THE RELATIONSHIP BETWEEN COOLING TEMPERATURE SETPOINTS AND BUILDING ENERGY CONSUMPTION: A CASE STUDY AT THE UNIVERSITY OF GEORGIA

by

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(Under the Direction of Thomas Lawrence)

ABSTRACT

Buildings account for roughly 40% of total energy consumption in the U.S. and roughly half of this is for indoor space cooling and heating. Anthropogenic greenhouse gas emissions (GHGs) are becoming a rising concern due to the onset of climate change and global warming. In order to mitigate against GHGs, namely CO_2, the impact of effective cooling temperature setpoint increase on building energy consumption is explored. The corresponding impact on utility costs, emissions, and thermal comfort is determined. Results found that increasing cooling temperature setpoints to 74ºF (23.3°C) and 76ºF (24.4°C) from normal operating conditions of 73ºF (22.8°C) during the cooling season can reduce chilled water consumption for space cooling at representative campus buildings by 19% to 40% respectively. This emphasizes the large opportunity that exists in temperature setpoint control to improve energy efficiency of buildings and mitigate CO_2 emissions that occur from energy consumption by buildings.

INDEX WORDS: HVAC, Energy efficiency, Thermal comfort, VAV, Cooling Temperature

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DEDICATION

This thesis is dedicated to the College of Engineering at the University of Georgia. I am thankful for the professors that have become trusted mentors and the peers that have become close friends throughout my time at this Institution. This thesis is also dedicated to those who have fully supported me throughout my journey at UGA. All that I was, all that I am, all that I will be, I owe in part to you all.

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CHAPTER 1

INTRODUCTION

This section provides background information and the motivation for this project, research objective and outline, and an overview of the structure of the thesis. The background section provides insight on the significance of, and motivation for, this research. The objective and outline section explain the purpose and goals of this research and identifies five central research questions the study hopes to answer. The thesis structure section identifies the organization of the thesis and what each major section contributes to the overall thesis.

1.1 BACKGROUND AND MOTIVATION FOR THIS PROJECT

Anthropogenic Greenhouse Gas (GHG) emissions are a rising concern due to the onset of climate change and global warming. Current global concentrations of atmospheric carbon dioxide (CO_2) now exceeded 400 ppm. The United States is the second largest emitter of CO_2 with China being the largest emitter [1, 2]. We now live in an era with the warmest temperatures ever recorded throughout human civilization, and the Intergovernmental Panel on Climate Change (IPCC) estimates that the surface air temperature has increased by 1.8ºF (1ºC) over last 115 years [3]. The IPCC also emphasizes the need to avoid an annual average global temperature rise of 3.6ºF (2ºC) to mitigate against the worse effects of climate change, with a goal of limiting warming to 2.7ºF (1.5ºC). Under this circumstance, the world will still have to adapt to changes in surface, atmospheric, and oceanic temperatures; melting glaciers and diminishing snow cover; increase in sea level rise and flooding events; increase in heatwaves and drought; as well as many other negative effects. Over the next few decades, annual average temperatures are excepted to rise by 2.5ºF (1.4ºC) in the U.S. relative to the recent past average from 1976 to 2005 under all plausible future climate scenarios [3]. Southeast Georgia is especially susceptible to the impacts of climate change in comparison to other states in the U.S., with warmer and drier periods than the 30-year period from 1971-2000 [4]. For example, the 2007 drought in Georgia caused an estimated $787 million loss in agricultural production and Hurricane Irma insured losses topped $500 million in 2017 [5, 6].

Residential and commercial buildings account for 38% of total energy consumption in the U.S. [7]. The production of electricity is a major source of GHG emissions from the combustion of fossil fuels. Thus, building energy efficiency is a crucial strategy for reducing GHG emissions from energy use by buildings. In Georgia, buildings account for 45% of total energy consumption, 7% higher than the national average [8]. As of 2016, the U.S. Energy Information Administration (EIA) estimates that Georgia consumed 2,839 trillion Btu of energy from all sources, representing 10% of the nation's energy consumption, with 1,271 trillion Btu for residential and commercial buildings alone. Heating, ventilation, and air conditioning (HVAC) systems in residential and commercial buildings are responsible for 62% and 44% of energy consumption, respectively, for heating, cooling, and ventilation [9]. Thus, improving HVAC operation and design offers a significant opportunity to improve energy efficiency of buildings and reduce GHGs emissions to mitigate against the onset of climate change.

One method to improve HVAC operation is to change temperature setpoints in buildings to minimize energy use for cooling and heating seasons. For example, the cooling setpoint may be increased in buildings to improve energy use during the cooling season. Such changes would depend on a variety of factors, such as building type, occupancy, weather, and thermal comfort. If shown, though, that these changes would have no significant impact on thermal comfort, there could be substantial improvements in energy use by buildings considering that space heating and cooling represents a large portion of building energy use (44-62%). Cooling setpoint temperatures are not already higher on the UGA campus due to operational management concerns about getting complaints about hot temperatures and humidity issues. Increasing cooling temperature setpoints would have substantial benefits regarding GHG reduction to help mitigate effects of climate change if such strategies were implemented on a large scale, as often setpoints are too low and cause energy waste [10]. Thus, the impact of temperature setpoint change on building energy efficiency needs to be fully explored to identify a viable method to improve HVAC performance and reduce externalities of energy consumption and production to mitigate climate change.

1.2 RESEARCH OBJECTIVE AND OUTLINE

As reported in the UGA Campus Sustainability Plan, operations at UGA resulted in emissions at an estimated 529 million pounds (249,000 tonnes) of CO_2 equivalent (CO_2e) emissions in 2014, including offsets of CO_2e by managed forestlands (154 million lbs, 70,000 tonnes) [11]. This is an 8% decrease from 2010 net emissions which were 595 million pounds of CO_2e (270,000 tonnes). 64.7% of this was due to electricity consumption and 19.2% was due to heating fuel combustion. In 2015, UGA launched a sustainability initiative to have 20% and 40% reduction of GHGs by 2020 and 2040 as a part of this plan compared to the baseline year of 2010. This includes strategies to improve HVAC performance, such as decommissioning aging chillers, campus wide building level energy and water metering to track utilities in real time, decommissioning of dual duct and multizone air systems that heat and cool in parallel, as well as other methods of improvement. Another potential method to improve campus sustainability is optimizing temperature setpoints in buildings on UGA’s campus to improve energy efficiency of

HVAC systems and reduce building energy use, particularly for the cooling season. The purpose of this research is to evaluate how temperature setpoint changes influence building energy consumption and associated negative externalities of energy production from building energy use on campus. This research hopes to prove that the cooling temperature setpoints can be adjusted in buildings on UGA's campus to improve building energy use by HVAC without compromising thermal comfort. This setpoint optimization will not only reduce utility bills for UGA but also have other societal and environmental benefits from the reduced emissions, which will be quantified in this report as well through a measure known as the Social Cost of Carbon. Thus, this report hopes to identify a balance between the people, profit, and planet regarding HVAC energy efficiency: people that use buildings and require a certain level of thermal comfort, profit required to pay for energy in buildings, and the planet which is affected through emissions from building energy consumption.

This research aims at answering 5 central research questions (RQs):

1. What is the impact of increased cooling temperature setpoints on building energy consumption?
2. Can HVAC temperature setpoints be increased during the cooling season, and if so by how much, without jeopardizing thermal comfort?
3. What is the feasibility of such cooling setpoint changes throughout the entire UGA campus?
4. How does the impact on building efficiency during testing periods compare with existing building energy codes?
5. How could setpoint changes contribute toward reaching UGA's 2040 Sustainability Plan goal?

Given the current uncertainty surrounding energy policy in the U.S. and the danger of climate change, the objective of this paper is to identify potential energy savings by improving temperature setpoint control in buildings. This is accomplished through a case study in Phase II of the Business Learning Community (BLCII) on UGA’s North campus in which cooling temperature setpoints are increased for several weeks in two stages during the cooling season and metered energy data is monitored through the campus Building Automation System (BAS) and monitoring software. Significant results are identified between improved temperature setpoints and energy efficiency, as well as improved environmental impact.

1.3 THESIS STRUCTURE

This thesis work consists of a literature review and empirical research. The thesis begins with a literature review of the impact of climate change and negative externalities of energy production. The cost of electricity in the U.S. is discussed, as well as implications of carbon pricing on electricity prices. Then, current types of HVAC systems and factors affecting HVAC systems such as climate zone, building construction, building type, and building age are discussed. While there are a variety of HVAC systems, the focus of this overview will be on Variable Air Volume (VAV) systems, as these are the most common types of HVAC systems in commercial buildings and are the systems employed in the case study buildings. In addition to these factors, the role thermal comfort and occupant behavior plays regarding HVAC performance is also explored, as HVAC performance and occupant behavior are highly coupled. Different measures to improve HVAC performance are explored, such as VAV modeling, predictive forecasting, building simulation, HVAC control systems, and demand response. The literature review concludes by analyzing building energy codes, energy benchmarking, and voluntary programs as a method of HVAC improvement.

The third section gives an in-depth explanation of the methodologies for the research, beginning with a description of the current HVAC system used in the Business Learning Community Phase II as well as operating conditions. The chilled and hot water consumption data must be normalized to account for temperature differences that occurred over May through August. A description of the Degree Day method used to normalize the data is described. Equations used to determine electricity and natural gas consumption for chilled and hot water consumption and emissions from such consumption are included, as well as thermal comfort testing methods.

The fourth and fifth sections list and interpret results from the mentioned methodologies in section three. A “low scenario” will be determined that quantifies the smallest impact on building energy efficiency by the cooling setpoint changes. A “high scenario” will be determined that quantifies the largest impact from temperature setpoint change in rooms. These scenarios will be compared to each other in terms of energy consumption, air pollutant emissions, utility cost, and the “real cost” of electricity for the entire cooling season. All changes made to the Business Learning Community Phase II throughout June, July, and August are compared to a baseline time period in which no setpoint changes were made. Thermal comfort survey results will also be analyzed to validate the different setpoint scenarios. At the end of this work, conclusions and recommendations are given for HVAC cooling setpoint control on campus. Limitations of the study and opportunities for future work are also identified.

CHAPTER 2

LITERATURE REVIEW

Conservation of energy resources and reduction of negative externalities of energy production, predominantly GHGs, are one of the most critical challenges of mitigating climate change in the 21st century. The Paris agreement set out a global action plan to avoid dangerous climate change by limiting global warming to 3.6ºF (2.0ºC) in 2015. Buildings account for roughly 40% of total energy consumption in the United State and roughly half of this consumption is for space heating and cooling and ventilation alone. Thus, there is significant opportunity to improve the efficiency of HVAC systems to improve building energy performance and subsequently mitigate against climate change. Improvement of the efficiency of HVAC systems predominantly relies on two factors, reasonable design and efficient operation. The focus of this literature review is the negative externalities of energy consumption and production and methods to mitigate against climate change by identifying efficient operation strategies for HVAC control to improve energy efficiency of buildings, with a focus on university campuses when noted. Specific control categories analyzed are black, grey, and white box models; common VAV control strategies; and control algorithms. Effectiveness of energy modeling and simulation of performance is also discussed.

2.1 EXTERNALITIES OF ENERGY CONSUMPTION AND PRODUCTION

Given that buildings consume on average 40% of energy produced in the U.S., it is important to improve energy efficiency of buildings to reduce consumption of energy and associated negative externalities or costs of energy production. As of 2017, the U.S. consumed

97.7 quadrillion Btu of energy with 37% coming from petroleum, 29% from natural gas, 14% from coal, 9% from nuclear electric power, and 11% from renewable energy such as biomass, solar, geothermal, wind, and hydroelectric [12]. Of this consumption, roughly 90%, or 87.5 quadrillion Btus was produced in the U.S. Thus, 35 quadrillion Btus of this energy was consumed by buildings alone, with 17.5 quadrillion Btus used for HVAC. For total energy consumed across the U.S., roughly 34% of natural gas, 91% of coal, 1% of petroleum, 57% of renewables, and 100% of nuclear power are used for electric power. 28% of natural gas is used in the residential and commercial sector for uses such as cooking, water heating, or space heating [13]. Power generation accounts for the vast majority of emissions such as SO_2, NO_x, $PM_{2.5}$, and NH_3 [14]. By 2011, emissions' marginal damages totaled over $130 billion dollars in the U.S. As of 2014, the U.S. is the second largest emitter of CO_2 emissions resulting from fuel combustion and some other industrial processes such as cement manufacturing and flaring [15]. This represents 15% of global CO_2 emissions falling behind China's 30%.

Global carbon emissions from fossil fuels have increased by 90% since 1970 [16]. This growth is predominantly from countries outside of the U.S., such as China, rapidly industrializing and relying largely on coal [17], as GHG emissions from electricity decreased here in the U.S. since the early 2000s [18]. This reduction is mainly due to a transition from coal to natural gas and increased energy from solar and wind. While warmer winter conditions have also reduced needed space heating and subsequent energy consumption, there has also been a simultaneous increase in summer temperatures, increasing space cooling needs which may offset savings generated from reduced space heating [19]. There are a variety of negative environmental effects throughout the whole life cycle of energy production. One of the largest concerns receiving attention worldwide is the threat of GHGs and climate change. Electricity production accounts for 28% of GHG emissions [18, 20]. In the U.S., coal accounts for 69% of CO_2 emissions and natural gas accounts for 29% of CO_2 emissions in the electric power sector [20]. It is not only the combustion of power generation fuels that are releasing GHGs, but the whole life cycle of fuel harvesting and combustion that are causing problems as well. For example, coal mining operations, such as consumption of diesel fuel for equipment or combustion of explosives, are large sources of GHG emissions [21, 22]. Fugitive emissions from coal mines themselves are also a problem and account for roughly 8% of global anthropogenic methane, although this issue is more specific to surface mines [23]. In the U.S., natural gas has replaced coal as the leading fossil fuel for electricity generation, predominantly because extraction of natural gas is more economically viable than coal. While overall CO_2 emissions from the combustion of natural gas are lower, escaped methane and CO_2 from the supply chain (processes and equipment to deliver to the consumer) is significant and varies widely, contributing to climate change [24, 25]. One study estimates that natural gas fired power plants contribute 3% of fugitive methane emissions in Europe and up to 16% for shale gas in the U.S., although this data is subject to natural fluctuations and uncertainties [26]. Fossil fuels are not the only emitters of GHGs. Renewable energy sources also emit GHGs over the course of their lifetimes. These are from upstream and downstream processes associated over the course of renewable energy life cycles such as mining of raw materials, manufacturing of turbines, shipping, and emissions associated with construction [27]. Such emissions are still significantly less than fossil fuel-based energy production. For example, onshore wind lifecycle GHG emissions, solar photovoltaic, biomass, solar thermal, and hydro system only range from 9.7 to 123.7, 53.4 to 250, 35 to 178, 13.6 to 202, and 3.7 to 237 gCO_2/kWh_e respectively[28]. The lifecycle GHG emissions for coal and natural gas plants range from 891 to 1,132 [27] and

417 to 473 gCO_2/kWh_e, respectively [29]. Lifecycle emissions from nuclear energy plants are roughly 21.08 to 33.01 gCO_2/kWh_e and comparable to that of renewable energy [28], although concern arises on how to manage radioactive nuclear waste [30, 31].

Emissions of GHGs have caused a warming of roughly 1.8ºF (1.0ºC) over the last 115 years [3]. With significant reduction in emissions, temperature rise may be limited to 3.6ºF (2.0ºC) to mitigate against the worst effects of climate change. Such effects include changing precipitation patterns [32-34]. Changes in precipitation patterns in combination with warming may lead to alterations of river flow regimes [35-37]. This effect may be exacerbated in areas with decreased rainfall patterns given the projected trends for extreme events such as drought [38-40]. In areas with increased rainfall events, flooding poses a serious threat [41, 42]. Urban areas are especially susceptible to extreme flooding events given the large amount of area covered by impervious surface causing increased runoff [43]. Extreme heat and cold waves may also occur due to changing climate [44-47]. Such events may lead to increased occurrence of wild fires, heat related health problems, mortality, and economic impacts [48-51]. Reduce snowpack, rising ocean temperatures, sea level rise, declining ocean oxygen concentration, slowing of Atlantic Meridional Overturning Circulation, and ocean acidification are other negative externalities associated with climate change and increased CO_2 levels in the atmosphere [52-56]. Many of these events depend on regional and climatic scenarios. For example, while heavy precipitation events are predicted to increase in the U.S., such increases occur predominantly in the northern U.S. during the winter and spring whereas the southwestern U.S. is projected to receive less precipitation in the winter and spring [3]. There are still large amounts of uncertainty regarding climate change and certain future climate scenarios [45, 57, 58]. While uncertainty does exist, there is consensus from the literature that climate change and global warming is occurring, and thus future climate scenarios need further study to reduce uncertainties and guide future energy mix scenarios.

There are also negative environmental effects outside of climate change associated with power generation. For example, underground coal fires are disasters associated with coal mining activities [59, 60]. Such disasters destroy and contaminate surface soils and enhances gas emissions. Coal mining also requires water and slurry injections which increase the risk of groundwater contamination [60]. Coal ash is also produced during the combustion process and is stored in open and unlined ash ponds leading to adverse environment impacts due to elevated levels of heavy metals and leaching into soils and groundwater [61, 62]. Natural gas fracking can also pollute groundwater sources, as methane migrates from fracking wells to nearby drinking water wells, surface water, and the atmosphere [63, 64]. For example, a study in the Appalachian Plateaus of northeastern Pennsylvania demonstrated that Methane was detected in 82% of drinking water samples, with an average concentration six times higher for homes less than 0.62 miles (1 km) from natural gas wells [65]. Ecological disturbances from power generation are an area of concern as well, as even "clean" power sources have negative environmental impacts. For example, renewable energy can require extensive land use and such installations act as environmental stressors that affect biodiversity and local ecological processes [66, 67]. For example, hydropower plants may change river base flow which negatively impacts fish habitats, such as in one study in which 68% of the ecological change of the Lancang River in the Qinghai Province of China was due to the hydropower plant [68].

