Lessons Learned in Energy Efficiency of Mini-Split HVAC Systems in Affordable Housing

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ABSTRACT

The road to energy-efficient housing is not without cracks and potholes. Many building stakeholders have pointed to the discrepancies that exist between simulated and measured efficiency results, where some have called it a post-occupancy gap, others have called it an energy efficiency information gap. The research presented in this thesis addresses that gap by detailing the results of two exploratory case studies of affordable housing projects in Virginia across three manuscripts.

The data utilized in the first manuscript includes measured data collected at the second level through the NEXI energy monitoring and feedback device, wherein we used descriptive statistics to investigate the impact of temperature on energy use over different timeframes. We had anticipated our findings may not all be consistent with previously existing studies. We found this to be true in many cases, but we also discovered interesting contradictions to our assumptions. This study thereby investigates the gap in energy performance within net-zero buildings and contributes to the existing body of literature by presenting the findings of this unique study.

The data utilized in Manuscript 2 and Manuscript 3 was utility data, which was reported as end-of-use monthly consumption values. We were able to investigate the impact of 3 different HVAC systems energy use by evaluating the energy and cost performance before and after the installation of newer, more efficient systems. We found that although all systems were performing below anticipated standards, the one-stage system outperformed in terms of efficiency, and the second-stage system outperformed in terms of cost. The findings in these studies emphasize the importance of energy education for residents to achieve greater efficiency gains.

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GENERAL AUDIENCE ABSTRACT

Humans are complex beings; hence the buildings they inhabit are complex systems. While breakthroughs in simulating, designing, and constructing high-performance buildings as well as advanced energy use technologies have been promising, many have fallen short of their ambitious goals primarily due to the complexity of building occupant behavior. Achieving energy efficiency requires thorough research before design and construction, the use of advanced technologies, and the incorporation of behavior-driven energy use dynamics. Furthermore, with the breadth of literature to support the delivery of individualized energy information in real-time to residents comes the opportunity to investigate further the impact of advanced technologies in high performing buildings that have fallen short of their optimistic design goals. This thesis consists of three manuscripts, which describe two exploratory case studies of high-performance residential homes in Virginia's affordable housing sector. The first manuscript, a journal paper, investigates the individual HVAC energy use of six senior residents, wherein we explore the interplay between temperature, energy use, and age across different timeframes. We find that, across different timeframes, energy use for senior citizens remains relatively consistent in high-performance homes. The second and third manuscripts are conference papers, which have been presented on and published in the respective conference proceedings. We quantitively investigated the energy performance of energy-efficient HVAC systems and compared predicted results and measured results. In conclusion, we hope to contribute to the body of literature, which investigates shortcomings in achieving energy-efficiency within high-performance homes.

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Dr. Frederick Paige drew me into this research through his devotion to utilizing engineering to address most critical social issues. Thank you for your commitment to engineering a healthier, more equitable world, and for encouraging your students to do the same. Dr. Farrokh Jazizadeh provided a wealth of knowledge on the functions of HVAC systems. I would like to thank them both for their patience and encouragement as I acquired new skills throughout my research journey.

The assistance provided by Dr. Quinton Nottingham was instrumental to the development of the statistical analysis methods applied throughout my research. Thank you for your support, I am grateful to have had the opportunity to work with and learn from you.

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ATTRIBUTION

This foreword describes the contribution of each of the authors for the three manuscripts within this thesis document.

Manuscript 1:

Fatemah Ebrahim – Fatemah reviewed the relevant literature, developed the methods, analyzed the data, and wrote the manuscript, which incorporated the feedback of the paper co-authors.

Frederick Paige – Dr. Paige collected and published the corresponding dataset that was analyzed in this manuscript. He also helped develop the research questions and methods applied. And he also provided multiple rounds of feedback on the manuscript.

Farrokh Jazizadeh – Dr. Jazizadeh helped develop the research questions and methods applied in this manuscript. He also provided multiple rounds of feedback on the manuscript.

Quinton Nottingham– Dr. Nottingham helped develop the statistical analysis methods that were applied in this manuscript. Dr. Nottingham also provided feedback on the manuscript.

Manuscripts 2-3:

Fatemah Ebrahim – Fatemah reviewed the relevant literature, developed the methods, analyzed the data, and wrote the manuscript, which incorporated the feedback of the paper co-authors.

Frederick Paige – Dr. Paige initiated the project and corresponding data collection with industry stakeholders and helped to develop the research questions explored in these papers.

Farrokh Jazizadeh – Dr. Jazizadeh helped develop the research questions and methods applied in this manuscript. He also provided multiple rounds of feedback on the manuscript.

Quinton Nottingham– Dr. Nottingham helped develop the statistical analysis methods that were applied in this manuscript. Dr. Nottingham also provided feedback on the manuscript.

INTRODUCTION

Various studies have spoken to the discrepancy that exists in high-performance homes, while some have described it as a post-occupancy gap (Agee et al. 2018), others have addressed it as the energy efficiency gap (Dietz 2010). Many questions arise about the efficacy of advanced technology installations in terms of performance and cost, as well as the impact of temperature at different timeframes on energy use in high-performing homes. As it pertains to occupancy, many studies have encouraged the incorporation of advanced metering initiatives to collect energy use data at a finer resolution and inform residents of their use in real-time for up to 12% energy savings (Ehrhardt-Martinez et al. 2010).

Throughout this thesis document, we have included the findings from two exploratory case studies across three manuscripts, which detail the HVAC energy use results in two housing communities in Virginia. The first manuscript investigates the energy use of six senior residents in Richmond, VA affordable housing community that was built to net-zero energy standards but has failed to perform to that standard. In the first manuscript we address questions of the impact of temperature on energy use and describe energy use across different timeframes to develop a better understanding of how time effects impact residents' consumption. The second manuscript and the third manuscript investigate the energy performance and cost performance throughout the pre-intervention and post-intervention period, wherein the intervention involves the installation of newer more energy-efficient HVAC systems. In these two manuscripts we address questions about the efficacy of these HVAC installations in terms of energy performance and cost performance. All three manuscripts attempt to further the knowledge that exists in realm of energy efficient affordable housing by detailing the methods and results from two ongoing case studies in Virginia.

Journal Paper:

Older and Colder: An Exploratory Case-Study of Senior Residents' HVAC Energy Use in Net-Zero Buildings

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Sustainable Cities and Society Journal

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ABSTRACT

The road to net-zero energy starts at home, where there is an opportunity to better align energy efficiency metrics with the dynamics of human behavior. This paper reports an exploratory case study that focuses on six senior residents' energy use within an affordable housing community in Richmond, VA. To better understand the conditions that impact the residents' HVAC energy use, this single-case study focuses on four variables: electricity consumption, outdoor temperature, time, and occupant behaviors. We have used the publicly available flEECe dataset, which contains nine-months of quantitative energy consumption data for each resident. Energy consumption data was collected by using a current transformed based Nexi energy monitoring system (meetnexi.com) at a 1 Hz sampling rate for various circuits within each apartment home. The data analysis uses the HVAC energy data to develop linear regression analyses, correlations, descriptive statistics, and determine peak energy use values during inclement weather events. Results indicate that (1) outdoor temperature had a minimal impact on energy consumption in these high-performance homes, (2) there is no statistically significant difference between weekday and weekend energy use of these senior residents, and (3) winter consumption patterns of senior residents in this net-zero housing property are a limiting factor to meeting performance metrics. The findings from this study suggest that within these buildings, there is an opportunity to improve efficiency by focusing on winter energy performance.

Keywords: Energy Performance, Energy Analysis, Mini-Split, HVAC Systems, Residential Housing, Net-Zero, Senior Housing, Affordable Housing, Low-Income

INTRODUCTION

Low-income households stand to gain the most from increases in energy efficiency which alleviate disproportionate energy expenses, improve thermal comfort, and enhance health and safety measures. Stricter energy codes have encouraged the construction of highly insulated homes with more efficient and advanced technologies (Gillingham et al. 2009). However, a misalignment between predicted or simulated energy use and actual or measured energy use in high-performing homes has often occurred (Hu 2019; Martinaitis et al. 2015; Palmer et al. 2013; Schakib-Ekbatan et al. 2015; Yang et al. 2016). Many energy efficiency gains are made through technology advancements, which may not be accessible to all demographics within affordable housing, such as senior residents.

Senior citizens are the fastest growing demographic in the world (United Nations 2019), which has created a rising demand for senior housing within the United States (The United States Census Bureau 2019). In this study, we refer to HUD regulations, which specify those who qualify for senior housing to be of 55 years of age or older (HUD 2013). Ensuring that the energy needs of the elderly are met plays a fundamental role in establishing an appropriate quality of life: one which promotes active and independent living for the elderly, while also alleviating the demand on health and aged care systems (WHO, 2002; Oswald et al., 2007; Miller et al., 2017). Researchers have found that senior residents described experiencing “frustration” with advanced technologies at home, which left them unmotivated and unsure of their ability to use them (Wang et al. 2019).

In this paper, we are interested in identifying opportunities to improve energy efficiency of senior residents’ HVAC energy use. This exploratory case study focuses on an affordable housing property for senior citizens in Richmond, VA. The property was designed as a net-zero building but has yet to operate at this standard. The property features six one-bedroom apartments, which each include a Nexi energy monitoring device that collects energy data from various circuits at a 1-Hz sampling rate. In this study, we explore four variables: electricity consumption, outdoor temperature, time, and building occupant behaviors. We explored the variables across different timeframes to better understand the opportunities that exist to improve upon energy performance. This study builds upon previous work (Paige et al. 2019b) to address the following questions within the context of this property:

1. What is the relationship between outdoor temperature and energy consumption?
2. How is energy use reflected across different timeframes (monthly; weekday versus weekend; inclement weather)?
3. To what extent are building occupant behaviors impacting energy consumption?

BACKGROUND

The residential building sector in Virginia should be energy efficient and equitable. Financial status stands as a barrier between residents and the adoption of energy-efficient technologies. Low-income residents, who are most heavily burdened by energy expenditures (Hernández and Bird 2010), are least likely to pay for expensive energy investments (Ehrhardt-Martinez and Donnelly 2010; Šćepanović et al. 2017). To bridge the gap between energy-efficient housing and affordability in the United States, the Low-Income Housing Tax Credit (LIHTC) subsidizes the adoption of green building design and construction within low- and moderate- income housing (Beheiry et al. 2006; Lee et al. 1995; Zhao et al. 2015, 2018). A plethora of studies exist discussing the significant role of federal support to increase energy efficiency in the affordable housing stock (Gillingham et al. 2009, 2012; McCoy et al. 2017; Trachtenberg et al. 2016; Zhao et al. 2015). In this study, we attempt to move the conversation forward by exploring opportunities to improve upon the energy efficiency of a senior living LIHTC property in Richmond, VA.

Outdoor Temperature Effects

Weather-related impacts on residential energy use is an important factor to consider when performing post-occupancy energy analyses (Agee et al. 2018; Bros-Williamson et al. 2016; Martani et al. 2011; Touchie et al. 2013; Wang et al. 2016). A prominent weather-related impact on residential energy use to explore is that of outdoor temperature. Identifying the correlation between energy use and outdoor temperature through regression analyses are common to the literature and have provided a variety of findings. Within high-performing homes, energy use is typically not significantly impacted by outdoor temperature (Csoknyai et al. 2019; Lee et al. 2014; Ueno and Loomis 2015; Zhao et al. 2017, 2018). However, there is evidence to support that outdoor temperature has a significant impact on energy use amongst senior citizens (Lee et al. 2014). Therefore, the relationship between outdoor temperature and HVAC energy use was deemed of interest for further exploration.

Timeframe Explorations

Previous studies have also addressed the impacts of household lifestyle on energy use by exploring different timeframes (cite 2 studies other than the Tso and Yau). One such timeframe of interest within building energy monitoring studies is that of weekday versus weekend energy use. A study in Hong Kong found no noticeable difference in the energy use of approximately 1500 households in a two-week study period across the weekdays and weekends (Tso and Yau, 2003). Meanwhile, a study of low energy senior houses in Australia found a slight increase in energy use during the weekends relative to the weekdays (Lee et al., 2014). As our study features active seniors who are working, we were interested in learning whether or not there were differences between their weekday and weekend energy use. We also found an opportunity to identify building occupant behaviors during two more timeframes of interest, which include the hottest week and the coldest week in the study.

Building Occupant Behaviors

Humans are complex beings; hence the buildings they inhabit are utilized in complex manners. Moreover, "buildings present a complex sociotechnical system that links society, occupants and the environment (Gulbinas and Taylor 2014; Zhao et al. 2017)." Affordable housing studies discuss the issue of *split incentives*, where landlords with residents who are responsible for paying energy bills are less likely to invest in energy efficiency (Gillingham et al. 2012; Melvin 2018). The role of financial aid in encouraging the adoption of green technologies, such as advanced metering initiatives, is crucial to addressing issues of energy poverty (Heyman et al. 2011). In this study, we investigate the impacts of building occupant behavior of a unique demographic of senior residents who are not financially incentivized to save energy, which is a critical area in need of investigation (Dakwale et al. 2011; McMakin et al. 2002; Paige et al. 2019a).

The definition of building occupant behavior is highly contextual and can be defined by varying levels of complexity (Chen et al. 2015; Laaroussi et al. 2020). Quantifying the impact of building occupant behaviors is a methodologically difficult task. While qualitative approaches within the social sciences attempt to define and interpret energy behaviors, quantitative approaches within engineering and economics attempt to quantify energy consumption by developing energy models (Lopes et al. 2012); with the aim of improving the accuracy of simulation tools by interpolating in behavioral aspects (Hong et al. 2015). Standard quantification methodologies utilized to investigate building occupant behaviors include everything from case studies, empirical studies, field studies, pre/post-occupancy, simulations, and surveys (Paone and Jean-Philippe 2018).

In this paper, we apply the case study methodology, and we identify building occupant behaviors through peak energy use analyses. The interactional occupant behavior investigated in this study is the interaction of residents with ductless mini-split heat pumps (MSHPs). The electrical demand values of residents MSHPs were analyzed using thresholds set by the manufacturer specified total input for cooling and heating seasons. We extract peak energy use values and cross-reference them with manufacturer specifications for heating capacity and cooling capacity to distinguish between occupant's energy use of one or both mini-split heat pumps of varying degrees within each apartment unit.

METHODS

Case Study Context

This study utilizes a subset of data from a single case study (Paige et al. 2019b), which is part of a statewide multiphase longitudinal affordable housing study in Virginia, USA (McCoy et al. 2015). This case study uses the mini-split heat pump energy consumption subset of data to explore the impact of outdoor temperature on energy consumption and the role of interactional behaviors on energy consumption of 6 senior residents. The case study includes nine months of energy data collected in an affordable housing community in Richmond, VA, which is not performing to the net-zero energy standard it was designed for. The case study also utilizes detailed architectural data, as shown below in Table 1, for each apartment unit within the housing community as well as manufacturer data for the ductless mini-split devices.

