EVALUATION OF THE NEST LEARNING THERMOSTAT IN A MULTIFAMILY APARTMENT SETTING

by

CHRISTOPHER MCHUGH

(Under the Direction of TOM LAWRENCE)

ABSTRACT

Since 2011, the Nest Learning thermostat, utilizing proprietary occupancy scheduling algorithms and sensors, has transformed the residential and small-commercial programmable thermostat market into a smart thermostat market. Due to usability and design challenges, a majority of people who have programmable thermostats do not properly operate them, often times leading to lower potential energy savings and even higher energy consumption than conventional non-programmable thermostats. Compared to previous thermostats however, the Nest thermostat is designed to learn its occupants' schedules and develop a heating and cooling schedule to best meet its occupants' thermal comfort needs, bridging the usability and functionality gap that exists with previous programmable thermostats. While most thermostat research is focused on single family homes, this study was conducted using a multifamily apartment complex, where occupants were not responsible for their bills. This study emphasizes the importance of using smart thermostats correctly to realize expected energy savings, and how even a "smart" thermostat can fail to save energy if its features are not used.

INDEX WORDS: smart thermostat, Nest thermostat, Internet of Things, HVAC, energy efficiency

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APARTMENT SETTING

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DEDICATION

I dedicate this thesis to my wife Laura Frances. For all the time you have been beside me in school, I’m happy to say these last 2 years we finally were married! Thank you for being patient and loving during my time as a graduate student here at the University of Georgia.

Your husband, Christopher.

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I would like to acknowledge Dr. Lawrence; without you as my professor, mentor, and friend, my time here at the University of Georgia College of Engineering wouldn't be the same. I remember the first time I heard someone talk about you; she said take Dr. Lawrence for heat transfer class, he's an awesome teacher! I'm glad I listened. You have a great teaching philosophy blending the engineering science with the way the real world works, and you have very good advice for all of us upcoming engineers here at the University of Georgia.

I also would like to acknowledge to Dr. Watson. Dr. Watson I remember the first talk that I heard you give about energy informatics in Dr. Lawrence's sustainable design class. The ideas you presented about integrating energy and information to reduce energy were fascinating to me. I am glad that I was able to take your course on energy informatics during my time as a Master's student.

Dr. Johnsen, your enthusiasm and love for technology has always made me appreciate and want to learn more about it. Thank you for all the help and guidance during my time here at the University of Georgia.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

Introduction

Background

Designed to overcome the shortcomings of programmable thermostats, smart thermostats employ occupancy-based temperature management and auto-scheduling. These devices allow remote user control to reduce energy consumption and improve usability. Smart thermostats such as the Nest thermostat from Google, Honeywell's Lyric, and the Ecobee3 thermostat are part of the growing list of smart home devices such as smart wall plugs, door locks, and light bulbs offered that use information (temperature, occupancy, humidity, location, etc.) to reduce energy consumption. While the projected savings for new smart thermostats are very appealing to the consumer, the history of programmable thermostat energy savings potential portrays a mixed reality for this emerging technology.

Empirical field data as well as building energy simulation models from as early as the 1970s suggest that for each degree Fahrenheit reduction in temperature during the nighttime could reduce heating energy use by approximately 3% (Nelson & MacArthur, 1978). The growing popularity of programmable thermostats over the last couple of decades has changed the consumer residential thermostat market. Programmable thermostats gained the support of the U.S. EPA in 1995 with the establishment of the ENERGY STAR program (Environmental Protection Agency (EPA), 2003). The EPA suggested that programmable thermostats could save an average residence upwards of $180 a year over manual thermostats (Environmental Protection Agency (EPA), 2003). Over time however, it became apparent through the rise of conflicting reports that these expected energy savings were not being realized. The mere availability of energy savings features was not sufficient to create savings (Sachs, et al., 2012). In response, the EPA discontinued the ENERGY STAR endorsement in 2009 citing that “while EPA recognizes the potential for programmable thermostats to save significant amounts of energy, there continue to be questions concerning the net energy savings and environmental benefits achieved under the previous ENERGY STAR programmable thermostat specification.” (Environmental Protection Agency (EPA), 2009).

A variety of research studies have been conducted to evaluate the performance and usability of programmable thermostats. It follows now that new research is needed to evaluate new smart thermostat models, which claim upwards of 12-15% potential energy savings over their predecessors (Nest Labs, 2015). Energy savings claims often times are based on best case scenarios in which the thermostat is properly used and maintained, which could be the critical disconnect between expected and realized energy savings (Meier, Aragon, Perry, Peffer, & Pritoni, Making Energy Savings Easier: Usability Metrics for Thermostats, 2011), (Peffer, Pritoni, Meier, Aragon, & Perry , 2011). Only with data from a multitude of socio-economic backgrounds could a generalized claimed ever be truly supported. This research study was conducted to assess the effectiveness of the Nest thermostat in a multi-family apartment setting, in which the residents were not responsible for their electric bill each month. While limited in the number of participants, the results from this research will give insight into the energy efficiency and usability of the Nest smart thermostat in a new context.

Field Test Site Description

The site, Brandon Oaks Family Housing community was selected based on discussion with the University of Georgia Housing facility management team. Brandon Oaks is a small community consisting of three multi-family apartment buildings named Buildings T, U, and V respectively. They share a center courtyard with a playset, as shown below. The front of Building T faces Northwest, Building U faces Northeast, and Building V faces Southeast. Each building has 2 floors above ground, referred to as upstairs and

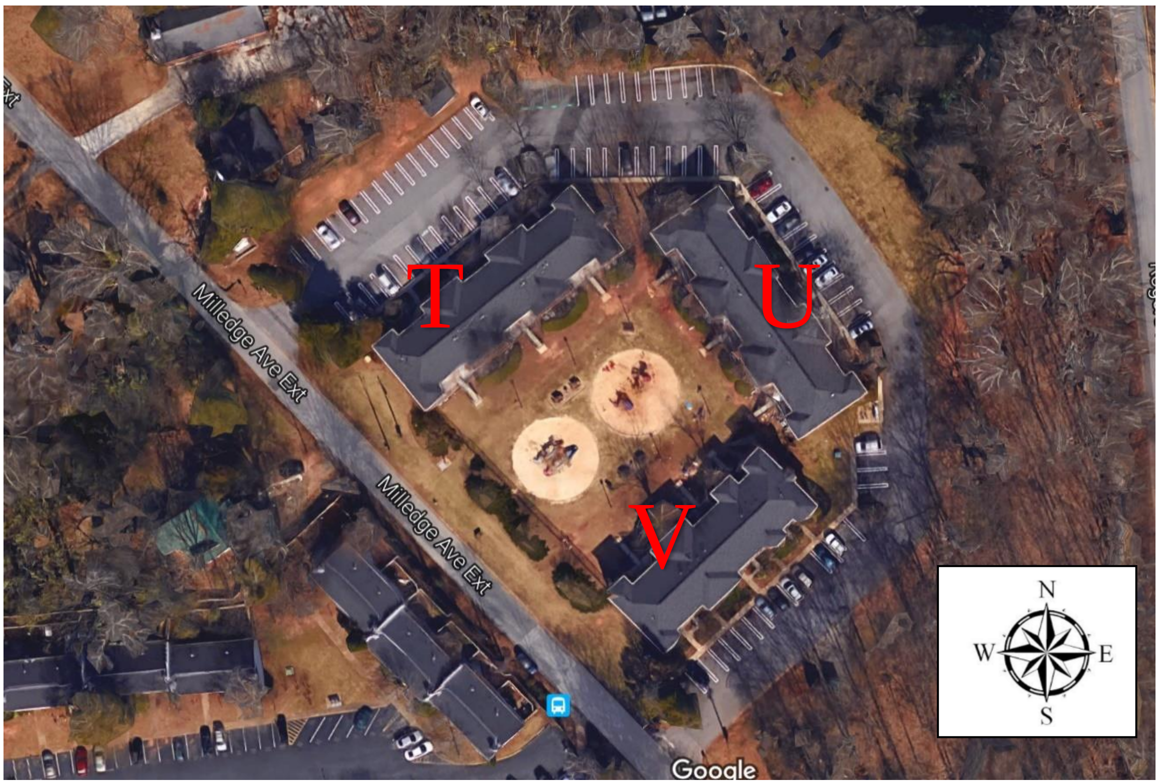

Figure 1 – Brandon Oaks Site Layout

downstairs in this study, and 12 exterior entrance apartments, except building V which has 10 apartments. Each apartment has its own Heating, Ventilation and Air Conditioning (HVAC) unit that is a split single zone air-side heat pump (uses outside air as a heat source in the winter and heat sink in the summer), containing an outside condenser and a heat pump inside, (typically found in a small closet or attic). During a renovation period in 2012, these were all were upgraded to identical Carrier Performance 13 Heat Pumps.

The University's Family and Graduate Housing Authority facility management team conducted the Nest thermostat installations during the first week of July, 2015. Based on installation constraints (not willing to install thermostats randomly) from Family Housing staff, the Nests were installed in each apartment of Building U and V, while Building T thermostats were left in place as the experimental control. The pre-existing thermostats that remained in the Building T units were conventional non-programmable White Rogers thermostats that were installed at the same time as the recent HVAC renovation. Preferably, each building would have Nest and control thermostat apartments randomized throughout to get a more representative sample that accounts for potential building orientation bias. To compensate for not being able to have the thermostats installed randomly throughout the buildings, building energy simulation modeling was used to determine the variations in expected energy usage as a result of different building cardinal orientation and apartment floor level (upstairs versus downstairs).

Field Test Instrumentation

The energy usage of each apartment's HVAC unit was derived from instantaneous current measurements using a CTV-A (AC Amperage to DC Voltage Transducer). Each CTV-A was rated for 2-20 Amps with an accuracy of +- 4.5% of full scale, which includes data logger accuracy. Reading response time (from 10% to 90% of amplitude) is approximately 440 milliseconds. The energy usage of each apartment's HVAC was recorded using an Onset Hobo U12-012 data logger. This data logger has an accuracy of +- 2mV +- 2.5% of absolute reading, which is included in the CTV-A accuracy of +- 4.5%

(Onset Computer Corporation, 2017). Each data logger was set to record the instantaneous current every 5 minutes through the duration of the study. The heat pumps installed in each apartment during the renovation period were Carrier Performance™ 13 Heat Pumps with the following specifications:

1. Seasonal Energy Efficiency Ratio (SEER) = 13
2. Energy Efficiency Ratio (EER) = 11
3. Heating Seasonal Performance Factor (HSPF) = 7.7
4. 208-230 V rating

For full specifications not listed, refer to (Carrier Corp, 2017).

The thermostats installed in the apartments of Buildings U and V are 2nd generation Nest Thermostats, and the control Building T apartments have manual thermostats manufactured by White-Rogers.

Figure 2 – Nest Thermostat 2ND Generation and White Rogers Manual Thermostat (Nest Labs, 2017) and (White-Rogers, 2017).

Field Test Participants

This study has a unique group of participants compared to previously published research studies. New occupants of this apartment complex are randomly assigned an apartment based on an application review by the University Housing Authority, and in order to live at Brandon Oaks, students are required to be registered in a Graduate Studies Program at the University or be a student with a family. The majority of the residents are foreign nationals enrolled at the University. Compared to other smart thermostat studies that were user opt-in, this study's participants had no knowledge of potentially receiving a Nest by living at Brandon Oaks Apartment Complex or had prior knowledge of the Nest installation work done in July, 2015.

Unique Characteristics of Study

As with all research, there are certain limitations of the study. This study has unique characteristics in that:

1. The occupants had no access to the Nest app that allows users to control their Nest with a smartphone or computer.
2. The occupants were all part of a similar demographic (college educated, foreign-nationals).
3. The occupants did not sign-up for this study, and were placed in Nest-installed apartments by random assignment.
4. The Nest thermostats are installed in apartments and not free standing homes, as compared to other published Nest studies.
5. This study is limited in size, only 34 apartments were monitored.

Of the other published studies about the interaction and energy efficiency of the Nest thermostat, each study had a population that was based on user opt-in participation, meaning that users signed up to be a part of the study. Potential reasons for users to sign up for those studies include:

1. The users are tech-savvy, potentially meaning they are already more inclined to be using their current thermostat correctly.
2. The users are aware of their energy usage and seek ways to improve efficiency above what an average participant would know to do.

These reasons are potential sources of bias in previously published studies compared to this research, in which the users were part of the study based on the random assignment to one of the apartment units with Brandon Oaks community equipped with a Nest thermostat, and the electricity bill was included in the overall flat monthly rent of the apartment. Thus, participants of this study had no incentive to save energy compared to participants of other studies.

Objectives of Study

The overall objective of this study is to provide a holistic evaluation of the Nest thermostat in an apartment setting. From this, the research conducted provides:

1. a quantitative evaluation of the energy consumption in apartments with a Nest thermostat compared to a conventional non-programmable thermostat.
2. an assessment of the energy savings performance in a setting in which the occupants are not responsible for the power bill, and not necessarily inclined to save energy.

3. an evaluation of the design and usability features provided by the Nest thermostat.

CHAPTER 2

Literature Review

Introduction

It is intended that this chapter will serve as supporting documentation to the subject matter and methodology presented in this thesis. First, a brief overview of the progression of thermostat technology will be used to highlight the important distinctions between the Nest thermostat and conventional programmable thermostats. Following this, pertinent research related to the overall effectiveness of thermostats to save energy and the usability challenges encountered in thermostat design will be discussed to lay the foundation for why more research should be conducted, especially with the rise of smart thermostat technology.

Progression of Thermostat Technology

The rise of the programmable thermostat over manual (non-programmable) thermostats took place during the 1990s when studies started promoting potential energy savings upwards of 30% that could be obtained by using a programmable thermostat. In 1995, the ENERGY STAR® label was added to programmable thermostats by the U.S. Environmental Protection Agency (EPA), with claims that homeowners could save around $180 a year (Environmental Protection Agency (EPA), 2009). Despite the energy efficiency claims, field studies began to show otherwise (Cross & Judd, 1997), (Haiad, Peterson, Reeves, & Hirsch, 2004), (Nevius & Pigg, 2000), (Shipworth, et al., 2010), showing no significant savings in residencies using a programmable thermostat compared to a non-programmable thermostat (Meier, Aragon, Peffer, & Pritoni, 2010). Due to the effort on behalf Alan Meier, et al. at Ernest Orlando Lawrence Berkeley National Laboratory the report: *Thermostat Interface and Usability: A Survey* contains a comprehensive compilation of supporting research on the topic of thermostat design and usability challenges (Meier, Aragon, Peffer, & Pritoni, 2010).

Internet of Things and the Nest Thermostat

The emerging market of smart home technology is one part of the expanding Internet of Things. The Internet of Things (IoT) is at its most basic definition, the collection of everyday items connected to the internet. Smart home items range from smart-lightbulbs and smart-plugs to smart thermostats and appliances, and more. Specifically, the smart thermostat grew out of the need for something better than the current technology. With the gathering evidence from research that programmable thermostats were not as efficient as advertised, whether that be because of technological design flaws or usability challenges, the Nest smart thermostat was developed with innovate features such as occupancy sensors, auto-scheduling, Wi-Fi-capability, and an app to overcome past challenges of programmable thermostats.

Evaluation of the 2013-2014 Programmable and Smart Thermostat Program by Cadmus Group

This study was initiated by the Vectren Corporation (Vectren), a natural gas and electric provider in the state of Indiana. In 2013-2014 Vectren offered a thermostat program to residential customers who at the time used manual thermostats. Using a subcontractor, Water and Energy Solution, Inc. (WES), 300 Nest and 300 programmable thermostats were installed in homes that were randomly selected from a pool of customers who previously underwent a home energy assessment through the Energizing Indiana Program. After installation, customers received training on how to properly operate their new thermostats. (Cadmus Group, Inc., 2015) A control group consisting of 3845 households using manual thermostats was also included as a baseline for the study.

Vectren hired Cadmus Group LLC to evaluate the program and determine the energy savings from the Nest thermostat compared to the baseline (manual thermostats) and conventional Honeywell TH211 programmable thermostats. (Cadmus Group, Inc., 2015) The main objectives of the evaluation were to evaluate the amount and percentage of gas saved on heating and electricity saved on cooling for each thermostat. To meet the objectives, Cadmus assessed energy savings and participant behavior using a combination of billing data, metered data, and customer surveys. (Cadmus Group, Inc., 2015)

During installation, the contractor (WES), surveyed participants use of their previous thermostat and demographics. Also, Onset UX100-003 data loggers were installed next to the thermostats to monitor inside air temperature, and Onset UX90-004 loggers were installed on each air conditioner's outside condenser to record run time, which was used to calculate HVAC energy usage. Energy savings were determined using pre- and post-installation data as shown below in Table 1 and Table 2. Table 1 shows that participants that received a Nest thermostat had heating gas adjusted gross savings of 12.5%, compared participants that received a conventional programmable thermostat with savings of 5.0% (Cadmus Group, Inc., 2015). From the installed temperature data loggers, it was also shown that Nest average home temperature was 0.2 degrees Fahrenheit lower than homes with a conventional programmable thermostat, and was on average 0.7 degrees lower during normal work hours during the week. This is assumed to be attributable to the

Nest Auto-Away feature, which sets back the temperature when the Nest senses no one is home (Cadmus Group, Inc., 2015).

Table 1 – Nest and Programmable Thermostat Gas Savings as Percentage of Heating Gas Usage

Thermostat Group	Group	Sample Size	Pre Usage (therms)	Savings (therms)	Savings (%)	Range of Savings (therms)	Range of Savings (%)
Nest	Participant	197	548	55	10.0%	47 to 63	8 to 11%
	Control	2,611	575	-14	-2.5%	-12 to -17	-2 to -3%
	Adjusted Gross	**197**	**548**	**69**	**12.5%**	**60 to 77**	**11 to 14%**
Programmable	Participant	184	602	15	2.5%	8 to 22	1 to 4%
	Control	2,611	575	-14	-2.5%	-12 to -17	-2 to -3%
	Adjusted Gross	**184**	**602**	**30**	**5.0%**	**22 to 37**	**4 to 6%**

Table 2 – Nest and Programmable Thermostat Electric Savings as Percentage of Cooling Electric Usage

Thermostat Group	Group	Sample Size	Pre Usage (kWh)	Savings (kWh)	Savings (%)	Range of Savings (kWh)	Range of Savings (%)
Nest	Participant	191	3,080	357	11.6%	206 to 508	7 to 17%
	Control	2,714	3,001	-70	-2.3%	-18 to -122	-1 to -4%
	Adjusted Gross	**191**	**3,080**	**429**	**13.9%**	**270 to 589**	**9 to 19%**
Programmable	Participant	205	2,537	273	10.8%	131 to 415	5 to 16%
	Control	2,714	3,001	-70	-2.3%	-18 to -122	-1 to -4%
	Adjusted Gross	**205**	**2,537**	**332**	**13.1%**	**181 to 483**	**7 to 19%**

As seen in Table 2, participants with both the Nest thermostat and programmable thermostat groups experienced approximately the same reduction in cooling electric consumption (13.9% and 13.1% respectively). It is noted that the Nest participants had a slightly higher average air conditioner run time of 1.8% compared to 1.2% for the programmable thermostat group. Based on the baseline usage for the Nest group, which was 21% higher than the baseline for the programmable thermostat group, this increase in run time was expected. It was assumed to be attributable to higher occupancy in the Nest group homes (Cadmus Group, Inc., 2015).