2.1.1 POWER GENERATION AND HEALTH

Power generation also poses a threat to human health. Until 1992, health was not a primary concern of sustainability efforts but with the serious threat of climate change increasing, health effect outcomes of climate change and mitigation policies began to be incorporated into sustainable policy decisions [69]. Changes in climate change resulting from negative externalities of energy production, predominantly GHGs, may lead to changes in ecosystems, water resources, and food security that all affect human health [70-75]. Not only is the impact of climate change on human health an issue, but also the pollutants emitted throughout the energy generation process. Air pollution caused by the combustion of fossil fuels may also have direct health effects such as asthma, cardiovascular disease, and other health problems [76-78]. Coal power generation is the most detrimental to human health. Carbon, sulfur, oxygen, hydrogen, and trace amounts of nitrogen and heavy metals are the main components of coal and thus the combustion of coal emits poisonous gases such as CO_2, SO_2, SO_3, NO_2, and NO [79]. These have serious health effects such as skin, cardiovascular, brain, blood, and lung diseases directly and indirectly, as well as various cancers. In particular, formation of the SO_2 gas may accelerate the rate of diseases and decrease life expectancy around power plants [80]. CO and CO_2 not only contribute to global warming but also lead to the interaction of CO_2 with particulate matter ($PM_{2.5}$) which alters air quality and may lead to increased asthma attacks and other respiratory and cardiovascular diseases [81, 82]. In China, air pollution is now the fourth largest contributor to disease with mortality of lung cancer increasing by 465% since 1978 [83]. In the U.S., the power mix has transitioned to predominantly natural gas. While it is unrealistic that all power plants in the U.S. be switched to natural gas, researches demonstrated that such a switch may be beneficial to human health by reducing SO_2 emissions and NO_x emissions by 90% and 60% respectively [84]. Methane emissions would increase by 80% to 120% which would be a significant concern for climate change impacts considering the global warming potential of methane is higher than CO_2. Also, a separate study showed that people who live in close proximity to multiple gas wells in densely developed shale basins experienced increased incidence of childhood leukemia, asthma attacks, congenital heart defects, low birth weight, and preterm birth compared to those who live with no production wells nearby [85]. Unconventional natural gas development in Pennsylvania has led to a variety of these health issues in local communities [86-88].

2.1.2 THE ENERGY-WATER NEXUS

There is also a link between energy and water use known as the energy-water nexus [89]. Water is used to generate electricity and energy is required to extract, convey, and deliver water for human use. Energy is also required to treat water to acceptable standards to protect human health. With the onset of climate change and global warming, allocation of water resources may change due to variations in rainfall and temperature patterns, subsequently affecting the nation's energy system since approximately 40% of freshwater withdrawals in the U.S. are for cooling thermoelectric power plants [89]. It is important to note that withdrawal designates water diverted from any surface or groundwater source. Consumption designates water withdrawn that is not returned to the source, as it has evaporated, been transpired by plants, or incorporated into other products. For example, many facilities use once through-cooling systems which take water from nearby sources, circulate the water as a heat sink, and discharge the now warmer water to local rivers and lakes [90]. Overall withdrawal is higher for once-through systems, but consumption is lower. Wet-recirculating or closed-loop systems reuse cooling water in a second cycle versus discharging water back into the original water resource [91]. Therefore, the consumption rate is higher for wet-recirculating due to evaporative losses, but the withdrawal rate is lower. Hybrid cooling incorporates both wet and dry cooling systems [92]. Thus, the level of water availability and level of water withdrawal and consumptions affects the type of cooling technology used in thermoelectric power generation processes [93-95]. This is also relevant to buildings, as cooling towers are widely used to remove heat from HVAC systems [96, 97]. Thus, buildings play a part in the energy-water nexus not only in how they use energy, but also how they use water to cool and heat spaces. More attention is being placed on cooling tower design for energy and water conservation [98-100].

The recent boom of hydraulic fracturing and horizontal drilling has increased the complexity of the relationship between energy and water resources due to the intensive water use in the drilling and fracturing processes for oil and gas extraction [101-103]. Other trends of concern are continued population growth in arid regions such as the Southwestern United States, new technology in energy and water domains causing shifting water and energy demand needs, and policy addressing water impacts of energy production are adding additional complexities [89]. An additional issue is the effect of climate change, as water demand and availability may change due to stresses associated with changes in the environment such as temperatures, evapotranspiration rates, and precipitation rates [104-106].

Drinking water treatment plants are highly energy-intensive facilities that actually contribute to climate change [107, 108]. Conveying such water from treatment plants may also be energy intensive [109, 110]. Since such consumption through treatment and conveyance consume energy, this then uses more energy which requires more water which then requires more treatment, demonstrating the energy-water nexus. With the onset of changing allocation of water resources, competition for water use may increase for activities such as power generation, agriculture, and human consumption [111-113]. Such competition should be considered when evaluating the water energy nexus and emphasis should be put on energy efficient operations to reduce energy consumption and subsequent water use.

2.2 ENERGY PRICING

The average price residential and commercial consumers pay for electricity in the U.S. is approximately 12 cents per kilowatt-hour and 16 cents per kilowatt-hour, although there's large variation of price per kilowatt-hour between states [114]. The key factors determining electricity pricing are fuel cost; cost to construct, maintain, and operate power plants; maintenance of transmission and distribution systems, weather conditions, and regulations [115]. Generation accounts for 59% of U.S. energy prices whereas distribution and transmission account for 28% and 13%, respectively [116]. A method used to compare relative energy prices is the levelized cost of energy (LCOE) which is a life cycle cost of a power generating facility. Figure 1 shows predicted 2020 energy prices based on U.S. EIA estimates for plants going into service in 2020. The LCOE is traditionally calculated by dividing the net present value of the capital investment of a technology by the discounted energy yields generated by that technology resulting in average costs per energy unit [117]. It includes capital costs, fuel costs, fixed and variable operations and maintenance costs, financing costs, and assumed utilization rate for each plant type [118]. The direct comparison of LCOE across technologies is not always an accurate representation for how fuel sources compare to one another and may be misleading, as the method to assess the economic competitiveness of various generation alternatives from utilization rates, existing resource mix, and capacity values can all vary dramatically across regions [119, 120]. It should also be noted that the cost of coal with 30% carbon capture and sequestration (CCS) is higher because Section 111(b) of the Clean Air Act requires conventional coal plants to be built with CCS to meet specific CO_2 emissions standards. Coal plants with 30% CCS were assumed to incur a 3% point increase due to the cost of capital to represent the risk associated with higher emissions.

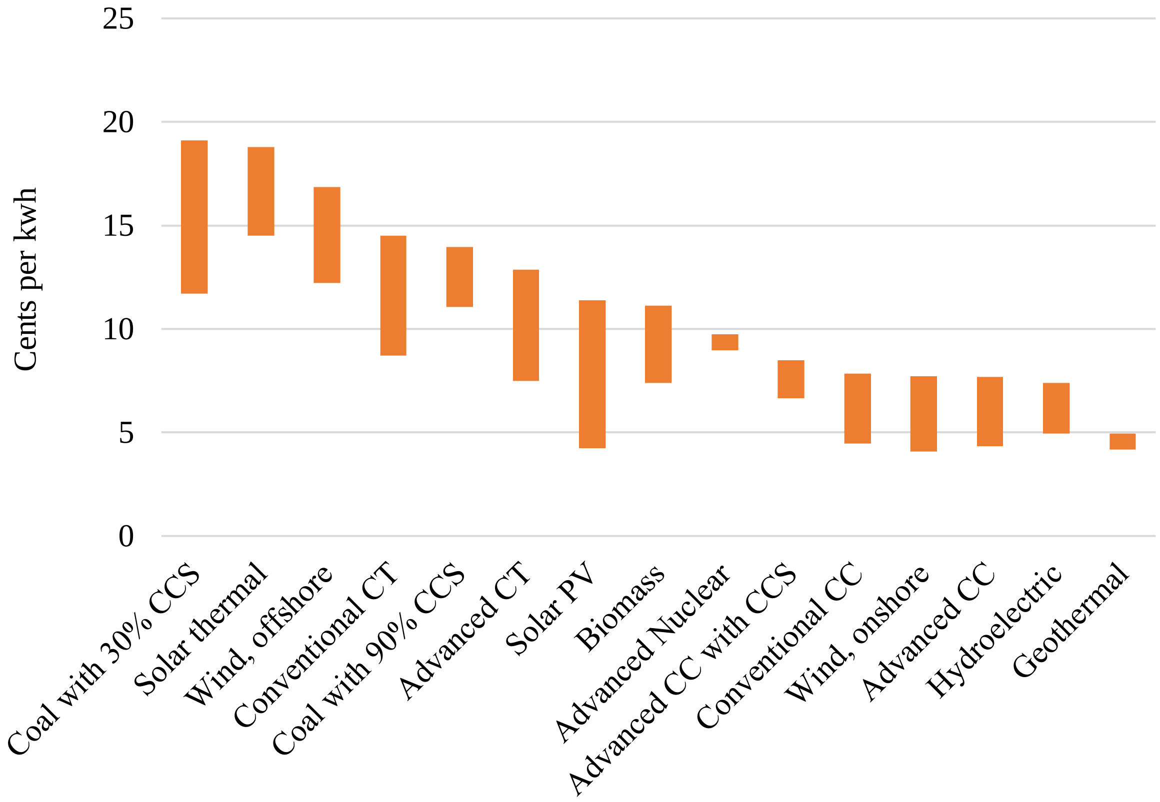

Figure 1. Regional variation across the U.S. in levelized cost of electricity for new generation resources entering service in 2022 (2018 prices in cents per kWh) [118]. CCS = carbon capture and sequestration. CC = combined cycle (natural gas). CT = combustion turbine (coal). PV = photovoltaic.

Current energy pricing in the United States does not fully reflect social and environmental externalities of energy production. Therefore, there has been research on including such costs in electricity pricing to mitigate against a global mean temperature rise of 2.7 ºF (1.5 ºC) to 3.6ºF (2ºC). Carbon pricing is a suggested method to accomplish such emissions reductions. The intent of such pricing methods is to encourage electricity conservation and reduce peak demand for electricity by charging more for carbon emissions. This is also meant to make other sources of electricity more competitive in the market, such as nuclear, which has a higher up-front cost compared to natural gas while having lower lifecycle GHG emissions. While the U.S. currently uses carbon pricing through carbon taxes and a tradable permit system for emissions, such policy instruments are subject to market failure. Marginal abatement costs shift overtime, and thus when abatement costs become equivalent to that of tax on emissions, incentive to invest in abatement technology decreases [121, 122]. Thus, a new suggestion is including a social cost of carbon (SCC) which is typically higher than existing carbon prices [123-125]. The SCC is calculated from integrated assessment models (IAMs) that combine climate science and economics. There is large uncertainty in quantifying the monetary benefit of emissions reductions, primarily the value of climate damages, catastrophic risks, discount rates, and lack of inclusion of co-pollutant impacts (SO_2, NO_x, $PM_{2.5}$) [123, 126]. Estimates of a SCC range from \$50 per metric ton of CO_2 emissions to \$80 per metric ton for mid-century emissions [127].

One study analyzed what energy sources would be most viable under such pricing in the U.S. [128]. This study not only included the SCC, but also costs from SO_2, NO_x, $PM_{2.5}$, PM_{10}, and CH_4 emissions over a power plant's lifecycle with capita and fuel processing. A scenario analyzing externalities, upstream on-time emissions, ongoing non-combustion emissions, and downstream one-time emissions demonstrated that wind was the lowest cost option, followed by natural gas combined cycle (NGCC), and then nuclear energy where wind power was marginal and gas prices are high. The study also found that if CO_2 prices were to become higher as listed in EPA's estimated SCC [129], wind, nuclear, and coal with CCS would increase while natural gas, coal, and utility scale PV plants would decrease. Such estimates are highly sensitive to carbon and natural gas prices. Another study had similar results, with nuclear, NGCC, and wind energy being the cheapest energy sources including negative impacts of energy production [130]. While there is uncertainty on what carbon pricing policies are best, the literature demonstrates that carbon pricing as currently implemented has been effective in regard to climate policy, but more stringent policy is still needed to mitigate against a warming of 3.6ºF (2ºC) [123, 131]. There is also still considerable debate around how responsive customers are to energy prices, as increased energy prices may not lead to significant reduction in demand [132, 133]. Use of real-time pricing (RTP) is one way to overcome this issue, as this allows participants to buy and sell wholesale electricity during the course of the day versus paying a relatively consistent energy price [134-136]. These types of intelligent energy pricing schemes are demand side management (DSM) strategies which incentivize electricity consumers to consume in patterns that provide an attractive trad-off between energy consumption by load shedding or shifting when prices are high. Also, while increasing the cost of energy prices to reflect social and environmental costs may reduce energy consumption, increasing the cost of such utilities may pose a severe financial burden on lower income households, as lower income households pay proportionally more of their income for energy costs [76, 137, 138]. Thus, there needs to be insulation between lower income households and rising energy prices to prevent this burden, especially for states whose population majority have lower incomes.

2.3 HVAC SYSTEMS

There is significant opportunity for emissions reduction by improving HVAC performance in buildings. For example, marginal abatement cost curves have identified improved HVAC performance as strategies that overtime have a negative monetary cost that also reduce GHG emissions [139, 140]. This means that such improvements would save money overtime, not cost money. These are limited by items such as a lack of awareness and acceptance, lack of developed market characteristics such as determination of total cost of technology at full penetration in the market, and high up-front costs of such technology [141].

Thus, the aim of this portion of the literature is to identify methods and strategies to overcome such difficulties.

There are various types HVAC systems for commercial buildings such as variable air volume (VAV), constant air volume (CAV), variable refrigerant flow (VRF), chilled beams, heat pumps, radiant floors, etc. to meat space cooling and heating needs. VAV air conditioning (AC) systems are the most common systems in commercial buildings [142, 143]. VAV systems create a constant temperature in a space by varying the volume of air supplied to condition a space instead of varying the temperature of supplied air. There are two main categories to provide cooling in VAV systems: direct expansion (DX) cooling coils or chilled water [142]. DX systems cool air directly with a refrigerant that passes through the tubes of the coil. Chilled water systems (CWSs) cool air by passing chilled water through the tubes of the coil. The VAV systems adjust the airflow to a room by opening or closing a mechanical damper or by controlling airflow through mixing boxes powered by VAV fans. If more cooling is needed, the damper is opened wider to increase the flow of cold air until the required temperature is reached. Opening the damper causes a pressure drop in the supply duct which signals the supply fan to increase the volume of air delivered. If the temperature in the room becomes too cool, the damper is gradually closed to reduce the flow of cool air to a space. Airflow changes are accomplished by variable speed drives (VSDs). Use of such VSDs has been shown to have energy savings of up to 38.9% over CAV systems by reducing fan power [144]. Economizers may be paired with VAV AC systems to reduce cooling costs by using outdoor air (OA) for free cooling when the OA is cooler than the indoor air (IA) to reduce compressor energy [142]. The economizer will switch back to a minimum ventilation position for OA when outdoor conditions are not favorable for cooling. This minimizes the operation of the fan which is the largest energy consumer in HVAC systems [145]. The energy performance of VAV systems varies significantly due to variation in system controls. In fact, one study demonstrated that energy performance for a simulated medium sized office building varied between 63.9% and 66.5% [146]. HVAC systems are very complicated, and their efficiency depends on a variety of factors such as system design, system setpoints, and system control strategies. Thus, such factors must be considered when choosing appropriate system setpoints and control strategies to maintain energy efficient operations.

2.3.1 FACTORS AFFECTING HVAC SYSTEM PERFORMANCE

Factors affecting the energy performance of HVAC systems include building construction, climate, building type, occupancy behavior and scheduling, etc. There are multiple sustainable building construction methods to improve thermal loading of buildings by choosing optimal building materials (such as insulation), window to wall ratio (WWR) and shading, building orientation, and building geometry [147-152]. Including opportunities for natural ventilation through windows has also shown to improve energy performance of buildings by reducing cooling loads during the summer [153], although this is only best suitable for certain climates and it is harder to include opportunities for natural ventilation in larger buildings. Sustainable building design in new construction is of particular importance because retrofitting of already constructed buildings to have more sustainable features may be difficult. For example, one study determined that buildings of 45 years of age and older had the least improved sustainable technologies in regard to building envelope and HVAC systems (as well as solar and wind energy) [154]. This may be attributed to high renovation costs associated with older buildings [155, 156] or difficulty finding an appropriate reuse for older buildings [157]. While such retrofits may have high capital costs in regard to HVAC specifically, appropriate economic analyses are crucial to determine payback periods for renovations as Rinaldi et al. demonstrated that occupants have difficulty adapting to uncomfortable conditions in older buildings without energy- and cost-intensive measures [158]. Longer periods of heating were needed to reach a certain comfort level, causing a higher fuel consumption.

Performance of HVAC systems can also vary significantly based on different climate zones. This is due to the relationship between OA temperature and space cooling and heating. One case study across the U.S. showed that annual energy consumption on a spatial scale of climate zones may vary from -17% to +21%, and for local scales vary anywhere from -20% to +24%, with buildings in the southeast having larger changes than those in other regions [159]. Global warming and climate change may also cause temperatures of certain regions to change, impacting HVAC performance in cold and hot climates where such effects of climate change are exacerbated [160-162]. There is a potential that reduced heating loads needed in cooler regions may balance out the increased cooling load needed in warmer regions, although this is only the case for regions with a mild climate [160]. Another study demonstrated that there are potential scenarios where cooling degree days (CDD) will not be offset by heating degree days (HDD), with increase for total energy consumption for a college campus ranging from less than 1% up to 9% for various climate change scenarios over different time periods [19]. While the literature seems to show consistency that climate change will affect HVAC performance due to increase or decrease in heating/cooling loads, the extent of such effects is still widely unknown.

Building types and functions also largely influence energy consumption of such buildings, as shown in results from the 2012 Commercial Building Energy Consumption Survey conducted by the U.S. Energy Information Administration (EIA) [163]. For example, Suh & Kim compared energy simulations of various community centers and found that having a sauna in one center increased the electricity consumption of this center by 3.6 times compared to the community center which did not have a sauna [164]. Some of this was due to additional thermal loads from the sauna which was important to account for in terms of HVAC energy consumption. Thermal loads for a fitness centers also contributed to larger HVAC energy consumption. For college campuses, energy use can vary largely by building use category such as residential, laboratory, academic, office, research, recreation, or library [165, 166]. Labs typically consume a larger portion of energy for HVAC than other building types due to the higher need for fresh outdoor air [167].

