Extrapolation model Paradise Valley

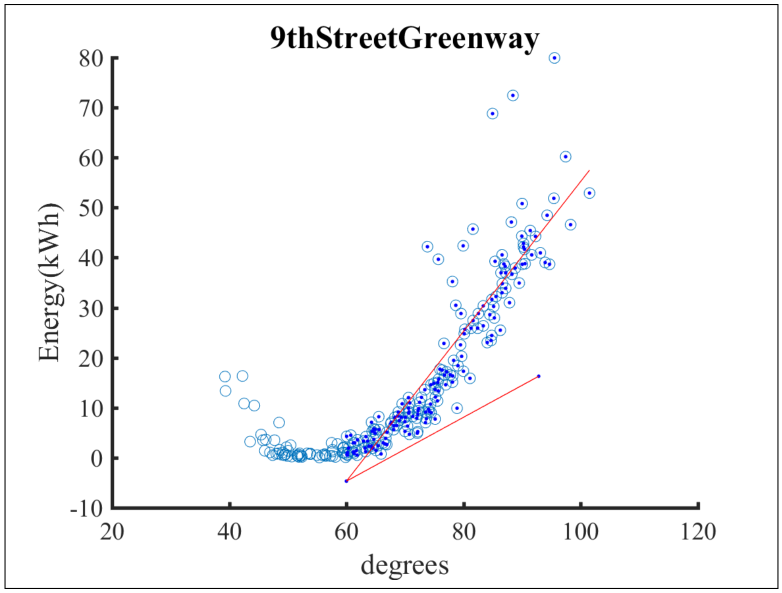

Figure B.15: Extrapolation model 9th Street & Greenway

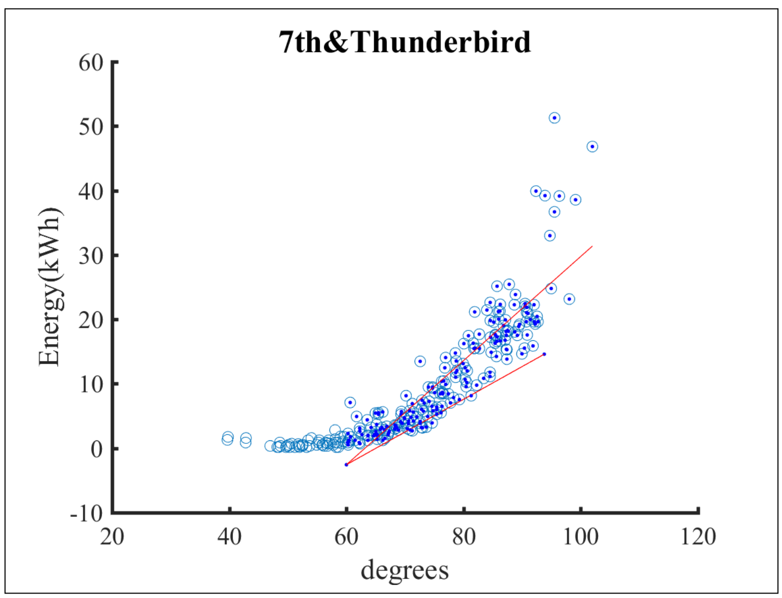

Figure B.16: Extrapolation model 7th & Thunderbird

APPENDIX C: COMPRESSOR RUN TIME CONVERSION TO ENERGY (kWh)

Assumption is typical retail branch uses 3 ton roof top units. We know 1 ton = 12,000 BTUs; therefore, we have 36,000 BTU's when compressor is on. Converting this to KW for mechanical power in equation C.1

$$36,000BTU's * \frac{1KW}{3412BTU's} = 10.55KW_m \tag{C.1}$$

Now we can convert mechanical power to electrical power by assuming the system coefficient of performance to be a value of 3.Equation C.2 shows the conversion to electrical power KW$_e$.

$$\frac{10.55KW_m}{3} = 3.51KW_e \tag{C.2}$$

The electrical power in equation C.2 can now simply be scaled with the cumulative site compressor run time in minutes and converted to kWh.