Table 1. Building Characteristics and Architectural Data

Characteristics	Case Project
Climate zone	U.S.A. 4A
Number of Apartments	6 units: A, B, C, D, E, F
PV-System	16.9 m^2, south-facing, 2.43 kWp
Living Area	Units A, B: 743.4 ft^2 (68.5 m^2); Units C, D, E, F: 717.3 ft^2 (66.6 m^2)
Building Volume	Units A, B: 7005.3 cf (198.4 m^3); Units C, D, E, F: 6814.4 cf (192.9 m3)
Heating System	Air-source heat pump 18 kBtuh, 9 HSPF
Cooling System	Air-source heat pump, 18 SEER
Distribution	2, Ductless air systems
Ventilation	Energy Recovery Ventilator
Windows U-value SHGC (g-value)	0.30 BTUh/ft^2/°F (0.95/W/m^2K) 0.28
Window to Wall Ratio	0.14
Wall U-value	0.04 BTUh/ft^2/°F (0.13/W/m^2K)
Roof/Attic U-value	0.03 BTUh/ft^2/°F (0.11/W/m^2K)
Enclosure Air Tightness	4.1 ACH50

A subset of the mini-split energy data is used in this study. The data repository includes energy data collected in two forms: 1) WegoWise utility tracking service, and 2) Nexi energy monitor data loggers (Paige et al. 2019a). For this study, we utilized the Nexi energy monitor data loggers for six apartment units collected from July 7th, 2017, through March 22nd, 2018. The Nexi energy monitoring device collects energy data at the 1 Hz sampling rate from various circuits. The data was collected at the circuit level for four circuits: 1) main, 2) water heater, 3) dryer, and 4) HVAC for each respective apartment unit. This study utilizes the calibrated CSV files, which log the (mini split) HVAC energy use data. Most significantly, to note for this study's purposes, the building is comprised of 6 similarly sized apartment units, each with a single senior citizen resident, with two ductless mini-split heat pumps (MSHP); one in the living room and the second in the bedroom.

The property is characterized by mildly humid weather in climate zone 4A, where its cooling season corresponds with May 29th through September 15th. Its heating season corresponds with November 30th through February 2nd, wherein the time between the two seasons usually corresponds with swing months. We investigated the impacts of outdoor temperature on energy use by segmenting the data according to seasons as shown below in Table 2. Hereafter, the data, analysis, and findings are discussed according to the periods mentioned below.

Table 2. Periods of Analysis

Summer	July 7th, 2017 – September 15th, 2017
Fall	September 16th, 2017 – November 29th, 2017
Spring	November 30th, 2017 – February 2nd, 2018
Winter	February 3rd, 2018 – March 22nd, 2018

In this paper, we identify building occupant behaviors through peak energy use analyses. The interactional occupant behavior investigated revolve around the interactions of residents with their thermostats, which are determined by cross-referencing electrical demand values with the manufacturer specified total input for cooling and heating seasons as shown in Table 3 below.

Table 3. Mini-Split Heat Pump Manufacturer Specified Total Input for Cooling and Heating Seasons

Cooling	Heating at 47 °F	Heating at 17 °F
0.690 kW	0.860 kW	0.700 kW

The manufacturer specifications are a valuable resource utilized to understand better the performance of the HVAC system at different outdoor temperatures. For this study's purposes, the interactional occupant behavior investigated revolve around the interactions of residents with their thermostats, which are determined by cross-referencing electrical demand values with the manufacturer specified total input for cooling and heating seasons listed below in Table 3. Notably, in this case, wherein occupant setpoint temperatures have not been made available, the authors relied heavily on the interpretation of electrical demand values at high data resolution levels, i.e., at a collection rate of 1-minute.

Data documentation and analyses

The flEECe dataset provides energy consumption data from Nexi energy monitoring device as raw uncalibrated CSV files and calibrated CSV files. For this study, we utilized the calibrated data, which have been converted from uncalibrated amperage/second/circuit measurements to calibrated kW/second/circuit measurements. The calibrated data, which we used, included measurements which allowed for analyses in 1-minute and 1-hour intervals. While the data repository (Paige et al. 2019a) includes uncalibrated data collected at the second level, the calibrated data to date is only at the hourly-level and minute-level.

The data processing and data analyses performed throughout this study include (1) regression analyses, (2) aggregated average energy profiles, and (3) scatterplot interpretation using descriptive statistics, and (4) the evaluation of peak energy use distributions. The authors separated the 9-month study period into four periods corresponding with the four seasons to identify trends in energy use and interactional occupant behavior.

Multiple software packages were utilized for the data analysis including Microsoft Excel, JMP Student Edition 14.1.0, and MATLAB_R2019a. Microsoft Excel was first used to convert the calibrated data from amps to kilowatts. The authors utilized JMP Student Edition 14.1.0 software for all regression analysis to investigate daily average energy use, including scatterplots and descriptive statistical analyses. The majority of data processing was performed using MATLAB_R2019, including the development of energy profiles, weekday versus weekend plots, and the evaluation of peak energy use values. To evaluate peak energy use values, the Signal Processing toolbox was employed. The toolbox allowed us to identify peak values, which indicated significant variances in energy use such as when significant demands are made on the HVAC systems.

Exploring the relationship between outdoor temperature and energy use

An exploration of daily energy use variations through regression analyses

We plotted total daily energy use of the entire building against daily average temperature for the summer, fall, winter, and spring seasons. The authors also plotted total daily energy use of each apartment unit against the average daily temperature for the summer, fall, winter, spring seasons. The plots are line fitted with a confidence interval of 95%. Statistical inferences are made from the plots through the coefficient of determination or R squared (R^2) value and the coefficient of variation (CV). Additionally, a comprehensive descriptive statistical analysis can be found in Appendices A for each apartment unit across the four seasons. For this study, R^2 values of 0.5 will be considered of moderate significance. The CV value also stands to evaluate the efficacy of the regression model and its predictive capabilities, wherein a CV value below or equal to 25%

indicates a good model fit with acceptable predictive capabilities (American Society of Heating 2013).

An exploration of month-by-month energy use through descriptive statistics

The authors used descriptive statistics to evaluate the relationship between temperature and energy use on a month-by-month basis of the mini-split heat pumps throughout the study. Studies where the climate is comparable include one administered in Hong Kong, which is categorized by subtropical mildly humid climate, found that energy use was significantly higher in the summer months than in the winter (Tso and Yau 2003). Contrastingly, studies performed in Sweden, which utilized submetering technology on passive houses to measure domestic energy use, found significantly higher use in the winter than in the summer (Bagge 2007; Bagge and Johansson 2011). The methods applied in these previous studies informed our exploration into the month-by-month energy use of each resident as logged through data collected at the 1-hour resolution.

Energy profiles across seasons for identifying occupant behavior patterns

We developed energy profiles for weekdays versus weekends to identify occupant behavior patterns by adopting different methods in the literature. Energy profile plots developed from metadata sets usually involve the development of aggregated average energy use plots. One Austin, TX based case study, found inconsistencies in high-frequency data for HVAC systems in 39 occupied residential buildings (Do and Cetin 2019), providing further evidence to support the noise associated with high-resolution data. We, therefore, adapted methods from both studies by integrating and aggregating the average values for data collected at both the 1-minute and 1-hour resolution, where the timeframes we were exploring had us developing plots for the weekday versus weekend temporal event.

Identifying interactional behaviors and user interactions through *'findpeaks'*

The authors utilized MATLAB_R2019a software at 1-minute interval to describe residents' interactional behaviors throughout two inclement weather events: the hottest week and the coldest week. We utilize the 'findpeaks' function to identify local maxima, or a data point "that is either larger than its two neighboring samples or is equal to [a positive infinity] *Inf* ("Find local maxima - MATLAB findpeaks" 2020)." We then plot all peak values throughout the designated period of analysis using color coding to distinguish between the different ranges of energy use peak values. The different ranges of energy use correspond with the manufacturer specifications for heating and cooling season. The thresholds are defined with reference to the manufacturer specifications for heating and cooling capacity, as detailed below in Table 4.

Table 4. Peak Energy Consumption Thresholds for Cooling Season and Heating Season Ranges

Cooling Range		Heating Range	
CR_1	$x \leq 0.500\ kW$	HR_1	$x \leq 0.500\ kW$
CR_2	$0.500\ kW \leq x \leq 0.690\ kW$	HR_2	$0.500\ kW \leq x \leq 0.860\ kW$
CR_3	$0.690\ kW \leq x \leq 1.38\ kW$	HR_3	$0.860\ kW \leq x \leq 1.72\ kW$
CR_4	$x \geq 1.38\ kW$	HR_4	$x \geq 1.72\ kW$

The lowest identified thresholds (CR_1, HR_1) correspond with the HVAC system running on automatic settings. The second to lowest identified threshold (CR_2, HR_2) correspond with the capacity for one mini-split at full capacity or a combination of both mini-splits at medium-low capacity. The next highest capacity (CR_3, HR_3) indicate that two mini-splits are on at medium-full capacity. The fourth and highest identified threshold (CR_4, HR_4) reflects energy use values above the manufacturer total capacity for two mini-split HVAC devices.

RESULTS

An exploration of daily energy use variations through regression analyses

In Figure 1, we have plotted total daily energy use of the entire building, the sum value of all apartment units' MSHP electricity use against daily average temperature for the summer season within the study period, which corresponds with July 7th, 2017 – September 15th, 2017, where temperatures range between 88°F and 61°F. The authors also plotted each apartment unit's daily energy use against the average daily temperature for the summer, as shown in Figure 1 below.

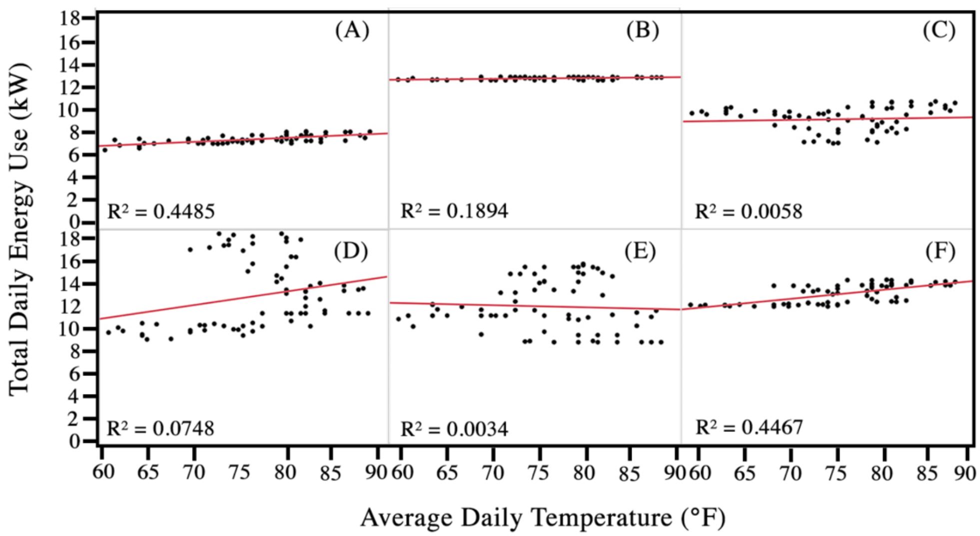

Figure 1. Summer Regression Analysis Scatterplots of Outdoor Temperature and Energy Use

Table 5 includes the summary statistics from the regression analyses, including the coefficient of determination or R squared (R^2) value, the coefficient of variation (CV), and the p-values for total daily energy use against daily average temperature during the summer season. These results indicate the consistency of high-performance buildings and highlight that little to no correlation can be found between temperature and energy use throughout the summer.

Table 5. Statistics Summary for Summer Regression Analysis Scatterplots

	Coefficient of Variation (CV)	R^2 Values	Prob > |t| *p*-value
Unit A	5%	0.45	<.0001
Unit B	0.9%	0.19	<.0001
Unit C	11%	0.01	<.0001
Unit D	23%	0.07	<.0001
Unit E	18%	0.00	<.0001
Unit F	6%	0.45	<.0001

The statistics summary values above indicate that during the summer there is no statistically significant correlation between total daily energy use and average daily temperature for each apartment unit. The CV values, which all remain below 25%, affirm the linear regression model's validity and its appropriate predictive abilities on the summer daily energy use and temperature dataset. R^2 values of each apartment are below 0.5, which is the threshold above which we are deeming values to be moderately significant. Finally, all *p*-values for the linear regression analyses are less than 0.05, indicating that there is no statistically significant relationship between total daily energy use and daily average temperature during the summer.

Additionally, the descriptive statistics values found in Appendices A of this paper reaffirm that within the summer season daily energy use is not dependent on outdoor temperature. This finding is consistent across all units, both at the lower ends of consumption and higher ends, wherein an increased dispersion of the data, such as in Apartment D, with a large mean value and correspondingly large standard deviation value as shown in Appendices A does not indicate a dependence of energy use on temperature. This remains true within apartment units where the data was not as dispersed, as indicated by the standard deviation. The average daily use values were not as high, such as in Unit A and Unit B. The concentration of the data points is therefore not a determining factor when it comes to the dependence of energy use on temperature. Both in the case that datapoints were highly dispersed and in the case that they were tightly fitted about the line, the temperature does not have a statistically significant effect on daily energy use.

During the following fall season, which corresponds with September 16th, 2017 to November 29th, 2017, temperatures range between 81°F and 34°F. Although most apartment units did not see a significant relationship between temperature and energy use, there were a few exceptions.

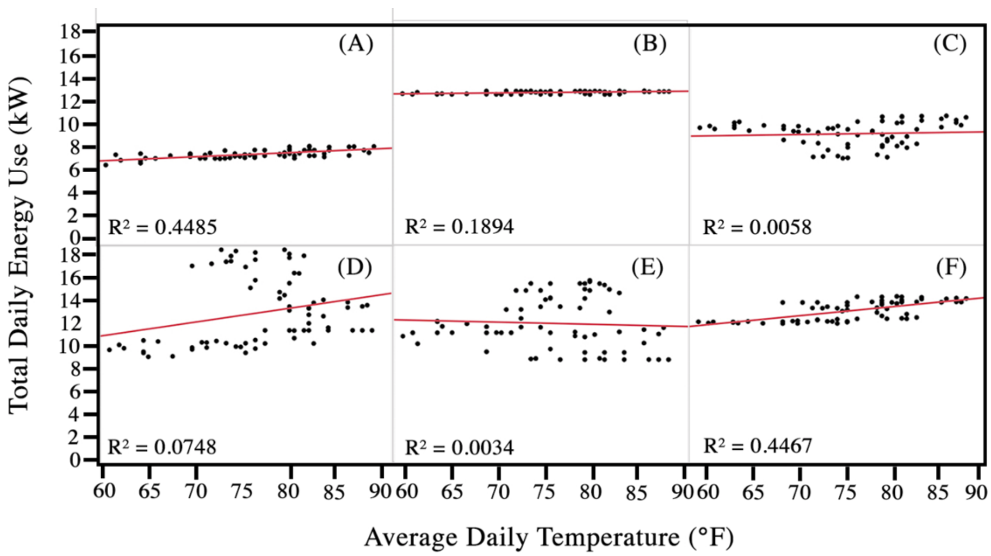

Figure 2. Fall Regression Analysis Scatterplots of Outdoor Temperature and Energy Use

Table 6 includes the summary statistics from the regression analyses, including the coefficient of determination or R squared (R^2) value, the coefficient of variation (CV), and the p-values for total daily energy use against daily average temperature during the fall season.

Table 6. Statistics Summary for Fall Regression Analysis Scatterplots

	Coefficient of Variation (CV)	R^2 Values	Prob > |t| *p*-value
Unit A	11%	0.33	<.0001
Unit B	9%	0.39	<.0001
Unit C	5%	0.13	<.0001
Unit D	16%	0.59	<.0001
Unit E	14%	0.01	<.0001
Unit F	10%	0.68	<.0001

The statistics summary during the fall suggests that there may be a statistically significant relationship between average daily temperature and total daily energy use. The CV values, which all remain below 25%, affirm the linear regression model's validity and its appropriate predictive capabilities during the fall. R^2 values of each apartment are not all below 0.5, which is the threshold above which we are deeming values to be moderately significant. The R^2 values for Unit D and Unit F, which are both above 0.5 suggest that average daily temperature may impact daily energy use during the fall. Contrastingly, all *p*-values for the linear regression analyses are less than 0.05, indicating that there is no statistically significant relationship between total daily energy use and daily average temperature during the summer.

During the winter season, which corresponded with November 30th, 2017 to February 2nd, 2018, temperatures range between 64°F and 10°F. We performed regression analyses for each apartment unit to test the relationship between average daily temperature and total daily energy use as shown below in Figure 3.