These variations in energy use by building type also largely depend on occupancy (how occupants occupy a buildings) and occupant behavior (how occupants behave in a building). Often times variation of simulated energy performance compared to actual energy performance is due to this occupancy diversity [164, 168, 169]. Such discrepancy is known as a ‘performance gap.’ This difference may be as much as 30% as Wilde demonstrated in a study on a campus building at Plymouth University [170]. Such a high difference may be due to the variable nature of campus buildings, as occupancy by students is highly inconsistent. Occupancy is stochastic in nature leading to diverse schedules and requirements for heating and cooling affecting energy efficiency at the zone and buildings level [171]. This may cause energy inefficiency due to a variety of factors such as loads occurring in unoccupied rooms (i.e. conference or print/copy room) or due to diversity in thermal preference by occupants. In order to overcome differences in occupant thermal preference, a group of researchers created occupant profiles based on patterns in energy use to predetermine optimal setpoints to please all occupants and reduce unnecessary loads [171-173]. In some instances, studies suggest moving occupants so that those with similar preferences are in the same zone [171, 174]. This is unrealistic in larger spaces as this may be disruptive or impossible to find similar HVAC preferences among a variety of occupants. Methods to reduce cooling or heating of unoccupied zones will be discussed later on through use of different HVAC control strategies. More research is needed to determine how to reduce performance gaps between models/simulations and actual performance of buildings.

Occupant behavior is largely influenced by thermal comfort. Thermal comfort depends on a variety of personal factors such as metabolic rate and clothing level, as well as environmental factors, such as air temperature, mean radiant temperature, air speed, and humidity [175]. There are two methods to model thermal comfort, the heat balance model and the adaptive approach [176]. Heat balance models are based on the physics of heat and mass exchanges between the human body and environment. The heat balance model originally came about from studies in climate-controlled chambers which led to questions as to if this model is lacking real-world parameters, and thus the adaptive approach was introduced. The adaptive approach measures thermal comfort in real world living and working conditions and uses occupant judgement to assess thermal comfort. The most popular method to measure thermal comfort is the Predicted Mean Vote (PMV) which is part of the heat balance model [177]. This method predicts the thermal sensation experienced by a group of people based on heat loss and metabolic rate under certain environmental conditions on a seven-point thermal sensation scale. The 7-point scale options are hot, warm, slightly warm, neutral, slightly cool, cool, and cold. While energy efficiency is important, thermal comfort must not be compromised in the process, as this may affect occupant productivity and happiness [178, 179]. This is particularly important, as decreased productivity of occupants may offset monetary savings generated by reduced energy consumption by HVAC systems [180-182]. What occupants deem as a thermally comfortable environment can be very different depending on the specific groups of occupants.

For example, studies have shown that student thermal preferences were not in comfort ranges provided in building standards [183-185]. There is opportunity for generating thermal profiles specific to certain groups of occupants to better predict thermal comfort zones in buildings as a measure of energy efficiency [186-188]. Thus, thermal comfort should always be considered when making changes to HVAC systems.

2.4 METHODS TO IMPROVE HVAC SYSTEM PERFORMANCE

In order to maintain certain levels of comfort and improve energy performance, there are a variety of methods that exist. Such methods include modeling/simulation, controllers, and control strategies. These methods and strategies will be discussed further in the following sections. Discussion of these methods is meant to provide a brief overview of modeling and control strategies commonly used in the field of HVAC design and operation.

2.4.1 MODELING

HVAC models may be continuous in state or have a discrete set of values; discrete in time to proceed in discrete steps; deterministic or stochastic; time varying; steady state or dynamic; or forward to forecast future output variables [189]. These models compromise primary and secondary HVAC components. A primary system converts fuel and electricity to produce heating and cooling (chiller, boiler, cooling tower, etc.) whereas a secondary system is what delivers the heating and cooling (air handling equipment, air distribution system, etc.). The two main types of VAV modeling are steady state versus unsteady state [142]. Steady state parameters do not vary with time whereas unsteady state parameters do vary with time to account for transient HVAC operations. There are three main types of unsteady state models: physics based (white box), data driven (black box), and hybrid (grey box) models. White box models, also known as mathematical, forward, or physics based models, are developed based on the fundamental laws of thermodynamics (mass balance, heat transfer, momentum, flow balance) and have several specific assumptions [190]. This type of model is best suited for the design phase to analyze performance of HVAC system components. Since these models rely heavily on assumption, the accuracy of such models is low. Such models include the zone model, cooling and heating coil model, mixing box model, damper model, valve model, fan and pump model, storage tank model, chiller model, heat pump model, boiler model, cooling tower model, and duct and pipe model [190, 191]. Black box models, also known as empirical, inverse, or data-driven models collect real system performance data and determine a relationship between input and output variables using mathematical techniques [190]. These types of models are more suitable for existing HVAC system performance improvements when sufficient data is available. While these models have higher accuracy than white box, they have poorer generalization ability because they can be more scenario specific depending on what input/output parameters are used (such as occupancy). These types of models also tend to degrade overtime as actual conditions shift away from training data sets. Such types of models include state-space, geometric, case-based reasoning, stochastic, instantaneous, frequency domain, data mining algorithm, fuzzy-logic, and statistical models [190, 191]. Grey box models, also known as hybrid models, combine the best qualities of white and black box modeling to overcome the shortcomings of each of those models [142]. The basic structure is formed from white box models while model parameters are determined using black box models [190]. These models have higher accuracy than white box models and better generalization capability than black box models, but are very complex and difficult to develop [191]. These models also still suffer from some of the flaws of white and black box models, as they need retuning when operating conditions change from historical system performance data, may be based on assumptions which are not achievable in real systems, and may be somewhat incomplete due to oversimplification of certain factors (occupancy, heat transfer, indoor thermal comfort) [190]. A more extensive overview of white, black, and grey box models with specific types and examples may be found in references 12, 48, 49, as a detailed analysis of such models is beyond the scope of this study.

2.4.2 BUILDING SIMULATION

Simulation is the concept of creating a computer model of existing or proposed VAV systems to better understand variables affecting the system and future behavior in real world conditions [142]. This is different from the previously mentioned modeling techniques as these create a computer model as an abstract representation of building energy performance. Examples of such simulation tools are TRNSYS, ESP-r, DOE-2, HVACSIM$^+$, Building Loads Analysis and System Thermodynamics (BLAST), Matlab/Simulink, EnergyPlus, SIMBAD, as well others. The Building Energy Software Tools (BEST) Directory run by the International Building Performance Simulation Association (formerly run by the U.S. Department of Energy) provides information about the various building simulation tools available [192]. These tools help predict heating and cooling loads or indoor thermal climate conditions of a space based on input parameters (building geometry, number of zones, internal heat loads, scheduling, climate, etc.). Such outputs are used to improve building design to reduce thermal loading or to select and improve HVAC system performance. The way these tools differ is by what they perform, although most can predict peak heating/cooling loads, total energy consumption, system performance, and costs [193]. Such models are as simple or complex as a user desires, i.e. a system without model feedback to the building model or a fully integrated model that accounts for system deficiencies when calculating building thermal conditions [189]. Model complexity is defined by scope (number of components in the model) and resolution (number of states per component). Each type of model requires different skill sets, modeling resolutions, and detail depending on the level of customization, with the cost of such models increasing with model complexity. This is due to higher computation times as well as the need for greater knowledge about simulation design. Thus, it is important to consider what information is desired when deciding on model complexity. Simplification may be needed as complexity increases to reduce computation time [194-196]. Examples of simplifications are not including certain building features (i.e. shading, geometry) or combining zones of similar temperature. Simplifications may lead to performance gaps as discussed earlier as these simplifications cause models to deviate from real-world conditions. While these tools are good for establishing baseline performance prediction, more research is needed to fine tune these models and reduce performance gaps between simulated models and real-world performance of buildings.

2.4.3 CONTROL STRATEGIES

There are various control strategies to improve HVAC performance. These strategies fall into two main categories, pressure dependent control (PDC) and pressure independent control (PIC) [142]. Pressure dependent strategies use thermostats fixed inside zones to directly control damper position, which in turn controls the volume of air reaching the zone, which is dependent on duct static pressure. Thus, the zone temperature sensor corrects the damper position, but responses may be slow. Pressure independent strategies use cascading control loops to directly control the volume of primary air. The first loop controls zone temperature and the output of this loop feeds into the second loop as a reset signal to determine the airflow required for space cooling and heating. The damper is then adjusted to maintain the temperature setpoint and thus is not under direct control but is a result of adjusting airflow through the terminal unit. Common control strategies in VAV systems are listed in Table 1. All of these are rule-based control strategies. Manjarres et al. used optimal on/off scheduling to reduce energy used for heating and cooling by 48% and 39%, respectively [197]. Energy savings via duct static pressure reset vary from 7%, 16%, and 3% between different studies [198-200]. Raftery et al. demonstrated energy savings of 29% through supply air temperature control strategies [201]. Demand controlled ventilation control strategies had fan energy use reduction of 10% to 93% depending on high or low occupancy [202]. An issue with such strategies is that from a cost benefit perspective, it is not clear for building managers as to what control strategy is not only financial beneficial, but also has significant reduction in energy use considering building type, HVAC system, and climate conditions [203]. Also, while rules-based systems are relatively simple, they can theoretically encompass multiple sub-systems, increasing complexity which increases cost to setup and maintain, reducing feasibility [204].

Table 1. Common control strategies in VAV air-conditioning systems [142].

Strategy	**Description**	**Examples**
Optimal Start/Stop	This strategy uses building automation system (BAS)[1] to determine the amount of time needed to meet the temperature setpoint of each zone. This strategy minimizes operating time to eliminate usage during periods of inoccupancy to create energy savings.	[205-207]
Duct Static Pressure Reset	This strategy varies the system supply airflow rate to reset duct static pressure via variable frequency drives (VFD) inlet guide vanes, eddy-current clutch, or outlet dampers. Pressure sensors control the devices for maintenance of a high level of constant static pressure set point value. As building loads increase or decrease, the static pressure id increased or decreased as wells to minimize energy usage. This may be done using a terminal box feedback technique or without.	[208-211]
Air Temperature Reset	This strategy either resets the supply air temperature (SAT) or the discharge air temperature (DAT). The SAT control strategy lowers or raises the SAT whereas the DAT control strategy lowers or raises the DAT. The SAT strategy aims to reduce energy associated with cooling loads when reheat may be required. The DAT strategy aims to reduce energy	[206, 212, 213]

	consumption associated with the entire HVAC system by minimizing pumping, cooling, and heating.	
Demand Control Ventilation Strategy	This strategy adjusts OA intake based on occupancy. As the actual occupancy of zones drops below design values, OA intake is reduced below design rates to conserve energy. This is accomplished via CO_2 sensors which detect the level of CO_2 in the air. If CO_2 values drop below the design value, the OA intake is reduced.	[214-219]

[1] A BAS is a centralized control system that utilizes computer networking of electronic devices to control HVAC, lighting, and other systems in buildings.

2.4.4 CONTROL ALGORITHMS

Control algorithms are also useful tools to manage and operate HVAC systems. Such methods are shown to be more sustainable and cost effective than replacing HVAC equipment with more recent technology, although they require accurate modeling and best-suited optimization techniques [190]. These types of algorithms solve optimization problems to minimize certain cost functions such as minimization of energy consumption and control effort while maximizing thermal comfort [220]. There are several types of control algorithms used in VAV systems. Table 4 lists types of control algorithms. For example, Xu et al. used a genetic algorithm to optimize temperature setpoints by minimizing the total cost through estimating total ventilation rates in a multi-zone AC system [219]. This resulted in cooling energy savings of 7%. Fuzzy logic controls (FLCs) was used for an HVAC system in a hospital building and the FLC method performed better in regard to overshoot, oscillations, and energy consumption than on/off or PI/PID controllers [221]. Fuzzy-genetic controllers were also found to outperform traditional PID controllers, with reduction in overshoot, hydronic energy consumption, and deviations from SAT setpoints [222]. There are also multiple types of direct digital control strategies (DDC) which utilize computer systems to control environmental conditions. Such systems offer increased reliability due to reduced need for decentralized communication, greater versatility, and improved system response since information is processed directly at the local area network [223]. While such methods shown in Table 2 offer improved HVAC system performance over more traditional control strategies, such models may be difficult to tune, have poor air distribution, be poor to converge, and be difficult to adjust [142].

Table 2. Control algorithms used in VAV systems [142].

Genetic Algorithms (GA)	These algorithms use Darwinian evolution theory to produce new populations with fitness values of higher average. The highest fitness value is the most optimal result. These are used to design VAV system and minimize cost, energy consumption, and improve comfort via algebraic equations.	[224-229]
Fuzzy Logic Control (FLC) Algorithms	These algorithms map input values to output values using *if-then* statements to create a set of linguistic rules. Such controls are used to improve energy efficiency of HVAC systems as well as improve IAQ and thermal comfort. Such algorithms generate accurate control of the system and conserve energy.	[230-237]
Fuzzy-Genetic Controllers	These algorithms combine GAs with FLC algorithms. The FLC algorithm may require many variables, increasing complexity. Thus, the GA component has fast and random search capabilities to look through these variables and choose the optimal operation.	[222, 238-241]
Baseline (BL) Control*	These algorithms generally fall into two types, single maximum and dual maximum BL control logic. Dual maximum BL use zone temperature measurements to determine temperature and flow rates of supply air specifically in single zones using VAV systems. The algorithm is carried out based on two maximum airflow setpoints whereas the logic in the single maximum BL control logic is carried out on one maximum airflow setpoint. Benefits include reduced reheat, fan energy, and overcooling of spaces to promote energy efficiency.	[242, 243]
Zone Level Feedback Control (Z-FC)*	This control algorithm measures occupancy and zone temperature to compute minimum permissible flow to maintain appropriate zone temperature based on occupancy. Thus, this algorithm optimizes a tradeoff between energy savings and thermal comfort.	[244-246]

AHU-Level Feedback Control (A-FC)*	These algorithms have four inputs, (1) SAT, (2) supply airflow rate, (3) condition air temperature, and (4) return air ratio. Based on the input values, the algorithm determines the return air, conditioned temperature based on mix air, and recalculates the return air to ensure satisfaction under zone humidity constraints. This reduces power consumption of the AHU to generate energy savings.	[247-249]
AHU-Level Model Predictive Control (A-MPC)*	These algorithms utilize the same inputs as the A-FC algorithms but operates using model predictive control to obtain control inputs by solving optimization problems with constraints. Such models require extra steps such as models of thermal dynamics and hygro-dynamics as well as weather and occupancy predictions. This method is widely used to improve comfort and energy savings.	[250-255]

[*] A type of direct digital control (DDC). DDC uses single computer or interconnected computer to control environmental conditions via a microprocessor on a closed control loop to control damper position.

2.4.5 CONTROLLERS

Existing HVAC systems utilize various controllers to manage system conditions. There are two main types of controllers, classical or optimal, predictive, and adaptive [142]. Today, the most common type of classical controller is the Proportional-Integrate-Derivate (PID) controller. These types of controllers adjust equipment settings based on conditions such as OA or IA temperature, humidity, etc. via SISO. They combine Proportional (P) and Proportional Integral (PI) controllers with a derivative function. The derivative aspect opposes any change from the specified settings and restricts the control system to a single set-point to minimize error. This may cause inefficiencies given that HVAC processes are highly nonlinear [256]. Other shortcomings include inconvenient tuning parameters, faint anti-interference, and large overshoot [257]. PID controllers also require accurate models of HVAC processes and effective controller design [258]. Such specific models and parameters lead to a lack of robustness in PID controllers [259]. Thus, while PID controllers are simple to operate and narrow the range of operation of VAV systems to eliminate large temperature oscillations, there are still disadvantages which led to the exploration of optimal, predictive, or adaptive controllers [142].

Optimal controllers provide desired indoor comfort with the least energy input under dynamic OA conditions and indoor loads via appropriate local controls and supervisory controls of HVAC systems [260]. Optimal or predictive controllers aim to account for future disturbances in HVAC system processes such as solar gains, presence of occupants, weather, etc. [261-264]. These types of controllers require building models. Adaptive controllers self-regulate and adapt to various changes in the environment or operating conditions [239]. These types of controllers still require more research, as the response to move away from PID controllers is slow, as such controllers may require high complexity and long computation times as well as an extensive knowledge of such systems [265]. Such computation times may be reduced by rewriting optimization problems into smaller but denser forms to allow the controller model to be as complex as possible without increasing solving time [266]. It is also difficult to guarantee robustness of such controllers due to the stochastic nature of building systems [267]. These controllers also behave similarly to black box models which are still trying to be fully understood, thus building operators are slow to move away from PID controllers which are better understood and simpler to operate [267]. Hybrid controllers are a recent development which combines PID controllers with predictive controllers. These types of controllers maintain the PID element, but the predictive/adaptive control is an add-on element [142, 268, 269]. For example, a one such study used a neural network (NN) to increase response speed and control precision in an HVAC system while the PID controller rejects disturbances in the system to minimize error [270].

2.5 TEMPERATURE SETPOINT CONTROL

Such control strategies discussed throughout Section 2.4 may be used to improve temperature setpoints in buildings. Levenmore et al. estimates that 15% of typical HVAC overall energy usage is avoidable through improved temperature control [10]. Norford et al. demonstrated that varying the supply air temperature had energy savings of 11-21% during the cooling season, but this is only optimal for temperate outdoor weather conditions with low humidity levels [212]. Ghahramani et al. demonstrated that building level daily optimal setpoint selection subject to thermal comfort constraints had savings of 17.64% to 38.37% depending on climate [271]. This study also demonstrated maximum energy savings of 50.91% with a control policy maintaining a fixed setpoint for the entire year in extreme climates, although such strategy may not provide a thermally comfortable environment for occupants. A setback of -5.4ºF (3ºC) in Australian office building during summer did not jeopardize thermal comfort or efficient working conditions [272]. Depending on climate and building size, simulation results demonstrate that increasing temperature setpoints from 72ºF (22.2ºC) to 73ºF (22.8ºC), 74ºF (23.3ºC), and 75ºF (23.9ºC) had energy savings of 7.5%, 12.7%, and 16.4% [273]. Since this research was calculated via simulation, real world energy savings may deviate from these values due to occupant thermal comfort requirements. While VAV systems offer many advantages in energy efficiency, changing the cooling or heating setpoint or SAT does not guarantee energy savings. For example, a common type of HVAC system applied is a VAV with reheat (VAV-RH) to improve humidity control [274]. Air is cooled below the dewpoint temperature to condense out moisture. This air is typically cooler than desired for occupant thermal comfort and heat is added to raise the temperature to the desired level, known as reheat. Thus, increased temperature setpoints may lead to higher energy consumption for reheat as the temperature difference between the dew point and the cooling setpoints are larger, requiring more reheat to reach the setpoint. Increasing the supply air temperature to reduce the energy needed for reheat may also lead to humidity control issues in the building, reducing thermal comfort, as well as increased fan energy to supply more air to satisfy the cooling load [142].