Energy Trust of Oregon Pilot Evaluation

From the fall of 2013 through the spring of 2014, the Energy Trust of Oregon ran a Nest thermostat heat pump control pilot evaluation to determine if installing the Nest is a viable strategy for properly controlling central electric heat pump operation in residential settings, as well as how to determine potential energy savings during the heating season (Apex Analytic, LLC, 2014). For the study, a total of 185 Nest thermostats were installed for free in participating air-source heat pump-heated homes. Energy savings were assessed by a combination of surveys and energy bill analysis.

The key findings of this study include:

1. The preliminary, weather-normalized, annual electric savings attributable to the Nest were 781 kWh per year or 4.7% of total electric usage and 12% of heating load. (Apex Analytic, LLC, 2014)
2. The most cited reason for participation in the study was to lower energy bills, with 88% of respondents listing it among their top three reasons for participating, followed by 49% wanting to save energy, and 45% to increase the comfort of the home. (Apex Analytic, LLC, 2014)
3. 92% of all second survey (spring 2014) found operating the Nest to be either “somewhat easy” or “very easy”. (Apex Analytic, LLC, 2014)
4. The Auto-Schedule feature was perceived to be the most useful, with 87% of the users in the second survey reporting that the feature was either “somewhat useful” or “very useful”. (Apex Analytic, LLC, 2014)

Nest White Paper

This white paper summarizes the results from three studies of Nest Learning Thermostat energy savings based on comparisons of utility bills from before and after installation. Two of the studies were each independently funded, designed and evaluated -- one conducted in Oregon and the other in Indiana. The third study was performed by Nest using a national sample of Nest customers across 41 states in the U.S. who had also enrolled in Nest's MyEnergy service.

The energy savings results of all three studies were similar -- showing Nest Learning Thermostat savings equal to about 10%-12% of heating usage and electric savings equal to about 15% of cooling usage in homes with central air conditioning. (Nest Labs, 2015)

Unlike other studies on thermostat efficiency, Nest Labs acquisition of MyEnergy allowed for an empirical assessment of energy savings by actual consumers based on changes in their energy usage rather than relying on assumed pre-thermostat behavior. The analysis was performed following the practices as defined by the US DOE Uniform Methods Project – specifically, the guidelines found in "Whole-Building Retrofit with Consumption Data Analysis Evaluation Protocol", which includes two methods for analyzing the energy usage data from before and after installation using a weather normalization procedure (a variable-base degree day regression model (Agnew & Goldberg, 2013).

CHAPTER 3

eQuest v3.65 Building Simulation Analysis

eQuest Building Simulation Analysis Introduction

This chapter describes the use of the energy modeling software eQuest v3.65 to predict the energy usage of each apartment in the Brandon Oaks community. The simulation results were used to determine correction factors that account for the differences in each apartment's energy usage such as floor level (upstairs versus downstairs), cardinal directional orientation, location (corner versus interior apartment), and shading factors from trees or adjacent apartment buildings. With these correction factors, energy data collected from each unit during the study was adjusted to compensate for the expected differences in energy consumption. This is intended to reduce any potential bias between comparisons. Other factors that can affect the energy consumption of the HVAC units include: the number of occupants, occupancy schedules, preferential temperatures, lighting and cooking patterns, etc. While these could be modeled and the predictions used for further adjustments, information on these parameters is not precisely known for each unit, therefore, adjustments for these factors were not done.

This chapter first overviews the eQuest energy model development process, followed by the results of the modeling simulations. Subsequently, there is a discussion of the implications using different correction factors poses on the energy savings calculations. Concluding the chapter, the formulation of the correction factors will be presented.

eQuest Modeling Process

Building energy simulation is used for a variety of reasons including: baseline modeling, code compliance, and energy usage prediction. Two of the fundamental and most widely-used software packages are EnergyPlus and eQuest, although other proprietary software packages are available from HVAC equipment manufacturers. While EnergyPlus has features for modeling that eQuest does not have, eQuest was chosen for this research project because of its established acceptance by the industry, perceived accuracy, and ease of use. Modeling in eQuest allows one to enter detailed information on the building design and operation, and it will use predetermined default design parameters based on typical values for the type of building being modeled if not modified by the user. This feature, helpful for when information about the building is missing or incomplete, was used when needed to aid in the model design process.

The first step in model development was to input the site-specific parameters such as Building Type, Location, and Usage Details.

Table 3 – Project and Site Parameters

Project and Site Data: General Information	
Building Type	Multifamily, Low-Rise (ext. entries)
State	Georgia
City	Athens
Analysis Year	2015
Usage Details	Hourly End-use Profile

By selecting the desired building type, Multifamily, Low-Rise (exterior entries), eQuest uses an autofill on subsequent screens of the Design Development Wizard with typical values for the selected building type: e.g., building size, HVAC system type(s), construction materials, operations scheduling and loading, etc. eQuest uses the location information to identify the corresponding weather file for the simulation (in this case, Athens Georgia). Weather data is in the TMY3 (Typical Meteorological Year, version 3) format as created by the National Renewable Energy Laboratory (NREL), and contains typical conditions for solar radiation and meteorological elements from typical months over the period of record (Wilcox & Marion, 2008).Utilities can be specified to predict cost from the energy simulation; however, this research was focused on the usage of the HVAC system and not the bill. Selecting the Hourly End-use Profile allows for a detailed HVAC operational schedule to be determined later in the model development process.

Using the eQuest graphical user interface, each apartment building footprint was drawn to scale. The dimension parameters were determined by taking measurements onsite and also by using Google Earth mapping software. Orientation of each apartment was input during this stage of the modeling too, with Building T facing Northwest, Building U facing Northeast, and Building V facing Southeast.

Shown below in Table 4, details pertaining to the building envelope were input in the model. While parameters such as construction and exterior finish (wood frame room, wood frame walls, gray shingles, and red masonry brick) were known, insulation parameters were not available. The values for the insulation were selected using typical values for a multifamily exterior entry (low-rise) apartment building from eQuest's predetermined default design parameters.

Table 4 – Building Envelope Parameters

	Building Envelope Constructions		
	Roof Surfaces	**Above Grade Walls**	**Ground Floor**
Construction	Wood Std. Frame	Wood Frame, 2x4, 16 in. o.c.	6 in. concrete
Ext Finish/Color	Roof Shingle, Gray, dark	Brick, red, masonry	N/A
Exterior Insulation	none	1/2 in. fiber bd. sheathing	N/A
Add. Insulation	none	R-11 Batt	N/A
Exposure	N/A	N/A	Earth Contact
Interior Finish	N/A	Drywall finish	Carpet with fiber pad

After going through the Project and Site Data menus, the HVAC system and operational parameters were entered. Each apartment has a split single zone air-source heat pump HVAC system that is ducted as seen in Table 5.

Table 5 - HVAC System Parameters

HVAC System Definition	
Cooling Source	DX Coils
Heating Source	DX Coils (Heat pump)
Heat Pump Source	Air
System Type	Split Single Zone Heat Pump
System per Area	System per Zone
Return Air Path	Ducted

The HVAC system design temperatures for cooling and heating shown below in Table 6 were determined by the typical values suggested by eQuest, as the values were not known.

Table 6 – HVAC System Design Temperatures

HVAC System Design Temperatures in Degrees in Fahrenheit			
Cooling Design		**Heating Design**	
Indoor	**Supply**	**Indoor**	**Supply**
75	55	72	90

Each apartment's HVAC system was modeled using the same thermostat operating temperature set points, as seen in Table 7. While the information about each apartment's actual set points was known, it was not input into the model. This was decided so that the difference in each model's simulation results could be attributed to the key parameters (building orientation, apartment location within the building, and shading factors) and not be influenced by the occupant's temperature preference.

Table 7 – HVAC System Set Points

HVAC Zones: Temperature and Air Flows in Degrees Fahrenheit			
Occupied		Unoccupied	
Cool	Heat	Cool	Heat
78	68	78	68

From a complexity standpoint, modeling multi-unit apartment building can be tedious; fortunately, Brandon Oaks apartments are all identical in design on the interior except for characteristics such as symmetry and location within the overall building. This made the zoning straightforward to apply to the model. A zone represents the total area associated with thermostat, which in this case is each individual apartment unit. Each zone was assigned a separate but identical HVAC system. As seen in Figure 3, the building footprint is broken down by apartment corresponding to individual zones.

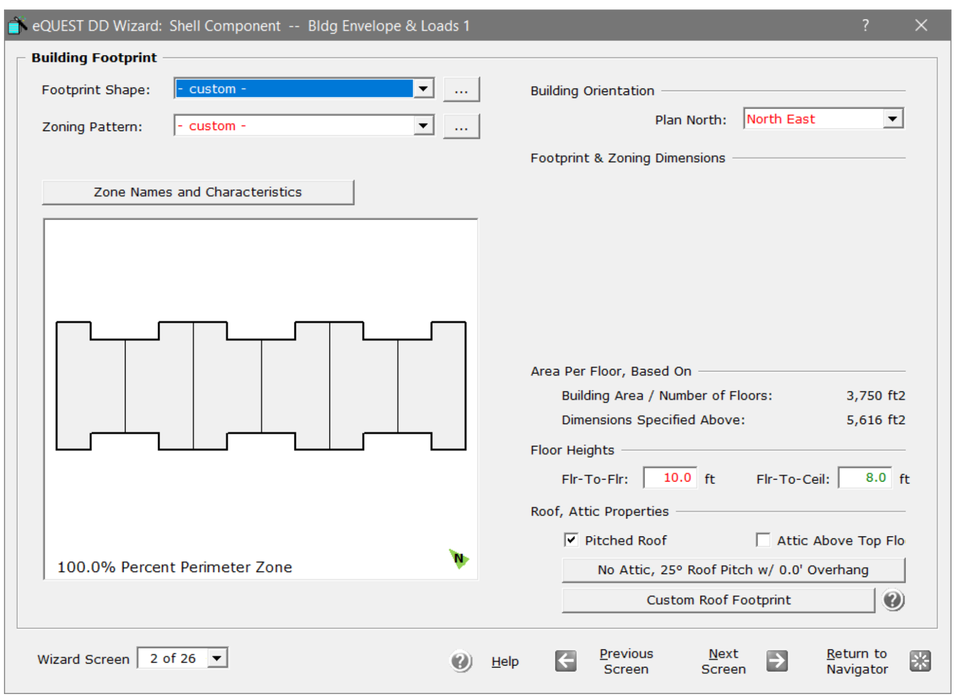

Figure 3 – Apartment HVAC Zoning Pattern

Each zone created in eQuest has its own designated meter that delinates each zone's energy usage by source. In this study, only the factors directly related to the HVAC energy usage were of concern, so they were the only systems selected below. Shown below in Figure 4, by assigning each desired HVAC system energy source to T-1, corresponding to Building T apartment unit 1, eQuest calculated summary and end-use totals for each category: Space Heating, Space Cooling, Heat Rejection, Ventilation Fans, and Supplemental Heat. This process was used for each apartment.

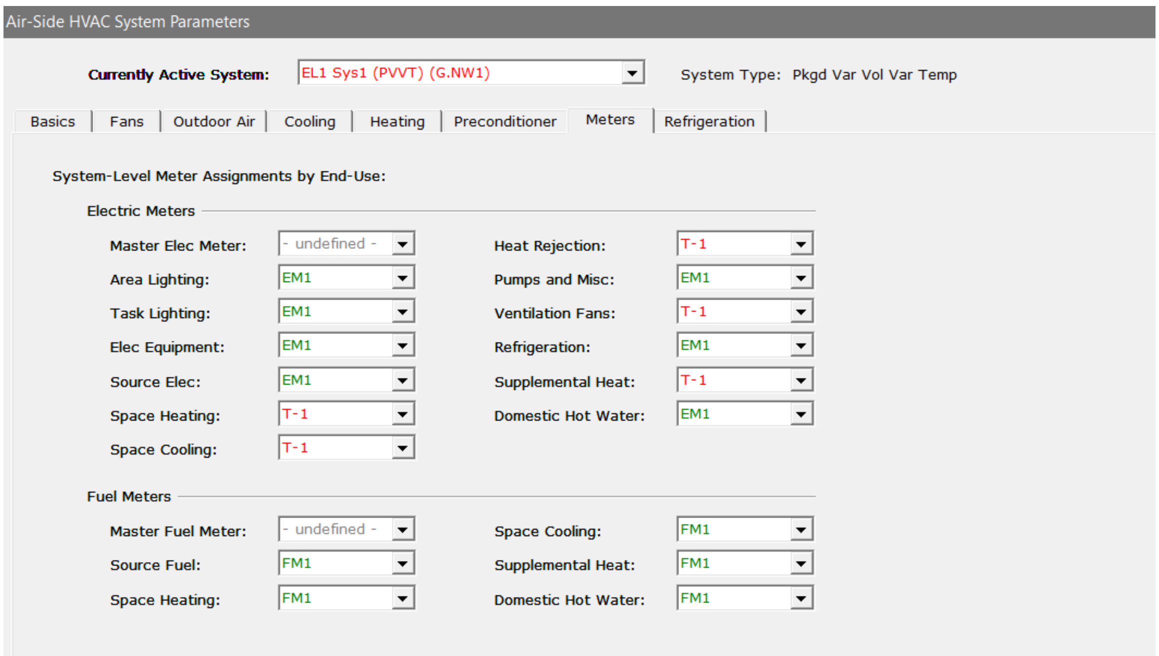

Figure 4 – Air-Side HVAC System Parameters

Subsequent menus in the modeling process were used to finalize the selection of windows and doors, create the decks that 2nd floor apartments have, and to place them accordingly on each building. Measurements made on site were taken using a standard 25-foot measure tape to determine the size and placement of the windows and doors. The dimensions of the front and back decks of the 2nd floor apartments were also recorded and input into the model during this stage. The decks were added to each model because of their potential to shade the ground-level apartments, affecting the amount of solar heat gain and consequently the potential HVAC usage.

Below in Figure 5 and Figure 6, the 3-dimensional models of Building T and Building U are shown to highlight the addition of shading factors added to each model. Building V, not pictured, also has the same shading factors applied. The shading factors were created in eQuest using the fixed building shade feature, in which the user can specify the location, dimensions, and transmittance of objects that potentially shade the building model. In Figures 5 and 6, the gray semi-circle surrounding the apartment building represents the tree-line of mature oak and pine trees surrounding the Brandon Oaks apartment complex. The location and dimensions of the tree-lines were determined using Google Earth and visual inspections.

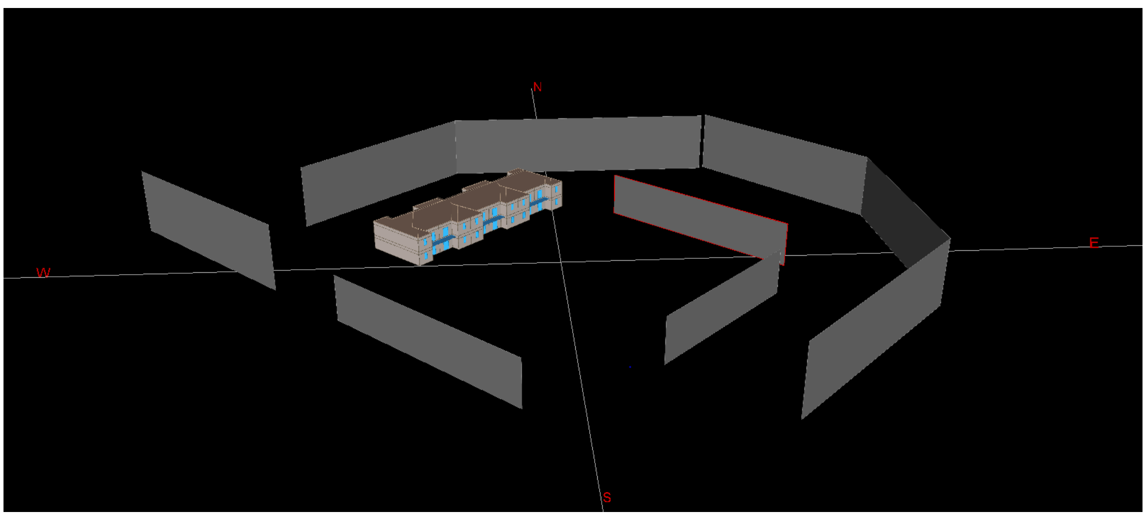

Figure 5 – Building T 3-D eQuest Model

Lastly, the lines perpendicular to the semi-circle in Figures 5 and 6 represent the potential shading as a result of an apartment building and another tree-line across the street from Brandon Oaks Community. (See Figure 1 for Google Earth image). The transmittance ratio of the adjacent apartment buildings in each of the energy models created was set at 0, meaning that they are opaque, and the transmittance ratio for all of the tree-lines was set to 0.50. In reality this value would vary throughout the year, being higher in the summer when the trees are densely covered in leaves and lower in the winter when the trees are bare. The value of 0.50 represents more of an average value considering the different seasons of the year, rather than having separate values for different seasons. (Lei, 2010)

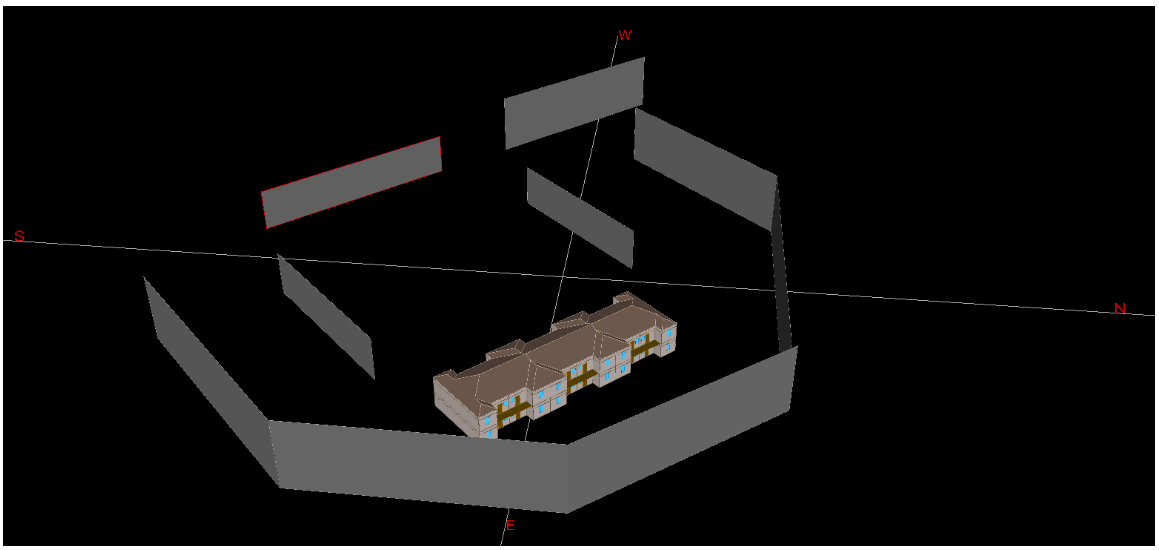

Figure 6 – Building U 3-D eQuest Model

eQuest Simulation Results

The predicted energy consumption results for each building were calculated using hourly predicted weather and energy usage data and then reported on a monthly basis by the eQuest model. Each building's energy model results are summarized by apartment for each month in total kWh. (See Appendix Figures 13 - 15). As expected, the data was bimodal, with the main peak energy use in the cooling season followed by a lower peak energy use in the heating season. Figure 7 conveys the monthly predicted energy usage for each apartment within Building T.