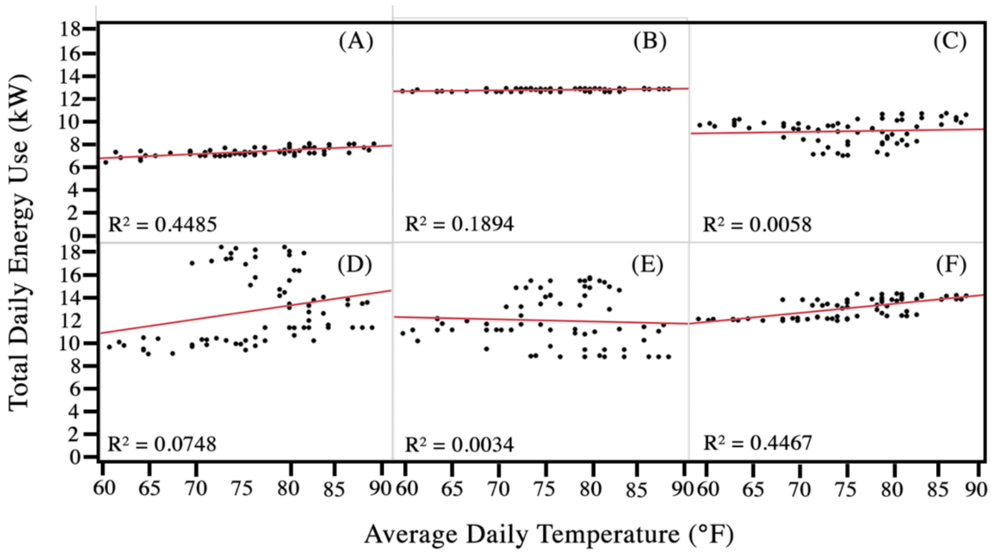

Figure 3. Winter Regression Analysis Scatterplots of Outdoor Temperature and Energy Use

Table 7 includes the summary statistics from the regression analyses, including the coefficient of determination or R squared (R^2) value, the coefficient of variation (CV), and the p-values for total daily energy use against daily average temperature during the winter season.

Table 7. Statistics Summary for Winter Regression Analysis Scatterplots

	Coefficient of Variation (CV)	R^2 Values	Prob > |t| *p*-value
Unit A	5%	0.01	<.0001
Unit B	11%	0.06	<.0001
Unit C	12%	0.07	<.0001
Unit D	13%	0.01	<.0001
Unit E	9%	0.03	<.0001
Unit F	10%	0.01	<.0001

The statistics summary values above indicate that during the winter there is no statistically significant correlation between total daily energy use and average daily temperature for each apartment unit. The CV values, which all remain below 25%, affirm the linear regression model's validity and its appropriate predictive abilities on the summer daily energy use and temperature dataset. R^2 values of each apartment are below 0.5, which is the threshold above which we are deeming values to be moderately significant. Finally, all *p*-values for the linear regression analyses are less than 0.05, indicating that there is no statistically significant relationship between total daily energy use and daily average temperature during the winter.

During the spring season, which corresponded with February 3rd, 2018 to March 22nd, 2018, temperatures range between 70°F and 26°F. We performed regression analyses for each apartment unit to test the relationship between average daily temperature and total daily energy use as shown below in Figure 4.

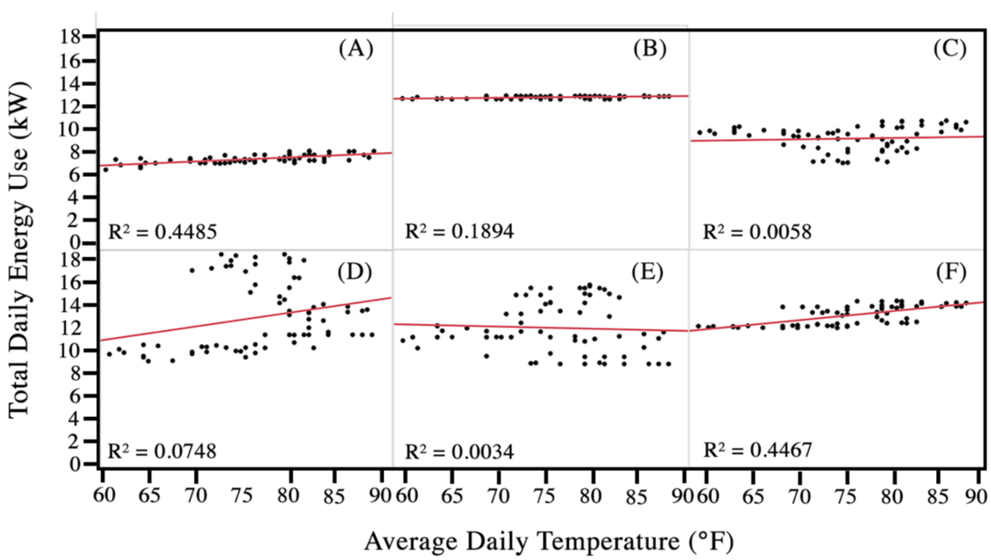

Figure 4. Spring Regression Analysis Scatterplots of Outdoor Temperature and Energy Use

Table 8 includes the summary statistics from the regression analyses, including the coefficient of determination or R squared (R^2) value, the coefficient of variation (CV), and the p-values for total daily energy use against daily average temperature during the spring season.

Table 8. Descriptive Statistics for Spring Regression Analysis Scatterplots

	Coefficient of Variation (CV)	R^2 Values	Prob > |t| *p*-value
Unit A	5%	0.02	<.0001
Unit B	5%	0.17	<.0001
Unit C	7%	0.25	<.0001
Unit D	6%	0.00	<.0001
Unit E	20%	0.02	<.0001
Unit F	3%	0.04	<.0001
All	4%	0.003	<.0001

The statistics summary values above indicate that during the spring there is no statistically significant correlation between total daily energy use and average daily temperature for each apartment unit. The CV values, which all remain below 25%, affirm the linear regression model's validity and its appropriate predictive abilities on the spring daily energy use and temperature dataset. R^2 values of each apartment are below 0.5, which is the threshold above which we are deeming values to be moderately significant. Finally, all *p*-values for the linear regression analyses are less than 0.05, indicating that there is no statistically significant relationship between total daily energy use and daily average temperature during the spring.

Timeframes of Interest

An exploration of weekday versus weekend energy use

Figure 5 shows a sample plot of the HVAC energy use of a single resident throughout the summer season. The sample plot, which captures aggregated average energy use throughout the summer for a single apartment, allows for comparison to be made between weekday and weekend energy use. The plot includes aggregates of data at the 1-hour resolution. Each apartment's plot during the study period was developed and referenced for analysis alongside the descriptive statistics in Appendices C.

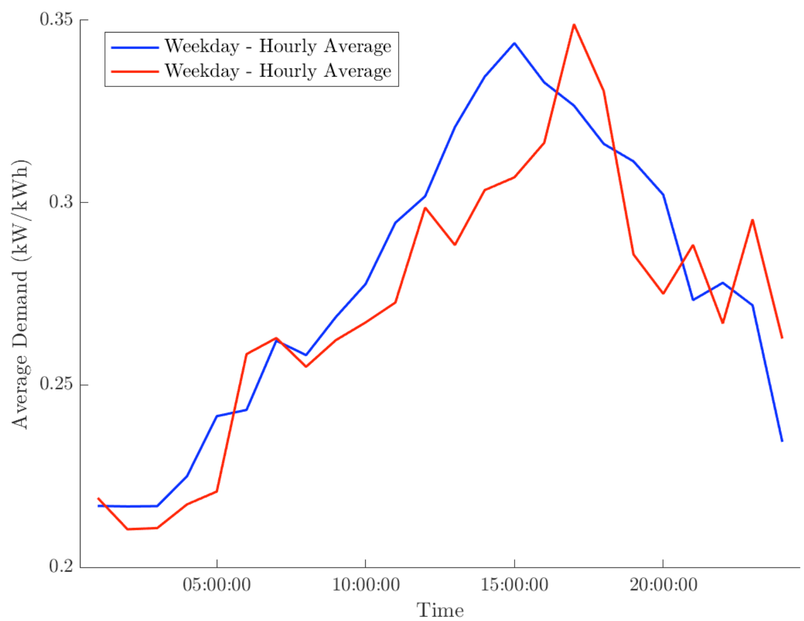

Figure 5. Sample Plot for Comparisons of Weekday and Weekend Energy Use Through Energy Profiles

Figure 5, although primarily included above as a sample of the plots developed, also helped inform the analyses for the energy use during the summer season of the resident in Apartment Unit A during the summer season. From this plot and the corresponding descriptive statistics shown in Table 12 and Table 16 in Appendices B, which include analyses of the weekday and weekend data, we find no statistically significant difference between weekday ($\overline{x}$ = 0.2778 kW) and weekend ($\overline{x}$ = 0.2718 kW) energy use within Apartment Unit A. Findings although distinct in their values for each resident, is consistent throughout all four seasons.

Within each apartment unit, there is no statistically significant difference between weekday and weekend HVAC energy use. The same analyses are performed for all apartment units across each season to understand energy use in this time better.

An exploration of month-by-month energy use through descriptive statistics

The corresponding descriptive statistics in Appendix C helped us describe energy use throughout each month. The total energy use values within the whole building were significantly higher during the heating season, particularly in December and January, which saw the highest building-wide total energy use value of 2400 kWh/month and 3400 kWh/month. This finding is consistent for the individual apartments as well, where all residents were found using more energy in January than any other month throughout the study as shown in Table 26 of Appendix C. The average energy use-value, measured at the 1-minute interval, throughout the study for each of the residents, shown below in Table 6, relative to their average energy use values during January were all significantly lower.

Table 9. Average Energy Use Value

Apartment A	Apartment B	Apartment C	Apartment D	Apartment E	Apartment F
0.3220 kW	0.4640 kW	0.3018 kW	0.4481 kW	0.5310 kW	0.6005 kW

Alongside their higher than usual total energy use values per month, we can affirm that the most energy-intensive month of the study was January for all residents. The study period coincided with extreme temperatures on both ends of the spectrum for the city of Richmond, VA. Data collection for this project started in July 2017, wherein the city experienced one of its hottest summers. Contrastingly, in the 2018 winter temperatures dropped 3 degrees below zero, which marked the coldest reading since 1985 (Boyer 2018, 2019). So, it is notable to find that winter energy use is more significant than summer energy use given that extreme temperatures has occurred during both seasons throughout this study period.

Identifying interactional behaviors and user interactions through *'findpeaks'*

Figure 6 shows two sample plots of the data analysis performed to compare the manufacturer specifications with peak energy use values in (1a) the hottest week and (2a) the coldest week for a single resident throughout the study period. The hottest week in the study corresponds with July 21st, 2017 – July 27th, 2017, where temperatures ranged between 68 °F – 100 °F. The coldest week in the study corresponds with January 7th, 2018 – January 13th, 2018 where temperatures ranged between -2 °F – 70 °F. The plots include data collected at the 1-minute resolution with corresponding color coordination to indicate the different ranges of energy use alongside percent distributions in each range and hourly outdoor temperature values. We developed plots for each apartment unit throughout the hottest week and the coldest week of the study, which can be referenced in Appendices A.

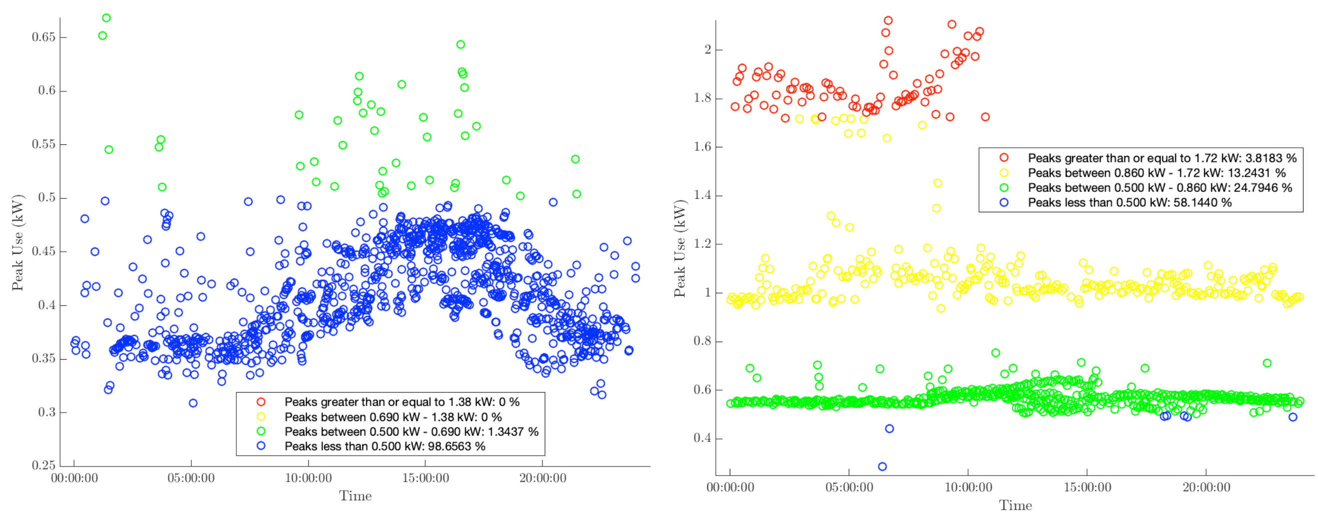

Figure 6. Sample Plots for Peak Energy Use Values in Inclement Weather

(a) Hottest Week, (b) Coldest Week

By cross-referencing the manufacturer specifications, we define four ranges of energy use for both inclement weather events in Table 10a and Table 10b below. The lowest identified thresholds (CR_1, HR_1) correspond with the HVAC system running on automatic settings. The second to lowest identified threshold (CR_2, HR_2) correspond with the capacity for one mini-split at full capacity or a combination of both mini-splits at medium-low capacity. The next highest capacity (CR_3, HR_3) indicate that two mini-splits are on at medium-full capacity. The fourth and highest identified threshold (CR_4, HR_4) reflects energy use values above the manufacturer total capacity for two mini-split HVAC devices.

Table 10a. Peak Distributions Throughout the Hottest Week

Cooling Ranges (CR)	CR_4	CR_3	CR_2	CR_1
	$x \geq 1.38$	$0.690 \leq x \leq 1.38$	$0.500 \leq x < 0.690$	$x < 0.500$
Apartment A	0%	0%	1.34%	98.66%
Apartment B	2.11%	14.15%	20.38%	63.36%
Apartment C	0.14%	2.93%	32.13%	64.79%
Apartment D	1.59%	21.56%	16.21%	60.64%
Apartment E	8.39%	17.55%	8.75%	65.31%
Apartment F	0.60%	10.46%	73.13%	15.82%

Table 10b. Peak Distributions Throughout the Coldest Week

	$x \geq 1.72$	$0.860 \leq x \leq 1.72$	$0.500 \leq x < 0.860$	$x < 0.500$
Apartment A	3.82%	13.24%	24.79%	58.14%
Apartment B	10.84%	22.10%	30.21%	36.85%
Apartment C	74.47%	10.25%	13.69%	1.59%
Apartment D	13.85%	19.52%	32.04%	34.56%
Apartment E	8.61%	33.65%	27.49%	30.25%
Apartment F	25.92%	62.48%	0.16%	11.44%

During the hottest week, we find that for five of the apartment units, energy use peak values remain within the lowest identified threshold. The lowest threshold indicates that for greater than 60% of the time, the mini-split heat pumps have the fan running for these four residents. For the resident in Apartment F, though, we see that majority of their peak energy use values are within the second threshold where 0.500 kW $\leq x <$ 0.690 kW. We thereby deduce that throughout the hottest week in the study, they are using both mini-split HVAC systems in tandem at a medium-low capacity or they are using one mini-split HVAC system at close to capacity. In the third range, where 0.690 kW $\leq x \leq$ 1.38 kW, we find percent distributions between 10% - 20% for Apartments B-F. And for Apartment A, we find the percent distribution within the third threshold and fourth threshold alike, to be zero. We thereby can conclude that throughout the hottest week the resident in Apartment A was most likely not using both mini-split HVAC systems. We also find close to zero for the percent distribution values in the fourth threshold, which indicates $x \geq$ 1.38 kW, for Apartments C and F. We find low percentage distributions in the remaining Apartments B (2.11%), D (1.59%), and E (8.39%).