2.6 ENERGY CODES, ENERGY BENCHMARKING, AND VOLUNTARY PROGRAMS

Energy codes, energy benchmarking, and voluntary energy programs are additional methods to promote energy efficiency in buildings. Building energy codes require a certain standard of energy performance for the design and construction of residential or commercial buildings. Such codes act as a "floor" for the minimum level and buildings may go beyond such requirements if desired. Energy benchmarking identifies how a building compares with other buildings of similar type and climate location. While this does not directly improve energy efficiency, it helps overcome barriers to energy efficiency by identifying opportunity for improvement in buildings. During the construction and operation, some building designers and operators may choose to go above code requirements. Examples of such efforts include voluntary programs such as Leadership in Energy and Environmental Design (LEED), Energy Star, Living Building Challenge, Net Zero Energy Buildings, as well as others which are all optional programs that hold a higher standard of energy efficiency.

2.6.1 BUILDING CODES

The Building Energy Codes Program (BECP) created by the U.S. Department of Energy (DOE) supports energy efficiency in buildings. Estimates show that this program, from 1992 to 2012, saved 4.8 quadrillion BTUs of energy, equaling a potential total of $44 billion in savings [275]. It is important to note that these estimates assume a 100% adoption and compliance rate by buildings (which is not the case) and thus is an overshoot. These estimates, though, still emphasize the large impact building energy codes can have in the U.S. Projecting these values out until 2040 demonstrates cumulative potential energy savings equivalent to 3,855 million tons of carbon by energy consumption reduction, equaling savings of $230 billion in utility bills. Another study demonstrates that cost-effective energy efficiency improvements in the U.S. building sector has the potential impact of reducing annual electricity and natural gas consumption by 20-30% over the next 10-15 years [276]. Thus, energy codes play an important role in mitigating against climate change while also providing economic incentives [277, 278].

In the U.S. energy codes apply to virtually all buildings, and there are multiple ways to meet such energy codes. Under the nation's federal structure, states develop, adopt, and implement building codes that go through frequent review cycles to keep up with innovation in technology. Currently, only 8 states do not have a statewide code or home rule for code adoption for commercial buildings as of December 2018 [279]. Typically states adopt the American Society of Heating Refrigeration and Air-Conditioning Engineers (ASHRAE) codes or the International Energy Conservation Code (IECC) developed by the International Conservation Council [279]. Different compliance paths to meet such codes are prescriptive, simple trade-off, simulated performance, or by point system [280]. Prescriptive sets performance requirements for each building. Simple trade-off is similar to prescriptive, but substitutions are allowed among code components. Simulated performance relies on building on energy simulation software to model energy use in a building compared to reference buildings or other requirements.

The involvement of the government in enforcing energy code policies has played a key role in encouraging designers of office buildings to opt for energy efficient systems [281]. In India, one study found that it is not necessarily the existence of energy codes that improve building energy efficiency but the regulation mandatory structure and enforcement structure that results in higher energy efficiency [282]. Such code adoption in India, such as the Energy Conservation Building Code, has the potential to reduce building electricity use by 20% in 2050 compared to a no policy standard [283]. Having a well-structured inspection system and supervision system has been shown to be key for successful implementation of building energy codes, and such methods have increased code compliance from 71 to 100% in China by 2012 [284]. Some countries are not quite as far ahead as the U.S. in regard to building code adoption. For example, adoption of energy codes in Australia has been relatively slow [285]. Russia has also had difficulty meeting energy intensity reduction objectives, with lack of motivation, lack of information, low level of research and development, lack of infrastructure, lack of financing, as well as a host of other reasons causing such issues [286].

The European Union (EU) implemented the 2010 Energy Performance of Buildings Directive (EPBD) and 2012 Energy Efficiency Directive as the EU's main legislative instrument to improve energy performance of buildings [287]. The 2010 EPBD makes it possible for consumers to make informed choices about strategies to improve building energy performance. The main goal of the 2010 EPBD is to have nearly zero-energy buildings by 2020. This has led to significant improvement, as buildings in the EU consume half as much as typical buildings in the 1980s. The EPBD was updated in 2016 as part of the Clean Energy for All Europeans package. This update promoted the use of smart technology in buildings and streamlined existing rules and acceleration of building renovations. Another updated was issued in 2018 with goals of accelerating cost-effective renovation of existing buildings and decarbonizing the building stock by 2050. Standards set by the EU EPBD are stronger than current U.S. building codes, as the EPBD includes standards for net-zero energy consumption by 2020, renewable energy programs, and certification programs and the U.S. codes do not include such features

[288]. The level of implementation of the EPBD is also national while in the U.S. code implementation is state by state.

There are many barriers to the successful implementation of energy codes. Authors note a lack of capacity to inspect buildings for meeting energy requirements as well as a lack of training and tools which undermines enforcement and compliance of energy codes [280]. Other studies also note such shortcomings. Levine et al. noted that state and local government face widespread challenges due to insufficient funding of code enforcement activity [276]. This is especially true for states or cities that have a lower capacity to have adequate agency staff resources to prepare grants or review buildings plants, do training, etc. [289, 290]. Another critical barrier to the investment in energy efficiency upgrades or improved energy management is lack of awareness about green technologies or misconceptions about potential financial benefits [280, 291-293]. Robustness of energy codes is also a concern for building professionals, as occupant behavior may have significant impacts on the performance of buildings [294]. Thus, these professionals question how one can tell a building is actually performing better due to this uncertainty, as it may be difficult to tell if the building is actually performing better or if occupants changed their behavior. While energy codes provide valuable improvement in energy savings, there seems to be a lack of funding and capacity by the government to ensure that requirements of such codes are continuously met, impeding the ability of such codes to realize full energy savings. It also seems another major issue is lack of knowledge or awareness about investments in energy efficiency upgrades also hinders code adoption and enforcement.

2.6.2 ENERGY BENCHMARKING

Energy benchmarking is another way to motivate improvement in the energy efficiency of buildings. Energy benchmarking strategies themselves do not improve energy efficiency but address and compare buildings of similar type and size to unlock new energy efficiency opportunities by promoting data-driven decision making. Building energy profiles for groups of buildings are generated based on location, use type, weather, etc. to compare building energy consumption against other similar building types or building performance baselines to indicate opportunities for improvement in regard to energy efficiency. The EU and other countries have mandated benchmarking programs for many years, but the U.S. is only now beginning such programs. As of 2016, 24 U.S. jurisdictions have adopted benchmarking and transparency requiring mandatory reporting of energy consumption for privately-owned commercial, multifamily buildings, or both [295]. Examples of existing models to perform energy benchmarking are ordinary least squares (OLS) (such as used in EnergyStar), data envelopment analysis (DEA), stochastic frontier analysis (SFA), and artificial neural networks (ANN) [296]. A study at the Georgia Institute for Technology identified that possible impacts of a national energy benchmarking mandate via an updated version of the National Energy Modeling System may have monetary savings of up to $13 billion by 2035 and reduced energy consumption of 160-180 TBtus by 2035 [297]. This reduction is estimated to come from energy used by space heating, space cooling, ventilation, lighting, water heating, cooking, and refrigeration. It should be noted, though, that researchers estimated roughly 90% of these energy savings would only benefit metropolitan areas, thus this may discourage more rural areas from adopting energy benchmarking policies. A different national study evaluating the effect of benchmarking and transparency policy in the U.S. identified that energy savings in such cities with these policies ranged on average from 3-8% [295]. These conclusions are based on average energy use over time and thus these correlations may not be causally attributable results.

There are claims that current benchmarking tools are not accurate or fair as they lack robustness and over-estimate efficiency of buildings. Specifically, such shortcomings of energy benchmarking tools include sensitivity to outliers in data which skews building efficiency scores, inability to normalize all variables, lack of theoretical maximum performance for buildings, and over-estimation of building efficiency [298]. There are also claims that data used to build benchmarking profiles are low-resolution and lack sufficient detail to effectively compare buildings [296]. While energy benchmarking is a valuable tool to identify opportunity for energy efficiency improvement of buildings, there is still a need for improvement of granularity of data used in energy benchmarking as well as a way to standardize data collection and reporting to compare results. Thus, new benchmarking tools are being created to overcome such shortcomings. Once such study claims that the EnergyStar algorithm accounted for 30% of variance in energy use intensity (EUI) when compared to the development of a new GREEN grading system [299]. This system used a non-linear algorithm to capture the complex relationship between variables that influence energy performance that best explain variations in EUI based on city specific data. It should be noted, though, that this study was conducted on residential properties whose energy patterns are much more variable than that of commercial buildings. Quantile regressions is another introduced method to assess building performance. Researches used quantile regression to create a cumulative distribution function of theoretical consumption levels for building according to certain quantiles [296]. Based on this function, buildings are given a building efficiency score known as QuantRank. Results emphasized that luxury type buildings (gym, spa, etc.) have large effects on consumption and that number of employees per area has a larger effect in inefficient buildings than efficient. Cooling degree days (CDD) also had a large effect on poor performing buildings. These results provide deeper insights for building operators to identify and prioritize building optimization strategies that may be overlooked in other strategies.

Most benchmarking systems focus on whole building performance, but some studies have explored energy benchmarking as a tool specifically to optimize HVAC performance. A study in China focused on identifying a simplified benchmarking energy consumption method specifically for air conditioning systems which cool large-scale commercial buildings [300]. Such benchmarking identified that the main sources of energy savings would be from envelope cooling energy, ventilation cooling energy, scheduling, and improved efficiencies of water pumps used by cooling towers. Another study specifically used a dual-benchmarking strategy to evaluate HVAC system operation in an airport HVAC system [301]. A control-perfect index (CPI) is generated based on exergy analyses to evaluate HVAC system operation to identify ideal operation and act as benchmark one. Then, the ideal operation is then used as the 2nd benchmark to estimate improving potential of HVAC system operation strategies. Thus, the 1st benchmark is used to evaluate the energy saving capacity compared to original control and the 2nd benchmark is used to evaluate the improving potential or disparity compared with operation level. This work found that varying the chillers ON/OFF mode with part load optimization has the best operation efficiency when compared to other methods. Another study created a control oriented HVAC model to perform HVAC performance benchmarking [302]. This research focused on modeling specific interactions between HVAC system components (condensing boilers, radiators, AHUs, heat pumps, chillers, fans, pumps, pipes, ducts, thermal zones). As many or as few components may be added to the model to evaluate system performance under various control strategies. This method reduced gas and energy consumption and dissatisfaction percentages. While there were improvements to the thermal environment, these improvements were based on simulations and not real-world tests. While energy benchmarking specifically for HVAC offers a useful tool to improve system control strategies, a downfall is that such methods would have to be employed separately outside of traditional energy benchmarking tools. Thus, methods to benchmark HVAC energy efficiency specifically needs to be incorporated into current energy benchmarking tools for ease of access.

2.6.3 VOLUNTARY PROGRAMS

Voluntary programs are another method to improve building energy performance. Through such programs, buildings that exceed minimum energy code requirements receive certain labels and certifications legitimizing improved building energy performance or sustainability. Voluntary programs include participating in green building certifications such as LEED, EnergyStar, Living Building Challenge, WELL Building Standard, economic incentive programs, as well as many other programs. Many of these programs focus on more than energy efficiency. Such voluntary programs came about in response perceived shortcomings of either free markets or existing building energy code regulations to encourage an efficiency level to mitigate harmful effects for GHGs and climate change [303]. Firms may choose to then participate in such programs to external and internal pressures to be more “green.” Typically, LEED building perform on average 25-30% better the national average of approximately 80 KBtu/ft^2 according to the 2012 Commercial Buildings Energy Consumption Survey (CBECS) [304, 305].

While typically LEED buildings have better performance, there is still need for improvements, as project EUIs deviate by over 25% for roughly half of LEED projects for new constructions [305]. This study also demonstrates that the performance baseline used by LEED (ASHRAE 90.1) had an average performance close to the average performance of the national building stock, although ASHRAE 90.1 has been updated since publication of this research as it is updated on a 3-year cycle. Such inefficiencies still exist in the LEED program today, as building energy benchmarking data in the City of Chicago shows that for offices, K-12 schools, and multifamily housing there are no significant source energy savings or reduction in greenhouse gas emissions relative to similar, conventional buildings [306]. Another study compared the performance of LEED versus non-LEED hospitals and analyses failed to demonstrate that achieving more LEED credits or LEED certification lowers operation and maintenance costs of healthcare facilities [307]. LEED certified buildings are not the only voluntary programs that suffering from weakness, as the Green Building Rating System is criticized for lacking requirements for healthy materials and friendlier environmental choices outside of energy consumption [308]. CASBEE and Green Star NZ are criticized for their limited applicability, although these programs are still relatively new and developing [309]. BREEAM, a rating system which targets European markets, is criticized for needing stronger assessment for new construction and communities [309]. Voluntary programs provide many benefits to creating a more sustainable built environment but suffer from shortcomings just as energy codes and energy benchmarking do. Not only are their needs for improving the stringency of such programs, but also improving transparency, as attaining green certification are often seen as time-consuming and high-spending [309-313].

The improvement of energy efficiency in buildings has great benefits to society given their large consumption of energy. Reducing energy consumption through improved energy efficiency reduces reliance on imported energy, reduces GHGs emissions and pollution, and improves public health at a national and global scale. Efficiency in HVAC design, control, and operation presents a significant opportunity to improve energy performance of buildings. Thus, it is important to choose and maintain proper control of HVAC systems throughout a buildings life. The following methods and results hope to demonstrate the benefits appropriate temperature setpoints in HVAC systems can have on improving the energy efficiency of buildings.

CHAPTER 3

METHODOLOGY

In 2015, the Office of Sustainability at UGA launched a sustainability plan to have 20% and 40% reduction of campus GHG emissions by 2020 and 2040, respectively, compared to the 2010 baseline [314]. The 20% reduction by 2020 has already been met. In order to quantify the impact temperature setpoint changes have on energy consumption and subsequent GHG emissions on UGA's campus, this study evaluates the impact of temperature setpoint changes made in select buildings on UGA's main campus. The following subsections describe analyses used to evaluate impact of temperature setpoint changes on energy consumption and thermal comfort. The next section analyzes results from such changes and implications for temperature setpoint changes on campus wide and individual buildings levels.

3.1 BUILDING HVAC SYSTEM BACKGROUND

The main Athens campus is divided into seven chilled water districts. The largest of these is known as District Energy Plant #1 (DEP-1), which serves the Business Learning Community buildings that are part of this study, as well as a number of other campus buildings such as the Tate Center, the Special Collections Library, Bolton Dining Commons, and two of the residence halls among others. In each district, buildings are connected together with underground pipes that allow them to share cooling resources. Electrically powered chillers use a refrigeration cycle to cool water which is used to provide conditioned, dehumidified air throughout the buildings. The chilled water (typically at 42ºF, 5.6ºC) is circulated through the piping networks by chilled water pumps [315]. Inside the various buildings is a separate chilled water distribution system. The pipes circulate the cool water to air handling units (AHUs) that passes through the cooling coils. The cooling coils absorb the heat out of the building air, producing cool, dehumidified air with a supply air temperature (SAT) of approximately 50ºF to 60ºF (10°C to 5.6°C) that is provided throughout the building. The SAT, which is low enough to remove moisture gained from outdoor ventilation air and any moisture gain from the building space, is typically held constant for consistent humidity control. Reheating of the SAT is necessary to prevent overcooling in some situations and ensures occupant thermal comfort, which will be discussed later. After providing the air cooling in the AHU, heat removed is transported through the chilled water return line to the district energy chillers where it is re-cooled and ready for circulation again. At the chillers, a separate water loop, known as condenser water, removes the rejected heat at the chiller condenser and transports this to the cooling towers that reject the heat to the atmosphere. The condenser water is sprayed into the cooling tower and come in contact with cooler, ambient air. The cooling towers typically reduce the condenser water within about 5ºF (2.7ºC) to 10ºF (5.6ºC) of the outdoor air wet-bulb temperature, as the high velocity air induces high evaporation rates from the large surface area created by the tiny droplets of condenser water being sprayed into the cooling tower [315].

In the study buildings, VAV systems are used to provide conditioned air throughout the space. VAV systems are the most common form of air conditioning in commercial buildings now and were discussed in more detail in the literature review section above. These systems will supply the cooled air to each room or temperature control zone. The SAT is generally maintained at a constant value and low enough to ensure humidity removal before supply back into the building space. The VAV terminal boxes adjust the air supply flow rate to the room to maintain the thermostat setpoint. A minimum amount of air flow is generally maintained to ensure some ventilation of the space. However, occasionally the cooling load of the space is not that high, and the minimum airflow rate may overcool the space. Thus, VAV systems will have a reheat function that reheats the air supplied to avoid overcooling of that particular room. This maintains acceptable humidity levels as well as thermal comfort. On UGA's campus, reheat is generally provided by hot water, with the heating source generated via the central steam plant. The steam plant mainly uses natural gas boilers, although there is one electric boiler that acts as a backup. Fuel oil is also available as a third fuel source, although this occurrence is rare. For the purposes of this study, it is assumed 100% of hot water is generated by natural gas since the electric boiler is rarely used.

CWSs operate more efficiently than decentralized HVAC systems for medium and large-sized commercial and industrial applications [315]. This is due to the lower cooling water temperatures and also allows flexibility in buildings zones with differences in load characteristics, such as campus buildings which may have classrooms, offices, and labs all within the same building. Using the chillers at DEP-1 is more energy efficient, as these larger chillers can be run at optimum efficiency rather than individual chillers running at partial loads at the various buildings when cooling demands are lower. Also, the DEP-1 uses waste heat from the chillers to generate hot water for nearby buildings and make-up water for the cooling tower is supplemented by harvested rainwater to compensate evaporative losses [316]. Condensate collected from the AHU air handling system is also used to supply water to fountains on UGA's campus.