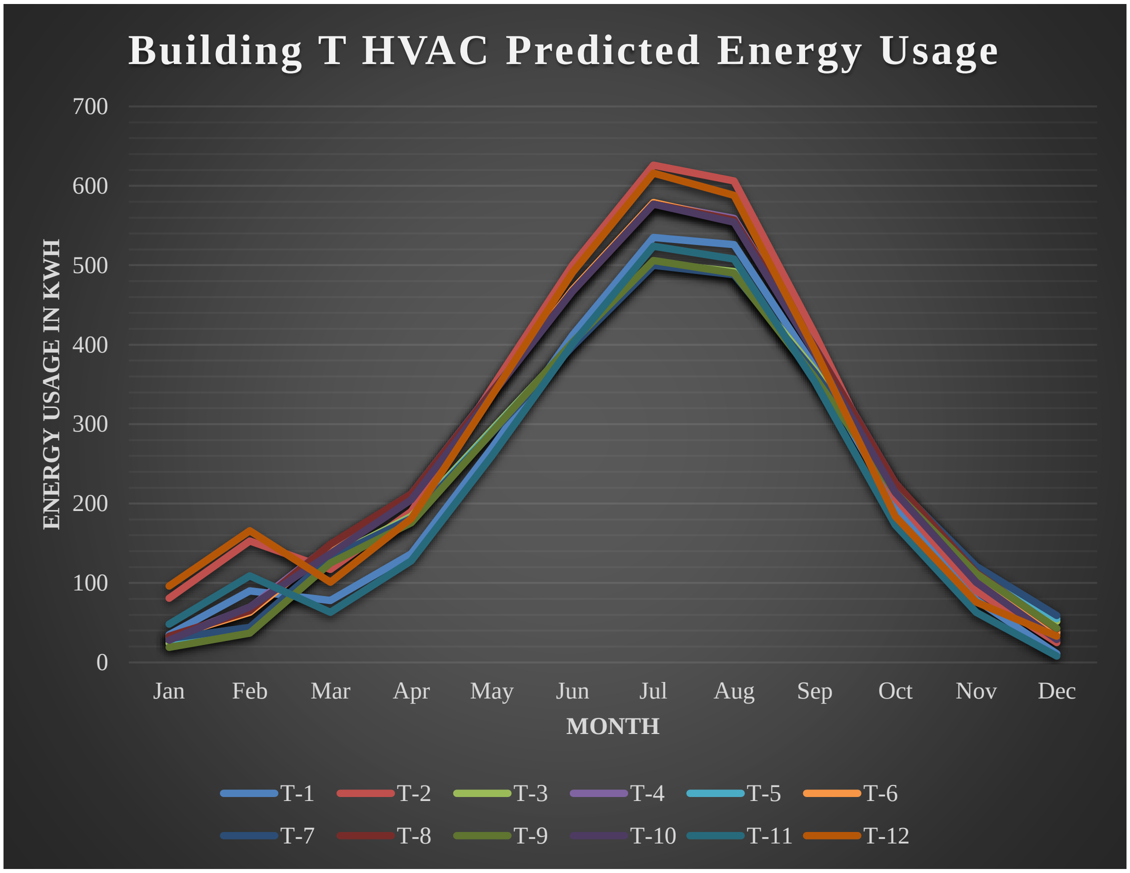

Figure 7 – Building T Predicted Energy Usage Graph

Looking at the graph, there is considerable variability among the apartments of Building T, which is quantified below in Table 8 along with the expected variability in the apartments of Building U and Building V. The heating season in Table 8 is defined as the months of December, January, and February, which have the most consistent mean temperatures: 45.4, 43.5, and 47.2 degrees Fahrenheit respectively, and the cooling season is defined as June, July, and August based on the mean temperatures: 77.5, 80.6, and 79.6 degrees Fahrenheit (See Appendix Table 47 Summary of Monthly Normals 1981-2010). The cooling and heating seasons were derived by using historic temperature data collected from nearby Athens Ben Epps Airport that is recorded and managed by the National Oceanic and Atmospheric Administration (NOAA). Table 8 shows the mean predicted energy use and sample standard deviation for each building. Calculated from the predicted mean seasonal energy use, the % Difference column shows the percent difference in predicted energy use of Building U compared to Building T as well as Building V compared to Building T. This was done according to the experimental setup, with Building T as the control.

Table 8 – Predicted Mean Seasonal Energy Use by Building Average Method

	Predicted Mean Seasonal Energy Use in kWH by Building Avg.		
Building	**Heating Season**	**Std. Deviation**	**% Difference**
T	51.8	23.8	
U	59.7	24.7	**15.2%**
V	73.1	46.5	**41.1%**
Building	**Cooling Season**	**Std. Deviation**	**% Difference**
T	508.9	60.4	
U	510.4	59.8	**0.3%**
V	523.1	59.9	**2.8%**

Looking at the % Difference column, there is considerable variation. During the heating season the predicted percent difference in energy use for the Nest-installed Buildings U and V is 15.2% and 41% when compared to the control Building T. The 15.2% predicted energy use increase of Building U can be explained by the building orientation and shading from the surrounding trees and structures, while the 41.1% increase in predicted energy use of Building V is better explained by a combination of building layout, orientation, and shading. Building V is unique from Building T and U as explained in CHAPTER 1; it has ten apartments instead of twelve apartments. Because of this layout difference, the apartments of Building V on the East of the building have more exterior wall space compared the apartments in Buildings T and U. (See Chapter 1, Figure 1). This increased amount exterior wall space has more potential for heat transfer to the surrounding outdoor environment. The same trends are also found in the predicted energy difference during the cooling season, with the exception that the predicted percent difference is much closer to the control building: 0.3% and 2.8% increase in predicted use for Building U and Building V, which is based on the mean values being compared.

Based on the variation observed when analyzing the overall predicted mean seasonal energy use, the predicted energy difference calculation was broken down by apartment floor (upstairs and downstairs). This was done to evaluate the predicted differences of apartments using a more representative grouping than what was previously determined using a total building average.

Table 9 – Predicted Mean Seasonal Energy Use by Upstairs Apartment Average Method

	Predicted Mean Seasonal Energy Use in kWH by Upstairs Avg.		
Building	**Heating Season**	**Std. Deviation**	**% Difference**
T - upstairs	60.50	33.19	
U - upstairs	71.06	33.60	**17.45%**
V - upstairs	91.87	54.21	**51.85%**
Building	**Cooling Season**	**Std. Deviation**	**% Difference**
T - upstairs	546.39	61.11	
U - upstairs	554.44	60.45	**1.47%**
V - upstairs	570.20	60.15	**4.36%**

Table 9 conveys the mean predicted seasonal energy use of the average for each building's group of upstairs apartments. For example, in Table 9 the predicted mean seasonal energy use for upstairs apartments in Building T during the heating season is 60.50 kWh. This represents an average of the predicted mean usage for every apartment on the upstairs level of Building T, corresponding to apartment units: T-2, T-4, T-6, T-8, T-10, and T-12. Table 10 contains the same comparisons for each building's group of downstairs apartments.

Table 10 – Predicted Mean Seasonal Energy Use by Downstairs Apartment Average Method

	Predicted Mean Seasonal Energy Use in kWH by Downstairs Avg.		
Building	**Heating Season**	**Std. Deviation**	**% Difference**
T - downstairs	43.17	15.73	
U - downstairs	48.39	16.78	**12.10%**
V - downstairs	54.40	39.02	**26.02%**
Building	**Cooling Season**	**Std. Deviation**	**% Difference**
T - downstairs	471.33	59.69	
U - downstairs	466.39	59.12	**-1.05%**
V - downstairs	475.93	59.78	**0.98%**

By comparing the percent difference values in Table 9 and Table 10 to the percent difference values in Table 8, one can see the implications of overlooking the distinction between upstairs and downstairs apartments. This can be seen clearly in Table 11, which shows the percent difference either overestimated or underestimated by using an entire building's average compared to a building's downstairs average or to a building's upstairs average. For example, the Difference column in Table 11 indicates that a predicted mean seasonal energy usage is <u>overestimated</u> when using the building average method compared to using the downstairs average or upstairs average method if the difference is a <u>positive</u> percentage. In addition, the Difference column also shows that the predicted mean seasonal energy usage is <u>underestimated</u> if the difference is a <u>negative</u> percentage. For Building V during the heating season, the difference between the predicted mean seasonal energy usage % Difference using the building average method and downstairs average method % Difference is 15.07%, which is calculated by subtracting the Downstairs Avg. Column from the Building Avg. Column (41.09% - 26.02% = 15.07%). The positive 15.07% indicates that using the Building Avg. predicted mean seasonal energy usage during the heating season for Building V would overestimate the predicted mean seasonal energy for an apartment located on the downstairs floor of Building V by 15.07%, whereas during the heating season for an apartment on the upstairs floor of Building V, its predicted mean seasonal energy usage would be underestimated by 10.76%, as indicted by a negative percentage value.

Table 11 – Comparison of Building Average Method versus Floor Average Methods

		Comparison of Building Average Method versus Floor Average Method		
Heating Season	**Building**	**Building Avg.**	**Downstairs Avg.**	**Difference**
	T			
	U	15.22%	12.10%	**3.12%**
	V	41.09%	26.02%	**15.07%**
	Building	**Building Avg.**	**Upstairs Avg.**	**Difference**
	T			
	U	15.22%	17.45%	**-2.23%**
	V	41.09%	51.85%	**-10.76%**
Cooling Season	**Building**	**Building Avg.**	**Downstairs Avg.**	**Difference**
	T			
	U	0.31%	-1.05%	**1.36%**
	V	2.79%	0.98%	**1.81%**
	Building	**Building Avg.**	**Upstairs Avg.**	**Difference**
	T			
	U	0.31%	1.47%	**-1.16%**
	V	2.79%	4.36%	**-1.57%**

Note that the Difference column in Table 11 is still in relation to the percent difference found when comparing a grouping of apartments in Building T against that same grouping in Building U or Building V. It is also important to notice that the seasonal differences are more pronounced using the upstairs average method than when using a downstairs average method. This seasonal variability seen in the two groups can be attributed to the heat transfer interaction between the roof and upstairs apartments. The increased amount of building envelope (presence of roof) that upstairs apartments have above their ceilings results in more conductive and convective heat transfer than downstairs apartments.

Correction Factors

With the predicted data, correction factors were developed to modify the actual observed data sets. This modification, as explained previously, is meant to account for the expected variation in energy usage due to the differences in building orientation, apartment location within each building, and the shading from surrounding buildings and environment. The calculation of each correction factor is determined by dividing the predicted mean seasonal energy usage of each Building U or Building V by the predicted mean seasonal energy usage of Building T. This gives the expected kilowatt-hour increase or decrease percentage for a given comparison based on the control building.

Equation 1:

$$Correction\ Factor = \frac{\text{predicted Building U or V group}}{\text{predicted Building T group}} * 100\%$$

Where, group refers to the group average method desired either building average or floor average method.

Correction factor tables can be referenced in the Appendix Tables 33 - 35, where each correction factor table corresponds to a group average method such as the building average and floor average methods discussed previously. For a given correction factor, the observed data is adjusted by using the following equation:

Equation 2:

$$Adjusted\ Observed\ Data = \\ Observed\ Data\ for\ Building\ U\ or\ V\ group \\ - (Observed\ Data\ for\ Building\ T\ group * Correction\ Factor)$$

Where, Observed Data for Building U or V refers to a specified time period such as heating or cooling season for either Building U or Building V and

Where, Observed Data for Building T and the correction factor both correspond to that same time period.

CHAPTER 4

Methodology

Introduction

To meet the quantitative objectives of this study, data was collected and compared between the control group and the test groups. Conventional energy studies monitor pre- and post-installation energy usage. This was planned, but the scope to which it was accomplished was limited by time constraints for the study and by the challenges associated with occupants moving in and out of apartments (something not typical to the other residential home studies). Pre-installation data is available for every apartment for the time period: April 2015 – June 2015. While not a full year as typically desired, the data gives some indication of the differences observed between the buildings. Energy models were developed and used to account for the expected differences between apartment buildings based on footprint and location. After correcting for expected differences, comparisons were made for both heating and cooling seasons, defined as the months of December through February and June through August respectively. This study was conducted over the course of summer 2015 through winter 2017, which contains one cooling season and two heating seasons.

The qualitative objectives of this study were limited from the beginning of the study because of restrictions with human test subjects in place by the University. It was intended to use pre- and post- installation questionnaires to assess the participant's knowledge and awareness of energy usage and thermostat technology. This was not accomplished due to the timing associated with getting institutional review board (IRB) approval, also known as research ethics board (REB). University network security issues were also the reason that occupants did not receive access to the Nest app. A procedure was eventually developed to allow for access, but it was not implemented in time for participants to use and evaluate. Inference was used to evaluate design and usability features of the Nest. Based on data collected by the researcher from each Nest account, interpretation was made as to common challenges faced by occupants when using the Nest. Information was also collected from the Family and Graduate Housing Maintenance staff about issues encountered during the study.

It is intended that through this study the basis for a larger test group would be justified, and with the results of this study, future research would be used to validate the effectiveness of the Nest thermostat to save energy in an apartment setting. Potentially the University of Georgia might also use the results of this study to determine if investing in Nest thermostats for the remaining Brandon Oaks apartment building T units and in other University Housing facilities is cost effective.

<u>Data Measurements</u>

As referenced in Chapter 1 Field Test Instrumentation, data loggers were used to record the CTV-A instantaneous current readings for the duration of the study. During installation, the logging equipment was set to record measurements every five minutes. This was decided so that the data could better capture when each HVAC unit was running or not running, as compared to taking measurements over longer time periods. Note that although the data was recorded every 5 minutes, it was reported by the data logging software as an hourly average. This is so that the data could be easily interpreted and used in energy calculations and matched with weather data if desired. Using the average hourly instantaneous current, the estimated monthly average daily kilowatt-hour usage was calculated. With the monthly average daily kilowatt-hour usage, equivalent comparisons were able to made between the model predicted data and the observed data sets. The advantage of using a monthly average daily kilowatt-hour usage instead of a sum monthly total kilowatt-hour is that the process of excluding missing data from the analysis is much easier to perform. Whereas an average can be compared directly to another average for a given month, a sum total that includes missing data would have to be corrected based on the number of times that data is excluded from the sum total in order to make a similar comparison based on another data set's period of reference.

Logger Bias Adjustments

The process to refine the raw data and determine the monthly average daily kilowatt-hour usage was done in parts starting with adjusting for potential data logger bias. As mentioned in Chapter 1 Field Test Instrumentation, the data loggers and CTV-A have a small amount of bias that can be seen. It is expected that when an HVAC unit is not running that the equipped CTV-A should not detect a current; however, looking at the data sets, a small current under 0.2 Amps was frequently detected across all of the loggers. To correct for the potential bias observed in the data sets a MATLAB script was created and implemented to modify each data set.

The script looped through each recorded current measurement in a data set and determined if the HVAC unit was running or not running based on the value of the instantaneous current. If an instantaneous current measurement was found to be less than 0.2 Amps, then it was set as the bias. This bias value was subtracted from every subsequent value until the HVAC unit was found to be turned on and then back off, in which case a new bias would be determined and used. Using this method, the bias is not reflected in the total energy usage calculation.

Table 12 – Measurement Bias Calculation Example

Timestamp	Current (Amps)	Corrected Current (Amps)
4/18/2015 11:00	0.062	0
4/18/2015 12:00	2.121	2.059
4/18/2015 13:00	0.028	0
4/18/2015 14:00	0.027	0
4/18/2015 15:00	0.025	0
4/18/2015 16:00	0.568	0.543

As seen above in Table 12, the first row has a current reading of 0.062 Amps, so it is set as the bias, since it is less than 0.2 Amps. On the following row, the HVAC current is 2.121, which is above 0.2 Amps, and thus determined to be running. Notice the Corrected Current column shows the values adjusted for the bias. The value of 2.059 is calculated by subtracting the bias value of 0.062 Amps from the current of 2.121 Amps at the 12:00 timestamp. Upon the next timestamp, the HVAC unit is determined to not be running, so the script sets a new bias value each iteration until it reaches a value above the 0.2 Amps threshold. At the 16:00 timestamp when the HVAC unit is determined to be running again, the previous bias of 0.025 Amps is subtracted to give a corrected current measurement of 0.543 Amps.

<u>Data Transformation</u>

After correcting each data set for the inherent logger bias, the data was transformed from an hourly average instantaneous current to a monthly average kilowatt-hour usage.