During the coldest week, each resident has a unique set of interactions with their thermostats where the percent distributions of peak energy use values vary across the board for all residents. In Apartment A, we find that the resident is for the most part using either one or two of their HVAC units, with most of the datapoints (58%) near the baseload value, where $x < 0.500$ kW and 25% within the second threshold, which indicate the use of either one mini-split at full capacity or two at medium-low capacity. Apartments B, E, and F saw a nearly even distribution across the lower two thresholds, where the percent distributions within the lowest two quadrants, $x < 0.500$ kW and $0.500 \text{ kW} \leq x < 0.860$ kW, were nearly 30% in each. In Apartment C, though, we see that the most significant amount of peak energy use values (75%) is within the fourth quadrant, which indicates that both of their HVAC systems were operating above capacity, which is an abnormality that should be furthered explored with the property manager and manufacturer. Apartment F also saw an interesting distribution where the majority of peak energy use values were in the third quadrant, where $0.860 \text{ kW} \leq x \leq 1.72$ kW, which indicates that both mini-split devices were on at medium-high capacity throughout the coldest week of the study.

DISCUSSION

Outdoor Temperature Effects

Our findings suggest that within this study there is no substantial correlation between energy use and outdoor temperature. This finding speaks to the efficacy of the tight insulation installed in these newly constructed buildings. During the summer, winter, and spring, we found little to no correlation between outdoor temperature and energy use. This building's architectural data indicates tight insulation and mini-split heat pump (MSHP) devices with high Seasonal Energy Efficiency Ratio (SEER) and Heating Seasonal Performance Factor (HSPF) ratings, mitigate the impacts of temperature on energy use. This finding agrees with the body of literature, which suggests that within high-performing homes, energy use is not significantly impacted by outdoor temperature (Csoknyai et al. 2019; Lee et al. 2014; Ueno and Loomis 2015; Zhao et al. 2017, 2018). One limitation of this investigation is that we were not able to contrast the energy use of different sociodemographic groups to one another as other Virginia-based studies have done (McCoy et al. 2015; Zhao et al. 2018).

In contrast our findings during the fall suggest a moderate correlation between outdoor temperature and energy use of senior residents. Although the statistical significance of this correlation is moderate, the finding itself is significant given the building and HVAC specifications. Given the architectural data and HVAC specifications, this finding brings into question broader climate-related impacts. A future opportunity for research involves assessing the relationship between other climate-related factors such as humidity. Within high-performing building studies suggest there is a shift in the balance of sensible and latent cooling loads. As insulation levels increase alongside advances in window technology, sensible cooling loads decrease. In turn latent cooling loads are increasing, which “may result in higher indoor humidity, occupant discomfort, and stunted adoption of high-efficiency homes” (Winkler et al. 2018). Richmond, VA is in Climate Zone 4A, which is categorized by mild subtropical humid climate. We infer that residents are using their HVAC systems to dehumidify as opposed to cool during periods of time with a moderate correlation between outdoor temperature and energy use.

Timeframe Explorations

The exploration of different timeframes provided insight into the patterns of senior residents’ HVAC energy use. With regard to weekday and weekend variations in energy use, the results showed little variation between the two periods of time. In an analysis of the month-by-month energy use, we find residents are using the most energy during the winter months. This finding is in line with previous literature, which discusses the propensity of older adults to use more energy for heating. However, this finding in tandem with the regression analyses findings suggest that with depth of analysis, we can find opportunities to improve upon performance metrics that we would not otherwise be able to identify through regression analyses alone.

While the heating season is the most energy-intensive season, that is also the season where we see the least consistency in energy use. This finding is evident through visual examination of both aggregated average plots, wherein the hourly aggregated average lines across all units do not have recurring and distinctive patterns in use. Additionally, the corresponding minute aggregated average lines see much more significant variation, as illustrated by the height of the peak signals. From which we also conclude that the number of interactions with the thermostat is most significant during the winter. The increased interactions of residents during the winter can be attributed to their discomfort with cold weather. This counteracts some of the power-saving advantages of inverter-based HVAC systems. As the load on the compressor increases during the winter, we see instances where either one or both mini splits are acting abnormally and using more energy than capacity.

Building Occupant Behaviors

Within residential buildings, occupants have a higher degree of control over energy use, and their behaviors play a significant role in impacting energy consumption (Mo et al. 2020). The definition of building occupant behavior is highly contextual and can be defined by varying levels of complexity (Chen et al. 2015; Laaroussi et al. 2020). Throughout this case study, we utilize quantitative analyses to investigate the building occupant interactions with their thermostats. We analyze peak energy use through MATLAB and develop plots while referencing manufacturer specifications for heating capacity and cooling capacity respectively. We are thereby able to distinguish between the energy use of a single or two mini-split HVAC systems within a single apartment. The dispersion of datapoints during the summer was towards the lower two quadrants of energy consumption, whereas the dispersion of datapoints during the summer was towards the upper towards the upper two quadrants of energy consumption. We can infer that residents are comfortable using one HVAC system during the hottest week of the study but not in the winter. In the winter, residents are using both HVAC systems to the point that we are also able to detect system abnormalities in numerous apartments during the coldest week of the study. Although outside of the scope of this paper, there is a potential to utilize advanced metering to detect and diagnose both malfunctions in sensor data collection as well as the operation of HVAC (Mattera et al. 2018).

CONCLUSION

Throughout this study, we had the unique opportunity to investigate and quantify the HVAC energy use of six senior residents within a net-zero energy affordable housing community alongside a limited number of NZB studies within the state (Agee et al. 2019; Paige et al. 2019a). This study contributes to a limited body of literature, which identifies a post-occupancy gap within NZBs (Agee et al. 2018; To et al. 2017; Zhou et al. 2016) and moves the conversation forward by identifying opportunities to improve upon energy performance. The difficulties which surround publishing findings from NZB residential projects with "*negative*" results (Šćepanović et al. 2017), can be surmounted by identifying opportunities that exist within them to improve upon performance metrics. We encourage the research community to do the same especially as it pertains to ambitious projects that have not yet met their performance goals.

This single-case study explores the HVAC energy use of six senior residents within a net-zero affordable housing community in Richmond, VA. Three variables were investigated for their impact on energy consumption: seasonality, outdoor temperature, and occupant behaviors across different timeframes and using different data resolutions. The motivation of this study was to better understand the opportunities that exist to improve upon energy performance within this affordable housing community. Results indicate that outdoor temperature had a minimal impact on energy consumption in these high-performance homes. Within the results, we do find a low-medium correlation between temperature and energy use in two apartment units ($R_F^2 = 0.68$, $R_D^2 = 0.59$) during the fall. There was also no statistically significant difference between HVAC energy use during the weekdays relative to the weekends, in spite the residents in this study describe themselves as active seniors who are work throughout the week. Finally, we found that winter behaviors of the senior residents in this net-zero housing study are a limiting factor in meeting performance metrics.

Our results highlight that the ductless MSHPs were more efficient during the cooling season, which is in line with other field studies in similar climates. Sutherland et al. (2016) reported superior performance of ductless MSHP during the cooling season and attributed it to successful control of interior moisture in hot-humid climates during the summer. Other studies reported moderate ductless MSHP energy savings during the cooling season in cool climates (Faesy et al. 2014). We move this conversation forward by suggesting that heating energy provides more opportunities for efficiency.

The residents were making greater demands on the MSHPs during the winter than any other time during the study. Our findings exist within a limited body of literature, which evaluates the measured field performance of ductless MSHPs (Faesy et al. 2014) in hot-humid climates during the heating season. This finding is significant given the context of this study as a net-zero building (NZB) property, which has yet to perform to this standard. Therefore, we infer that limited solar resources during the wintertime paired with abundant occupant use of the MSHPs are one of the hinderances to achieving the NZB goals of this project.

Through this study, we concur that building occupant behaviors play a significant role in the ductless MSHP winter energy performance. While the term “building occupant behaviors” encompasses a myriad of human interactions, in this study we focus on the quantitative analysis of their energy use. We identify residents’ use of one or both MSHPs within their apartment unit. Residents were demanding more energy throughout the winter, as exhibited by their use of both MSHPs throughout the coldest week in the study. This finding contrasted with their energy use throughout the hottest week in the study, where they were comfortable using a single MSHP.

Insert new transition. Moving forward, it would be beneficial to explore the motivations, such as comfort issues, behind their increased energy throughout the winter. In similar conditions, Roth et al. (2013) cited comfort issues as one of the main hinderances to achieving optimal energy performance of ductless mini-split heat pumps during the heating season. In a study featuring multi-split heat pumps, occupants described their discomfort in experiencing different temperatures across different rooms (Sutherland et al. 2016). A limitation of this study is that ambient temperature and thermostat setpoints have not yet been made available. Investigations of potential room-to-room differences in ambient temperature would also increase the understanding of the impact residents’ comfort levels have on their HVAC energy use throughout the household.

This work provides many opportunities for future work. First, the dataset used in this study is a publicly available dataset (Paige et al. 2019a), which we encourage the use of and invite researchers to contact the corresponding authors for assistance in leveraging this data. Second, we encourage the utilization of both the quantitative and qualitative portions of the dataset to expand on the original objectives of this project (Paige et al. 2019b). Third, we encourage the adoption or *adaption* of methods applied in this study for similar studies to investigate a limited body of literature, which exists surrounding senior residents in NZBs. Finally, for future work data collection could be updated and collected for longer periods of time after senior residents have received energy education during the winter.

COMPETING INTERESTS

The authors declare no competing interests.

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APPENDICES

Appendix A. Descriptive Statistics for Daily Use

Table 11. Descriptive Statistics for Daily Energy Use (kW) During the Summer Season

Summer (N = 71)						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	545.8290928	1.604656402	7.68773	N/A	7.627008463	0.36194
Unit B	935.7014394	0.31251259	13.1789	N/A	13.2368439	0.1169
Unit C	699.437613	3.624889297	9.85123	N/A	10.11738146	1.06648
Unit D	933.4100337	9.282024584	13.1466	N/A	11.85127802	2.99057
Unit E	862.0374877	6.785764158	12.1414	N/A	11.61053494	2.2109
Unit F	944.754794	2.30507663	13.3064	N/A	13.51618132	0.81233
Sum of All Units	4921.17046	11.85657486	11.552	N/A	11.70015089	4.28241

Table 12. Descriptive Statistics for Daily Energy Use (kW) During the Fall Season

Fall (N = 65)						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	636.2483831	3.167	8.48331	N/A	8.7226	0.91218
Unit B	1084.119952	5.089	14.4549	N/A	14.341	1.24979
Unit C	793.2042689	2.538	10.5761	N/A	10.616	0.58107
Unit D	857.4074173	6.665	11.4321	N/A	11.663	1.77365
Unit E	963.7410215	7.079	12.8499	N/A	12.608	1.7988
Unit F	1062.788059	3.202	12.8499	N/A	14.066	1.22397
Sum of All Units	5397.509101	10.74	71.9668	N/A	12.234	3.895

Table 13. Descriptive Statistics for Daily Energy Use (kW) During the Winter Season

Winter (N = 75)						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	428.1937955	1.085	6.5876	N/A	6.6571	0.31505
Unit B	1038.652209	6.884	15.9793	N/A	16.165	1.75762
Unit C	701.8183135	3.655	10.7972	N/A	11.431	1.25472
Unit D	740.8956071	4.533	11.3984	N/A	11.27	1.5331
Unit E	963.1517666	5.439	14.8177	N/A	14.672	1.37903
Unit F	922.8772986	3.478	14.1981	N/A	15.195	1.36223
Sum of All Units	4795.58899	12.4	73.7783	N/A	12.45	6.06386

Table 14. Descriptive Statistics for Daily Energy Use (kW) During the Spring Season

Spring (N = 48)						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	287.7315931	0.834	5.99441	N/A	5.8575	0.31048
Unit B	521.4693106	2.415	10.8639	N/A	10.876	0.56913
Unit C	429.7304887	2.008	8.95272	N/A	8.7973	0.5949
Unit D	491.9855108	2.732	10.2497	N/A	10.323	0.62413
Unit E	599.5452935	8.287	12.4905	N/A	12.586	2.45172
Unit F	562.0384755	0.959	11.7091	N/A	11.623	0.33943
Sum of All Units	2892.500672	10.7	60.2604	N/A	10.429	2.34327

Appendix B. Descriptive Statistics for Weekdays versus Weekends

Table 15. Descriptive Statistics for Aggregated Average Weekday Use for the Summer

Summer						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	6.6683	0.1263	0.2778	0.2167	0.2754	0.0406
Unit B	10.4741	0.2444	0.4364	0.3277	0.4383	0.0787
Unit C	8.2612	0.2474	0.3442	0.2255	0.348	0.0849
Unit D	9.538	0.4992	0.3974	0.2265	0.3098	0.1757
Unit E	10.3559	0.4421	0.4315	0.2831	0.3809	0.142
Unit F	10.6979	0.269	0.4457	0.3202	0.4349	0.0897
Sum of All Units	55.9955	1.7297	2.3331	1.6509	2.172	0.5791

Table 16. Descriptive Statistics for Aggregated Average Weekday Use for the Fall

Fall						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	6.5037	0.1435	0.271	0.2023	0.2836	0.0475
Unit B	6.5631	0.0424	0.2735	0.2509	0.272	0.0121
Unit C	5.3331	0.061	0.2222	0.1861	0.2277	0.0196
Unit D	7.4377	0.1537	0.3099	0.2493	0.2888	0.0493
Unit E	9.7652	0.0855	0.4069	0.3685	0.4053	0.0218
Unit F	6.1457	0.125	0.2561	0.207	0.2464	0.0417
Sum of All Units	41.7484	0.4091	1.7395	1.5578	1.7274	0.1316

Table 17. Descriptive Statistics for Aggregated Average Weekday Use for the Winter

Winter						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	11.6427	0.2581	0.4851	0.3755	0.46	0.0844
Unit B	17.5342	0.2879	0.7306	0.5604	0.7448	0.085
Unit C	8.5991	0.14	0.3583	0.3129	0.344	0.042
Unit D	15.2952	0.2906	0.6373	0.4686	0.6698	0.1021
Unit E	18.7828	0.3161	0.7826	0.6531	0.7684	0.1029
Unit F	22.2544	0.2975	0.9273	0.7749	0.9593	0.0857
Sum of All Units	94.1084	1.5459	3.9212	3.1604	3.9651	0.4603

Table 18. Descriptive Statistics for Aggregated Average Weekday Use for the Spring

Spring						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	6.6419	0.1403	0.2767	0.2171	0.2731	0.0422
Unit B	11.4049	0.1829	0.4752	0.3882	0.4691	0.0493
Unit C	6.8543	0.1631	0.2856	0.2194	0.2738	0.0508
Unit D	12.1714	0.2818	0.5071	0.369	0.5194	0.091
Unit E	12.9688	0.2805	0.5404	0.4327	0.5277	0.0685
Unit F	23.2414	0.3413	0.9684	0.7986	0.9806	0.1116
Sum of All Units	73.2826	1.1286	3.0534	2.4746	3.0916	0.3377

Table 19. Descriptive Statistics for Aggregated Average Weekend Use for the Summer

Summer						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	6.5236	0.1395	0.2718	0.2104	0.2695	0.0375
Unit B	10.6353	0.2166	0.4431	0.3507	0.4222	0.0719
Unit C	8.3359	0.2845	0.3473	0.2384	0.3468	0.0859
Unit D	9.3964	0.3585	0.3915	0.2362	0.3863	0.1276
Unit E	10.775	0.5847	0.449	0.2217	0.3946	0.1825
Unit F	10.4495	0.2609	0.4354	0.3179	0.4235	0.0826
Sum of All Units	56.1156	1.6066	2.3381	1.6891	2.3591	0.5186