3.2 BUILDING OPERATING CONDITIONS

The UGA main campus is in Athens, Georgia, U.S.A. roughly 60 miles (96.6 km) northeast of downtown Atlanta. The main campus is 762 acres (3 km^2) with an overall building portfolio that consists of an approximate total floor area of 16 million square feet (1.5 km^2). This area lies within the humid, subtropical region and has hot and humid summers and mild winters. The average high temperature in the summer of 2018 was 89.7ºF (32.6ºC) and the average precipitation was 5.54 inches [317]. The annual average high, low, and overall average temperatures in 2018 were 74.2ºF(23.4ºC), 52.8ºF (11.6ºC), and 63.5ºF (17.5ºC), respectively [317]. The data collected for this research was collected from Amos Hall, Benson Hall, and Moore-Rooker Hall during parts of the cooling season of 2018. Each of these Halls is part of one building known as the Business Learning Community Phase II (BCLII). The BLCII is 6 stories tall, full air-conditioned, and opened in 2017. The buildings have a combined floor area of 145,769 ft^2 (13,542 m^2). The HVAC system in the BLCII operates on a START/STOP schedule in which the HVAC systems begins cooling before the scheduled occupancy time from 7AM to 7PM on weekdays. The HVAC system begins cooling before the scheduled occupancy time from 9AM to 4PM on weekends. The normal scheduled occupancy average cooling temperature setpoint is 73ºF (22.8ºC). The unoccupied scheduled cooling setpoint occurs from 7PM to 7AM for weekdays and is 80ºF (26.7ºC). For weekends, the unoccupied scheduled time is 4PM to 9AM. All analyses for the purposes of this study apply to the occupied schedule from 7AM to 7PM for weekdays only given that setpoint changes only occur during occupied schedules and it is assumed weekdays are when building occupancy is highest. The BLC Phase II is connected to a BAS which records all data used in this analysis. For the purposes of this study, the term "effective cooling temperature" refers to the global setpoint change made in the BAS, as this is the terminology used in the BAS. This term is used interchangeably with "cooling temperature setpoint." The uses of the BLCII is mainly for classrooms spaces, although there are faculty and staff offices within the building as well.

The effective cooling temperature setpoints were adjusted to 74ºF (23.3ºC) and 76ºF (24.4ºC) over various periods of time in the BLCII. This was done globally through the BAS. The first test period was from June 22nd until July 9th and temperature setpoints were adjusted to 74ºF (23.3ºC). The second test period was from July 23rd until August 16th and temperature setpoints were adjusted to 76ºF (24.4ºC). The third test period was from August 17th until August 23rd and temperature setpoints were adjusted to 74ºF (23.3ºC). The fourth and final test period was from August 24th until August 30th and temperature setpoint were adjusted to 76ºF (24.4ºC). A summary of testing periods and cooling temperature setpoints is in Table 3.

Table 3. Testing periods with corresponding dates and effective cooling temperature setpoint.

Test	**Time Period**	**Cooling Temperature Setpoint (℉)**	**Cooling Temperature Setpoint (℃)**
Baseline	5/1/18 - 5/31/18	73	22.8
1	6/22/18 - 7/9/18	74	23.3
2	7/23/18 - 8/16/18	76	24.4
3	8/17/18 - 8/23/18	74	23.3
4	8/24/18 - 8/30/18	76	24.4

While these setpoints were globally set, occupants are able to change zone temperature setpoints within +/- 2ºF (1.1ºC) of the cooling temperature setpoints. Operative temperatures ranged between 69.4ºF (20.8ºC) and 82.3ºF (27.9ºC) during testing periods. This includes temperatures for unoccupied and occupied scheduling of the building, as the BLCII operates on a START/STOP schedule. If looking at occupied setpoints alone, operative cooling temperatures range between 72ºF (22.2ºC) to 78ºF (25.6ºC). A total of 27 rooms were monitored for HVAC system setpoints during the testing periods. The setpoints monitored were cooling temperature, heating temperature, zone temperature, and SAT. The BAS recorded these values in 5-minute intervals, and the hourly averages were computed and used in this study. OA conditions were also monitored and included the dry bulb outdoor air temperature (OAT) and relative humidity (RH). The BAS recorded these values in 5-minute or 30-minute intervals. This data came from sensors located on the building. OA condition recordings were compared to data from the weather station at the Chicopee Complex as well as the Athens Ben-Epps Airport weather station. Overall building level energy usage data in Btu/hr was monitored using the campus BAS for chilled water and hot water consumption in 5-minute increments and these were used to compute hourly averages. The sum of the hourly averages was used to determine the building energy consumption per day.

3.3 BUILDING OUTDOOR AIR TEMPERATURE AND HUMIDITY SENSORS

The building OAT and RH sensors are located on the outside of the buildings. These sensors read the dry bulb air temperature and relative humidity and are currently used by the BAS for HVAC operating parameters. The Chicopee weather station located at the Facilities Management building is also used by the BAS to operate the HVAC system. The accuracy of the building sensors is determined by comparing the readings to the Chicopee weather station located at the Facilities Management Department as well as comparing readings to the Athens Ben-Epps Airport weather station. Statistical analysis is done to determine if the mean difference between the building sensors, Chicopee weather station, and Athens Ben-Epps weather station are significant. This analysis is used to determine if operating the HVAC system according to information from the building sensors is viable.

3.4 COMPARING BUILDING ENERGY CONSUMPTION IN TESTING PERIODS TO BASELINE OPERATION

The BLCII BAS records energy demand for chilled water (for cooling) and hot water (for heating) meters is assumed to be the energy consumption for HVAC specific operations. The energy consumption data for hot water and chilled water can be weather dependent. When making comparison in efficiency between the testing periods and baseline operating conditions in May, these values are adjusted based on the actual cooling degree days (CDDs) during each period to account for variations in outdoor air temperature over the testing periods with baseline operations [166]. A degree day compares how much the average outdoor temperature for a location is above or below a standard base temperature (65ºF, 18.3ºC) [318]. CDDs measure how much and for how long an outside temperature was above the base temperature, in which space cooling would be necessary. Heating degree days (HDDs) measure how much and for how long an outside temperature was below the base temperature in which space heating would be necessary. Only CDDs are used to normalize this data, as there was only one HDD from May through August when testing was conducted. Figure 2 contains maximum, minimum, and average temperatures as well as CDDs used in this study. This data came from building sensors located on the BLCII. Energy use is also normalized by floor area to identify building energy use intensity (EUI) and draw conclusions about energy consumption of buildings of similar type on UGA’s main campus.

After normalizing the data by CDD, comparisons are made between the May baseline chilled and hot water consumption and the chilled and hot water consumption that occurred during test periods. The percent change between the normalized energy consumption during testing periods and the May baseline is identified. This percent change is used to estimate what

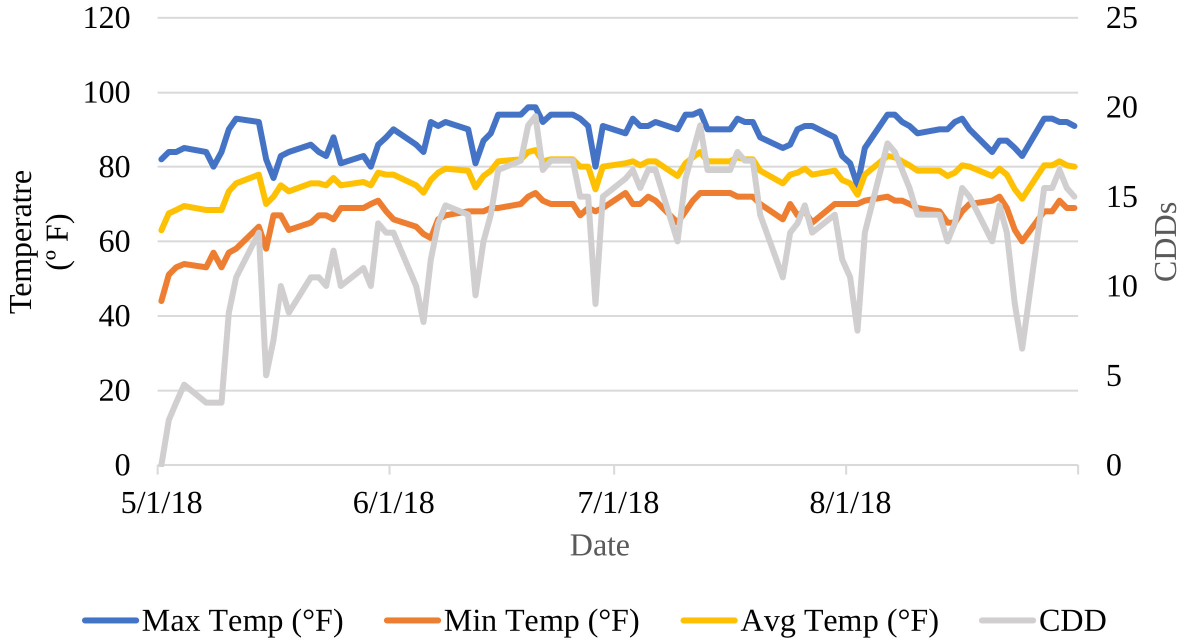

Figure 2. Maximum, minimum, and average temperatures and degree days occurring from May through August. This data is pulled from Weather Underground [319]. The left axis is for temperature data and right axis is for amount of cooling degree days.

the energy consumption during the testing periods would have been if the cooling setpoint changes were not made. These estimates are then compared to the actual energy consumption during each of the testing periods to identify avoided utility costs, emissions, and SCC.

3.5 COST OF ELECTRICITY

Utility costs were analyzed to determine the impact HVAC operation has on utility costs for UGA. UGA currently accounts for these costs based on 10 cents per ton-hr for chilled water, for some situations these are billed to other operations and for the remainder of the cases these are what are assumed to be internal costs. This is equivalent to 0.0284 cents per kWh given that 1 ton of cooling (12,000 Btu/hr) is equivalent to and 3.52 kW is equivalent to one kWh. Regarding hot water, UGA currently charges $10 per 1000 lb of steam which captures the cost of natural gas and operating the boilers. Assuming a nominal boiler efficiency of 80%, a value of

950 Btu/lb is used to convert hot water consumption to steam consumption for cost estimates. Note that these prices are specific to UGA and its economics. For the purposes of this work, all cost estimates are in terms of 2018 dollars.

3.6 EXTERNALITIES OF BUILDING ENERGY CONSUMPTION

Buildings mainly consume secondary energy, such as electricity, and chilled water or hot water that are created by electricity and steam, respectively. Secondary energies are forms of energy which are transformed from primary sources of energy such as coal, natural gas, or fuel oil, nuclear energy, or renewable energy. Therefore, the consumption of secondary energy by buildings ultimately comes from primary energy consumed at power plants, leading to negative externalities of energy production, particularly energy produced by non-renewable energy sources. While buildings themselves are not directly responsible for such externalities such as air, land, and water pollution, their consumption of secondary energy subsequently leads to these externalities at the power plant. The Georgia energy mix is seen in Figure 3.

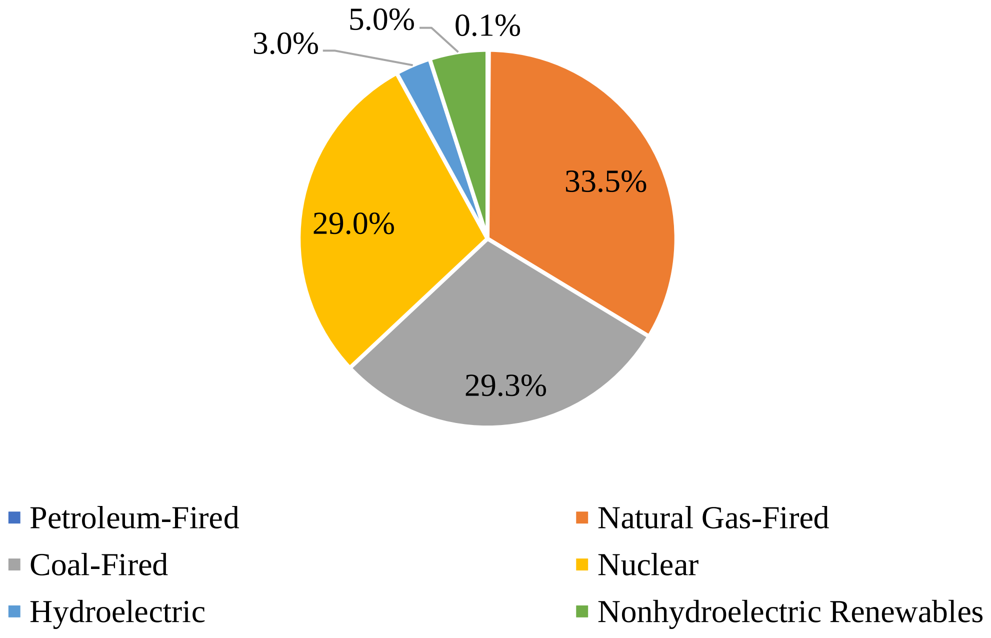

Figure 3. Georgia Electricity generation by source [320]. The 0.1% is for petroleum-fired fuel sources.

As mentioned earlier, the chilled water is generated by electrically powered chillers. The hot water is generated by steam created by natural gas boilers. There are emissions associated with the consumption of the given fuel sources. The major GHGs are CO_2, CH_4, N_2O, CHC-12, HFC-23, SF_6, and NF_3 [321]. CO_2 is the major GHG of concern from power generation and is the focus of this study regarding GHGs. Power generation typically does not cause emission of CHCs, HFCs, SF_6, or NF_3 and thus is not included in this study [322] Criteria Air Pollutants (CAPs) are also emitted through power generation, such as SO_2, NO_x, $PM_{2.5}$, and PM_{10}. While these are not GHGs, they are hazardous to human health and the environment. Only CO_2, SO_2, and NO_x are analyzed for emissions from electricity because there is credible data for these emissions provided by the EIA. Calculating emissions factors for electricity consumption specific to the UGA campus was beyond the scope of this study given that emission factors are extremely variable, as emissions from fuel combustion depend on rank and composition of the fuel, firing conditions, load, type of control technologies, and level of equipment maintenance [323]. SO_2, NO_x, $PM_{2.5}$, PM_{10}, and VOC emissions are calculated for natural gas consumption for the hot water consumption, as the required parameters are known based on an approximate efficiency in converting natural gas consumption to hot water generation and accurate emissions factors are provided by the EPA AP-42 Natural Gas Combustion document [323]. The UGA boilers have a capacity of 100 MMBtu/hr and have no emission controls. Appropriate emission factors are used according to these parameters. The energy consumption for chilled water (electricity) and hot water (natural gas) are multiplied by their respective emissions factors in Table 4 and 5 to determine the amount of emissions caused by energy consumption in the BLCII.

The emissions factors for electricity are based on the energy mix in Figure 2. As mentioned, emissions factors are highly variable. The findings in this report are only estimates and do not reflect the actual emissions by the University of Georgia.

Table 4. Emissions from electricity generation for Georgia [324].

Emission	Emission Factor	Unit
SO_2	0.8	lbs/MWh
NO_x	0.7	lbs/MWh
CO_2	946	lbs/MWh

Table 5. Emissions from natural gas boilers by technology type [323]. These factors are not specific to natural gas combustion and do not change based on geographic location.

Emission	Emission Factor	Unit
SO_2	0.6	lb/10^6 scf
NO_x	190	lb/10^6 scf
CO_2	120000	lb/10^6 scf
PM_{10}	5.7	lb/10^6 scf
$PM_{2.5}$	1.9	lb/10^6 scf
VOC	5.5	lb/10^6 scf

3.7.1 ENERGY CONVERSION FOR CHILLED AND HOT WATER CONSUMPTION

The chillers used to generate chilled water are powered via electricity. The hot water used for reheat is generated by steam, that for the UGA campus is primarily generated via natural gas boilers. The primary energy inputs used to generate the secondary energy (electricity and steam) that is converted to generate the chilled water and hot water must be calculated using emissions based on the factors listed in Tables 4 and 5. Based on an average of 5-minute intervals as recorded by DEP-1 over the 12 month time period of this study (excluding periods when the chilled water plant was not operating and during startup transient periods) the chillers consumed 0.61 kW per ton of chilled water generated. This conversion factor is used to determine how much electricity the chillers are using to generate the chilled water. This value represents chiller efficiency, pump, and cooling tower fan energy used by the CWS, and is assumed to be constant during the period of this study. Thus, the electricity consumed to generate chilled water is calculated via Equation 1.

$$E_{\mathrm{CHW,Chiller}}\ (\mathrm{kWh}) = E_{\mathrm{CHW}}\left(\frac{\mathrm{Btu}}{\mathrm{hr}}\right) \times \frac{1\ \text{Ton of Cooling}}{12{,}000\,\frac{\mathrm{Btu}}{\mathrm{hr}}} \times \frac{0.61\ \mathrm{kW}}{1\ \text{Ton of Cooling}} \qquad \text{(Eq.1)}$$

where,

$E_{\mathrm{CHW,Chiller}}$ = Electricity consumed by the chiller to generate chilled water

E_{CHW} = Cooling provided by the chilled water

As for the hot water, approximately the conversion between heating energy consumed at the AHU and the amount of natural gas consumed to provide that heat is based on 100 cubic feet (CCF) of natural gas being equal to 1.037 therms, where one therm equals 1000,000 Btu. Boilers at the steam plant are assumed to be 80% efficient on average, although overall system efficiency may vary as function of load on each boiler and fuel source at any given time. For the purposes of this study, it is assumed that the steam is generated by 100% natural gas. Thus, Equation 2 is used to calculate the natural gas consumed by the boilers to generate steam for the hot water assuming an 80% efficiency.

$$E_{\mathrm{HW,\ NG}}\left(\frac{\mathrm{CCF}}{\mathrm{hr}}\right) = E_{\mathrm{HW}}\left(\frac{\mathrm{Btu}}{\mathrm{hr}}\right) \times \frac{\text{Therm}}{100{,}000\ \mathrm{Btu}} \times \frac{\text{CCF Natural Gas}}{1.037\ \text{therm}} \times \frac{1}{0.80} \qquad \text{(Eq. 2)}$$

where,

$E_{\mathrm{HW,\ NG}}$ = Natural gas consumed

E_{HW} = Reheat provided by the hot water

3.7 THE SOCIAL COST OF CARBON

The current price of electricity does not reflect all social and environmental costs of energy consumption and energy production (the externalities). In order to account for a full cost of electricity, the current cost of electricity will be adjusted based on the SCC associated with the CO_2 emission factors listed in Table 4 and 5 for electricity and natural gas. Values used for the SCC are from the U.S. EPA [129], although this is just the best approximation available in the literature [129]. The SCC used in this study may be seen in Table 6.