The calculation from hourly average instantaneous current to monthly average kilowatt-hour is as follows.

Equation 3:

$$\frac{\text{hourly average instantaneous current} * \text{voltage}}{1000\ watts\ per\ kilowatt} * 24\ hour\ per\ day$$
$$= average\ daily\ kilowatthours$$

Where, voltage is the voltage supplied to the unit is assumed to be 220 volts.

Equation 4:

$$\frac{\sum average\ daily\ kilowatthours}{recorded\ days\ per\ month} = monthly\ daily\ average\ kilowatthours$$

Where, recorded days per month is the number of days without missing data for each apartment's data set.

Handling of Missing Data

During the study, some of the data loggers lost power, and consequently, did not record measurements until restored. When calculating the average daily kilowatt-hour, it is important to note that gaps in the data set were handled accordingly so as to not influence the averages calculated. Using recorded days per month instead of the number of days in each month, the calculated monthly daily average reflects a true daily average for each month and is not influenced by zero value days when the loggers failed. The amount of missing data varies for each data logger; overall however, there were not very many gaps in the data because the batteries inside each data logger were replaced as needed during routine maintenance trips (roughly every 6-8 weeks), in which data was saved from each logger to an excel database and battery levels were checked. (See Appendix Tables 44-46).

Handling of Bad Data

There were several data loggers throughout the study that failed in other varying capacities to accurately record the data, whether that be because of data logger malfunction or CTV-A malfunction. (See Appendix Tables 44-46). The data derived from such events was handled in the following ways:

1. The data logger of Building T apartment 4 (T-4) returned no values throughout the duration of the study. As such the energy usage information from T-4 is unknown and therefore excluded from this study.
2. The data logger of Building T apartment 8 (T-8) and Building U apartment 19 (U-19) began to return extremely high values after a routine maintenance visit during November 2015, as such the corrupt data (November 2015 – December 2015) is excluded from the energy usage calculations.
3. The data logger of Building T apartment 11 (T-11) began to return extremely high values after a routine maintenance visit during August 2016. Unfortunately, from August through the end of the study in February 2017, the data logger continued to have issues with recording values, as such the corrupt data is excluded from the energy usage calculations.
4. The Nest thermostat installed inside of Building U apartment 20 (U-20) was removed due complaints of the occupants and replaced with the Nest thermostat installed originally in U-23 by Family and Graduate Housing Maintenance Staff. This was decided by the maintenance group because at the time no one was living in apartment U-23 and it was convenient. Whether there was actually a malfunction or not, the data from U-23 after the switch at the beginning of

2016 was excluded since the Nest Thermostat was not installed through the duration of the study. Note that human interaction such as this will be addressed in Chapter 6 Human Factors Analysis.

5. The data logger of Building V apartment 28 (V-28) incorrectly was set to record temperature readings for a period of time between downloading the data on January 25, 2016 and February 18, 2016. Therefore, this energy data is excluded from the data set. Since the analysis is conducted using a monthly average daily kilowatt-hour use, the missing days are excluded in the averaging process.
6. The data logger of Building V apartment 30 (V-30) began to return extremely high values after a routine maintenance visit during August 2015. Unfortunately, from August through November 2016, the data logger continued to have issues with recording values, as such the corrupt data is excluded from the energy usage calculations.
7. The data logger of Building V apartment 32 (V-32) began to return extremely high values after January 2016. Unfortunately, from January 2016 through the duration of the study, the data logger continued to show high recorded values; however, since no cause was pinpointed, this was attributed to being an outlier in a small sample size.

Statistical Methods

The Analysis of Variance method was used in this study to assess the statistical significance between groups. For each comparison drawn the ANOVA method was used with the following hypotheses and assumptions. The analyses performed were all calculated using JMP statistical software combined with datasets compiled in Microsoft Excel 2016.

H_0: $\mu_1 = \mu_2 = \mu_3 = \ldots = \mu_k$

where, μ = treatment mean (building mean) and k = number of buildings (3)

H_a: at least two of the μ are different

1. Each of the 3 treatment response distributions is normal.
2. The 3 normal distributions have identical standard deviations.
3. There is independence between treatment groups.
4. Occupants were randomly assigned to a treatment group.

Following the method, if a statistically significant difference was determined, the use of the post hoc method, Tukey-Kramer Honest Significant Difference (HSD) was used to compare the comparisons between every group to determine which groups were statistically significantly different from one another. Note, ANOVA analysis general assumptions and procedures, as well as for the Tukey-Kramer HSD method, can be found in (Peck & Devore, 2010).

CHAPTER 5

Study Results

Results Introduction

This chapter highlights the results of the study. First the pre-Nest installation data results are shown followed by the post-Nest installation results. Figure 8 below provides a visual look at the data for the duration of the study. Consistent with the predicted monthly energy usage graphs in the Appendix Figures 13 - 15, the data is bi-modal for each year. The main peak for each year occurs during the summer cooling seasons, followed by a smaller peak during the winter heating seasons. After determining which data should be excluded from the calculations, comparisons using the same group averaging methods established in Chapter 3 were drawn.

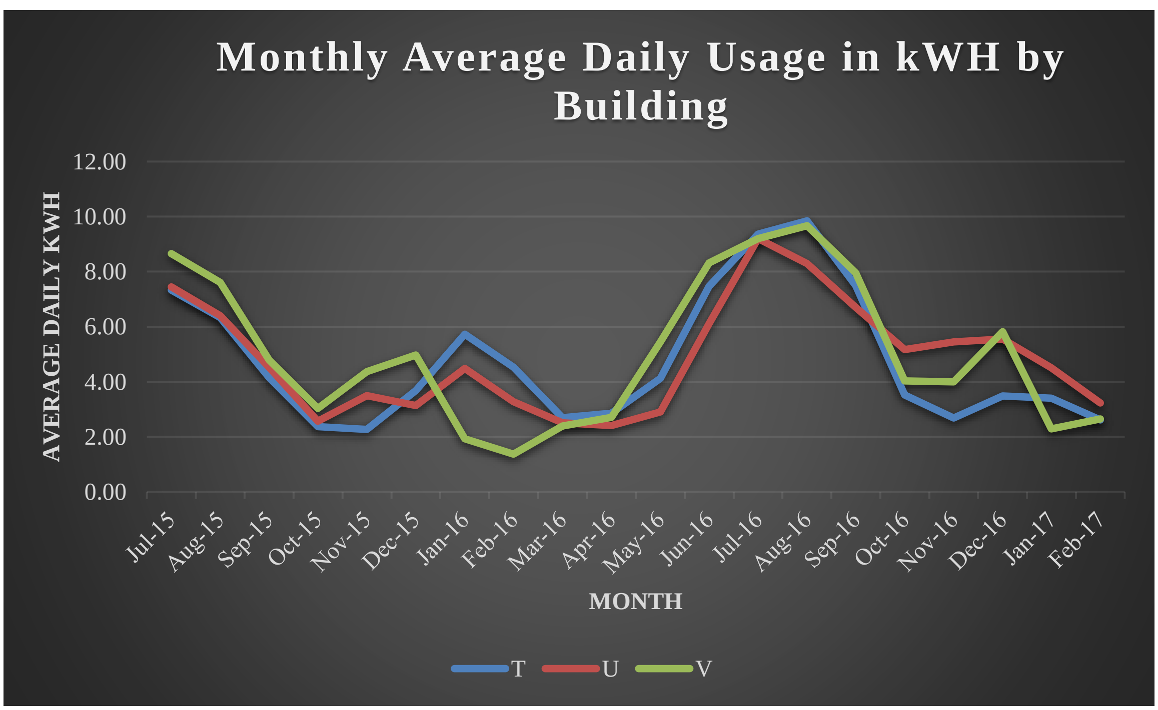

Figure 8 – Monthly Average Daily Usage Graph in kWh by Building Average

Pre-installation Data Results

Below, Table 13 shows each building's monthly daily average usage in kilowatt-hours for the pre-Nest installation period: April 2015 – June 2015. Although there is only three months of collected pre-Nest installation data and not many definitive conclusions can be drawn, the data gives insight into the observed differences between buildings at the time when each building's apartment unit was equipped with the same thermostat.

Table 13 - Pre-Nest Installation Results by Building Average

		Monthly Average Daily in kWh by Building Average					
		Observed				Adjusted	
pre-Nest installation	**Timestamp**	**T**	**U**	**V**		**U**	**V**
	Apr-15	1.80	4.93	4.20		4.88	4.33
	May-15	3.86	5.14	5.91		5.07	5.84
	Jun-15	5.85	6.90	8.17		6.87	7.96
Percent Difference			**U vs. T**	**V vs. T**		**U vs. T**	**V vs. T**
	Apr-15		174.3%	134.0%		171.44%	140.76%
	May-15		32.9%	52.8%		31.28%	51.21%
	Jun-15		18.0%	39.7%		17.53%	36.16%

Post-Nest Installation Data Results

This section summarizes the results for the 2015 - 2016 Heating season, 2016 Cooling season, and 2016 - 2017 Heating season with Nest thermostats installed in Building U and Building V. In the proceeding pages, the results will be presented for building average comparisons, as well as for floor level average comparisons. Each section is in chronological order starting with the 2015 – 2016 Heating season. Lastly, comparisons will be drawn between groups of apartments that used the Nest correctly and incorrectly versus the control group where used correctly means that all of the Nest smart features were enabled through the duration of the study, and used incorrectly means some or all of the smart features such as Eco-Temps or Auto-Schedule were disabled at some point in the study.

In Appendix Table 36, the monthly average daily usage results by building for the duration of the study are shown. The defined heating and cooling seasons are derived from the data within the table. The table is separated by the actual observed measurements and the adjusted measurements. Each row of the adjusted data was calculated using the appropriate correction factor. Additionally, Table 37 and Table 38 in the Appendix correspond to the upstairs and downstairs apartment averages for each building. For each section the results will be in table format, where the percent difference rows represent the energy savings or increase for a given comparison. A positive percentage indicates an increase in energy usage over Building T, and a negative percentage specifies a decrease in energy usage over Building T.

Post-Nest Installation Results by Building Average

The 2015 - 2016 Heating season shown in Table 14 corresponds to the period: December 2015 – February 2016. During this season, Building U consumed 6.21% less energy than the control Building T, and with the correction factors applied, the energy savings equal 21.3% for Building U compared to Building T. Additionally, Building V consumed 0.19% less energy than Building T, which corresponds to an adjusted 41.74% energy savings over Building T.

Table 14 – Post-Nest Installation Results by Building Average

		Monthly Average Daily in kWH by Building Average					
		Observed				**Adjusted**	
Percent Difference	**Timestamp**		**U vs. T**	**V vs. T**		**U vs. T**	**V vs. T**
	2015-16 Heating		-6.21%	-0.19%		-21.30%	-41.74%
	2016 Cooling		-11.20%	4.65%		-11.51%	1.85%
	2016-17 Heating		57.33%	45.67%		42.24%	4.12%

During the 2016 Cooling season (June – August), the adjusted comparisons for Building versus Building T equaled a 11.51% reduction in energy usage, while Building V used 1.85% more energy than Building T. The following 2016 – 2017 Heating season comparisons were substantially different than the previous 2015 – 2016 Heating season. Building U consumed an adjusted 42.24% more energy than Building T, while Building V consumed 4.12% more energy.

Post-Nest Installation Results by Upstairs Apartments Average

The results were also calculated for each floor level to evaluate the potential energy savings for a given building's floor. In Table 15 below, Building U upstairs apartments consumed 1.77% more energy than Building T upstairs apartments for the 2015 – 2016 Heating season, while Building V saved 26.76% in comparison. Over the 2016 Cooling season, Building U saved 5.13% energy over Building T, as compared Building V, which used 25.28% more energy. During the 2016 – 2017 Heating season, Building U used 23.02% more energy than Building T, as compared to the previous 2015 – 2016 Heating season where it only used 1.77% more energy. For Building V compared to Building T, 53.98% less energy consumed during the 2016 – 2017 Heating season, almost double the reduction in energy from the previous heating season.

Table 15 - Post-Nest Installation Results by Upstairs Apartment Average

		Monthly Average Daily Usage in kWH of Upstairs Apartments				
		Observed			Adjusted	
Percent Difference	Timestamp		U vs. T	V vs. T	U vs. T	V vs. T
	2015-16 Heating		19.03%	25.08%	1.77%	-26.76%
	2016 Cooling		-3.65%	29.65%	-5.13%	25.28%
	2016-17 Heating		40.28%	-2.15%	23.02%	-53.98%

Post-Nest Installation Results by Downstairs Apartments Average

Similarly, in Table 16 below, Building U downstairs apartments consumed 47.17 % less energy than Building T downstairs apartments for the 2015 – 2016 Heating season, while Building V saved 56.21% in comparison. Over the 2016 Cooling season, Building U saved 18.13% energy over Building T, as compared Building V, which used 22.75 % less energy. During the 2016 – 2017 Heating season, Building U used 81.56% more energy than Building T, as compared to the previous 2015 – 2016 Heating season where it used 47.17% less energy. For Building V compared to Building T, there was 120.31% more energy consumed during the 2016 – 2017 Heating season, as compared to energy savings in the previous heating season.

Table 16 - Post-Nest Installation Results by Downstairs Apartment Average

			Monthly Average Daily Usage in kWH of Downstairs Apartments				
			Observed			Adjusted	
Percent Difference	**Timestamp**		**U vs. T**	**V vs. T**		**U vs. T**	**V vs. T**
	2015-16 Heating		-35.15%	-29.15%		-47.17%	-56.21%
	2016 Cooling		-19.18%	-21.77%		-18.13%	-22.75%
	2016-17 Heating		93.58%	147.37%		81.56%	120.31%

Nest-installed Apartments Used Correctly or Incorrectly Vs. Control

Lastly, comparisons were drawn between Nest-installed apartments that were used correctly versus Building T apartments and Nest-installed apartments used incorrectly versus Building T. Table 17 below, highlight the difference between the comparisons. For adjusted Nest-installed apartments that were used correctly, Building T apartments used more energy during each season. For the 2015 – 2016 Heating season, Nest-installed apartments used correctly consumed on average 31.73% less energy than Building T. During the 2016 Cooling season, the adjusted savings equaled 51.07% over the control group, followed by 0.07% savings during the 2016 – 2017 Heating season. In contrast Nest-installed apartments used incorrectly consumed more energy for each season compared to the control group.

Table 17 – Nest-installed Apartments Used Correctly or Incorrectly Versus Control Apartments

		Monthly Average Daily Usage in kWH by Nest Used Correctly or Incorrectly				
		Observed			**Adjusted**	
Percent Difference	**Timestamp**	**Correctly vs. T**	**Incorrectly vs. T**		**Correctly vs. T**	**Incorrectly vs. T**
	2015-16 Heating	-10.23%	28.61%		-31.73%	2.17%
	2016 Cooling	-29.57%	6.06%		-51.07%	4.74%
	2016-17 Heating	21.43%	111.46%		-0.07%	86.94%

Chapter 6

Analysis of Results

Introduction

The analyses in this chapter follow the order of results in Chapter 5. For each comparison group, the statistical methods discussed in Chapter 3 were used to evaluate the statistical significance of the results. Discussion of the results will be included for each section.

Pre-Nest Installation Analysis

Looking at pre-installation data comparison results in Table 13, the data suggests that Building U and Building V used more energy than Building T for each monthly daily average, even when adjusted by the corresponding monthly correction factors (See Appendix Table 33 for monthly correction factors by building average). The variation seen when comparing Building U versus Building T and Building V versus Building T highlights the effect of a small sample size (number of apartments).

Using the single-factor analysis of variance (ANOVA) method shown in Table 18, at least two of the means of each building's pre-installation monthly average daily usage were found to be statistically significantly different from one another: One-way ANOVA ($F(2,222) = 28.84$, $p = 9.96393E-14$).

Table 18 - Pre-installation by Building Average ANOVA Results

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	2	452.7878	226.394	28.8436	<.0001*
Error	215	1687.5415	7.849		
C. Total	217	2140.3292			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T	75	4.70947	0.3235	4.0718	5.3471
U	75	8.12024	0.3235	7.4826	8.7579
V	68	7.0094	0.33975	6.3397	7.6791
Std Error uses a pooled estimate of error variance					

After determining a statistical significant difference among buildings, the Tukey-Kramer procedure was used to determine which building means differ. Below in Table 19, the output from the JMP stastical software package shows that for every comparison each building is found to have a stastically significant different mean. The connecting letter report conveys a difference in groups if levels are connected by the same letter.

Table 19 - Pre-installation Results by Building Average Tukey-Kramer HSD Results

Connecting Letters Report					
Level				**Mean**	
U	**A**			8.120238	
V		**B**		7.009395	
T			**C**	4.709475	
Levels not connected by same letter are significantly different					

<u>Post-Nest Installation Analysis: 2015 – 2016 Heating Season</u>

For the 2015 – 2016 Heating season, ANOVA was conducted to determine if the difference in means between each building was statistically significant. Seen below in Figure 9, Building U had the largest mean usage followed closely by Building V and T.

The results from the analysis shown in Table 20 suggest that there is no statistically significant difference in the building means, as indicated by the probability (P value). With a probability value of 0.5196 which is above the confidence level α = 0.05, the null hypothesis that there is no significant difference between buildings for the 2015 – 2016 Heating season was rejected.