Table 20. Descriptive Statistics for Aggregated Average Weekend Use for the Fall

Fall						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	7.2176	0.2531	0.3007	0.2064	0.2907	0.0804
Unit B	6.2171	0.1146	0.259	0.2194	0.2472	0.0342
Unit C	5.5325	0.0811	0.2305	0.1884	0.2375	0.0235
Unit D	7.1439	0.1278	0.2977	0.24	0.296	0.0358
Unit E	9.7088	0.2279	0.4045	0.3281	0.386	0.0574
Unit F	6.222	0.1322	0.2592	0.204	0.2519	0.0453
Sum of All Units	42.0419	0.6948	1.7517	1.4354	1.7419	0.2228

Table 21. Descriptive Statistics for Aggregated Average Weekend Use for the Winter

Winter						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	11.3426	0.246	0.4726	0.3797	0.4491	0.0724
Unit B	15.6477	0.3055	0.652	0.4746	0.6841	0.0924
Unit C	8.436	0.163	0.3515	0.3033	0.3418	0.0447
Unit D	14.1486	0.2459	0.5895	0.4816	0.6077	0.07
Unit E	18.0418	0.3637	0.7517	0.6163	0.7283	0.0971
Unit F	19.9392	0.2605	0.8308	0.7186	0.8289	0.0871
Sum of All Units	87.5559	1.3624	3.6482	3.026	3.5882	0.4047

Table 22. Descriptive Statistics for Aggregated Average Weekend Use for the Spring

Spring						
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	8.0443	0.1536	0.3352	0.2726	0.3354	0.0464
Unit B	11.4929	0.255	0.4789	0.3658	0.4661	0.0747
Unit C	6.7578	0.1443	0.2816	0.2119	0.2701	0.0463
Unit D	12.3913	0.3233	0.5163	0.3372	0.5102	0.1034
Unit E	12.7538	0.3807	0.5314	0.3581	0.4989	0.1332
Unit F	23.2438	0.3851	0.9685	0.7745	0.955	0.1301
Sum of All Units	74.6839	1.2127	3.1118	2.4872	3.0713	0.4348

Appendix C. Descriptive Statistics for Monthly Use

Table 23. Descriptive Statistics for July Energy Use (kW)

	July					
	Total use (kW)	Range	Mean	Mode	Median	Std. Dev.
Unit A	170.143965	0.639	0.2836	0.1818	0.196	0.1187
Unit B	321.741477	2.2748	0.5435	0.1825	0.5153	0.259
Unit C	231.438189	1.3909	0.3904	0.1772	0.3815	0.1788
Unit D	273.243998	2.3158	0.4629	0.1849	0.3808	0.3402
Unit E	320.919313	3.2054	0.5397	0.1849	0.1988	0.5093
Unit F	313.038065	1.2979	0.5309	0.1825	0.5364	0.1729
Sum of All Units	1630.525007	6.8931	2.7509	1.0504	2.5141	1.0539

Table 24. Descriptive Statistics for Average Hourly August Energy Use (kW)

	August					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	212.197195	1.2275	0.2852	0.1811	0.1983	0.1238
Unit B	315.626819	2.1333	0.4258	0.1825	0.4361	0.2225
Unit C	255.373134	1.1919	0.3442	0.1772	0.3452	0.1504
Unit D	290.311518	2.2778	0.3868	0.1843	0.2011	0.277
Unit E	311.171274	2.904	0.4237	0.1849	0.1965	0.396
Unit F	326.594626	0.9988	0.4397	0.1829	0.4768	0.1572
Sum of All Units	1711.274566	5.9229	2.3054	1.0571	2.1346	0.7966

Table 25. Descriptive Statistics for Average Hourly September Energy Use (kW)

	September					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	201.760341	1.4369	0.2802	0.1814	0.1944	0.1455
Unit B	216.922424	1.6059	0.2965	0.1831	0.1974	0.1599
Unit C	183.659861	1.3843	0.2526	0.1713	0.1779	0.1187
Unit D	240.086562	2.2541	0.3336	0.1843	0.1978	0.2543
Unit E	238.035175	2.6846	0.3241	0.1849	0.1923	0.1923
Unit F	247.565726	0.4788	0.3399	0.1868	0.3190	0.1441
Sum of All Units	1328.0301	0.1681	0.0761	0.0442	0.0688	0.0266

Table 26. Descriptive Statistics for Average Hourly October Energy Use (kW)

	October					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	176.580071	1.2912	0.2373	0.1809	0.1863	0.1407
Unit B	159.44092	1.9349	0.214	0.1825	0.1885	0.089
Unit C	150.012598	1.0534	0.2014	0.1713	0.1745	0.0692
Unit D	195.880445	2.3021	0.2625	0.1843	0.1965	0.1726
Unit E	217.530445	1.9007	0.2919	0.1849	0.1884	0.2541
Unit F	195.125504	0.4061	0.2611	0.1827	0.185	0.1137
Sum of All Units	1094.569983	3.2003	1.4682	1.0435	1.2822	0.481

Table 27. Descriptive Statistics for Average Hourly November Energy Use (kW)

	November					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	219.475116	1.5626	0.3097	0.1801	0.1873	0.1993
Unit B	220.61484	3.3143	0.3097	0.1826	0.1947	0.2571
Unit C	176.153506	1.5221	0.2448	0.1713	0.1749	0.1454
Unit D	230.63726	2.3143	0.3215	0.1843	0.1969	0.2079
Unit E	401.808352	2.8742	0.566	0.1849	0.6002	0.3818
Unit F	137.380363	0.3956	0.1903	0.1801	0.1807	0.0447
Sum of All Units	1386.069437	5.5141	1.9372	1.0223	1.8222	0.7108

Table 28. Descriptive Statistics for Average Hourly December Energy Use (kW)

	December					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	307.132097	2.4099	0.4125	0.1719	0.3354	0.2987
Unit B	496.549089	3.1750	0.6707	0.1708	0.5784	0.4528
Unit C	219.234186	2.0369	0.2993	0.1707	0.1945	0.2127
Unit D	374.925889	1.9871	0.5125	0.1760	0.5427	0.3391
Unit E	541.631288	3.6417	0.7370	0.1760	0.7008	0.7008
Unit F	424.092177	3.2881	0.5936	0.1801	0.1802	0.6711
Sum of All Units	2363.5647	0.4496	0.1344	0.0419	0.1215	0.0623

Table 29. Descriptive Statistics for Average Hourly January Energy Use (kW)

	January					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	416.903825	2.82439869	0.55914631	N/A	0.45864917	0.47826509
Unit B	568.505006	3.27339468	0.76357237	N/A	0.59558167	0.56018218
Unit C	317.044552	2.16975544	0.42085659	N/A	0.19912253	0.36637911
Unit D	561.033324	3.68475991	0.74445835	N/A	0.56298267	0.55029116
Unit E	623.536963	3.13216704	0.81593733	N/A	0.79511277	0.79511277
Unit F	913.868264	3.23444461	1.21572314	N/A	1.35252722	0.71326605
Sum of All Units	3400.891934	0.52723029	0.18832059	N/A	0.16972967	0.09937875

Table 30. Descriptive Statistics for Average Hourly February Energy Use (kW)

	February					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	199.332082	2.5502	0.2966	0.1725	0.1762	0.2375
Unit B	331.546121	2.5723	0.4869	0.1683	0.5669	0.3450
Unit C	186.119605	1.9738	0.2755	0.1713	0.1970	0.1790
Unit D	333.779318	1.8922	0.4938	0.1760	0.5104	0.3487
Unit E	354.881339	2.9177	0.5314	0.1855	0.5603	0.5603
Unit F	623.365518	2.2062	0.9192	0.1694	1.1618	0.5715
Sum of All Units	2029.0240	0.3577	0.1251	0.0423	0.1179	0.0595

Table 31. Descriptive Statistics for Average Hourly March Energy Use (kW)

	March					
	Total Use (kWh)	Range	Mean	Mode	Median	Std. Dev.
Unit A	159.194627	3.01930818	0.3055	N/A	0.1776	0.2291
Unit B	250.613747	3.24832068	0.4761	0.1677	0.2267	0.3701
Unit C	156.393665	2.0851968	0.2972	0.1713	0.1972	0.1931
Unit D	284.50827	2.22330357	0.5429	N/A	0.549	0.3227
Unit E	290.493119	2.89094454	0.5521	N/A	0.5879	0.3513
Unit F	549.464724	2.52193992	1.0446	N/A	1.306	0.5021
Sum of All Units	1690.668152	N/A	N/A	N/A	N/A	N/A

Conference Paper 1:

Monitoring HVAC System Performance in Real Time for Affordable Housing Units

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ABSTRACT

HVAC systems are a top contribution to residential building energy consumption and thermal performance. This study demonstrates the ability for property managers of affordable housing units to monitor the performance of their HVAC systems across their building stock using smart devices and cloud computing. This paper presents a case study of an affordable housing development in Virginia which was recently renovated to improve and explore HVAC system performance with high financial precision to meet evolving federal regulations. Real-time building energy usage at the circuit-level, resident perceptions, property manager perceptions, and building specifications are all combined to provide a detailed understanding of current and future practices for wirelessly monitoring HVAC equipment. This paper focuses on HVAC performance describing the selection, utilization, and performance of appropriately sized and comparable one stage, two-stage, and variable speed HVAC systems. Preliminary data analysis has shown great potential for updating previous processes to calibrate inaccurate perceptions of behavior-driven energy use; leverage cloud computing for data analytics and visualization to improve data accessibility; and the inclusion of socio-political impacts into decision-making tools. We have also found a critical need to better incorporate the variability of system performance due to the high potential for installation errors and user errors. The findings of this study extend beyond the context of HVAC systems to various building systems that can be connected to the internet of things (IoT). The methodology of this study also provides guidance for better academic-industry-citizen engagement for the real-world testing and design of engineered infrastructure systems.

Keywords: HVAC Systems, Internet of Things, Affordable Housing, Sustainable Housing, Smart Thermostats, Energy Monitoring

INTRODUCTION

Deciding between paying energy bills or buying groceries is a tradeoff many low-income residents have to make. The 2015 Residential Energy Consumption Survey (RECS) reported that 31% of US households faced difficulties when paying their energy bills and 20% of the US households reported reducing expenses spent on food and medication to instead pay their energy bills (“2015 RECS: Overview,” 2015). Difficulty accessing energy disrupts almost every aspect of modern life, which includes refrigerating food and drinks or working through the night. Therefore, this tradeoff which many low-income residents have to make, illustrates that energy security is a basic human need. Access to energy not only ensures that functioning in daily life but it also paves the way to a better standard of living, health care, and well-being of all individuals within a society. Furthermore, improving the energy efficiency of low-income housing units to match the level of the average US home would alleviate approximately 35% of the total energy burden on the people who need it most (Drehobl and Ross, 2016). There is a need to break this negatively reinforcing cycle of energy inefficiency, energy burden, and social inequality across low-income vulnerable communities.

This paper highlights the initial data-driven findings of a longitudinal field study, with an industry partner, which provides energy consumption data for an affordable housing community that caters to low-income residents. The industry partner recently upgraded the HVAC systems in their housing community and would like to investigate the benefits and drawbacks of this energy investment. The field study method is an underutilized method in academia due to the difficulty of accessing data and the extensive time required, but it allows us to analyze the energy performance and cost performance of these new systems alongside manufacturer specifications, utility company data, and landlord feedback and input.

METHODS

This paper reports the initial findings of a longitudinal field study, which documents the upgrades of one-stage, two-stage, and variable speed HVAC system upgrades across 39 different units in an affordable housing community in Montgomery County, Virginia. The initial findings reported within this paper include: (1) a preliminary analysis of data collected from 9 different units within the housing community, which includes energy analysis in terms of the performance of the respective HVAC systems while following the traditional model of energy analysis; (2) an exhaustive analysis of data collected from 35 units within the housing community, which includes energy analysis of the performance of the respective HVAC systems while following the traditional model of energy analysis; and (3) the study also introduces the second stage of the study, which will incorporate data from circuit-level eGauge data collected at the breaker panel within each household.

Manufacturer Specifications

The property managers evaluated numerous factors from the manufacturer specifications to determine which HVAC systems to install. The main factors that were taken into consideration upon determining system efficiency were the System Energy Efficiency Ratio (SEER) rating and cooling capacity. The SEER Rating on the single-stage, two-stage, and variable speed HVAC systems were 16, 17, and 18, respectively. Additionally, the cooling capacity of the single-stage, two-stage, and variable speed HVAC systems selected were 18,000-60,000 Btuh, 24,000-60,000 Btuh, and 24,000-60,000 Btuh, respectively. A higher SEER rating typically corresponds to more energy savings and greater comfort levels as it is used as a standard ratio for describing a system's efficiency (Wang et al. 2012). Similarly, a higher cooling capacity indicates an increased ability to remove heat from a building.

Data Monitoring and Analysis of Performance

The data analysis process is made possible through the data provided by the electric utility company, which is the property's energy provider. This data is reported on an aggregated monthly average basis, which displays total kilowatt-hours for two households within a single duplex unit. Additionally, these reported values are an aggregated monthly average of the energy consumption of all of the appliances within the building. Data analysis is performed across two time periods, P_1 and P_2, as shown in *Table 32* below, each corresponding with a different status in the project timeline.

Table 32. Analysis Periods Overview

Period	Corresponding Months	Status
P_1	November 2017 - May 2018	Pre-Intervention
P_2	November 2018 - May 2019	Post-Intervention

The time periods and corresponding months specified were in accordance with those provided to the researchers through the electric utility company. The status of pre-intervention is used to describe the period of time in which all of the HVAC systems installed across the different duplexes in the housing community were older one-stage HVAC systems. And the status of post-intervention corresponds to the period of time when new HVAC systems were installed across the community's duplexes.

Moreover, the time periods and their corresponding months fit relatively well into Virginia's heating season. Since Virginia is in climate zone 4A, it's heating season usually corresponds with the months of November to May and its cooling season usually corresponds with June – October. The month of May, however, is considered a swing month, which lies between seasons. Therefore, in order to take into consideration, the seasonal time effects in terms of energy and cost performance, we incorporated the heating degree days (HDD) into the normalization calculations for all of the months except May. For the normalization calculations associated with the month of May across both periods P_1, P_2, we normalized against cooling degree days (CDD). Degree days are a means of accounting for weather-related energy demands (Quayle and Diaz 1979), which help energy analysts account for the relationship between outdoor air temperature and energy consumption within a building. Both the HDD and CDD values were pulled directly from the weather station closest to the housing community studied (National Climatic Data Center 2017-2019) and used in the normalization calculations we performed.

The normalized energy consumption was utilized to perform an energy analysis on both pre-intervention energy performance and cost, as well as post-intervention energy and cost. The energy performance and cost analyses included the comparison of three one-stage HVAC systems, 27 two-stage HVAC systems, and five variable speed systems. Moreover, the data analysis surrounded the analysis of: (1) an analysis of energy performance pre-intervention and post-intervention, (2) One-Way Analysis of Variance (ANOVA) for energy performance, and (3) a cost performance for the pre-intervention and post-intervention periods. These analyses helped the researchers evaluate the efficacy of the system upgrades in terms of energy performance and cost performance across the entire affordable housing community. These analyses and their findings will help the researchers explain the urgency of updating the traditional energy analysis model.

Analysis of Cost Performance

In terms of cost analysis, the standard formula for Return on Investment was used as shown in *Equation 1* below. Such factors include the symbols described below in Table 33 as well as those shown in *Equation 2* below.