Table 6. The SCC associated with CO_2 emissions [129]. Inflations rates used in this calculation are from the Bureau of Labor Statistics [325].

Pollutant	**Cost ($/ton/year - 2007$)**	**Cost ($/ton/year - 2018$)**
CO_2	$36.00	$48.08

In contrast, source energy accounts for the amount of energy consumed to generate the one unit of energy consumed on-site by a building. Thus, source energy accounts for primary energy (coal, natural gas, etc.) used to generate secondary energy (electricity, chilled water, hot water, etc.) consumed by the building. Source energy also accounts for transmission and distribution losses and inefficiencies that occur and is a better reflection of actual building energy consumption relevant to society in general. To calculate source energy, a source to site ratio is also needed to determine the actual energy used between primary and secondary energy and account for inefficiencies. All source ratios used are from the EnergyStar Portfolio Manager [326]. The source ratio for electricity consumption by the chillers is 2.8, which means that 2.8 units of primary energy are consumed on average per unit of site electrical energy consumed. This ratio is used to estimate the emissions and marginal damages for chilled water consumption only. Using these values, site versus source energy is compared for chilled water consumption if setpoint changes were made throughout the entire cooling season. This is meant to emphasize the large impact that using source instead of site energy may have when considering building efficiency and emissions. For electricity, the energy costs that is owed to Georgia Power will reflect the amount of energy consumed at the source, since Georgia Power pays for that energy as well in their generation facilities.

3.8 THERMAL COMFORT VALIDATION

Thermal comfort surveys were sent out via Qualtrics during the baseline data gathering and the summer testing periods to evaluate thermal comfort. Appendix A outlines the survey structure. A total of 228 surveys were collected throughout the baseline and the testing periods. Respondents had the capability to take the survey more than once, and thus, some responses are from the same person given that people may have occupied different buildings within the BLCII at different times. These surveys were distributed via Qualtrics. Temperature setpoint changes were complete before any classes took place during each testing period, and thus no changes were made while a class was taking place. The students and faculty were not informed of temperature changes. Occupants were asked which building they were in most recently and on what date, and then were asked to answer all questions in regard to this building and date. Occupants were asked to express their thermal sensation vote based on the categorical ASHRAE seven-point scale [327] which is based on a -3 vote for a cold response and a +3 for a hot response. They were also asked how satisfied they were in regard to the building indoor environmental quality in terms of lighting, humidity, temperature, indoor air quality, and acoustics. Occupants were also required to choose their clothing level from predefined options. Relevant demographic information was also recorded such as gender, age, and ethnicity.

CHAPTER 4

RESULTS

The follow sections describe the results from this study. The accuracy of the building data monitoring sensors is explored in Section 4.1. Section 4.2 analyzes the impact of the cooling setpoint changes on building cooling system energy consumption. Section 4.3 describes how the results of this field testing can be used to estimate the impact of cooling setpoint changes if made for the entire cooling season. Section 4.4 analyzes thermal comfort responses. Section 4.5 discusses UGA campus buildings with distribution by programmatic use.

4.1 ACCURACY OF OAT AND RH DATA FOR THE BLCII

The BLCII HVAC system currently regulates the operation based on current OA condition readings from sensors located on the building. These sensors read OAT and RH. The facilities management division at UGA also uses the Chicopee weather station to regulate HVAC operations for other various campus buildings and has considered using readings from the Chicopee station instead of sensors located on the BLCII. As seen in Figure 4, there the Chicopee station temperature readings tend to be lower than readings at the BLCII.

In order to ensure accurate operating conditions for the HVAC system at BLCII based on OA data, the data from both sources is compared to readings from the Athens Ben-Epps weather station run by the National Oceanic and Atmospheric Administration through statistical analysis. The Chicopee weather station is approximately 1.2 miles from the BLCII and the weather station located at the Athens Ben-Epps Airport is approximately 4.2 miles from the BLCII. A summary of the results of this comparison is given in Table 7. A 95% confidence interval is assumed for all analyses. As seen from the P-value for each test, all mean differences between data sets are statistically significant ($P < 0.05$). The readings from the BLCII building sensors are the least statistically different from the Athens Ben-Epps station, and thus it could be assumed that the building sensors are more accurate than the Chicopee station.

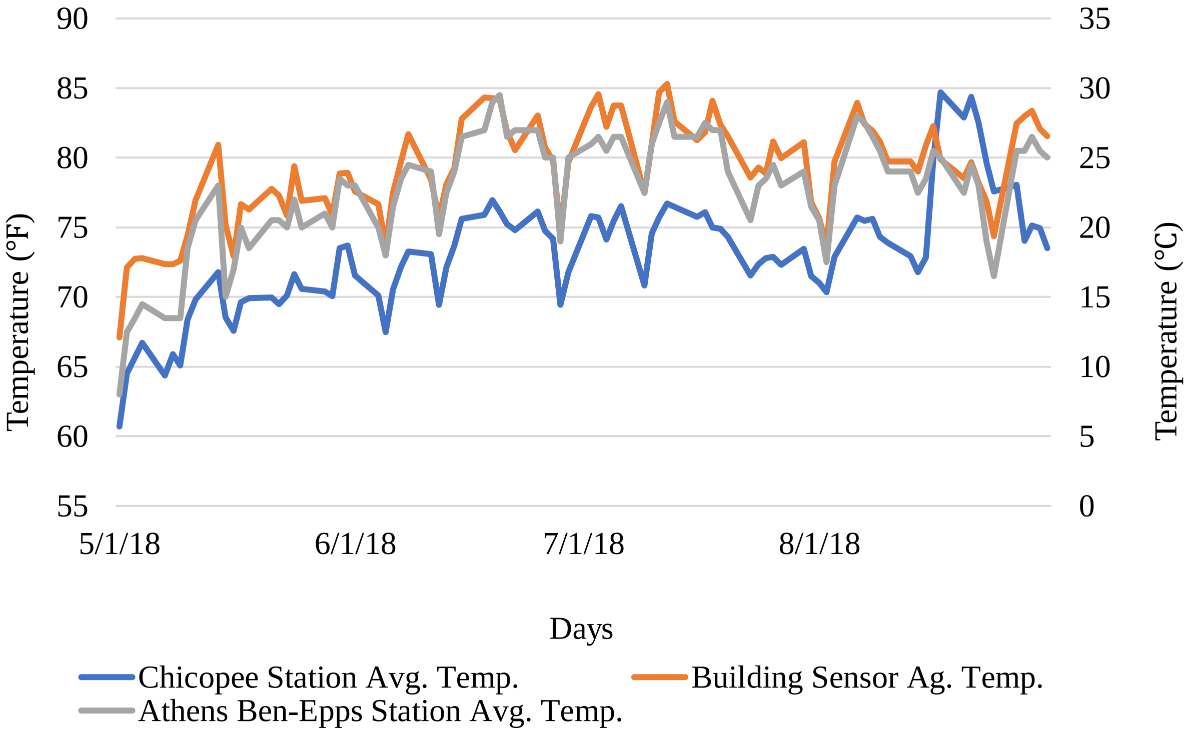

Figure 4. Comparison between the BLCII building sensor, Chicopee weather station, and Athens Ben-Epps Airport weather station temperature readings.

Table 7. Statistical analysis of differences between temperature readings for the BLCII building sensors, Chicopee weather station, and Athens Ben-Epps weather station.

BLDG/CHICOPEE

t-Test: Two-Sample Assuming Equal Variances

	Bldg	*Chicopee*
Mean	79.15	73.05
Variance	13.55	17.55
t Stat	10.31	

P(T<=t) one-tail	4.18E-20	
t Critical one-tail	1.65	

BLGD/ATHENS BEN-EPPS

t-Test: Two-Sample Assuming Equal Variances

	Bldg	*Ben-Epps*
Mean	79.15	77.70
Variance	13.55	18.28
t Stat	2.42	
P(T<=t) one-tail	0.0082	
t Critical one-tail	1.65	

CHICOPEE/ATHENS BEN-EPPS

t-Test: Two-Sample Assuming Equal Variances

	Chicopee	*Ben-Epps*
Mean	73.05	77.70
Variance	17.55	18.28
t Stat	-7.32	
P(T<=t) one-tail	4.15E-12	
t Critical one-tail	1.65	

4.2 IMPACT OF COOLING TEMPERATURE SETPOINT CHANGES

The cooling temperature setpoints changes were made in the BLCII to determine the impact of setpoint changes on HVAC energy consumption. The setpoint changes were either changed to 74°F (23ºC) or 76°F (24ºC). This section analyzes the impact the setpoint changes had on energy consumption. These values represent the total consumption during 7AM-7PM on weekdays only given that occupancy is highest during weekdays and the building HVAC operation schedule is set for unoccupied outside of 7AM-7PM. Table 8 summarizes the total energy consumption that occurred per square foot of building area during each time period. Table 9 summarizes the normalized energy consumption for each time period. The consumption is normalized by the CDDs experienced during this testing period as shown in from Figure 2 to account for differences in outdoor air temperature over the course of the baseline and testing periods. Comparing the testing period setpoint changes to the baseline operating conditions during May in Table 8, the setpoints in the BLCII reduce chilled water consumption by a maximum of 40.2% (test period one) and a minimum of 19.2% (test period three) compared to the May baseline. For hot water consumption, setpoints in the BLCII reduced consumption by a minimum of 27.5% (test period two) and a maximum of 60.8% (test period three) compared to the May baseline. Although savings for hot water consumption were experienced during the testing periods, it is unlikely that these are a result of the cooling temperature setpoint changes. Section 5.1 will discuss why such results for hot water consumption are not likely to result from cooling setpoint changes. Estimates for avoided hot water consumption and externalities is included based on findings during the testing periods through Section 4.3. This is done to quantify the impact reduced hot water consumption would have throughout the cooling season in comparison to reduced chilled water consumption. All sections following 4.3 do not include estimates for avoided hot water consumption.

Table 8. Chilled and hot water consumption per square foot during the baseline and testing periods at the BLCII.

	Test Dates	**Cooling Setpoint**	**CHW Btu/ft^2**	**HW Btu/ft^2**
Baseline	5/1-5/31	73°F (22.8ºC)	1510.1	429.5
Test 1	6/22/-7/9	74°F (23.3ºC)	890.8	181.1
Test 2	7/23-8/16	76°F (24.4ºC)	1538.9	436.7
Test 3	8/17-8/23	74°F (23.3ºC)	424.2	58.5
Test 4	8/24-8/30	76°F (24.4ºC)	416.3	92.6

Table 9. Normalized chilled and hot water consumption per square foot and CDD during the baseline and testing periods at the BLCII.

	Test Dates	Cooling Setpoint	Normalized CHW Btu/ft^2-CDD	Normalized HW Btu/ft^2-CDD	CDDs	Days in Period[1]
Baseline	5/1-5/31	73°F (22.8ºC)	8.2	2.3	184	23
Test 1	6/22/-7/9	74°F (23.3ºC)	4.9	1.0	182	12
Test 2	7/23-8/16	76°F (24.4ºC)	6.0	1.7	258	19
Test 3	8/17-8/23	74°F (23.3ºC)	6.6	0.9	64	5
Test 4	8/24-8/30	76°F (24.4ºC)	4.9	1.1	85	5

[1] Days in period only accounts for weekdays.

4.2.1 AVOIDED UTILITY COSTS

Based on the percent difference in energy consumption between test periods and the May baseline, avoided utility costs are estimated for testing periods. Table 10 compares actual consumption to the estimated consumption that would have occurred if the cooling setpoint changes were not made in the BLCII. Table 11 summarizes avoided utility costs from electric consumption by the chillers and steam consumption used for hot water. The total avoided utility cost is $1,700 for chilled water and hot water consumption over the 41 days of testing.

Table 10. Actual chilled and hot water consumption compared to estimated values if setpoint changes were not made.

	CHW Actual (Btu/ft^2)	CHW Estimated if No Change (Btu/ft^2)	HW Actual (Btu/ft^2)	HW Estimated if No Change (Btu/ft^2)
Test 1	890.84	1248.96	181.13	284.81
Test 2	1538.90	1959.38	436.70	556.70
Test 3	424.23	505.83	58.54	94.14
Test 4	416.32	582.72	92.55	129.54

Table 11. Avoided utility costs for chilled water and hot water in the BLCII during testing periods.

	Avoided CHW (Btu/ft^2)	**Avoided HW (Btu/ ft^2)**	**CHW Avoided Costs**	**HW Avoided Costs**
Test 1	358.12	103.68	$435	$159
Test 2	420.48	120.00	$510	$184
Test 3	81.60	35.60	$99	$54
Test 4	166.40	36.99	$202	$56
TOTAL	**1030**	**300**	**$1,250**	**$450**

4.2.2 AVOIDED EMISSIONS

The estimated avoided emissions from chilled water and hot water consumption from changing the cooling temperature setpoints are given in Table 12. Approximately 6.10, 5.30, and 7,200 lbs of emissions were avoided from SO_2, NO_x, and CO_2, respectively, if basing emissions estimates on average electricity production in Georgia from values in Table 4. Table 13 estimates avoided emissions from hot water production given the setpoint changes. Avoided emissions for SO_2, NO_x, PM_{10}, $PM_{2.5}$, and VOCs are 0.010, 3.4, 0.10, 0.03, and 0.10 lbs. Avoided emissions from CO_2 are approximately 2,164 lbs. The emission factors used here are based on U.S. average provided by the EPA in the AP-42 Compilation of Air Emission factors.

Table 12. Avoided emissions for chilled water consumption in the BLCII during testing periods. All values are calculated based on emission factors in Table 4 in Section 3.7.

	SO_2 (lb)	**NO_x (lb)**	**CO_2 (lb)**
Test 1	2.12	1.86	2510
Test 2	2.49	2.18	2947
Test 3	0.48	0.42	572
Test 4	0.99	0.86	1166
TOTAL	**6.10**	**5.30**	**7200**

Table 13. Avoided emissions for hot water consumption during each testing period. All values are calculated based on emission factors in Table 5 in Section 3.7.

	SO_2 (lb)	NO_x (lb)	CO_2 (lb)	PM_{10} (lb)	$PM_{2.5}$ (lb)	VOC (lb)
Test 1	0.004	1.20	755	0.04	0.01	0.03
Test 2	0.004	1.40	887	0.04	0.01	0.04
Test 3	0.001	0.27	172	0.01	0.00	0.01
Test 4	0.002	0.56	351	0.02	0.01	0.02
TOTAL	**0.010**	**3.40**	**2170**	**0.10**	**0.03**	**0.10**

4.2.3 AVOIDED SOCIAL COST OF CARBON

Table 14 summarizes the avoided SCC from the emission listed in the previous section. Costs were estimated using information provided in Table 5 in Section 3.8. Given that emissions outside of CO_2 are provided in terms of in terms of cost per ton of emission for a whole entire year, the cost associated with such pollutants was multiplied by a correction factor to scale for the fact that this study occurred over a period less than one year. This factor was the amount of days that occurred over the test period divided by the amount of days in one year. The total avoided SCC from the setpoint changes for chilled water is $173. Table 15 summarizes the avoided SCC from the emissions produced by hot water consumption and subsequently natural gas combustion. The total avoided SCC damages is $52.

Table 14. Avoided SCC for chilled water consumption in the BLCII based on costs provided in Table 6 in Section 3.8.

Test 1	$60.34
Test 2	$70.86
Test 3	$13.75
Test 4	$28.04
TOTAL	**$173**

Table 15. Avoided SCC for hot water consumption in the BLCII based on costs provided in Table 6 Section 3.8.

Test 1	$18
Test 2	$21
Test 3	$4
Test 4	$8
TOTAL	**$52**

4.2.4 THE COOLING SETPOINTS IN THE BLCII

This section analyzes the actual operating conditions in each of the monitored rooms during the testing periods as compared to what the expected cooling setpoint might be. The thermostats used in these buildings allow for the occupants to change setpoints by +/- 2°F (1.1ºC) from the global setpoint value in the BAS. The average temperature setpoint for each from 7AM-7PM during testing periods is determined from the information recorded by the BLCII. The average standard deviation from the cooling setpoints is identified.

Table 16 shows the average temperature setpoints for nine rooms located in Amos Hall in the BLCII as well as the standard deviation of the temperature from 7AM-7PM in each room. The difference between the effective cooling setpoint and actual cooling temperature setpoints is designated by ΔT, given that occupants may change setpoints by +/- 2°F (1.1ºC) from the effective. The average ΔT for tests one through four are 0.1, -0.5, -0.5, and -0.8 and the standard deviations are 1.45, 1.35, 1.58, and 1.59. The average temperature setpoints for nine rooms in Benson Hall are in Table 17. The average ΔT for tests one through four are -0.62, -0.87, -0.73, and -1.12 and the standard deviations are 1.76, 1.25, 1.33, and 1.19. The average temperature setpoints for nine rooms in Moore Rooker Hall are in Table 18. The average ΔT for tests one through four are -0.06, -0.43, -0.29, and -0.49. and the standard deviations are 1.80, 1.51, 1.78, and 1.77. The average OAT and average CDD per day values are listed in Table 19. Standard deviations are also listed for both. This is for weekdays only from 7AM until 7PM and is based on the temperature sensors located on the building.

Table 16. Average IAT, standard deviation, and difference between effective and actual cooling temperature setpoints in Amos Hall. All temperatures are rounded up.