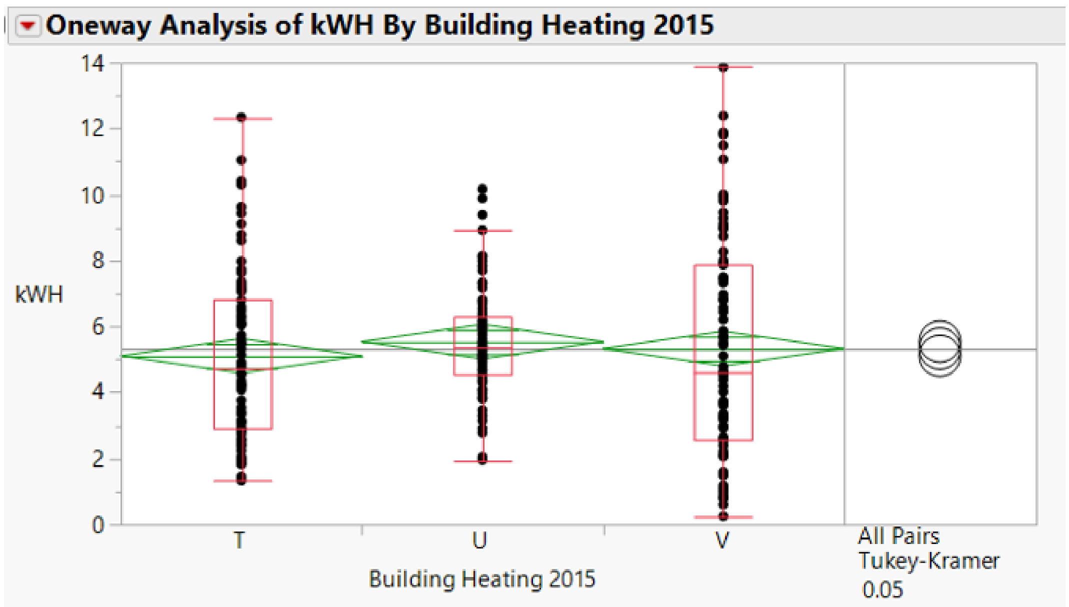

Figure 9 – 2015 - 2016 Heating Season by Building Average Box Plot

Since there is no statistically significant difference in the means, the use of the Tukey-Kramer HSD method was not used, as it would not give any more insight into the difference in means of each building. Note that although the ANOVA analysis was inconclusive about a statistical difference between the buildings, there is a still an observed difference between the buildings. With a small sample size of apartments, the statistical analysis has a smaller chance of finding a significant difference when the variation is small. As seen in Table 20, the difference in means between the buildings ranges from 5.109 to 5.54, which is approximately 8%.

Table 20 - 2015 - 2016 Heating Season by Building Average ANOVA Results

Summary of Fit					
Rsquare			0.004838		
Adj Rsquare			-0.0253		
Root Mean Square Error			2.541105		
Mean of Response			5.327436		
Observations (or Sum Wgts)			273		
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	2	8.476	4.23802	0.6563	0.5196
Error	270	1743.4486	6.45722		
C. Total	272	1751.9247			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T	91	5.10988	0.26638	4.5854	5.6343
U	91	5.54144	0.26638	5.017	6.0659
V	91	5.33099	0.26638	4.8065	5.8554
Std Error uses a pooled estimate of error variance					

Additional analysis of floor averages for each building instead of building averages was used to determine if there was any difference between building floors during the 2015 – 2016 Heating season. Table 37 and Table 38 in the Appendix show the data for the duration of the study by using upstairs apartments' average and downstairs apartments' average respectively. It was expected that there would be a difference between floors. As predicted in the eQuest simulations, upstairs apartments on average should consume more energy than downstairs apartments based on their location in relation to how much solar heat gain they receive from the sun and shading they receive compared to downstairs apartments, which was observed as shown below in Figure 10.

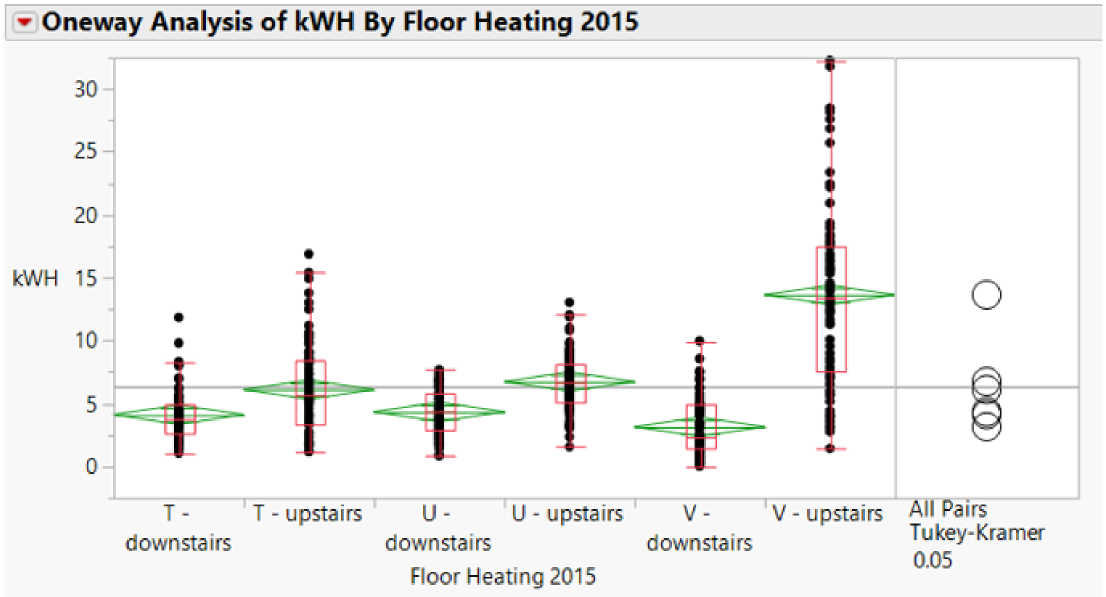

Figure 10 – 2015 - 2016 Heating Season by Floor Average Box Plot

In contrast to the statistical results of the 2015 – 2016 Heating season by building average, the comparison of floors within each building suggests that there is a statistically significant difference, as seen in Table 21 below.

Using the Tukey-Kramer HSD method as shown below in Table 22 and Table 23, three conclusions can be drawn from the results.

1. For a given building, there is a statistically significant difference between upstairs and downstairs during the 2015 – 2016 Heating season.
2. When comparing each building's downstairs apartments group, there is no statistically significant difference.
3. Building V-upstairs has a statistically significant mean compared to Building U-upstairs and Building T-upstairs groups.
4. Downstairs apartments with a Nest installed saved more energy compared to the control than upstairs apartments with a Nest.

Table 21 – 2015 - 2016 Heating Season by Floor Average ANOVA Results

Summary of Fit					
Rsquare			0.46889		
Adj Rsquare			0.463973		
Root Mean Square Error			3.722601		
Mean of Response			6.347298		
Observations (or Sum Wgts)			546		
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	5	6606.536	1321.31	95.3479	< .0001*
Error	540	7483.188	13.86		
C. Total	545	14089.723			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T-downstairs	91	4.1141	0.39023	3.348	4.881
T-upstairs	91	6.1057	0.39023	5.339	6.872
U-downstairs	91	4.3414	0.39023	3.575	5.108
U-upstairs	91	6.7415	0.39023	5.975	7.508
V-downstairs	91	3.1454	0.39023	2.379	3.912
V-upstairs	91	13.6358	0.39023	12.869	14.402
Std Error uses a pooled estimate of error variance					

Compared to previously published studies, the results for the 2015 – 2016 Heating season show the Nest thermostat saving more energy by percentage. The Nest-installed apartments in Building U and V on average consumed 21.30% and 41.74% respectively less energy than the control apartment. Due to the small sample size, these savings could be higher than previous studies that had more participants; however, it does not invalidate the fact that in this case, the apartment groups with the Nest installed saved energy in comparison to the apartments with the control thermostat. The lack of significant difference between downstairs apartments for a given building is noteworthy. It suggests that the environment does not influence the downstairs apartments as much as upstairs apartments, meaning less variation between each building's downstairs apartments.

Table 22 – 2015 - 2016 Heating Season by Floor Average Tukey-Kramer HSD Results

HSD Threshold Matrix						
Abs(Dif) - HSD	**V-upstairs**	**U-upstairs**	**T-upstairs**	**U-downstairs**	**T-downstairs**	**V-downstairs**
V-upstairs	-1.5784	5.3159	5.9518	7.7161	7.9433	8.9121
U-upstairs	5.3159	-1.5784	-0.9425	0.8218	1.0491	2.0178
T-upstairs	5.9518	-0.9425	-1.5784	0.1859	0.4132	1.3819
U-downstairs	7.7161	0.8218	0.1859	-1.5784	-1.3511	-0.3824
T-downstairs	7.9433	1.0491	0.4132	-1.3511	-1.5784	-0.6096
V-downstairs	8.9121	2.0178	1.3819	-0.3824	-0.6096	-1.5784
Positive values show pairs of means that are significantly different						

Table 23 - 2015 - 2016 Heating Season by Floor Average Connecting Letters Report

Comparisons for all pairs using Tukey-Kramer HSD				
Level				**Mean**
V-upstairs	A			13.63579
U-upstairs		B		6.741519
T-upstairs		B		6.105658
U-downstairs			C	4.341364
T-downstairs			C	4.114094
V-downstairs			C	3.145362
Levels not connected by same letter are significantly different				

<u>Post-Nest Installation Analysis: 2016 Cooling Season</u>

Comparing the means of each building during the 2016 cooling season, there is evidence to suggest that at least two of the three buildings are statistically significantly different, as evident by a P value less than 0.0001* shown in the Appendix Table 40. Using the Tukey-Kramer HSD method, it was assessed that each building's mean energy usage is statistically significantly different form one another, with Building V consuming the most energy followed by the control Building T and then Building U.

Table 24 - 2016 Cooling Season by Building Average Tukey-Kramer HSD Results

HSD Threshold Matrix			
Abs(Dif) - HSD	**V**	**T**	**U**
V	-0.6414	0.0728	2.2631
T	0.0728	-0.6414	1.5488
U	2.2631	1.5488	-0.6414

Table 25 - 2016 Cooling Season by Building Average Connecting Letters Report

Connecting Letters Report				
Level				**Mean**
V	**A**			9.315064
T		**B**		8.600793
U			**C**	6.410563
Levels not connected by same letter are significantly different				

The difference between at least two floors during 2016 Cooling season are also shown to be statistically significantly different. Looking at Appendix Table 41, the results of the ANOVA analysis suggest with a P value less than < 0.0001* there is evidence to reject the null hypothesis that there is no difference between each building's upstairs and downstairs apartments. After rejecting the null hypothesis for the 2016 Cooling season ANOVA analysis, the Tukey-Kramer HSD method was used, and similarly to the results of the 2015 – 2016 Heating season the results of the test indicate that there is a statistically significant difference between floors, except for Building U floors.

Table 26 - 2016 Cooling Season by Floor Average Tukey-Kramer HSD Results

HSD Threshold Matrix						
Abs(Dif) - HSD	**V-upstairs**	**T-upstairs**	**T-downstairs**	**V-downstairs**	**U-downstairs**	**U-upstairs**
V-upstairs	-0.9315	1.7721	2.8692	4.1442	4.4325	4.5892
T-upstairs	1.7721	-0.9315	0.1656	1.4406	1.729	1.8856
T-downstairs	2.8692	0.1656	-0.9315	0.3435	0.6319	0.7886
V-downstairs	4.1442	1.4406	0.3435	-0.9315	-0.6431	-0.4864
U-downstairs	4.4325	1.729	0.6319	-0.6431	-0.9315	-0.7748
U-upstairs	4.5892	1.8856	0.7886	-0.4864	-0.7748	-0.9315
Positive values show pairs of means that are significantly different						

Table 27 - 2016 Cooling Season by Floor Average Connecting Letters Report

Comparisons for all pairs using Tukey-Kramer HSD					
Level					**Mean**
V-upstairs	A				11.852878
T-upstairs		B			9.149337
T-downstairs			C		8.05225
V-downstairs				D	6.77725
U-downstairs				D	6.488905
U-upstairs				D	6.332221
Levels not connected by same letter are significantly different					

Compared to the analysis of floor level during the 2015 – 2016 Heating season, there is more variation found to be statistically different. Downstairs apartments within Building T were determined to have a higher mean than Building U and V downstairs apartments, whereas in the previous heating season all of the downstairs apartment groups were found to have no statistical significant difference. It is noteworthy that the savings realized during the 2015 – 2016 Heating season were not realized during the 2016 Cooling season. Some difference between heating and cooling savings potential is expected, but not to the point where Nest-installed apartments consume more energy than non-Nest apartments. Possible explanations as to why this occurred include sample size and the beginnings of people interacting with their Nest thermostat by turning off the smart features. Based on meetings with the Family Housing Maintenance staff, during the first year several occupants requested that the Auto-Schedule (self-learning) feature be turned off on their Nest due to erratic behavior. Unfortunately, surveys were not returned by occupants. The insight from occupants that had negative experiences with the Nest Auto-Schedule feature would be very insightful to assess the design of the Nest.

Post-Nest Installation Analysis: 2016 - 2017 Heating Season

The 2016 – 2017 Heating season results in comparison to the previous heating season show increased usage when compared to the control building. ANOVA was used to determine if the differences were statistically significant, see Appendix Table 42. Based on the analysis, there is evidence to suggest a difference in at least two of the building averages. Using the Tukey-Kramer HSD method shown below in Table 28, Building U and V are determined to be statistically significantly different from the control, but not from each other.

Table 28 - 2016 - 2017 Heating Season by Building Average Tukey-Kramer HSD Results

HSD Threshold Matrix			
Abs(Dif) - HSD	**U**	**V**	**T**
U	-0.6518	-0.5961	0.71875
V	-0.5961	-0.6518	0.66296
T	0.71875	0.66296	-0.6518

Table 29 - 2016 - 2017 Heating Season by Building Average Connecting Letters Report

Connecting Letters Report				
Level				**Mean**
U	**A**			4.703468
V	**A**			4.64768
T		**B**		3.332885
Levels not connected by same letter are significantly different				

Lastly, the results from comparing different floors were determined to be statistically significantly different too, see Table 43. Assessing the differences, the Tukey-Kramer HSD method was used as shown below in Table 30, and based on the results, there is evidence that floors differ but not as determined in previous seasons. For Building U and Building T there is statistical evidence to suggest a difference between upstairs and downstairs, however this is not the case for Building V. When comparing floors from different buildings, each building's upstairs or downstairs is not significantly different from every other building's upstairs or downstairs.

Table 30 - 2016 - 2017 Heating Season by Floor Average Tukey-Kramer HSD Results

HSD Threshold Matrix						
Abs(Dif) - HSD	**U-upstairs**	**V-downstairs**	**T-upstairs**	**V-upstairs**	**U-downstairs**	**T-downstairs**
U-upstairs	-0.9716	0.1328	0.8037	0.8482	1.841	2.8069
V-downstairs	0.1328	-0.9716	-0.3007	-0.2562	0.7366	1.7025
T-upstairs	0.8037	-0.3007	-0.9716	-0.9271	0.0657	1.0316
V-upstairs	0.8482	-0.2562	-0.9271	-0.9716	0.0212	0.9871
U-downstairs	1.841	0.7366	0.0657	0.0212	-0.9716	-0.0057
T-downstairs	2.8069	1.7025	1.0316	0.9871	-0.0057	-0.9716
Positive values show pairs of means that are significantly different						

Table 31 - 2016 - 2017 Heating Season by Floor Average Connecting Letters Report

Comparisons for all pairs using Tukey-Kramer HSD				
Level				**Mean**
U-upstairs	A			6.1097443
V-downstairs		B		5.0053592
T-upstairs		B		4.334474
V-upstairs		B		4.2900015
U-downstairs			C	3.2971926
T-downstairs			C	2.3312958
Levels not connected by same letter are significantly different				

Referring to Table 38 in the Appendix, downstairs apartments in Building U consumed 81.56% more energy than downstairs apartments in Building T, while downstairs apartments in Building V consumed 120.31% more energy than downstairs apartments in Building T. Compared to the previous 2015 – 2016 Heating season, the results of this heating season were not expected to be worse in terms of energy savings. Yet, the Nest-installed apartments downstairs group actually used more energy than the control downstairs apartments. This increased usage could possibly correspond with the effects of small sample size and occupants disabling their Nest smart features.

Post-Nest Installation Analysis: Nest Used Correctly vs. Incorrectly

With the observed results showing a decrease in energy savings over the duration of the study, the critical comparison between Nest thermostats used correctly versus incorrectly supports the claim of smart thermostats potential energy savings. Table 32 below details the percentage of Nest thermostats used correctly and incorrectly.

Table 32 – Percentage of Nest Thermostats Used Correctly and Incorrectly

Building	Nest used correctly	Nest Offline	Nest Self-Learning Off	Nest Eco-temps Off
U	3	4	4	1
V	3	2	4	4
Total	6	6	8	5
% of Study	27.3%	27.3%	36.4%	22.7%

By the end of the study only 27.3% of the Nest thermostat were being used with all of their smart features enabled. Referring back to Table 17, these apartments consumed on average less energy than the control apartments. For the Nest thermostats used incorrectly whether that be because they were offline or the self-learning (Auto-Schedule) or Eco-temps (automatic setback) was disabled, on average consumed more energy than the control thermostats. Figures 11 and 12 below, show an example of the schedules from apartments where the Nest is used correctly versus an apartment with a Nest used incorrectly. Note, the lack of set points throughout a day for the Nest used incorrectly. Rather than letting the Nest make adjustments throughout a day, occupants of the apartment using the Nest incorrectly make temperature adjustments manually.