Table 33. Cost Analysis Nomenclature

Symbol	**Unit**	**Description**
ROI	%	Return on Investment
CI	$	Cost of Investment
GI	$	Gain from Investment
TED	kWh/month	Total Energy Difference
AVPT	$/kWh	Average Virginia Power Tariff
LS	years	Lifespan of HVAC System

$$ROI = \frac{GI - CI}{CI} \times 100$$

Equation 1. Return on Investment

$$GI = TED \times 7\ months \times AVPT \times LS$$

Equation 2. Gain from Investment

Furthermore, the formula for *Equation 2. Gain from Investment includes* factors such as Total Energy Difference (TED), Average Virginia Power Tariff (AVPT), and the Lifespan of the HVAC System (LS). The TED was found by calculating the difference in energy consumed for each duplex comparatively across the years P_{2-1} for each month and then multiplied by 7 months, which was the duration of both P_1 and P_2. The AVPT is a value for the state of Virginia's standard rates and charges, which was reported by the energy provider. The LS value is the average lifespan of the HVAC system, which is approximately 20 years according to the US Department of Energy ("Central Air Conditioning" n.d.).

RESULTS

The results reported in this paper surround the values reported by the electric utility company, which reports aggregated monthly average values for each of the duplexes. While each duplex includes two townhomes, the values provided are an average of these two townhomes for each month across three time periods. The preliminary analysis consisted of an unevenly distributed sample size of thirty-five duplexes, which included three one-stage HVAC system installations, twenty-seven two-stage HVAC system installations, and five variable speed HVAC systems.

Analysis of Energy Performance

The aggregate energy consumption for the thirty-five units across the two time periods was normalized against HDD and CDD to produce the values displayed in Figure 7 below.

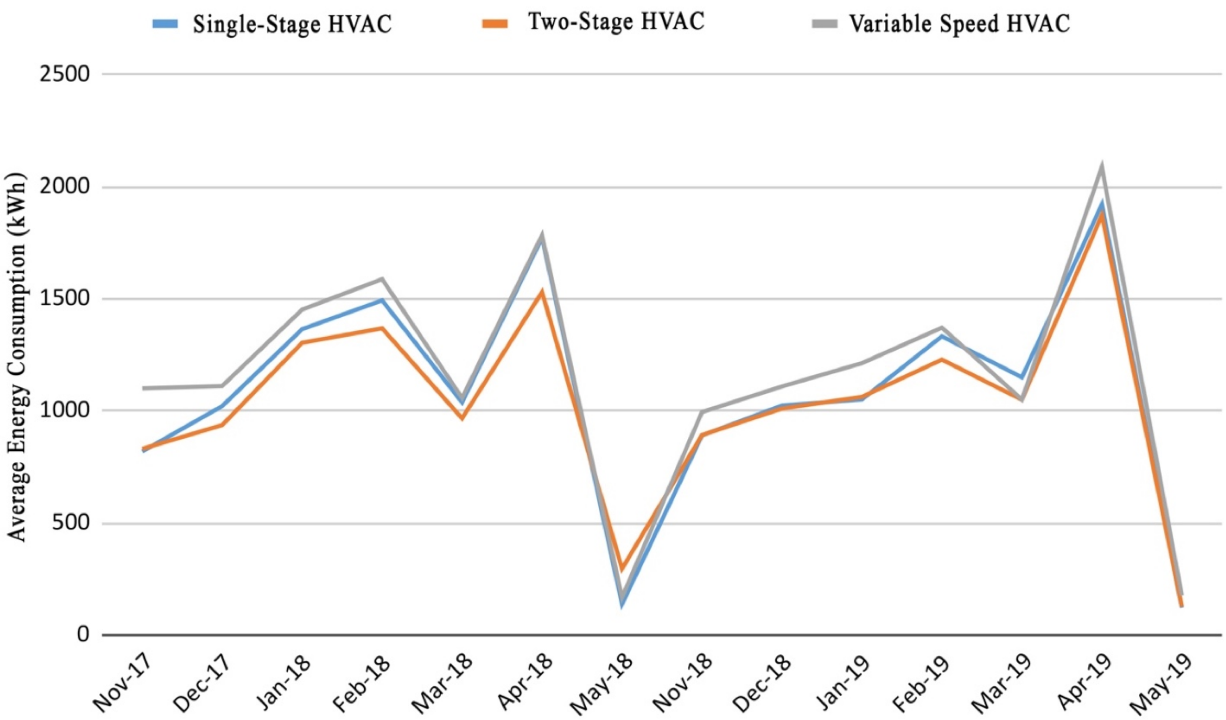

Figure 7. Total Average Energy Consumption (kWh/month)

The energy data monitored indicates that the residents with variable speed HVAC systems installed in their households were consistently using more energy than those with one-stage HVAC systems or two-stage HVAC systems. To further evaluate the energy consumption, we calculated the average energy consumption for each household pre-intervention and post-intervention. While all of the pre-intervention households included one-stage HVAC systems, the post-intervention time period included the installation of new one-stage, two-stage, and variable speed HVAC systems as illustrated in Figure 8 below.

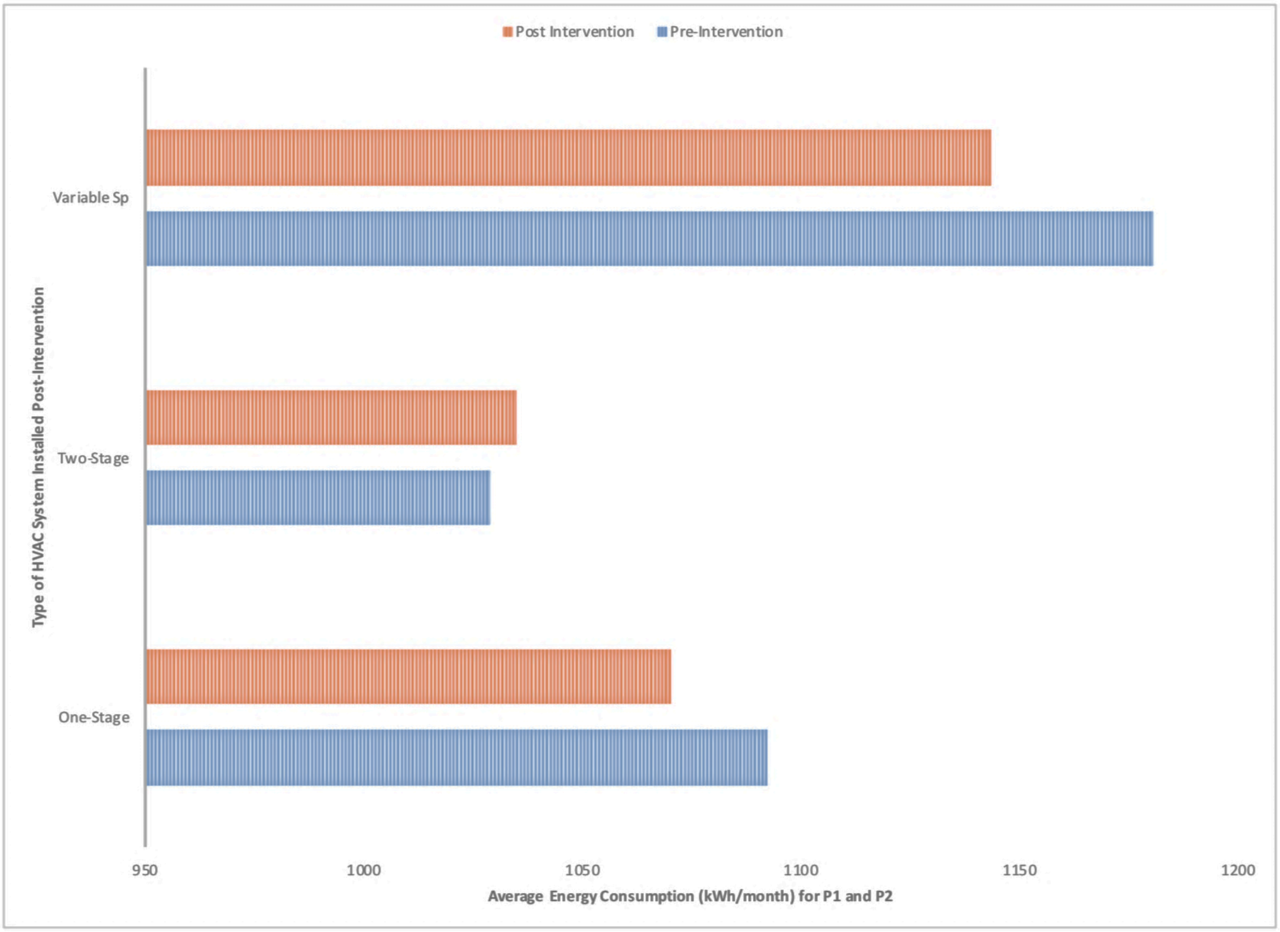

Figure 8. Average Energy Consumption (kWh/month) of Pre-Intervention and Post-Intervention

Through the calculation of the average energy consumption before and after the installation of new HVAC systems, as shown above, we were able to make two crucial findings. The first finding was that overall energy consumption in all of the buildings decreased after the installation of new HVAC systems. Moreover, during the pre-intervention period, the installed HVAC systems throughout all of the duplexes in the affordable housing community were single-stage HVAC systems. During the post-intervention period these HVAC systems were removed, and new one-stage, two-stage, or variable speed HVAC systems were installed.

ANOVA Testing for Energy Performance

One-way ANOVA testing was used to test the multiple treatments; or the installation of three different systems, to compare the average energy consumed for each respective HVAC system and determine whether there is a significant difference between the average energy used by the three systems. The input values for analysis were the aggregated monthly averages of the 35 units normalized against HDD and CDD for each respective system. In order to perform ANOVA, there are three assumptions that must hold: (1) the observations are normally distributed for each group, (2) all groups have equal variances, and (3) the error terms have a mean value of zero and are independent. While assumptions (2) and (3) hold, the assumption of normality is violated through visual inspection of the exhaustive data histograms for all of the HVAC systems across the three time periods respectively. In addition to a visual inspection of the histograms, a formal test of normality was also performed to deduce that the data does not follow the condition of normality. Therefore, in order to satisfy the condition of normality, the $\log_{10}(x)$ transformation, where x denotes the normalized kWh/month, was performed (Nottingham and Hawkes, 2013). The data points total sample size is 432 values, which excludes 82 outliers. All of the removed outliers corresponded with the month of May in both time periods. After the removal of the 82 outliers, the sample sizes for the normalized energy consumption of the duplexes with one-stage, two-stage, and variable speed HVAC systems were 36, 336, and 60 values respectively. This data is then plotted in three separate histograms each corresponding with one-stage, two-stage, and variable speed HVAC systems respectively as shown below in Figure 9.

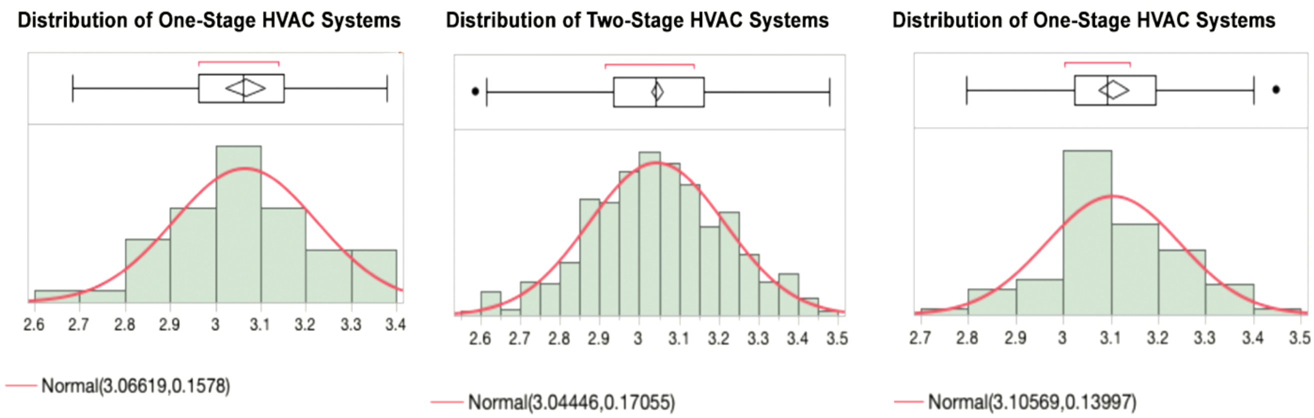

Figure 9. Distributions of Total Energy Consumption of Buildings with One-Stage, Two-Stage, and Variable Speed HVAC Systems

All three histograms appear, through visual analysis, normally distributed. The final and definitive check for normality is the formal test of normality, also known as the Goodness-of-Fit-Test, a summary of its results is shown in Table 34 below.

Table 34. Goodness-of-Fit Test for HVAC Systems

Shapiro-Wilk W Test		
HVAC System	W	*p*-value
One-Stage	0.981109	*p*-value = 0.5868
Two-Stage	0.995814	*p*-value = 0.2403
Variable Speed	0.984715	*p*-value = 0.4232

The W values for all three HVAC systems are within the critical value accepted range, which is 1.00 < W < .95 range, indicating that the datasets for each follow the conditions of normality. The null hypothesis is that the data follows a normal distribution and accordingly, a small p-value would indicate a rejection of the null hypothesis, which would mean that the data is not normally distributed (Nottingham and Hawkes, 2013). But in all three cases the p-value is greater than 0.05, which indicates that the null hypothesis holds true and the data is normally distributed. Thereafter, the One-Way ANOVA was paired with the Tukey's HSD multiple comparison procedure to perform the pairwise comparisons between all three HVAC systems. Thus, we compared the means of untransformed energy consumption of the one-stage HVAC system with the two-stage HVAC system, and the one-stage HVAC system with the variable speed HVAC system, and the two-stage HVAC system with the variable speed HVAC system as shown in Table 35 below.

Table 35. Summary of One-Way ANOVA Comparisons

One-Stage versus Two-Stage	$\bar{x}$ = 2411.242466 kWh/month	p-value = 0.378384	Not statistically significant
One-Stage versus Variable Speed	$\bar{x}$ = 2461.3406 kWh/month	p-value = 0.854014	Not statistically significant
Two-Stage versus Variable Speed	$\bar{x}$ = 2392.69697 kWh/month	p-value = 0.415509	Statistically significant

The untransformed data was used in the Tukey's multiple comparison procedure in order to analyze the energy performance of each of the duplexes and their corresponding HVAC systems directly as opposed to the transformed data. Through these analyses, we found that there was a statistically significant difference between the means of the energy consumed with two-stage versus variable speed HVAC systems installed. There is a statistically significant difference in the amount of energy consumed in the duplexes, which had two-stage HVAC systems installed compared to those with variable speed HVAC systems.

Analysis of Cost Performance

To analyze the cost performance of the HVAC system upgrades, calculations for Return on Investment were performed on all 35 units which consisted of first calculating the Gain from Investment (see *Figure 10* below). The Gain from Investment was determined by calculating the Total Energy Difference (kWh/month) between the second time period and the first time period. Additionally, the average Virginia power tariff and the lifespan of the HVAC systems was factored into the calculations.