May Baseline									
Room	*B200F*	*B317*	*B331*	*B361*	*B452*	*B195B*	*B100*	*B220A*	*B200B*
Avg (°F)	76	73	73	76	73	76	76	72	73
Avg (°C)	24	23	23	24	23	24	24	22	23
Stdev	0.000	0.032	0.000	0.000	0.000	0.042	0.000	0.141	0.035
Test 1 @ 74°F (23°C)									
Room	*B200F*	*B317*	*B331*	*B361*	*B452*	*B195B*	*B100*	*B220A*	*B200B*
Avg (°F)	76	75	73	72	73	74	76	73	74
Avg (°C)	24	24	23	22	23	23	24	23	24
Stdev	0.000	0.044	0.000	0.000	0.000	0.000	0.000	0.000	0.046
ΔT (°F)	2	1	-1	-2	-1	0	2	-1	1
Test 2 @ 76°F (24°C)									
Room	*B200F*	*B317*	*B331*	*B361*	*B452*	*B195B*	*B100*	*B220A*	*B200B*
Avg (°F)	77	74	75	74	75	76	78	75	76
Avg (°C)	25	23	24	23	24	24	26	24	24
Stdev	0.141	0.056	0.050	0.050	0.185	0.050	0.050	0.050	0.045
ΔT (°F)	1	-2	-1	-2	-1	0	2	-1	0
Test 3 @ 74°F (23°C)									
Room	*B200F*	*B317*	*B331*	*B361*	*B452*	*B195B*	*B100*	*B220A*	*B200B*
Avg (°F)	76	72	73	72	72	74	76	73	73
Avg (°C)	24	22	23	22	22	23	24	23	23
Stdev	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.187
ΔT (°F)	2	-2	-1	-2	-2	0	2	-1	-1
Test 4 @ 76°F (24°C)									
Room	*B200F*	*B317*	*B331*	*B361*	*B452*	*B195B*	*B100*	*B220A*	*B200B*
Avg (°F)	78	74	75	74	74	76	78	75	75
Avg (°C)	26	23	24	23	23	24	26	24	24
Stdev	0.197	0.197	0.197	0.197	0.197	0.197	0.197	0.197	0.180
ΔT (°F)	2	-2	-1	-2	-2	0	2	-1	-1

Table 17. Average IAT, standard deviation, and difference between effective and actual cooling temperature setpoints in Benson Hall. All temperatures are rounded up.

May Baseline

Room	*A112*	*A403*	*A110*	*A425*	*A304*	*A318*	*A202A*	*A101*	*A101C*
Avg (ºF)	72	76	72	75	75	75	74	70	72
Avg (ºC)	22	24	22	24	24	24	23	21	22
Stdev	0.089	0.061	0.020	0.000	0.000	0.040	0.014	0.000	0.083
Test 1 @ 74ºF (23ºC)									
Room	*A112*	*A403*	*A110*	*A425*	*A304*	*A318*	*A202A*	*A101*	*A101C*
Avg (ºF)	76	75	74	74	74	72	73	70	72
Avg (ºC)	24	24	23	23	23	22	23	21	22
Stdev	0.080	0.132	0.171	0.000	0.000	0.006	0.000	0.000	0.000
ΔT (ºF)	2	1	0	0	0	-2	-1	-4	-2
Test 2 @ 76ºF (24ºC)									
Room	*A112*	*A403*	*A110*	*A425*	*A304*	*A318*	*A202A*	*A101*	*A101C*
Avg (ºF)	76	77	74	76	76	74	76	74	74
Avg (ºC)	24	25	23	24	24	23	24	23	23
Stdev	0.069	0.310	0.050	0.050	0.075	0.050	0.050	0.050	0.050
ΔT (ºF)	0	1	-2	0	0	-2	0	-2	-2
Test 3 @ 74ºF (23º)									
Room	*A112*	*A403*	*A110*	*A425*	*A304*	*A318*	*A202A*	*A101*	*A101C*
Avg (ºF)	74	76	72	74	74	72	74	72	72
Avg (ºC)	23	24	22	23	23	22	23	22	22
Stdev	0.000	0.364	0.000	0.000	0.341	0.000	0.000	0.000	0.000
ΔT (ºC)	0	2	-2	0	0	-2	0	-2	-2
Test 4 @ 76ºF (24ºC)									
Room	*A112*	*A403*	*A110*	*A425*	*A304*	*A318*	*A202A*	*A101*	*A101C*
Avg (ºF)	76	77	74	76	75	74	76	74	74
Avg (ºC)	24	25	23	24	24	23	24	23	23
Stdev	0.197	0.666	0.197	0.121	0.464	0.197	0.197	0.197	0.197
ΔT (ºF)	0	1	-2	0	-1	-2	0	-2	-2

Table 18. Average IAT, standard deviation, and difference between effective and actual cooling temperature setpoints in Moore Rooker Hall. All temperatures are rounded up.

May Baseline									
Room	*C217*	*C200B*	*C318*	*C326*	*C310A*	*C418*	*C404B*	*C400*	*C208*
Avg (ºF)	72	76	75	76	73	73	76	76	76
Avg (ºC)	22	24	24	24	23	23	24	24	24
Stdev	0.015	0.000	0.040	0.000	0.030	0.000	0.000	0.000	0.001
Test 1 @ 74ºF (23ºC)									
Room	*C217*	*C200B*	*C318*	*C326*	*C310A*	*C418*	*C404B*	*C400*	*C208*
Avg (ºF)	72	75	72	76	72	73	76	73	76
Avg (ºC)	22	24	22	23	22	23	24	23	24
Stdev	0.000	0.000	0.006	0.000	0.050	0.000	0.000	0.069	0.000

ΔT (°C)	-2	1	-2	2	-2	-1	2	-1	2
Test 2 @ 76°F (24°C)									
Room	*C217*	*C200B*	*C318*	*C326*	*C310A*	*C418*	*C404B*	*C400*	*C208*
Avg (°F)	74	77	74	77	74	75	78	76	77
Avg (°C)	23	25	23	25	23	24	26	24	25
Stdev	0.050	0.050	0.050	0.141	0.050	0.050	0.072	0.071	0.079
ΔT (°F)	-2	1	-2	1	-2	-1	2	0	1
Test 3 @ 74°F (23°C)									
Room	*C217*	*C200B*	*C318*	*C326*	*C310A*	*C418*	*C404B*	*C400*	*C208*
Avg (°F)	72	75	72	76	72	73	76	72	75
Avg (°C)	22	24	22	24	22	23	24	22	24
Stdev	0.000	0.000	0.000	0.000	0.100	0.000	0.069	0.205	0.299
ΔT (°F)	-2	1	-2	2	-2	-1	2	-2	1
Test 4 @ 76°F (24°C)									
Room	*C217*	*C200B*	*C318*	*C326*	*C310A*	*C418*	*C404B*	*C400*	*C208*
Avg (°F)	74	77	74	78	74	75	77	74	78
Avg (°C)	23	25	23	26	23	24	25	23	26
Stdev	0.197	0.197	0.197	0.197	0.161	0.197	0.210	0.197	0.197
ΔT (°F)	-2	1	-2	2	-2	-1	1	-2	2

Table 19. Average outdoor air temperatures and cooling degree days per day for the May baseline and testing periods.

May Baseline			
	OAT (°F)	*OAT (°C)*	*CDD*
Avg	76.84	24.91	15.2
Stdev	5.40		14.50
Test 1			
Avg	82.53	28.07	17.5
Stdev	5.16		5.16
Test 2			
Avg	81.19	27.33	16.2
Stdev	4.79		4.79
Test 3			
Avg	79.61	26.45	14.6
Stdev	4.38		4.38
Test 4			
Avg	83.47	28.59	18.5
Stdev	6.54		6.54

4.3 IMPACT OF COOLING SETPOINT CHANGES FOR THE COOLING SEASON

This section estimates what the additional avoided chilled and hot water consumption for the entire cooling season might be based on the percent avoided consumption percentages determined in section 4.2 from the testing periods. These tests estimate the savings for chilled water use ranged from 19.2% to 40.2%, and the savings from hot water use ranged from 27.5% to 60.8%. The chilled and hot water consumption from 7AM-7PM on weekdays when setpoint adjustments would be in effect was the basis of this analysis. The cooling season occurred from May through September as shown in Figures 5 and 6 by the increase in temperature corresponding with the increase in chilled water consumption by the building over the same time period. Note that there is nearly always a demand for some cooling in the building regardless of the time of year since some of the spaces are isolated from the ambient. The data in Figure 6 represents the daily chilled water consumption pulled from the BAS. The hourly average for chilled and hot water consumption for each month is found for 7AM to 7PM and used to estimate what the energy consumption would have been over the course of that month. The average hourly values are added together to get a total daily consumption during occupied cooling setpoints and multiplied by the amount of days in that month. This method also helps compensate for the gap in chilled water consumption recording due to the BAS failing to record chilled and hot water consumption for an extended period lasting from August 30 until September 30th. The same method was used throughout section 4.2. Figure 7 establishes the relationship between daily CDDs and chilled water consumption. As the amount of CDDs increase, the chilled water consumption for space cooling also increases. The R-squared value is 0.32, which is a weak positive correlation.

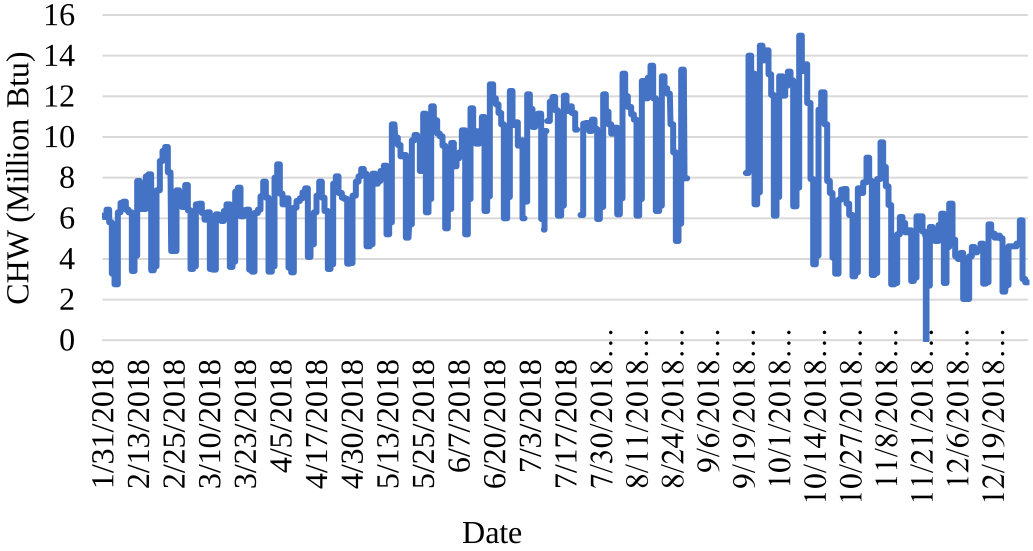

Figure 5. Chilled water consumption in the BLCII for 2018.

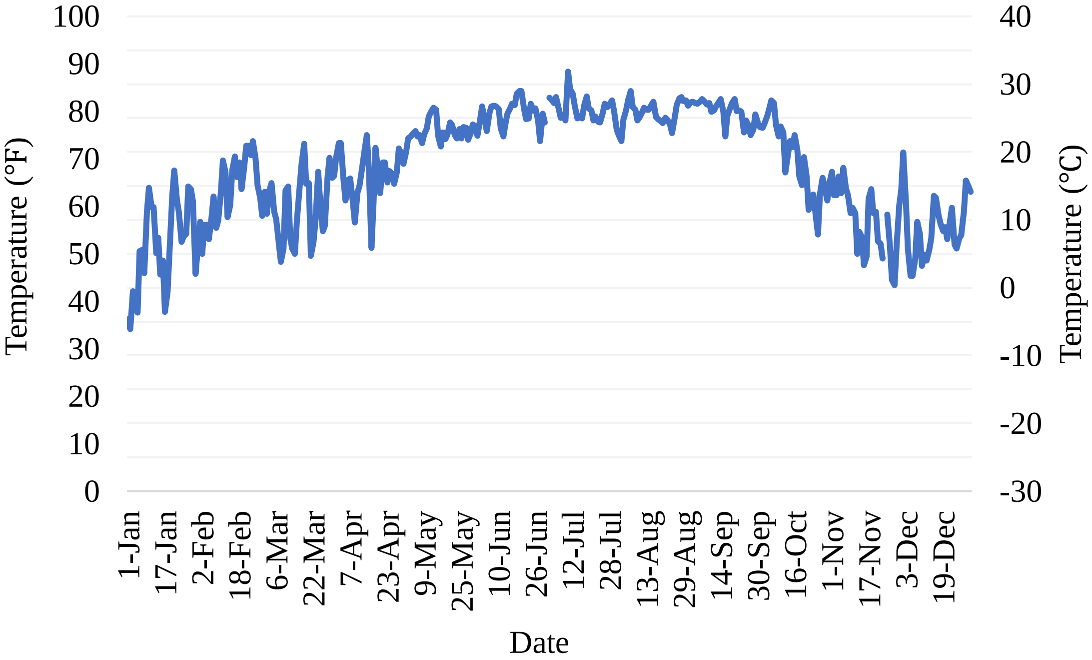

Figure 6. Outdoor air temperature readings from the BLCII building sensors for 2018.

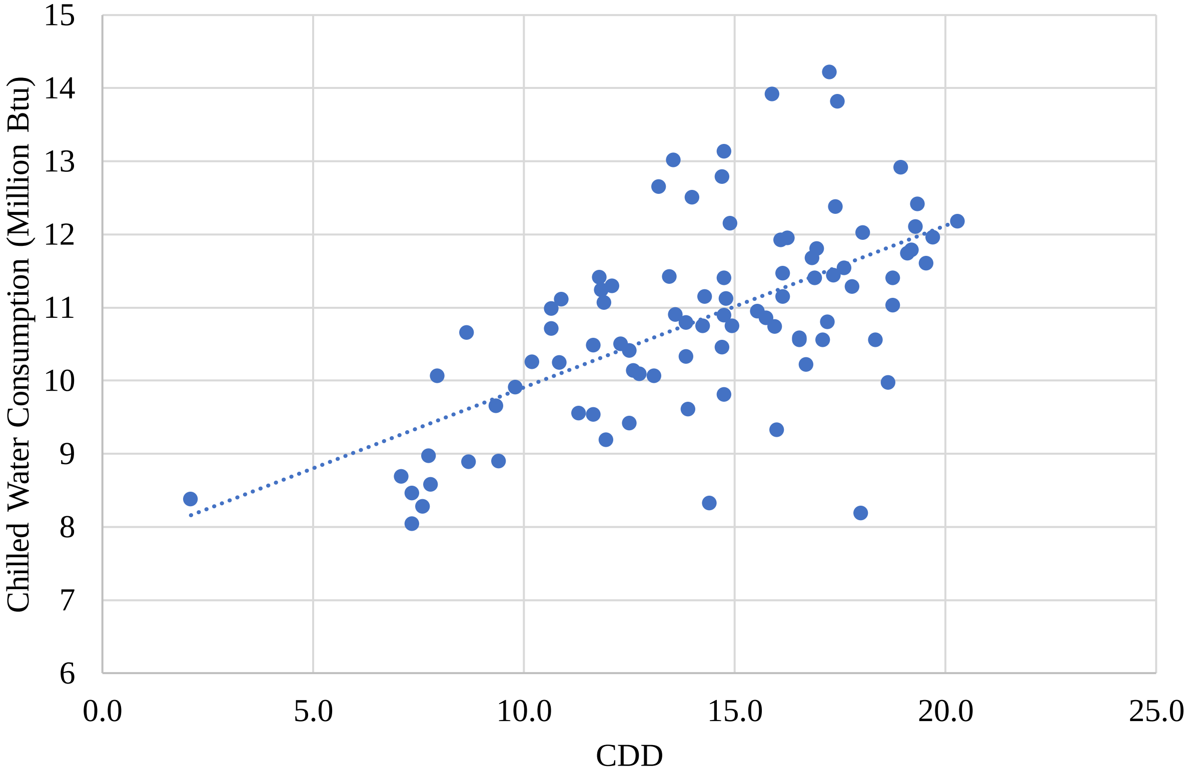

Figure 7. Relationship between daily CDDs and the BLCII chilled water consumption for weekdays only from 7AM to 7PM.

Table 20 estimates the additional savings that could have occurred over the cooling season if the setpoint changes had been made over the entire cooling season. The avoided consumption estimates do not include data from the testing periods since avoided consumption already has been occurred over that period. The low scenario represents the 19.2% savings. The high scenario represents the 40.2% savings. An estimated additional avoided consumption of 136,034,537 Btu to 284,822,767 Btu for chilled water consumption could have occurred depending on the setpoint adjustments if they had occurred over an entire cooling season.

Table 20. Estimated avoided chilled water consumption in the BLCII if effective cooling setpoint changes were made during the whole cooling season.

	Low Scenario (Btu)	High Scenario (Btu)
May	42386759	88747277
June	30549976	63964012
July	12895297	26999529
August	N/A[1]	N/A[1]
September	50202722	105111948
TOTAL	**136034754**	**284822767**

[1] Given that all days outside of August 31st occurred during testing periods, it is assumed that essentially no additional savings would occur outside of those already identified Section 4.2 (Similarly for Tables 21-27).

Table 21 identifies the additional avoided consumption for hot water consumption that would have occurred if setpoints were changed during the entire cooling season. The low scenario represents the 27.5% savings. The high scenario represents the 60.8% savings. An estimated total savings of 42,960,107 Btu to 97,736,621 Btu for hot water consumption could have occurred depending on the setpoint adjustments in the BLCII.

Table 21. Estimated avoided hot water consumption in the BLCII if effective cooling setpoint changes were made during the whole cooling season.

	Savings Low Scenario (Btu)	Savings High Scenario (Btu)
May	17287058	38220114
June	8900746	19678741
July	6246947	13811432
August	N/A	N/A
September	10525356	26026334
TOTAL	**42960107**	**97736621**

4.3.1 ADDITIONAL AVOIDED UTILITY COSTS

Table 22 identifies the additional avoided utility costs that could have occurred if the cooling temperature setpoints were changed over the remainder of the cooling season outside of the test periods. A total of $1,134 to $2,374 additional savings may have occurred. Table 23 identifies the savings that would have occurred for hot water consumption. Savings range from $358 to $815.

Table 22. Additional avoided utility costs for chilled water consumption in the BLCII if effective cooling setpoint changes were made during the whole cooling season.

	Low Scenario	**High Scenario**
May	$353	$740
June	$255	$533
July	$108	$225
August	N/A	N/A
September	$418	$876
TOTAL	**$1,134**	**$2,374**

Table 23. Additional avoided utility costs for hot water consumption in the BLCII if effective cooling setpoint changes were made during the whole cooling season.