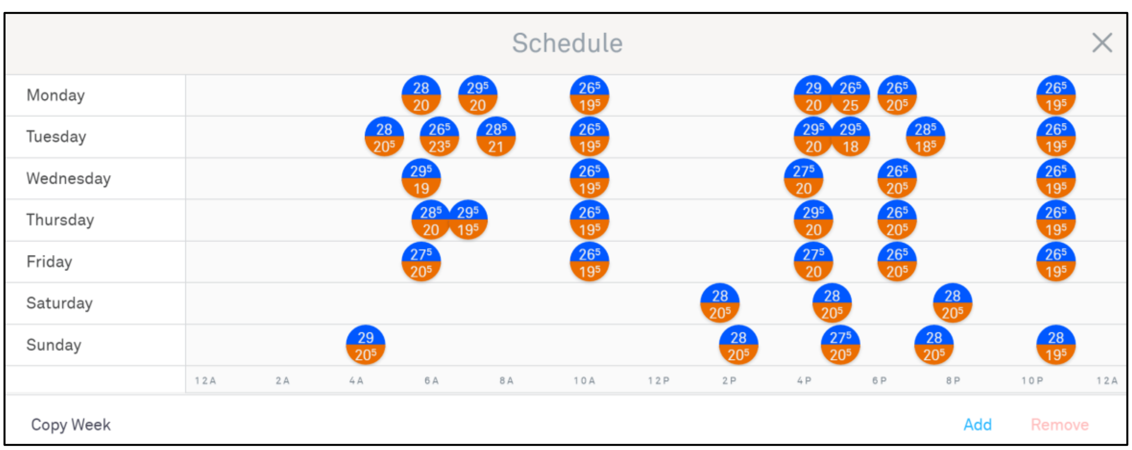

Figure 11 – Apartment U-18 Nest Auto-Schedule Enabled

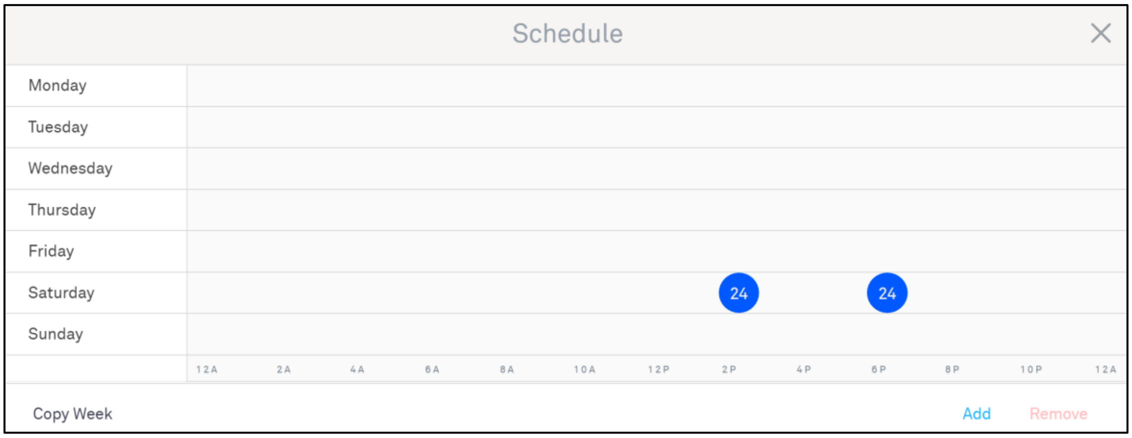

Figure 12 – Apartment V-34 Nest Auto-Schedule Disabled

Chapter 7

Conclusion

Past failure of conventional programmable thermostats to save energy is attributed to the inability of occupants to correctly maintain and operate their thermostat. From the results and analysis of the study, one can see the importance of properly using the Nest thermostat. While the Nest offers smart features such as auto-scheduling, occupancy sensors, and Wi-Fi capability, many participants in this study decided over time to disable those features. Without such features, Nest-installed apartments on average consumed more energy than the control apartments (See Chapter 5, Table 17). Whereas during the 2015 – 2016 Heating season, the Nest-installed apartments on average used less energy than the control apartments; by the following 2016 – 2017 Heating season, the Nest-installed apartments both on average consumed more energy than the control apartments. Comparing Nest-installed apartments where the occupants used their Nest correctly, meaning all of the smart features were enabled, energy savings were realized for each season during the study, also seen in Table 17.

Challenges associated with offering Nest thermostats in a multifamily apartment setting include:

1. Turnover between tenants
2. Maintaining control of the Nest app accounts between tenants
3. Evaluating the effect paying for the energy bill has on motivation to save energy

These challenges could be addressed in a future study with more planning to provide potential Nest energy savings results that include the use of the Nest app and consistent occupants between seasons. Allowing access to the Nest app could be made easier with the implementation of a third-party administrative software program that allows an admin to make changes to who has access to a Nest without having to manually make changes for each Nest. To evaluate the effect monetary incentives has on the energy efficiency of the Nest, a study could be conducted where some occupants are offered monetary incentive to save energy and where the other participants are not. The results could be used to validate if incentives affect an occupant's interaction with a Nest thermostat.

This study serves to highlight the potential energy savings and challenges of properly maintaining and operating the Nest thermostat in a multifamily apartment setting. While limited in size compared to previously published Nest studies, the results provide a basis for conducting further research of larger scope to assess the effectiveness of the Nest thermostat in an apartment setting. Only with more research, will the potential energy savings offered by smart thermostats such as the Nest over conventional non-programmable and programmable thermostats be validated. The validation of the smart thermostat technology will help to finally bridge the interaction gap between thermostats and humans, leading to more energy efficient indoor temperature management.

APPENDIX

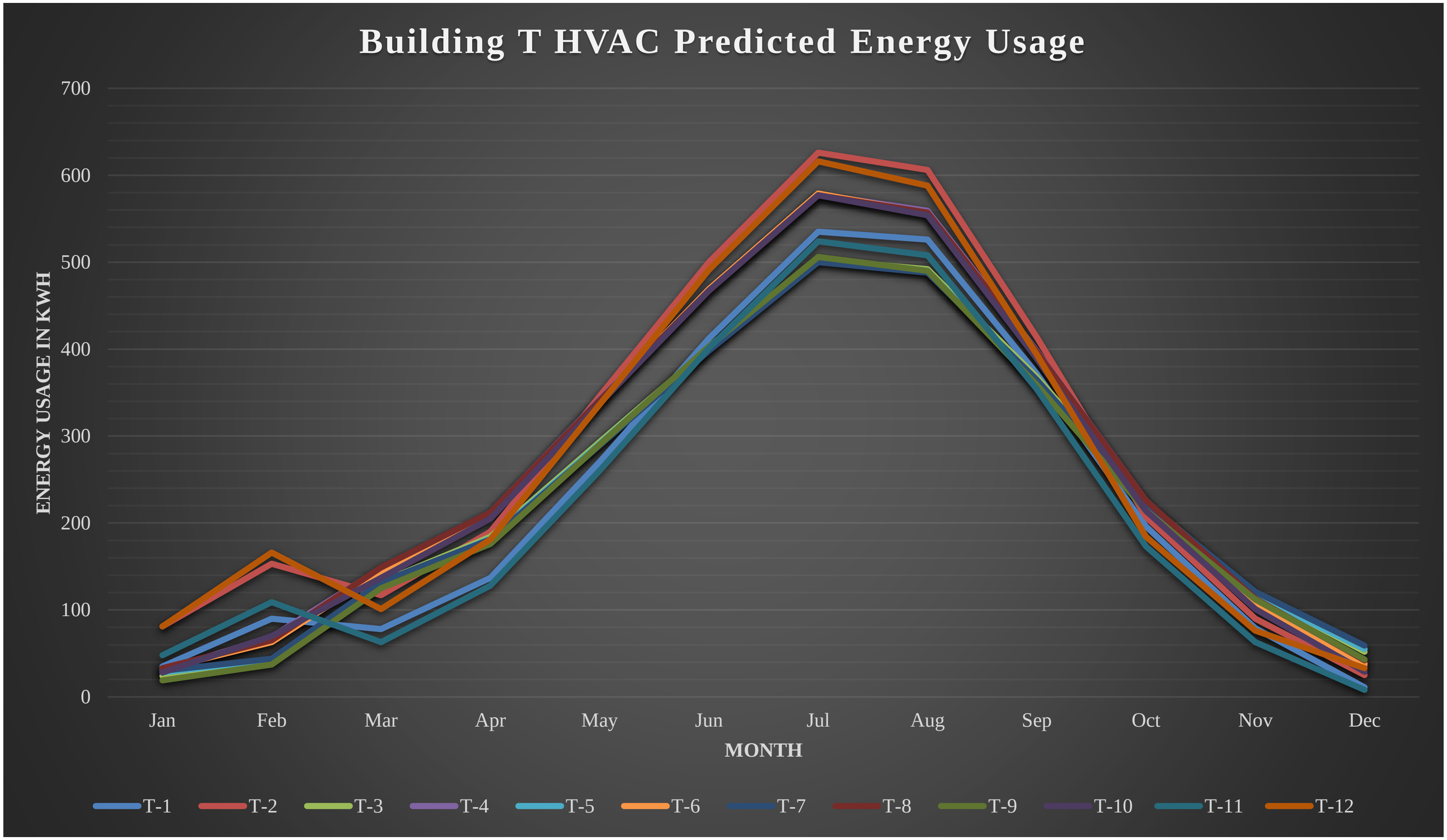

Figure 13 – Building T HVAC Monthly Predicted Energy Use

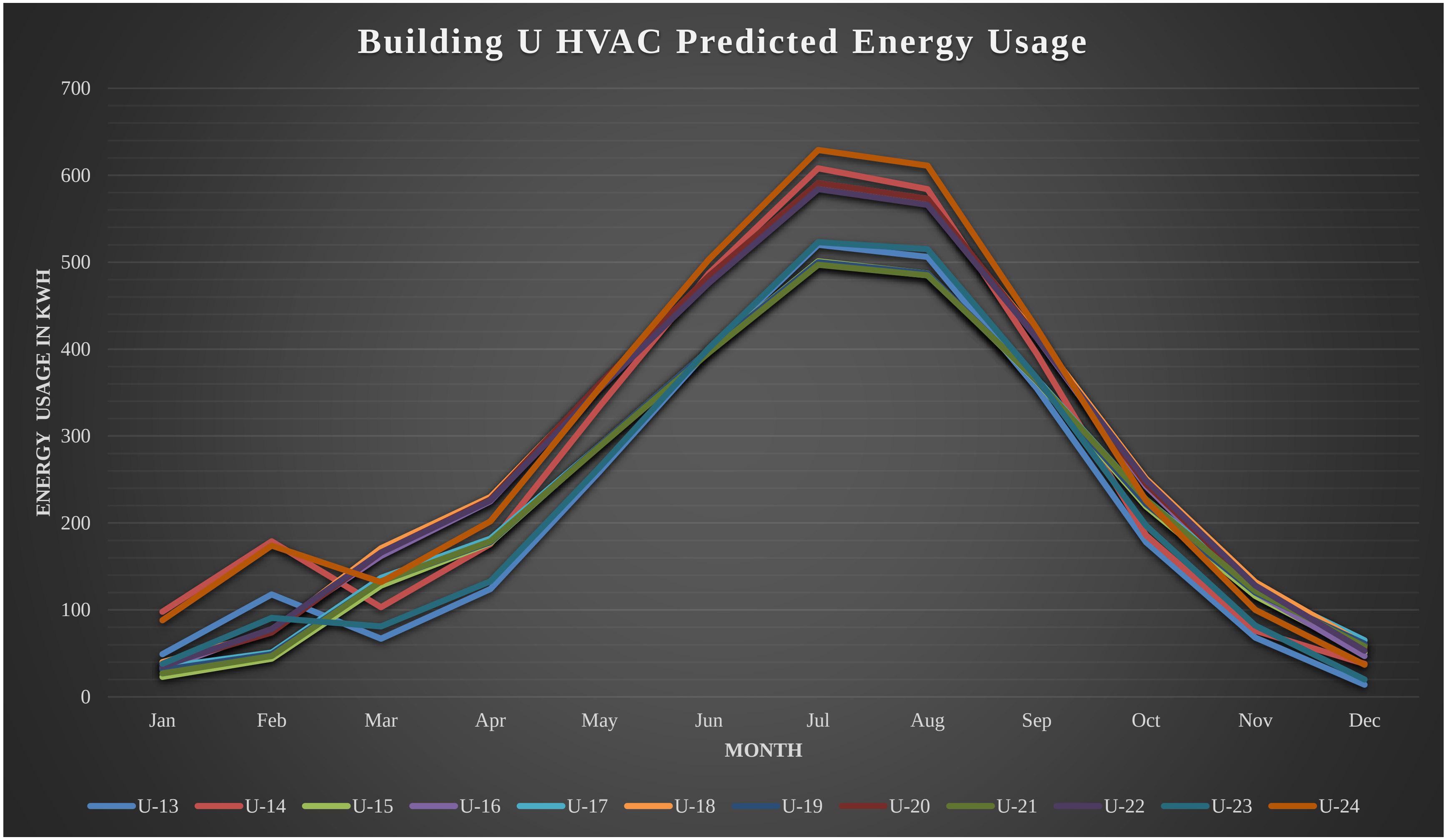

Figure 14 – Building U HVAC Monthly Predicted Energy Use

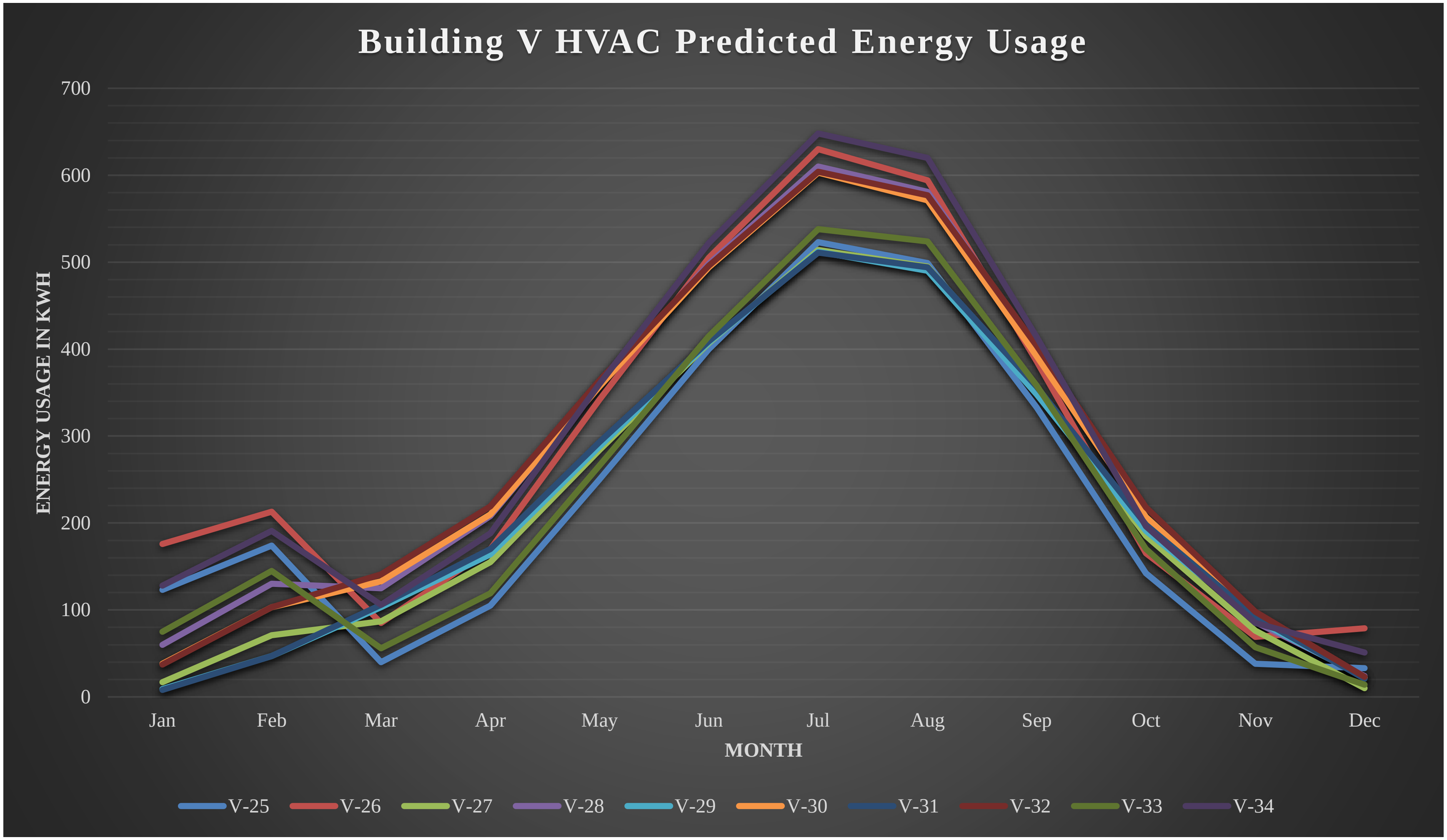

Figure 15 – Building V HVAC Monthly Predicted Energy Use

Table 33 - Predicted Monthly Average Daily Usage and Correction Factors for Building Average Method

	Predicted Monthly Average Daily Usage in kWH by Building Avg. Method				Correction Factors by Building Avg. Method	
Timestamp	**T**	**U**	**V**		**U vs. T**	**V vs. T**
January	1.30	1.43	2.16		9.92%	66.36%
February	2.73	3.04	4.22		11.25%	54.45%
March	3.91	4.24	3.17		8.45%	-19.07%
April	6.10	6.28	5.69		2.82%	-6.71%
May	10.04	10.21	10.20		1.66%	1.59%
June	14.66	14.73	15.18		0.47%	3.52%
July	17.81	17.82	18.36		0.05%	3.10%
August	17.24	17.32	17.56		0.44%	1.87%
September	12.68	12.93	12.48		1.99%	-1.53%
October	6.78	7.17	6.05		5.74%	-10.76%
November	3.36	3.65	2.61		8.86%	-22.32%
December	1.16	1.51	0.96		29.93%	-16.75%
Heating Season	1.73	1.99	2.45		15.08%	41.55%
Cooling Season	16.57	16.62	17.04		0.31%	2.80%

Table 34 - Predicted Monthly Average Daily Usage and Correction Factors for Upstairs Average Method

	Predicted Monthly Average Daily Usage in kWH by Upstairs Avg. Method				Correction Factors by Upstairs Avg. Method	
Timestamp	**T**	**U**	**V**		**U vs. T**	**V vs. T**
January	1.61	1.77	2.83		10.00%	75.60%
February	3.37	3.78	5.10		12.29%	51.54%
March	4.28	4.84	3.81		13.07%	-11.06%
April	6.72	7.14	6.63		6.37%	-1.24%
May	10.98	11.39	11.49		3.77%	4.66%
June	15.90	16.18	16.77		1.78%	5.45%
July	19.10	19.30	19.97		1.04%	4.53%
August	18.39	18.69	18.99		1.67%	3.26%
September	13.24	13.75	13.31		3.86%	0.51%
October	6.85	7.52	6.39		9.73%	-6.73%
November	3.32	3.78	2.87		14.07%	-13.57%
December	1.09	1.56	1.28		43.35%	17.64%
Heating Season	2.02	2.37	3.07		17.26%	51.83%
Cooling Season	17.80	18.06	18.57		1.48%	4.37%

Table 35 - Predicted Monthly Average Daily Usage and Correction Factors for Downstairs Average Method

	Predicted Monthly Average Daily Usage in kWH by Downstairs Avg. Method				Correction Factors by Downstairs Avg. Method	
Timestamp	**T**	**U**	**V**		**U vs. T**	**V vs. T**
January	0.99	1.09	1.50		9.78%	51.30%
February	2.10	2.30	3.34		9.59%	59.12%
March	3.55	3.65	2.53		2.88%	-28.73%
April	5.49	5.41	4.75		-1.52%	-13.40%
May	9.10	9.02	8.91		-0.89%	-2.11%
June	13.43	13.28	13.59		-1.08%	1.23%
July	16.52	16.34	16.76		-1.11%	1.45%
August	16.10	15.94	16.14		-0.97%	0.28%
September	12.12	12.11	11.66		-0.05%	-3.77%
October	6.72	6.83	5.72		1.68%	-14.88%
November	3.39	3.52	2.35		3.76%	-30.87%
December	1.23	1.45	0.65		17.98%	-47.37%
Heating Season	1.44	1.61	1.83		12.02%	27.06%
Cooling Season	15.35	15.19	15.50		-1.05%	0.98%