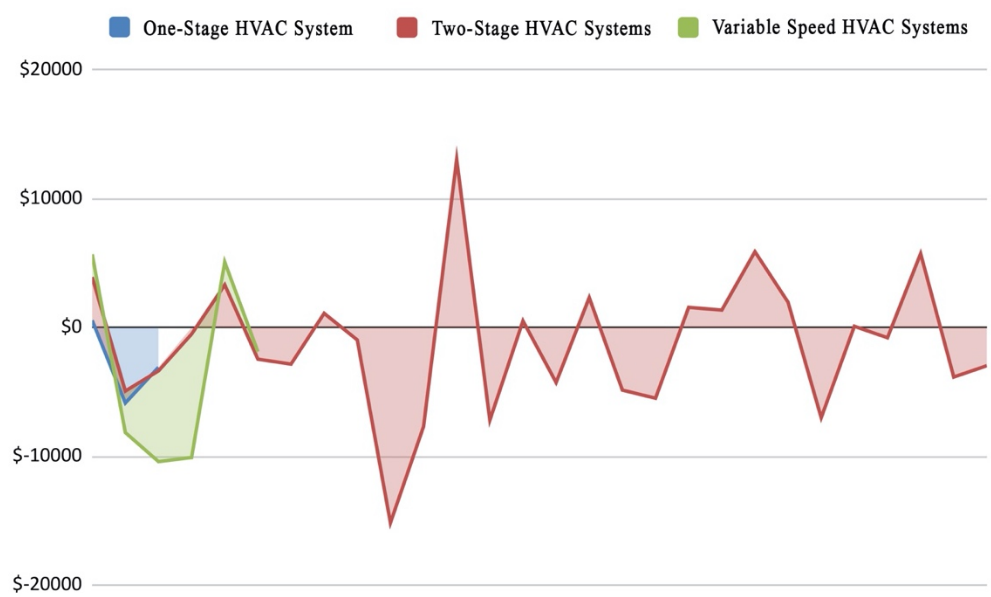

Figure 10. Gain from Investment for One-Stage, Two-Stage, and Variable Speed HVAC Systems

The majority of the values shown in *Figure 4* above correspond with negative values, meaning that there was no gain from the investment over the lifespan of the HVAC system for all three systems. With more variable speed HVAC systems than any other system, we made more calculations in order to perform the ROI calculations. The average ROI for each HVAC system is shown in Table 11 below.

Table 36. Average ROI for One-Stage, Two-Stage, and Variable Speed HVAC Systems

HVAC System	Return on Investment
One-Stage	-40.40%
Two-Stage	-81.73%
Variable Speed	-54.14%

All three systems yielded a negative Return on Investment over the lifespan of the HVAC system. The most significant loss of capital is associated with the Two-Stage HVAC system, which yielded a -81.73% ROI. The one-stage HVAC system proved to be the soundest investment from an economic standpoint where it yielded a -40.40%, which although a sunk cost, was not as steep as its two counterpart HVAC systems.

DISCUSSION

Manufacturer Specifications

Through the manufacturer's specifications, there is overlap between cooling capacities of the two-stage HVAC system and the variable speed HVAC system. Although there is overlap between the cooling capacity of the one-stage, two-stage, and variable speed HVAC systems, looking at both the cooling capacity and the SEER rating points to the superior performance of the variable speed HVAC system. The SEER rating specifically points to the fact that the variable speed HVAC system should outperform the one-stage and two-stage HVAC systems when installed. But through both the energy performance and cost performance analyses, the results of the analyses contradicted the manufacturer specifications.

Data Monitoring and Analysis of Performance

One of the foundations of energy analysis for this paper, was the normalization calculations, which were contingent upon incorporating HDD or CDD. A higher reported HDD value would indicate that on a specific day, more energy will be used to heat the building. And contrastingly, a higher reported CDD value would indicate that on a specific day, more energy will be used to cool the building. The months that had higher HDD values than CDD values, which were all months except May 2018 and May 2019 were normalized using the HDD value. And since May 2018 and May 2019 saw higher CDD values, which corresponds with residents cooling their buildings, the energy consumption for those months for each system were normalized against CDD. Normalizing energy consumption against HDD and CDD essentially allowed us to compare all of the different buildings and different HVAC systems with weather-related energy impacts factored into analyses. Additionally, incorporating the CDD values for the month of May across both time periods along with the removal of the outliers allowed us to meet the conditions of normality in order to apply ANOVA testing.

Analysis of Energy Performance

Furthermore, the normalized energy consumption values were then used for all of the energy performance analyses. That is not to say though that we were able to perfectly incorporate weather-related energy demands into the normalization calculations for May, especially since most of the outliers in the energy performance analysis still corresponded to those months. This raises the question of whether normalizing against the higher of the two values, HDD or CDD, is in fact an effective normalization tool for swing months such as May where resident interactions with the systems are abnormal compared to other months. This also prompts better incorporation of energy-driven behavior use of residents, which is the direction this longitudinal study is heading.

In order to perform the analysis of energy performance, we first evaluated the normalized total average energy consumption across both the pre-intervention and post-intervention time period. This helped to narrate the story of energy consumption across the two time periods and specifically when looking at each month in each respective time period. Upon inspection, this analysis did not seem to definitely illustrate which buildings with one-stage, two-stage, and variable speed HVAC systems was performing better in terms of energy efficiency. Therefore, we performed a comparative analysis of the average energy consumption for each newly installed HVAC system and this allowed us to compare the performance before and after intervention.

While the researchers had hypothesized that the variable speed system upgrades would provide the highest energy savings for each duplex post-intervention, both the total average energy consumption and the average energy consumption analysis depicted otherwise. The total amount of energy consumed decreased after the installation of new HVAC systems, which was a finding that was consistent with expectations based on manufacturer specifications. The buildings with variable speed HVAC systems installed did not see the greatest energy savings, rather those buildings are the ones that were found to be consuming the most energy. The two-stage HVAC system was found to outperform the two other systems in terms of energy savings after the installation of the new systems. This finding is counter to manufacturer specifications of variable speed HVAC system SEER rating, which is superior to that of the two-stage HVAC system.

While the manufacturer specifications provide that variable speed HVAC systems outperform two-stage HVAC systems, the preliminary results from the field study proved otherwise. Both the preliminary analysis and the exhaustive analysis included two forms of analysis, which include (1) total energy consumption (kWh/month) and (2) average normalized energy consumption (kWh/month) of each HVAC system, though they provided different results, the findings of which are summarized in Table 12 below.

Table 37. Summary of Findings of Superior HVAC System Energy Performance

Total Energy Consumption (kWh/month)	**Average Energy Consumption (kWh/month)**
One-Stage HVAC System	Two-Stage HVAC System
Two-Stage HVAC System	Two-Stage HVAC System

The superior performance of the two-stage HVAC system across both tests could provide important insight into residents' interaction with these systems. While variable speed HVAC systems are designed to outperform their counterparts, that is only if residents are aware of how to use these systems, which may not be the case in this housing community. These initial findings encouraged us to perform a one-way ANOVA analysis to test the multiple treatments; or the installation of three different systems. We hoped to compare the means of the energy consumed for each respective HVAC system and determine whether there is statistical significance between these means.

Before applying the one-way ANOVA test, we checked for the condition of normality, which was not initially met until the normalized energy data was transformed and the outliers were removed. Then, One-Way ANOVA was paired with a Tukey's HSD multiple comparison analysis where we found a statistically significant difference between the means of the normalized total energy consumption in the buildings with two-stage HVAC systems and that of the variable speed HVAC system. This was an interesting finding because although the two HVAC systems are very similar in terms of manufacturer specifications, specifically their cooling capacities, the buildings with two-stage HVAC systems were found outperforming. And the statistical significance points to the fact that not only are residents with two-stage HVAC systems using less energy, but they are actually using significantly less energy than those with the superior HVAC system. This calls into question the behavior-driven energy use of the residents, the level of detail of data collection and reporting, and the efficacy of traditional energy analysis.

Furthermore, the authors would also like to acknowledge that the data has numerous limitations as the data provided was through the utility company, who provided average aggregated totals of the energy consumption per kWh/month for all of the duplexes, which house two townhomes, as opposed to providing the energy consumed within each townhome. The reported values are also of the energy consumption of all appliances as opposed to each individual appliance. This makes it difficult to deduce whether the reduction in energy consumption can be associated directly with the HVAC systems or if other systems are coming into play. Information about the number and age of the residents, which was requested by the researchers to better understand the behavior-driven energy usage, was denied. The aforementioned limitations are recurring in the traditional model of energy analysis. Additionally, the distribution of the systems across the 35 units is not even, which meant that in order to each the condition of normality and apply ANOVA testing during the exhaustive analysis, we had to eliminate 82 outliers.

Analysis of Cost Performance

The findings made through the analysis of cost performance were also counter to expectations in numerous ways. The initial assumption had been that the energy performance analysis results and the cost performance results would be mirror images of one another. And where there were significant energy savings, we would see significant cost savings. But that was not the case where we saw no return on investment on all three HVAC systems. Additionally, we found that the one-stage HVAC system would cost the least loss of capital through its lifespan. This was while the expectation was that we would find the two-stage HVAC system, which saw the best energy performance out of the two other systems, was the most cost-efficient energy investment. This proved to be false and the two-stage HVAC system performed the worst in terms of cost.

CONCLUSIONS

This paper reports the initial findings of a longitudinal field study, which is just in its beginning phases, but the findings thus emphasize the need to update the energy monitoring and analysis process to increase accuracy and efficiency. While the results found thus far were contrary to expectations and manufacturer specifications of each of the respective systems, this suggests that when upgrading and installing new systems, energy literacy for all building stakeholders is equally as important as the systems being installed. Additionally, field observations by the research team have uncovered resident and landlord errors in the use of the thermostats controlling the system. Performing qualitative analyses such as surveys to better understand the occupants' experiences with the HVAC system upgrades are underway and will provide insight into similar projects. The preliminary data analysis emphasizes the need to update previous processes of energy analysis to accurately communicate and make decisions regarding energy-efficient technologies while leveraging cloud computing for data analysis and visualization to serve as a decision-making tool.

ACKNOWLEDGMENTS

The authors would like to thank their industry partners and the residents of the housing community being studied for their cooperation and commitment to delivering more energy-efficient buildings.

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Conference Paper 2:

A Case of Optimizing HVAC System Performance When Every Dollar Counts

The ASCE Construction Research Congress (CRC) Conference – 2020

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ABSTRACT

Building stakeholders must invest an increasing number of resources in the process of delivering energy-efficient buildings as energy efficiency standards become more aggressive, and building systems become more complex. This paper documents the earlier stages of a larger project, which is a joint venture between Virginia Tech and an industry partner, to predict the benefits and drawbacks of energy investments in the residential housing sector. As such, existing processes for predicting the benefits and drawbacks of energy-efficient technologies in buildings can be improved in the areas of comprehensiveness, precision, accuracy, and elegance. This study presents an exploratory and descriptive field study of an affordable housing development in Virginia, which was recently renovated to improve and explore system performance of one-stage, two-stage, and variable speed HVAC systems. Utilizing this study design, the researchers performed energy analyses on nine duplexes, which include two households per unit, to evaluate the efficacy of the energy investments alongside an updated model of energy analysis. Building upon manufacturer specifications, the researchers had hypothesized that the variable speed HVAC systems would outperform the other two systems in terms of energy savings. Preliminary analyses utilizing pre-existing models of energy monitoring and energy analysis proved contrary to the hypothesis. Data collected and analyzed thus far are considered preliminary results, which support the researchers' case for updating energy monitoring and energy analysis processes. The preliminary data analysis has shown great potential for updating previous processes to calibrate inaccurate perceptions of behavior-driven energy use; leverage cloud computing for data analytics and visualization to improve data accessibility; and the inclusion of socio-political impacts into decision-making tools. The findings of this study transfer beyond the context of HVAC systems to various building systems. The methodology of this study also provides guidance for better academic-industry-citizen engagement for the real-world testing and design of engineered infrastructure systems.

Keywords: HVAC Systems, Low-Income Housing, Energy Monitoring, Energy Analysis

INTRODUCTION

The case for the adoption of energy-efficient technologies in residential homes is a case for social equity. Recent studies confirm that the majority of low-income households, those with incomes at or below 80% of the area median income (AMI), face a disproportionately higher energy burden than the average household in the same county or metropolitan area (Drehobl and Ross 2016). Energy burden refers to the percent of gross household income spent on energy-related expenditures (Baxter 1998). Low-income households pay more per square foot than the average household because of poor insulation, inefficient appliances, and poor weatherization among other things which are characteristic of many low-income homes (Hernández and Bird 2010).

Furthermore, there are two main energy assistance programs sponsored by the US government, which include the Low-Income Heating Assistance Program (LIHEAP) and the Low-Income Housing Tax Credit Program (LIHTC). These policies, though, have continually fallen short of providing assistance to all of those who need it. LIHEAP serves to subsidize the heating and energy bills for low-income households providing everything from fuel assistance, crisis assistance, cooling assistance, and weatherization measures (Perl 2014). And while 37.1 million households were qualified as low-income, LIHEAP assistance was only provided to 8.1 million households in the year 2010 (“FY 2010 LIHEAP Report to Congress” 2010).

Additionally, many low-income residents are not the owners of their own homes, but rather they are renters in privately owned low-income housing communities. LIHTC was designed to promote the development of affordable housing communities, it fails to account for the fact within these rented households, 79% of low-income tenants are responsible for paying electric and utility bills (Hernández and Bird 2010). This provides little to no incentive for landlords to improve the energy efficiency of their buildings, also known as the split-incentive phenomenon (Gillingham et al. 2012). And since governments play a vital role in financing low-income housing, increasing the efficiency of low-income housing units is a large investment opportunity for the government both at the state and national level. Energy programs for low-income households need to provide a wider variety of assistance, such as the ability for both homeowners and renters to execute upgrades while tracking their return on investment.

Furthermore, while there are multiple federal housing policies that are meant to aid and alleviate energy burden on vulnerable populations in some cases they act as policy-related drivers to energy burden. Understanding the impact of integrating different energy-efficient technologies is a critical step in decision making for the allocation of funds for all residential building stakeholders. Therefore, in this paper conducting a field study allows the researchers to perform energy monitoring and energy analyses in the real-world context.

The field study method is an underutilized method in academia due to the difficulty of accessing data and the extensive time required. Through this field study though we are able analyze economic and energy benefits alongside manufacturer specifications, utility company data, and landlord feedback and input. We therefore hope to help bridge the gap between energy efficiency and accessibility to calibrate inaccurate perceptions of behavior-driven energy use; leverage cloud computing for data analytics and visualization to improve data accessibility; and the inclusion of socio-political impacts into decision-making tools. The findings of this study transfer beyond the context of HVAC systems to various energy efficient technologies. And the collaboration across academia and industry is a model, which the researchers hope will help to inform future studies.

METHODS

This field study, performed in a multifamily affordable housing community in Montgomery County, Virginia (termed EMP hereafter) documents the upgrades of one-stage, two-stage, and variable speed HVAC systems across 9 different duplexes, which include a total of 18 HVAC systems. A summary of the processes performed and proposed in this paper include: 1) traditional energy analysis of 9 units as shown in Figure 11 below. 2) the proposal of an updated model of energy analysis, which includes circuit-level eGauge data collection at the breaker panel within each household.

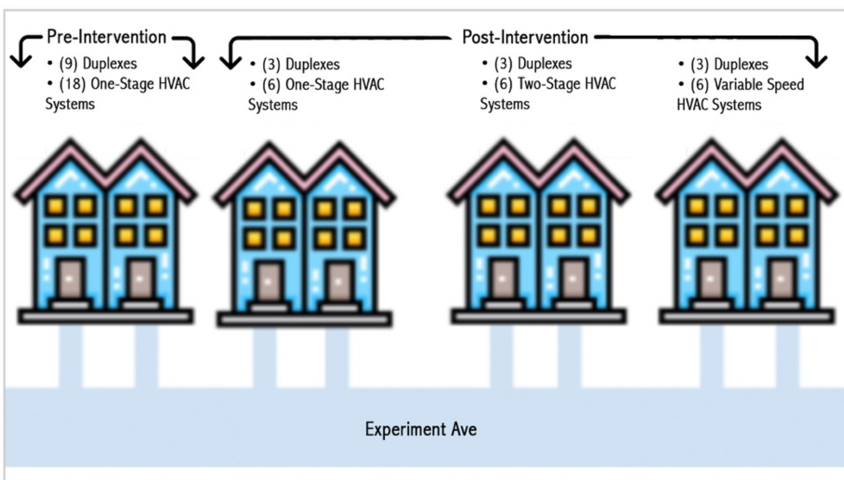

Figure 11. Sample Map of HVAC Systems Installations

Across the 9 duplexes, EMP installed 3 one-stage HVAC systems in 3 duplexes, 3 two-stage HVAC systems in 3 duplexes, and 3 variable speed HVAC systems in 3 duplexes, respectively.