Table 36 - Observed Data: Monthly Average Daily Usage by Building

		Monthly Average Daily in kWH by Building Average					
		Observed				Adjusted	
	Timestamp	T	U	V		U	V
post-Nest Installation	Jul-15	7.33	7.45	8.88		7.45	8.65
	Aug-15	6.33	6.43	7.73		6.40	7.61
	Sep-15	4.15	4.60	4.72		4.51	4.79
	Oct-15	2.38	2.71	2.78		2.57	3.03
	Nov-15	2.27	3.70	3.86		3.50	4.37
	Dec-15	3.68	4.24	4.35		3.13	4.97
	Jan-16	5.73	5.06	5.73		4.49	1.92
	Feb-16	4.53	3.78	3.84		3.27	1.37
	Mar-16	2.70	2.74	1.88		2.51	2.40
	Apr-16	2.86	2.49	2.52		2.41	2.71
	May-16	4.12	2.98	5.51		2.91	5.44
	Jun-16	7.47	6.15	8.58		6.11	8.32
	Jul-16	9.36	9.21	9.49		9.20	9.20
	Aug-16	9.85	8.34	9.85		8.30	9.67
	Sep-16	7.49	6.85	7.84		6.70	7.96
	Oct-16	3.52	5.37	3.65		5.17	4.03
	Nov-16	2.69	5.68	3.40		5.45	4.00
	Dec-16	3.49	6.59	5.24		5.55	5.82
	Jan-17	3.41	4.85	4.55		4.51	2.29
	Feb-17	2.62	3.53	4.07		3.23	2.64
Seasonal							
	2015-16 Heating	4.65	4.36	4.64		3.66	2.71
	2016 Cooling	8.89	7.90	9.31		7.87	9.06
	2016-17 Heating	3.17	4.99	4.62		4.51	3.30

Table 37 - Observed Data: Monthly Average Daily Usage of Upstairs Apartments

		Monthly Average Daily Usage in kWH of Upstairs Apartments					
		Observed				Adjusted	
	Timestamp	**T**	**U**	**V**		**U**	**V**
post-Nest Installation	**Jul-15**	6.19	9.06	11.37		9.00	11.09
	Aug-15	5.75	7.72	8.63		7.63	8.44
	Sep-15	3.16	4.67	4.65		4.54	4.63
	Oct-15	2.42	2.71	3.55		2.47	3.72
	Nov-15	2.50	3.62	6.05		3.27	6.39
	Dec-15	3.21	4.07	7.20		2.68	6.64
	Jan-16	6.51	7.87	7.68		7.22	2.76
	Feb-16	5.18	5.78	3.74		5.14	1.07
	Mar-16	3.32	2.78	1.59		2.35	1.96
	Apr-16	3.60	3.51	2.59		3.28	2.64
	May-16	4.52	3.37	7.22		3.20	7.01
	Jun-16	8.25	7.54	11.50		7.39	11.06
	Jul-16	10.13	10.63	11.33		10.53	10.87
	Aug-16	9.04	8.25	12.71		8.10	12.42
	Sep-16	7.18	5.80	9.46		5.52	9.42
	Oct-16	3.67	3.69	4.05		3.34	4.29
	Nov-16	3.50	3.73	4.52		3.24	5.00
	Dec-16	4.76	7.99	6.68		5.92	5.84
	Jan-17	4.48	5.85	3.24		5.40	-0.15
	Feb-17	3.71	4.32	2.74		3.86	0.83
Seasonal							
	2015-16 Heating	4.96	5.91	6.21		5.05	3.64
	2016 Cooling	9.14	8.81	11.85		8.67	11.45
	2016-17 Heating	4.31	6.05	4.22		5.31	1.99

Table 38 - Observed Data: Monthly Average Daily Usage of Downstairs Apartments

		Monthly Average Daily Usage in kWH of Downstairs Apartments					
		Observed				Adjusted	
	Timestamp	T	U	V		U	V
post-Nest Installation	Jul-15	8.48	5.84	6.39		5.94	6.27
	Aug-15	6.91	5.14	6.83		5.21	6.81
	Sep-15	5.13	4.53	4.80		4.53	4.99
	Oct-15	2.33	2.71	2.00		2.67	2.35
	Nov-15	2.04	3.78	1.67		3.71	2.30
	Dec-15	4.16	4.40	1.50		3.65	3.47
	Jan-16	4.95	2.24	3.77		1.75	1.23
	Feb-16	3.88	1.79	3.94		1.42	1.64
	Mar-16	2.08	2.69	2.18		2.63	2.78
	Apr-16	2.12	1.47	2.45		1.50	2.73
	May-16	3.72	2.58	3.80		2.62	3.88
	Jun-16	6.69	4.76	5.66		4.83	5.58
	Jul-16	8.60	7.78	7.64		7.87	7.52
	Aug-16	10.65	8.43	6.99		8.53	6.96
	Sep-16	7.79	7.90	6.23		7.91	6.52
	Oct-16	3.37	7.05	3.26		7.00	3.76
	Nov-16	1.88	7.64	2.27		7.57	2.85
	Dec-16	2.22	5.20	3.80		4.80	4.85
	Jan-17	2.34	3.84	5.86		3.62	4.66
	Feb-17	1.53	2.74	5.40		2.59	4.49
Seasonal							
	2015-16 Heating	4.33	2.81	3.07		2.29	1.90
	2016 Cooling	8.65	6.99	6.77		7.08	6.68
	2016-17 Heating	2.03	3.93	5.02		3.68	4.47

Table 39 - Observed Data: Monthly Average Daily Usage of Nest-installed Apartments Used Correctly and Incorrectly

		Monthly Average Daily Usage in kWH by Nest Used Correctly or Incorrectly					
		Observed				Adjusted	
	Timestamp	T	Correctly	Incorrectly		Correctly	Incorrectly
2015-16 Heating	Dec-15	3.68	3.23	4.26		2.44	4.08
	Jan-16	5.73	5.64	7.38		4.40	5.40
	Feb-16	4.53	3.65	6.30		2.67	4.77
2016 Cooling	Jun-16	7.47	4.58	8.66		2.97	8.53
	Jul-16	9.36	7.44	9.78		5.43	9.65
	Aug-16	9.85	6.77	9.86		4.65	9.77
2016-17 Heating	Dec-16	3.49	5.06	7.34		4.31	7.12
	Jan-17	3.41	3.46	6.72		2.73	5.47
	Feb-17	2.62	3.03	6.05		2.47	5.19
Seasonal	Heating 2015	4.65	4.17	5.98		3.17	4.75
	Cooling 2016	8.89	6.26	9.43		4.35	9.31
	Heating 2016	3.17	3.85	6.71		3.17	5.93

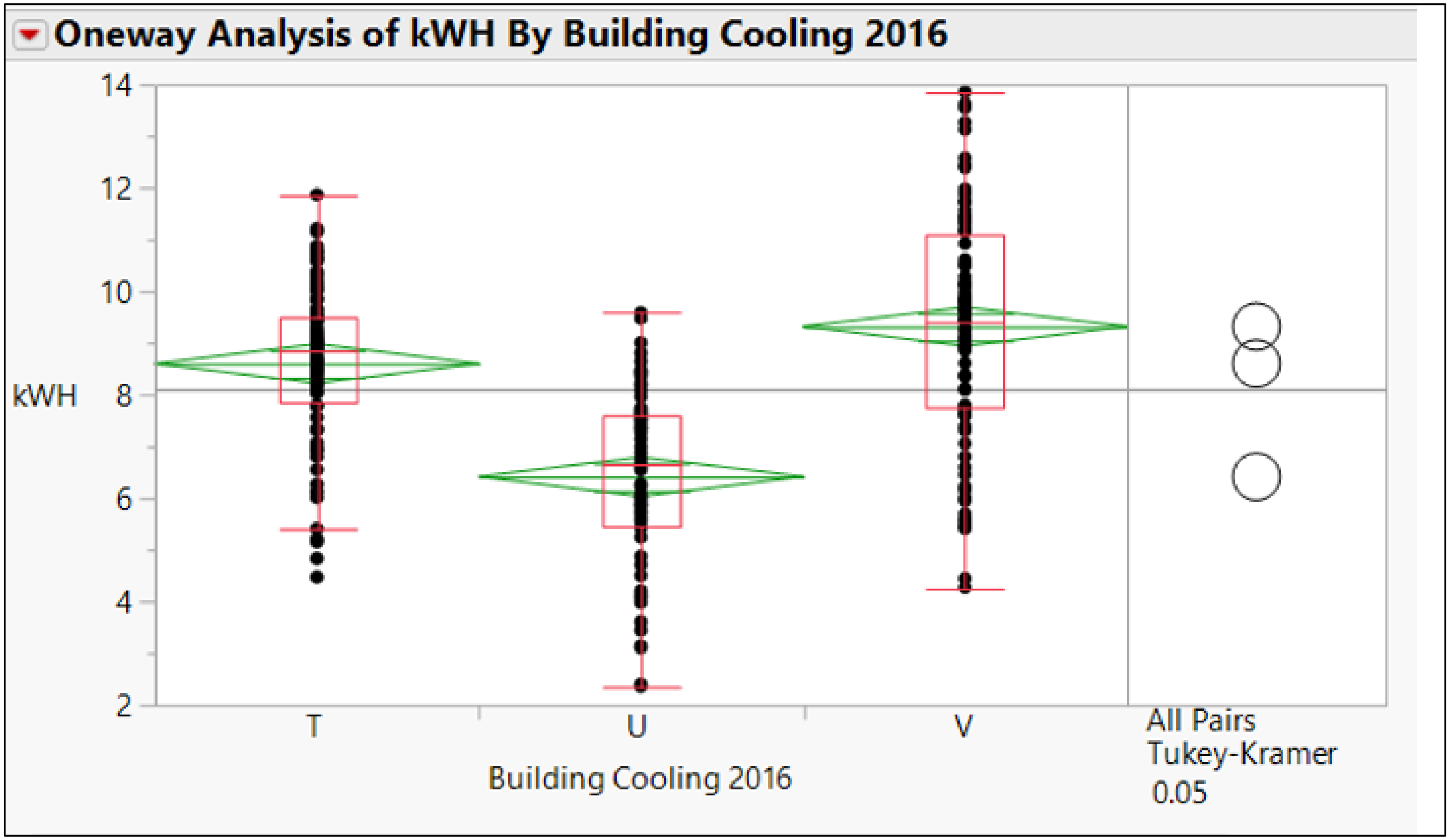

Figure 16 – 2016 Cooling Season by Building Average Box Plot

Table 40 - 2016 Cooling Season by Building Average ANOVA Results

Summary of Fit					
Rsquare			0.311782		
Adj Rsquare			0.30674		
Root Mean Square Error			1.84602		
Mean of Response			8.108807		
Observations (or Sum Wgts)			276		
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	2	421.4648	210.732	61.8384	< .0001*
Error	273	930.3269	3.408		
C. Total	275	1351.7917			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T	92	8.60079	0.19246	8.2219	8.9797
U	92	6.41056	0.19246	6.0317	6.7895
V	92	9.31506	0.19246	8.9362	9.694
Std Error uses a pooled estimate of error variance					

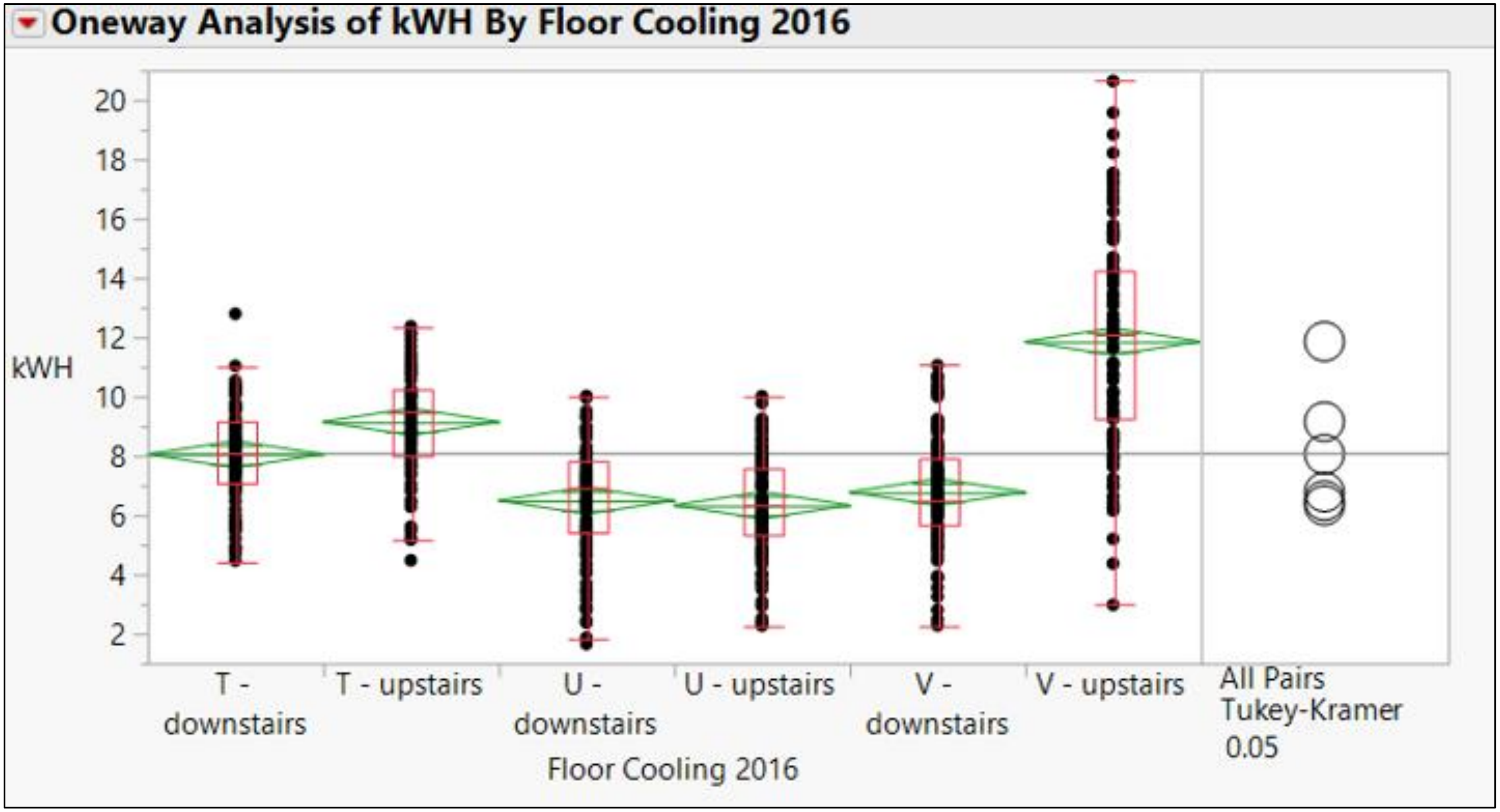

Figure 17 - 2016 Cooling Season by Floor Average Box Plot

Table 41 - 2016 Cooling Season by Floor Average ANOVA Results

Summary of Fit					
Rsquare			0.438943		
Adj Rsquare			0.433805		
Root Mean Square Error			2.209029		
Mean of Response			8.108807		
Observations (or Sum Wgts)			552		
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	5	2084.4763	416.895	85.4327	< .0001*
Error	546	2664.377	4.88		
C. Total	551	4748.8533			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T-downstairs	92	8.0522	0.23031	7.6	8.505
T-upstairs	92	9.1493	0.23031	8.697	9.602
U-downstairs	92	6.4889	0.23031	6.037	6.941
U-upstairs	92	6.3322	0.23031	5.88	6.785
V-downstairs	92	6.7773	0.23031	6.325	7.23
V-upstairs	92	11.8529	0.23031	11.4	12.305
Std Error uses a pooled estimate of error variance					

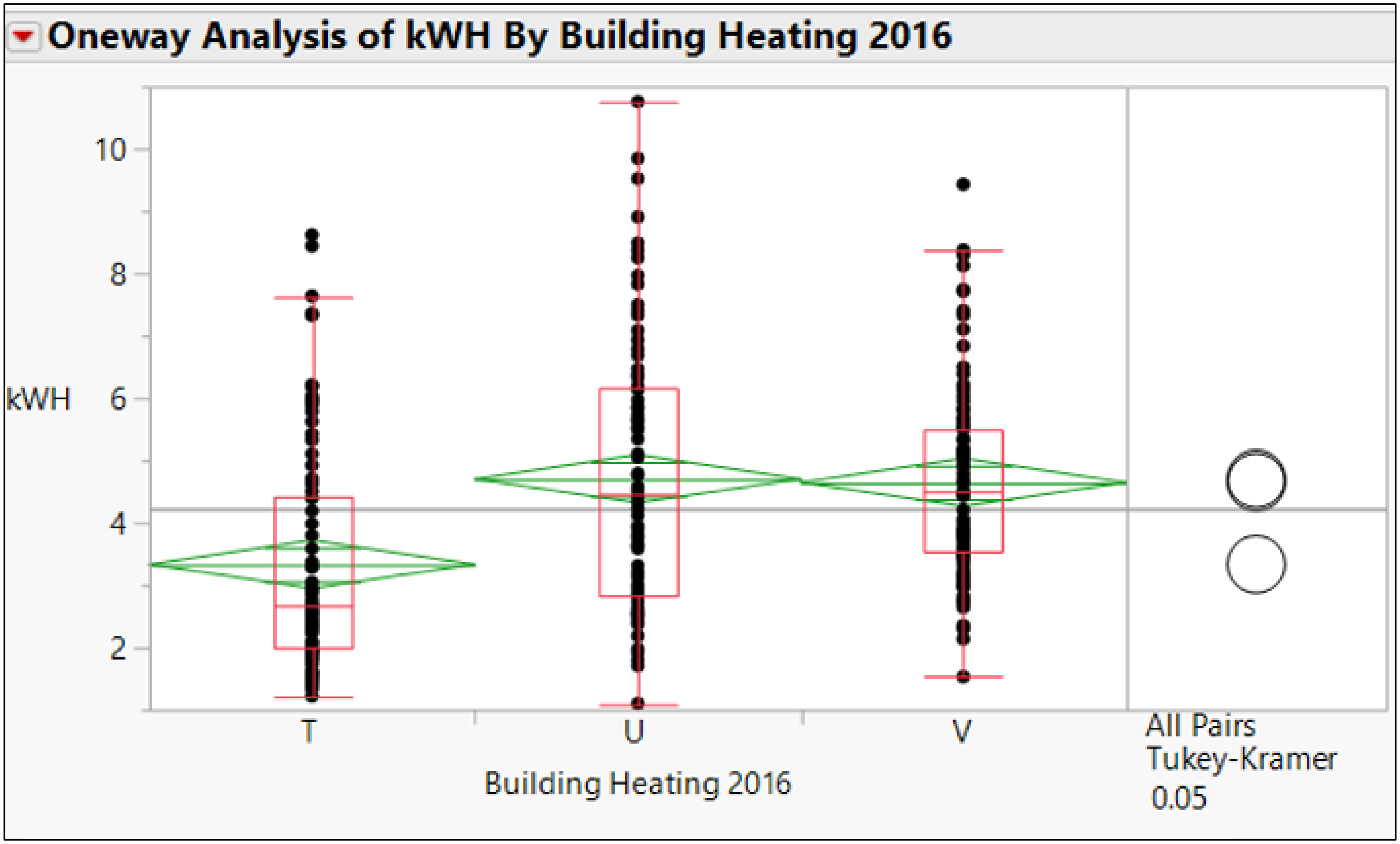

Figure 18 - 2016 – 2017 Heating Season by Building Average Box Plot

Table 42 - 2016 – 2017 Heating Season by Building Average ANOVA Results

Summary of Fit					
Rsquare					0.105431
Adj Rsquare					0.09873
Root Mean Square Error					1.855238
Mean of Response					4.228011
Observations (or Sum Wgts)					270
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	2	108.309	54.1545	15.7339	< .0001*
Error	267	918.9893	3.4419		
C. Total	269	1027.2982			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T	90	3.33288	0.19556	2.9479	3.7179
U	90	4.70347	0.19556	4.3184	5.0885
V	90	4.64768	0.19556	4.2626	5.0327
Std Error uses a pooled estimate of error variance					

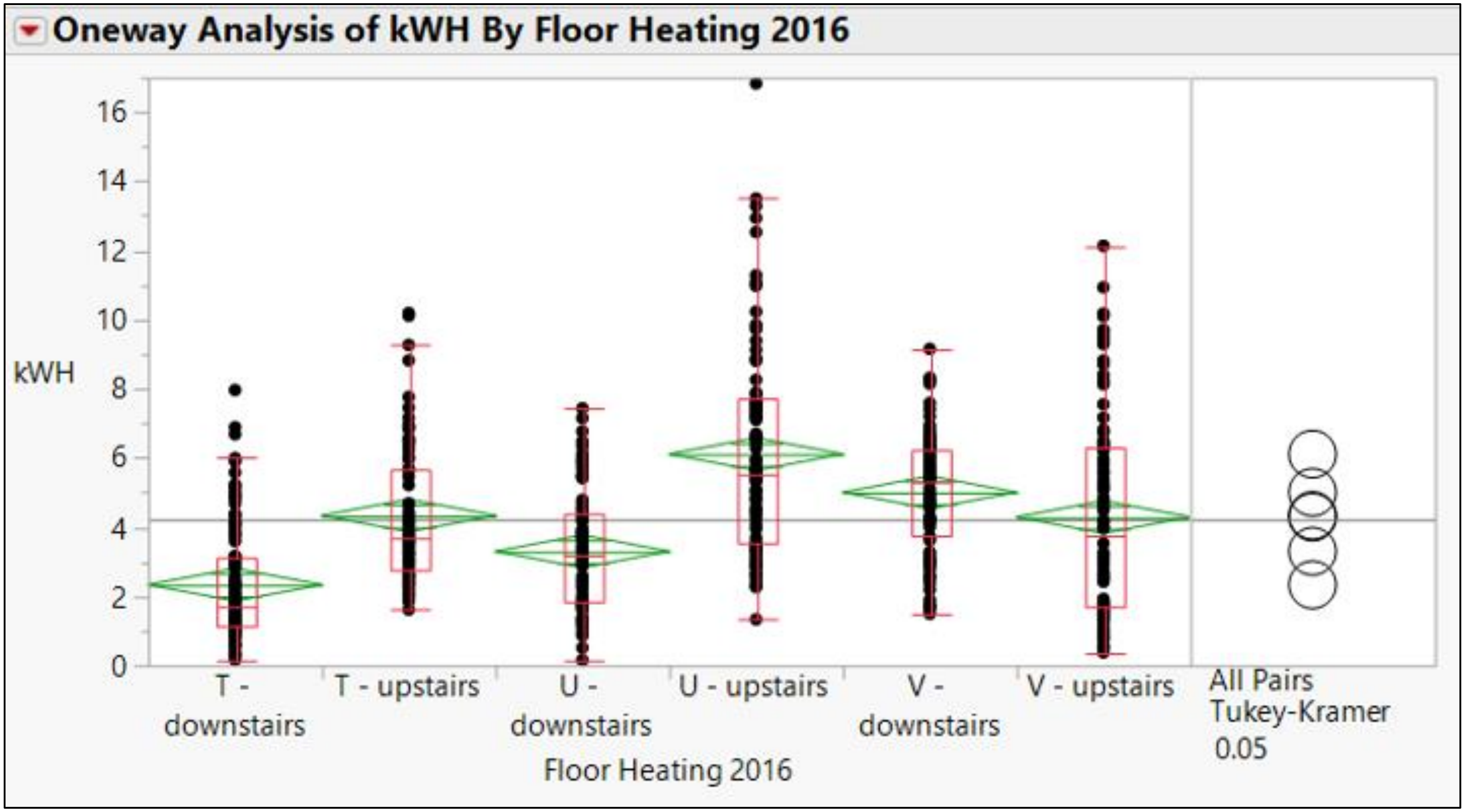

Figure 19 - 2016 – 2017 Heating Season by Floor Average Box Plot

Table 43 - 2016 – 2017 Heating Season by Floor Average ANOVA Results

Summary of Fit					
Rsquare			0.218701		
Adj Rsquare			0.211386		
Root Mean Square Error			2.278745		
Mean of Response			4.228011		
Observations (or Sum Wgts)			540		
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
Building	5	776.1887	155.238	29.8955	< .0001*
Error	534	2772.8905	5.193		
C. Total	539	3549.0792			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
T-downstairs	90	2.3313	0.2402	1.8594	2.8032
T-upstairs	90	4.33447	0.2402	3.8626	4.8063
U-downstairs	90	3.29719	0.2402	2.8253	3.769
U-upstairs	90	6.10974	0.2402	5.6379	6.5816
V-downstairs	90	5.00536	0.2402	4.5335	5.4772
V-upstairs	90	4.29	0.2402	3.8181	4.7619
Std Error uses a pooled estimate of error variance					

Table 44 – Observed Monthly Average Daily Usage of Building T Apartments

Timestamp	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9	T-10	T-11	T-12
Apr-15	2.78	2.69	1.42	0.00	0.00	0.32	6.21	1.70	0.26	2.38	0.17	1.83
May-15	2.24	7.04	3.64	0.00	1.49	3.35	7.19	2.97	1.75	5.98	2.47	3.64
Jun-15	5.07	8.09	4.13	0.00	3.63	6.51	9.00	4.31	6.45	9.69	6.95	0.52
Jul-15	15.87	6.48	4.98	0.00	6.91	7.85	9.74	4.68	6.98	10.25	6.43	1.67
Aug-15	11.07	6.25	6.37	0.00	7.71	5.56	8.40	5.71	4.84	6.23	3.07	5.00
Sep-15	5.31	2.79	6.04	0.00	5.97	2.90	7.32	2.81	3.57	4.02	2.58	3.30
Oct-15	1.72	0.60	2.49	0.00	2.69	0.23	4.03	5.10	1.54	2.39	1.51	3.78
Nov-15	2.97	0.08	1.51	0.00	0.59	0.20	2.50	38.22	0.66	3.73	4.01	5.98
Dec-15	5.55	0.01	1.87	0.00	6.50	0.17	1.87	30.39	0.00	4.74	5.00	7.90
Jan-16	10.30	0.00	2.39	0.00	2.63	2.81	2.41	9.74	4.10	8.69	7.88	11.29
Feb-16	7.54	1.99	0.87	0.00	2.78	0.75	2.47	7.30	3.00	6.68	6.61	9.18
Mar-16	2.84	6.32	0.47	0.00	3.02	0.46	2.50	3.58	1.79	3.46	1.85	2.76
Apr-16	2.72	7.03	1.46	0.00	3.90	0.71	2.92	2.63	1.70	3.77	0.00	3.87
May-16	5.86	8.86	3.67	0.00	5.77	1.91	4.48	2.79	1.81	5.64	0.73	3.37
Jun-16	10.79	12.81	5.71	0.00	10.91	5.58	8.08	5.52	1.72	11.28	2.96	6.05
Jul-16	14.51	14.09	5.19	0.00	12.94	6.70	9.35	6.99	4.98	15.34	4.61	7.50
Aug-16	14.85	13.66	3.61	0.00	12.26	5.87	10.48	5.80	5.67	11.96	17.05	7.93
Sep-16	13.70	11.97	2.71	0.00	9.96	3.63	8.54	3.73	4.06	9.59	52.08	6.99
Oct-16	5.92	8.09	0.73	0.00	5.96	0.77	5.69	1.38	1.91	4.05	50.70	4.05
Nov-16	2.61	5.64	0.18	0.00	2.45	0.73	3.10	4.85	1.03	3.99	50.26	2.30
Dec-16	5.19	4.72	1.14	0.00	0.00	2.97	0.99	9.06	3.76	6.98	51.38	0.05
Jan-17	4.87	5.67	0.89	0.00	1.14	1.59	1.21	7.61	3.58	5.75	51.14	1.78
Feb-17	3.31	6.66	0.08	0.00	1.64	0.34	1.40	4.82	2.76	3.91	50.48	2.80

Highlighted cells indicate data that was excluded from calculations for the varying reasons listed in Chapter 4.

Table 45 - Observed Monthly Average Daily Usage of Building U Apartments

Timestamp	U-13	U-14	U-15	U-16	U-17	U-18	U-19	U-20	U-21	U-22	U-23	U-24
Apr-15	7.59	16.56	12.76	12.24	3.89	2.47	4.19	3.00	0.89	3.65	3.00	0.98
May-15	4.72	15.97	7.14	10.21	3.60	3.96	4.56	8.27	1.84	3.29	5.73	2.64
Jun-15	5.69	24.75	7.20	12.98	0.98	5.45	31.68	14.62	1.24	8.76	7.10	5.00
Jul-15	7.67	29.86	11.13	10.90	0.44	7.85	75.32	10.38	0.99	9.28	8.98	6.91
Aug-15	7.29	32.00	6.86	11.19	1.16	3.76	57.42	9.03	4.10	8.24	6.28	6.39
Sep-15	7.74	32.14	3.98	7.53	0.96	2.04	3.65	5.84	3.64	4.59	7.21	3.33
Oct-15	5.76	27.47	1.91	3.95	0.53	4.63	4.01	2.14	1.46	2.22	2.58	0.59
Nov-15	8.64	23.83	4.94	5.89	1.51	4.99	69.66	4.41	1.24	2.65	2.58	0.18
Dec-15	8.25	23.69	5.91	5.50	3.92	5.68	51.65	5.75	1.75	3.42	2.18	0.02
Jan-16	20.19	6.94	2.34	6.75	0.50	7.94	2.97	12.39	5.29	9.80	0.09	3.41
Feb-16	20.00	4.63	1.33	6.01	1.75	6.19	2.28	10.23	3.58	5.96	0.00	1.66
Mar-16	8.35	2.68	1.51	4.06	0.90	2.07	0.86	4.94	1.82	0.17	0.17	33.16
Apr-16	3.13	3.88	1.04	3.91	0.55	1.10	1.13	5.69	1.49	0.07	0.12	6.44
May-16	4.61	4.69	3.27	3.68	0.91	1.88	1.25	6.52	2.88	0.09	1.09	31.11
Jun-16	6.76	21.44	8.32	4.83	0.76	4.88	3.33	9.75	4.62	0.65	3.48	3.69
Jul-16	8.74	29.84	9.13	4.60	10.27	7.30	4.97	9.46	5.78	2.06	3.80	10.55
Aug-16	8.74	15.03	8.50	7.15	13.00	6.46	4.94	10.80	6.95	0.41	4.32	9.64
Sep-16	4.34	12.30	14.13	5.67	11.51	5.06	3.54	7.99	5.98	0.04	4.56	3.72
Oct-16	2.48	6.58	14.15	4.34	7.82	1.09	25.72	5.21	3.76	0.07	1.17	4.87
Nov-16	6.06	9.17	14.40	2.62	7.58	1.44	23.20	6.13	2.51	0.80	0.12	2.21
Dec-16	2.83	18.95	13.79	7.85	2.06	4.20	3.09	10.94	4.22	2.26	0.00	3.72
Jan-17	5.85	13.81	7.32	4.40	0.50	3.02	0.81	8.37	4.75	2.30	0.00	3.19
Feb-17	0.32	9.92	7.41	3.19	1.51	1.44	0.46	5.88	3.98	3.26	0.14	2.24

Highlighted cells indicate data that was excluded from calculations for the varying reasons listed in Chapter 4.

Table 46 - Observed Monthly Average Daily Usage of Building V Apartments

Timestamp	V-25	V-26	V-27	V-28	V-29	V-30	V-31	V-32	V-33	V-34
Apr-15	1.24	3.22	1.70	4.10	4.89	9.46	1.10	2.19	5.32	8.83
May-15	1.40	7.36	2.94	9.93	2.66	8.15	3.38	6.73	3.78	12.71
Jun-15	7.82	11.32	4.86	14.63	4.64	10.25	3.58	10.67	2.00	11.92
Jul-15	9.69	14.54	5.56	16.52	5.95	8.99	5.66	14.36	5.11	2.42
Aug-15	8.18	12.28	5.53	11.44	5.50	6.21	5.99	11.53	8.93	1.68
Sep-15	6.36	5.74	4.48	6.77	2.93	2.22	4.20	7.70	6.02	0.82
Oct-15	2.96	3.34	1.93	6.34	1.03	1.43	1.36	6.56	2.73	0.11
Nov-15	2.10	4.15	2.70	105.36	0.91	24.53	0.85	13.53	1.81	0.47
Dec-15	0.34	6.10	2.30	105.36	1.30	29.10	1.14	14.75	2.42	0.76
Jan-16	5.45	11.40	1.71	0.00	0.11	26.55	4.68	31.58	6.91	3.96
Feb-16	7.51	6.40	2.16	0.08	0.71	19.38	3.11	31.86	6.19	4.73
Mar-16	3.55	3.98	2.19	0.35	0.58	30.42	1.07	31.67	3.50	0.44
Apr-16	2.67	4.14	3.17	0.04	1.01	31.04	2.20	33.91	3.19	3.59
May-16	3.77	7.45	4.81	3.09	2.38	34.74	4.05	34.85	3.98	11.12
Jun-16	8.35	13.61	6.58	8.91	3.19	38.56	5.36	33.73	4.80	12.00
Jul-16	10.61	18.16	7.83	10.94	4.76	37.12	8.17	29.05	6.85	4.89
Aug-16	7.30	20.46	8.26	10.27	2.15	32.20	8.84	17.01	8.42	7.41
Sep-16	8.76	16.34	6.80	7.40	2.26	29.36	6.24	22.97	7.09	4.62
Oct-16	3.99	6.91	5.17	2.78	1.08	26.34	2.88	22.23	3.20	2.44
Nov-16	3.06	10.92	2.06	2.22	1.70	20.98	0.95	31.54	3.58	0.43
Dec-16	5.86	16.94	2.81	3.24	3.97	6.07	1.32	21.86	5.02	0.48
Jan-17	13.07	5.36	4.55	3.43	4.38	3.79	1.47	25.37	5.84	0.38
Feb-17	13.12	4.27	1.88	2.12	3.91	2.63	0.82	31.03	7.26	1.95

Highlighted cells indicate data that was excluded from calculations for the varying reasons listed in Chapter 4.

Table 47 - Summary of Monthly Normals 1981-2010 from Athens Ben Epps Airport Weather Station

Mean							Cooling Degree Days						Heating Degree Days			
							Base (above)						Base (below)			
Month	Daily Max	Daily Min	Mean	Long Term Max	Long Term Min Std. Dev.	Long Term Avg Std. Dev.	55	57	60	65	70	72	55	57	60	65
1	53.9	33.1	43.5	3.6	3.4	3.3	12	6	2	-7777	-7777	0	368	425	513	667
2	58.2	36.3	47.2	3.4	2.5	2.7	24	14	5	1	-7777	0	241	287	362	498
3	66.2	42.5	54.3	3.3	2.5	2.7	98	70	38	10	1	-7777	118	152	213	340
4	74.0	49.3	61.7	2.9	2.7	2.5	226	180	119	47	10	4	26	40	70	148
5	81.8	58.2	70.0	2.3	2.7	2.2	466	405	316	182	76	46	1	2	6	27
6	88.7	66.4	77.5	3.2	1.7	2.1	676	616	526	378	233	179	0	0	-7777	1
7	91.4	69.8	80.6	3.0	1.3	2.0	794	732	639	484	329	268	0	0	0	0
8	89.9	69.3	79.6	2.9	1.5	2.0	763	701	608	453	298	238	0	0	-7777	-7777
9	84.0	62.7	73.3	2.3	1.8	1.6	551	491	402	260	136	95	-7777	-7777	2	10
10	74.4	51.5	63.0	2.4	3.4	2.4	264	213	146	62	16	8	17	28	55	125
11	65.2	42.4	53.8	3.3	3.6	3.1	84	60	33	9	1	1	120	156	219	345
12	55.7	35.0	45.4	4.4	4.3	4.2	23	15	8	1	-7777	0	322	376	462	610
Summary	73.6	51.4	62.5	3.1	2.6	2.6	3981	3503	2842	1887	1100	839	1213	1466	1902	2771

@ Denotes mean number of days greater than 0 but less than 0.05.
-7777: a non-zero value that would round to zero
Empty or blank cells indicate data is missing or insufficient occurrences to compute value

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