It is important to state that each duplex is comprised of two housing units with independent HVAC systems. And although there are two HVAC systems per duplex, energy data is reported as an average total of both systems within a duplex per month. It is also important to note that all units being studied have an equal building square footage, and the authors can thereby compare each unit to the other appropriately.

Manufacturer Specifications

The EMP property managers evaluated the manufacturer specifications, whereby numerous factors were taken into consideration including System Energy Efficiency Ratio (SEER) Rating, the cooling capacity, and the corresponding number of models for each HVAC system as shown below in Table 13. The SEER rating is a standard ratio used to describe the system efficiency, whereby a higher SEER rating typically corresponds to more energy savings and greater comfort levels (Wang et al. 2012). Additionally, cooling capacity is used here to indicate the ability of an HVAC systems ability to remove heat from a building. As such, a higher value for cooling capacity indicates an increased ability to remove heat from a building.

Table 38. Overview of Manufacturer Specifications of HVAC Systems

	One-Stage	Two-Stage	Variable Speed
SEER Rating	16	18	18
Number of Models	9	4	9
Cooling Capacity (Btuh)	18,000-60,000	24,000-60,000	24,000-60,0000

Additionally, cost was also a factor taken into consideration upon upgrading and replacing the preexisting HVAC systems at EMP. In order to maintain the anonymity of the manufacturer, a range of models for each respective HVAC system and their SEER Rating as well as cooling capacity have been listed above and the exact cost of the systems has not been shared in this paper. Rather the percent change, as shown in *Equation 1* below, is calculated to evaluate the relative difference in cost between the One-Stage HVAC system and the Two-Stage HVAC system. Additionally, *Equation 2* shown below, is used to calculate the relative difference in cost between the One-Stage HVAC system and the Variable Speed HVAC system.

$$C_{OS} = \text{Cost of One-Stage HVAC System}$$

$$C_{TS} = \text{Cost of Two-Stage HVAC System}$$

$$C_{VS} = \text{Cost of Variable Speed HVAC System}$$

$$\text{\% Difference} = \frac{|C_{OS} - C_{TS}|}{\left(^{(C_{OS} + C_{TS})}/_{2}\right)} \times 100 \qquad \textbf{(1)}$$

$$\text{\% Difference} = \frac{|C_{OS} - C_{VS}|}{\left(^{(C_{OS} + C_{VS})}/_{2}\right)} \times 100 \qquad \textbf{(2)}$$

Traditional Data Collection

The energy data collected was provided by the property manager, which includes the aggregated energy consumption for two housing units within one duplex, which means that although there are two separate apartments within each duplex, data collected reports an average of the two apartments within the single building per month. Data is provided through a major electric utility company and is reported on an aggregated monthly average basis, which displays total kilowatt-hours drawn from the grid. Data analysis has been performed across two-time intervals, Y_1, Y_2, as shown in Table 14 below.

Table 39. Analysis Periods Overview

Time Interval	Month	Duration	Period
Y_1	January 2017 – May 2017, November 2017 – May 2018	12 Months	Pre-Intervention
Y_2	November 2018 – May 2019	7 Months	Post-Intervention

The time intervals, Y_1, Y_2, selected reflect the availability of data, which was made possible through the electric utility company providing energy to the EMP community.

Historic Data Analysis

For the specified time intervals, reflected in Table 2, heating degree days were taken into consideration. Since Virginia is in climate zone 4A, it's heating season often starts in November and ends in May. Therefore, accounting for the heating degree days helped the researchers take into consideration the seasonal time effects in terms of HVAC system performance. Degree days calculations are one means for measuring weather-related energy demands (Quayle and Diaz 1979). The values for heating degrees used in the normalization calculations, were pulled directly from the National Oceanic Atmospheric Administration (NOAA) database for the weather station closest to the housing community studied (National Climatic Data Center 2017-2019).

Furthermore, normalizing energy consumption against HDD allows us to factor in weather-related energy demands and compare different buildings and systems to one another in terms of energy consumption. The normalized energy consumption for all nine units was analyzed in three ways, which were in par with traditional energy analysis techniques; 1) percent difference calculations of HVAC systems cost, 2) average aggregate energy consumption comparison, 3) paired t-test analysis. These analyses helped the researchers evaluate the efficacy of the system upgrades in all nine units, which included 18 different households, before and after the intervention or installation of new more energy efficient HVAC systems.

Sub-circuit Level Data Collection and Visualization

The proposed updated model of data collection, analysis, and visualization surrounds the analysis of sub-circuit level energy. In doing so, we will install eGauge sensors, through which we collected the data with a sampling frequency at 1 Hz. Historic data of energy consumption provided by utility companies is usually hard to come by or in this case highly limited. These limitations and the corresponding results of analyses support the case for detailed sub-circuit level data to better analyze the performance of the HVAC systems. By monitoring the HVAC systems directly at the panel, less noise will be introduced into the consumption comparisons. The process of energy monitoring and energy analysis, which was followed throughout the traditional data collection and analysis processes, will be updated, as detailed in *Figure 2*, to incorporate the greater level of detail of data provided at the sub-circuit level.

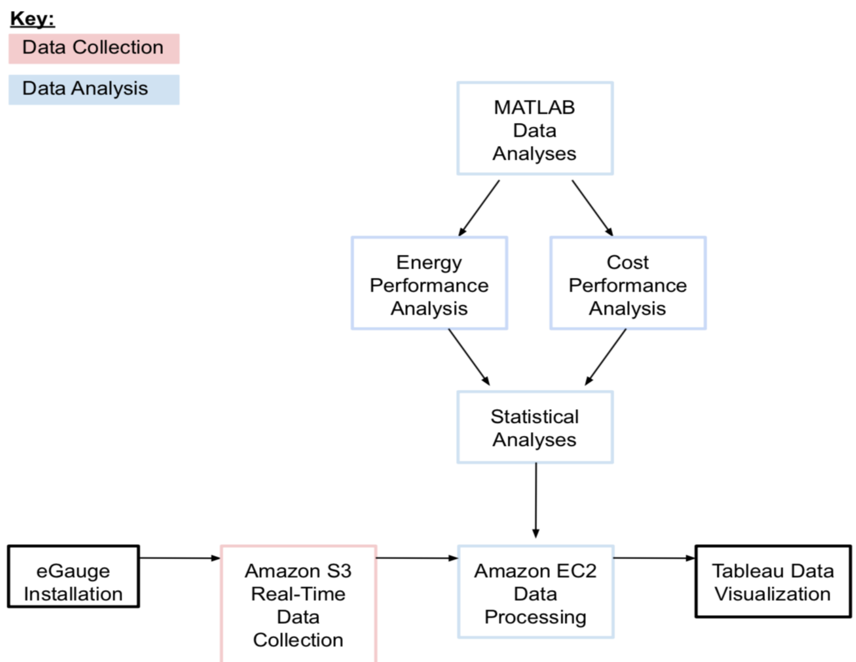

Figure 12. Map of Methods for eGauge Data

The eGauge data storage and visualization will be done through Amazon Web Services (AWS), as shown in Figure 12. The Amazon Simple Storage Service (Amazon S3) allows for second data to be stored in real-time beyond the constraints of the eGauge onboard storage. Amazon EC2 allows for the seamless and automatic transmission of data without having to set up and maintain an on-premises server (Aboulnaga et al. 2009). Amazon Athena will also be utilized, which will allow the researchers to analyze the data being stored in Amazon S3 using standard SQL series (Burns 2017). Finally, the data visualization process, which the industry stakeholders stand to gain the most from, will be through the seamless incorporation of Tableau into the AWS solution designed for this project.

PRELIMINARY RESULTS

The preliminary analysis, which surrounded the historic data collection and analysis process, includes data evaluated from nine housing units with two households per unit. Three of the nine buildings included one-stage HVAC system upgrades, three other units included two-stage HVAC system upgrades, and the three other units included variable speed HVAC system upgrades. These nine duplexes were among 30 other duplexes in EMP, but they were specifically were chosen due to their homogeneity when it pertains to occupancy and consistency in sample sizes, i.e., 3 duplexes with the same HVAC systems, distributed across evenly. These nine units were consistently occupied throughout the three periods of data collection and were therefore determined to be most appropriately comparable to one another.

Percent Difference in Cost of HVAC Systems

Additionally, one of the prime factors taken into consideration by the EMP property managers upon deciding whether to upgrade the pre-existing One-Stage HVAC systems or replace them with Two-Stage HVAC systems or Variable Speed HVAC systems was cost. The relative difference in cost between the One-Stage HVAC system and the Two-Stage HVAC system provided that the cost of the Two-Stage HVAC system is 4% higher than that of the One-Stage HVAC system. The relative difference in cost between the One-Stage HVAC system and the Variable Speed HVAC system, as calculated through *Equation 2* below, provided that the cost of the Two-Stage HVAC system is approximately 20% higher than that of the One-Stage HVAC system. And the percent difference in cost between the two-stage HVAC system and the variable speed HVAC system is 16% for the latter system.

Average Normalized Energy Consumption (kWh/month) of Each System

The average aggregate energy consumption across the nine different units were normalized against the heating degree days to produce the values displayed in Figure 13 below.

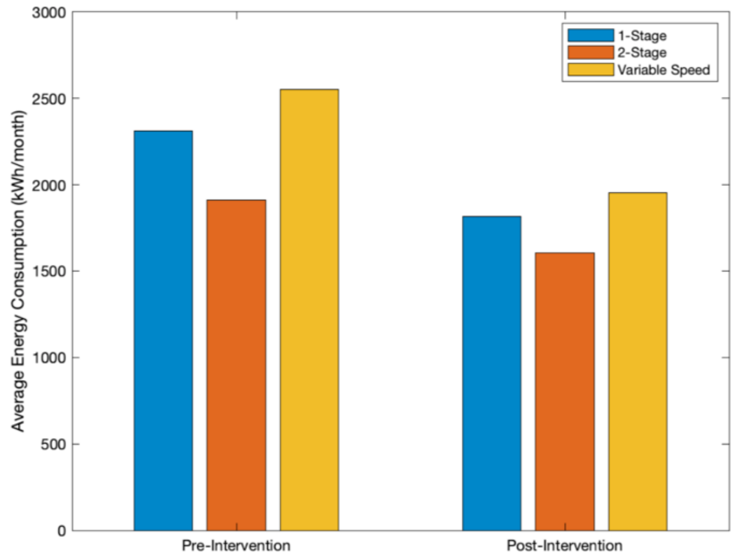

Figure 13. Average Normalized Energy Consumption (kWh/month) of Each System

Calculating the average energy consumption across each of the different systems for both the pre-intervention and post-intervention periods helped us gain more insight into whether the intervention of upgrading or installing new HVAC systems made a substantial difference or not. In general, each of the HVAC systems saw an improvement in performance as indicated above and used less energy than they did during the pre-intervention period. Contrary to expectations built upon manufacturer specifications though, is that the two-stage HVAC system saw the best performance post-intervention. Not only did the two-stage HVAC systems outperform, but the variable speed HVAC systems were actually found to be the worse in terms of energy performance whereby they consumed approximately 5% and 20% more energy on average than one-stage and two-stage HVAC systems respectively.

Paired T-Test Analysis

The paired t-test was employed to compare the two population means in each of the samples before and after the intervention, which entailed comparing the means of the energy consumption of the HVAC systems before the intervention and installation of new one-stage, two-stage, and variable speed HVAC systems, respectively, as summarized in Table 15 below. The test returns a decision for the null hypothesis, which distinguishes between whether or not the difference in the mean between the datasets is zero. Using monthly measurements doesn't show any significant difference.

Table 40. Paired T-Test Summary of Pre- and Post- Intervention

Intervention Type	Null Hypothesis	*p*-value
One-Stage HVAC System	Rejected	0.378384
Two-Stage HVAC System	Rejected	0.854014
Variable Speed HVAC System	Rejected	0.415509

By performing the paired t-test on the three different datasets before and after the intervention, we were able to conclude in all three cases that the null hypothesis was accepted.

DISCUSSION

Percent Difference in Cost of HVAC Systems

The variable speed HVAC system came at price that was 20% and 16% more expensive than the one-stage and two-stage HVAC systems respectively. This finding along with the energy performance of the variable speed HVAC system as illustrated through the post-intervention analyses, puts into question the efficacy of this energy investment.

Average Normalized Energy Consumption (kWh/month) of Each System

The mean values of the normalized energy consumption for each system per month were plotted in correspondence with the pre-intervention and post-intervention periods. Through this analysis we were able to deduce that although the intervention proved to save energy on average across all systems, which was in line with expectations. The fact that the variable speed HVAC system was not outperforming the other two systems was not in line with expectations. These unexpected results could be due to a variety of factors, including residents' lack of knowledge with regards to utilizing variable speed systems. During the later stages of this study, we will address the issue of energy literacy amongst residents to better inform them of how to best use these systems.

Paired T-Test Analysis

The paired t-test helped analyze whether or not installing new one-stage, two-stage, and variable speed HVAC systems made a significant difference in terms of energy performance. And in all three cases that the paired t-test was performed, the null hypothesis was accepted, which meant that there has not yet been a statistically significant difference between the means of the HVAC system performances before and after intervention. This emphasizes the importance of continuing to analyze the systems to see if further into study the difference between the performance of the energy performance before and after intervention is significant or not.

CONCLUSION

In these preliminary stages, the researchers are conducting an in-depth analysis of the available options for collecting, analyzing, and communicating energy data. Results were contrary to expectations and manufacturer specifications of each of the respective systems, whereby a variable speed system should theoretically outperform one-stage and two-stage HVAC systems. The superior performance of the two-stage HVAC system in *Preliminary Results*, suggests that residents with variable speed systems in their households may not be using them correctly. Field observations by the research team have uncovered user errors in the use of the thermostats controlling the system. Further qualitative inquiries of the occupants' experiences with the HVAC systems are underway.

Furthermore, the authors would also like to acknowledge that the historic data has numerous limitations as the data provided was passed down by EMP through the utility company. One of the more significant limitations includes the fact that the utility company has provided an average aggregated total of the energy consumption per kWh/month as opposed to providing the energy consumed within each household. Neither are researchers allowed access to information such as setpoint temperatures or the ages of residents within the units.

ACKNOWLEDGMENTS

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CONCLUSION

The manuscripts within this study affirm the need to further our understanding of the real-world performance of energy efficient affordable housing. In the first manuscript, we find that amongst senior citizens in net-zero affordable homes relatively no statistically significant relationship between temperature and energy use, which affirms previously existing studies on high-performance homes and energy-efficient HVAC systems. Although there were some discrepancies in this finding, particularly in the fall, where we suggest the impact of humidity created a mild-moderate correlation between energy use and temperature. Another finding throughout this study was that there was no discernible difference between energy use throughout the weekdays relative to the weekends. And finally, we found that the heating season was the most energy-intensive season, which saw the highest energy demand from all residents. As the fastest growing global population, this manuscript utilized and adapted methods existing in the literature to explore the interplays between older age, energy use, and climate in net-zero affordable housing and we encourage future researchers to do the same and to utilize the corresponding datasets utilized in this study, which have been made publicly available.

The first manuscript saw many intersections with the second and third manuscript, where both sought to bridge the energy efficiency gap through exploratory case studies analyzing energy efficient HVAC systems in the affordable housing sector. In the second and third manuscripts, recommendations that could contribute to bridging the energy efficiency gap include energy education and incorporation of advanced metering initiatives to provide residents with real-time information on their energy use. Next steps for this study also include the incorporation of qualitative studies to better understand the energy use behaviors of residents', which are preventing the efficient use of the newer HVAC systems.