	Low Scenario	**High Scenario**
May	$144	$319
June	$74	$164
July	$52	$115
August	N/A	N/A
September	$87.71	$216.89
TOTAL	**$358**	**$815**

4.3.2 ADDITIONAL AVOIDED EMISSIONS

The additional avoided emissions for implementation of the cooling setpoint during the remainder of the cooling season outside the test periods is estimated in this section. In Table 24 the avoided emissions for chilled water consumption are estimated. Avoided CO_2 emissions are the most significant, ranging from 6,542 to 13,697 lbs between the low and high scenarios. The same estimates but for hot water consumption are in Table 25. Just as with chilled water consumption, CO_2 emission avoidance is the most significant, ranging from 6214 lbs to 14,137 lbs.

Table 24. Estimated avoided emissions for chilled water consumption for the cooling season if effective cooling temperature setpoints were made.

	Low Scenario		
	SO_2 (lb)	*NO_x (lb)*	*CO_2 (lb)*
May	1.72	1.51	2038
June	1.24	1.09	1469
July	0.52	0.46	620
August	N/A	N/A	N/A
September	2.04	1.79	2414
TOTAL	**5.53**	**4.84**	**6542**
	High Scenario		
	SO_2 (lb)	*NO_x (lb)*	*CO_2 (lb)*
May	3.61	3.16	4268
June	2.60	2.28	3076
July	1.10	0.96	1298
August	N/A	N/A	N/A
September	4.27	3.74	5055
TOTAL	**11.58**	**10.13**	**13697**

Table 25. Estimated avoided emissions for hot water consumption for the cooling season if effective cooling temperature setpoints were made.

	Low Scenario					
	SO_2 (lb)	*NO_x (lb)*	*CO_2 (lb)*	*PM_{10} (lb)*	*$PM_{2.5}$ (lb)*	*VOC (lb)*
May	0.01	3.96	2501	0.12	0.04	0.11

June	0.01	2.04	1288	0.06	0.02	0.06
July	0.00	1.43	904	0.04	0.01	0.04
August	N/A	N/A	N/A	N/A	N/A	N/A
September	0.01	2.41	1523	0.07	0.02	0.07
TOTAL	**0.03**	**9.84**	**6214**	**0.30**	**0.10**	**0.28**
High Scenario						
	SO_2 (lb)	*NO_x (lb)*	*CO_2 (lb)*	*PM_{10} (lb)*	*$PM_{2.5}$ (lb)*	*VOC (lb)*
May	0.03	8.75	5529	0.26	0.09	0.25
June	0.01	4.51	2847	0.14	0.05	0.13
July	0.01	3.16	1998	0.09	0.03	0.09
August	N/A	N/A	N/A	N/A	N/A	N/A
September	0.02	5.96	3765	0.18	0.06	0.17
TOTAL	**0.07**	**22.38**	**14137**	**0.67**	**0.22**	**0.65**

4.3.3 ADDITIONAL AVOIDED SOCIAL COST OF CARBON

Tables 26 and 27 estimate the avoided SCC for chilled and hot water consumption that would have occurred if the cooling setpoint changes had been made over the entire cooling season. This is in addition to the avoidance estimated for the testing periods. The total avoidance of the SCC for chilled water consumption ranges from \$157 to \$329. The total avoidance for the SCC for hot water consumption ranges from \$149 to \$339.

Table 26. Avoided SCC for chilled water consumption if effective cooling setpoint changed were made for the entire cooling season.

Low Scenario	
May	\$49
June	\$35
July	\$15
August	N/A
September	\$58
TOTAL	**\$157**
High Scenario	
May	\$103
June	\$74

July	$31
August	N/A
September	$122
TOTAL	**$329**

Table 27. Avoided SCC for hot water consumption if effective cooling setpoint changed were made for the entire cooling season.

Low Scenario	
May	$60
June	$31
July	$22
August	N/A
September	$37
TOTAL	$149
High Scenario	
May	$133
June	$68
July	$48
August	N/A
September	$91
TOTAL	$340

4.4.4 TOTAL SAVINGS FOR THE ENTIRE COOLING SEASON INCLUDING TESTING PERIODS

This section discusses the total amount of savings that could have occurred over the entire cooling season including the testing periods. The cooling season lasted 106 days. The testing occurred over 41 days of this period through parts of June, July, and August. The testing periods avoided a total estimated chilled water energy consumption of 1,030 Btu/ft^2. This is equivalent to 150 million Btu of chilled water consumption. Based on the range of 19.2% to 40.2% avoided consumption during testing periods, savings for the remainder of the cooling season for chilled water consumption may range from 136 million Btu to 285 million Btu. Thus, total avoided chilled water consumption including testing periods and non-testing periods ranges from 228 million Btu to 476 million Btu for the cooling season if setpoint changes had been implemented over the entire course of the cooling season.

The avoided hot water consumption during testing periods was 300 Btu/ft^2. This is equivalent to 43 million Btu. Based on the range of hot water reduction estimated from testing periods, savings could be from 27.5% to 60.8%, or a range of 43 million Btu to 98 million Btu per results from the testing periods. Including testing and non-testing periods, avoided hot water consumption ranges from 73 million Btu to 166 million Btu. Estimates of savings based on temperature setpoint changes for chilled and hot water consumption for the entire cooling season are both listed in Table 28. Further estimates for avoided hot water consumption are no longer included in the following sections given the lack of evidence supporting a correlation between increased cooling temperature setpoints and reduced hot water consumption for reheat.

Table 28. Range of estimated of avoided utility costs, emissions, and SCC for chilled and hot water consumption if effective cooling setpoint change had been made for the entire cooling season including testing and non-testing periods.

Chilled Water									
	Consumption (Btu)	*Utility Costs*	*SO_2 (lb)*	*NO_x (lb)*	*CO_2 (lb)*	*PM 10 (lb)*	*PM 2.5 (lb)*	*VOC (lb)*	*SCC*
Low Scenario	227730572	$1,898	0.93	8.10	10951				$263
High Scenario	476442344	$3,970	1.94	16.95	22911				$550
Hot Water									
	Consumption (Btu)	*Utility Costs*	*SO_2 (lb)*	*NO_x (lb)*	*CO_2 (lb)*	*PM 10 (lb)*	*PM 2.5 (lb)*	*VOC (lb)*	*SCC*
Low Scenario	73760190	$776	0.05	16.89	10669	0.51	0.17	0.49	$256
High Scenario	165896653	$1,746	0.12	37.99	23997	1.14	0.38	1.10	$577

4.4 SITE VERSUS SOURCE ENERGY CONSUMPTION

The impact source versus site energy consumption has on the range of avoided chilled water consumption is analyzed in this section. Estimates are based on the range of consumption listed in Table 28 for the low and high scenario for chilled water consumption. Table 29 compares site versus source energy for chilled water consumption. Table 30 lists the emissions that would be caused if source energy was considered instead of site.

Table 29. Site versus source energy consumption for chilled water consumption in the BLCII.

	Site Energy (kWh)	Source Energy (kWh)
Low Scenario	11576.3	32413.7
High Scenario	24219.2	67813.6

Table 30. Emissions and SCC associated with site energy consumption for chilled water consumption in the BLCII.

	Consumption (kWh)	SO_2 (lb)	NO_x (lb)	CO_2 (lb)
Low Scenario	32414	2.59	22.69	30663
High Scenario	67814	5.43	47.47	64152

4.5 THERMAL COMFORT RESULTS

Thermal comfort results are summarized in the following figures. Results were collected for both the May baseline and the subsequent testing periods. Figures 8 and 9 show responses for the May baseline (73°F, 22.8°C) for satisfaction with the IAT and thermal comfort. All responses came from participants located in Benson Hall. Responses are estimated to represent roughly 30% of occupants. This is based on the amount of faculty and staff located in the building given that majority of responses were from occupants age 25 and older. The average age of undergraduate students is traditionally 18-21. A majority of respondents were satisfied with the IAT (61%) but also felt the thermal environment was on the cooler side (61%) with a plurality voting that their thermal comfort level was slightly cool (32%).

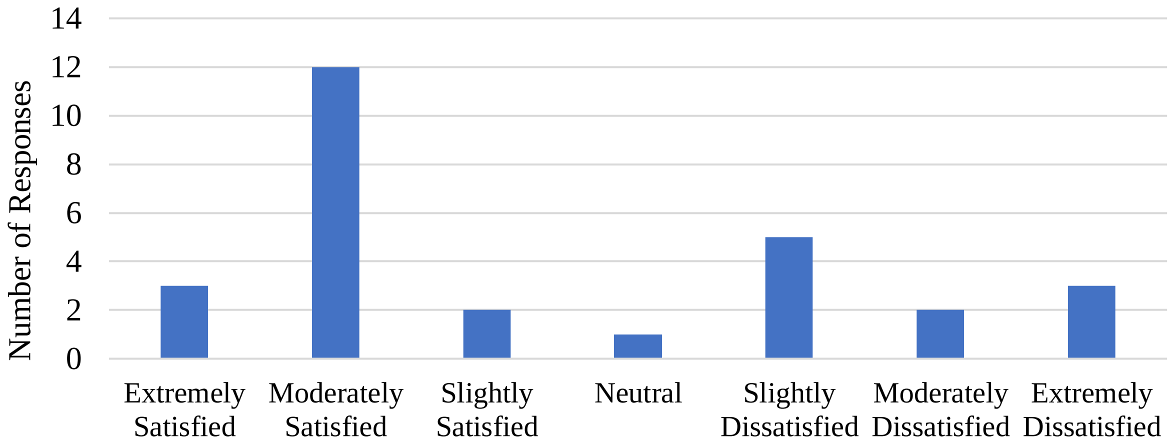

Figure 8. Responses for satisfaction with the IAT for the BLCII during May baseline operating conditions of 73ºF (23ºC).

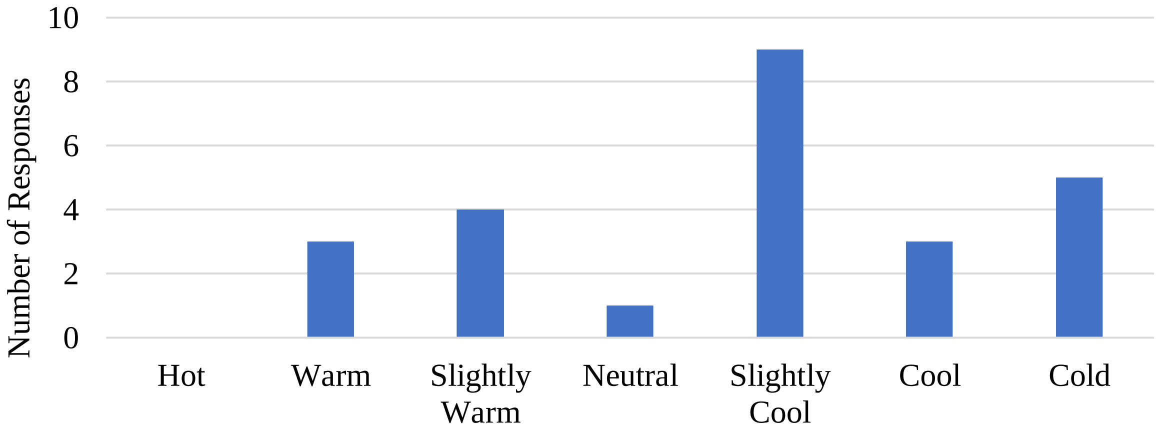

Figure 9. Responses for thermal comfort in the BLCII during May baseline operating conditions of 73ºF (23ºC).

Figures 10 and 11 show responses for the first test period at 74°F (23.3°C). Responses are estimated to represent roughly 10% of occupants based on the amount of faculty and staff that occupy the building given that all responses were from those 25 and older. 44% of responses were from Amos Hall while 24% and 32% of responses were from Benson and Moore Rooker Hall. A majority of respondents were satisfied with the IAT (52%) and majority felt the thermal environment was on the cooler side (61%), with a plurality voting that their thermal comfort level was either slightly cool or neutral (52%).

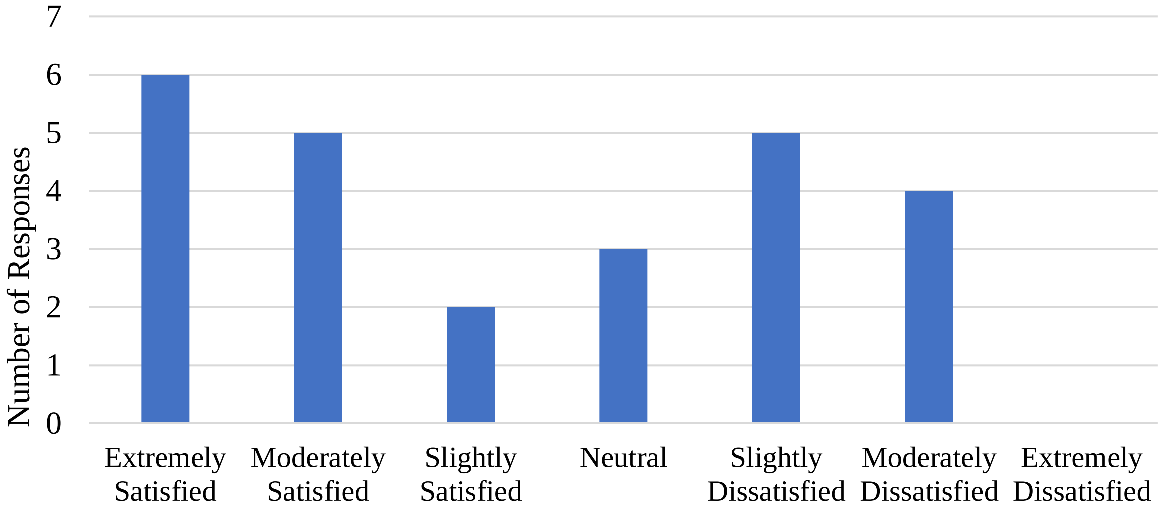

Figure 10. Responses for satisfaction with the IAT for the BLCII during test one with an effective cooling setpoint of 74°F (23.3ºC).

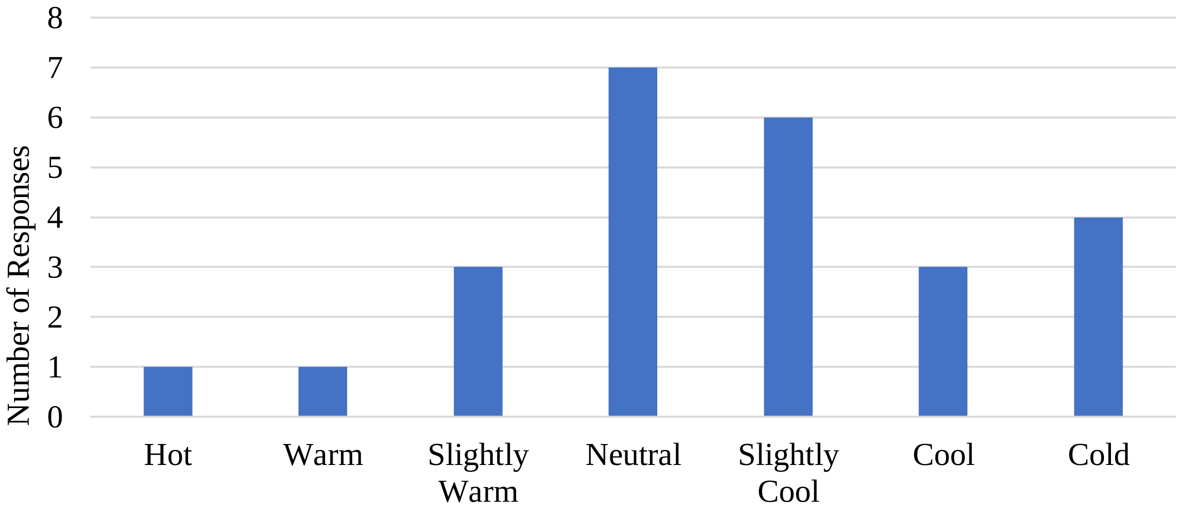

Figure 11. Responses for thermal comfort for the BLCII during test one with an effective cooling setpoint of 74°F (23.3ºC).

Figures 12 and 13 show responses for the second test period with a setpoint of 76°F (24.4°C). Responses are assumed to represent roughly 9% of occupants based on the amount of faculty and staff that occupy the building given that all responses were from those 25 and older. 30% of responses were from Amos Hall while 35% and 35% of responses were from Benson and Moore Rooker Hall. Majority of respondents were satisfied with the IAT (65%). Majority of respondents felt the thermal environment was on the cooler side (60%).

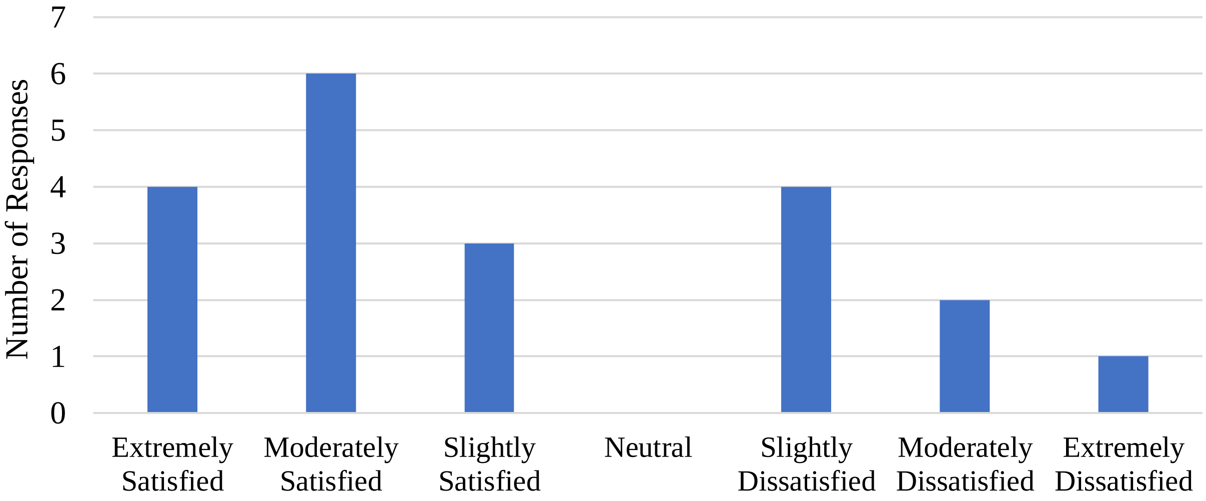

Figure 12. Responses for satisfaction with the IAT for the BLCII during test two with an effective cooling setpoint of 76°F (24.4ºC).

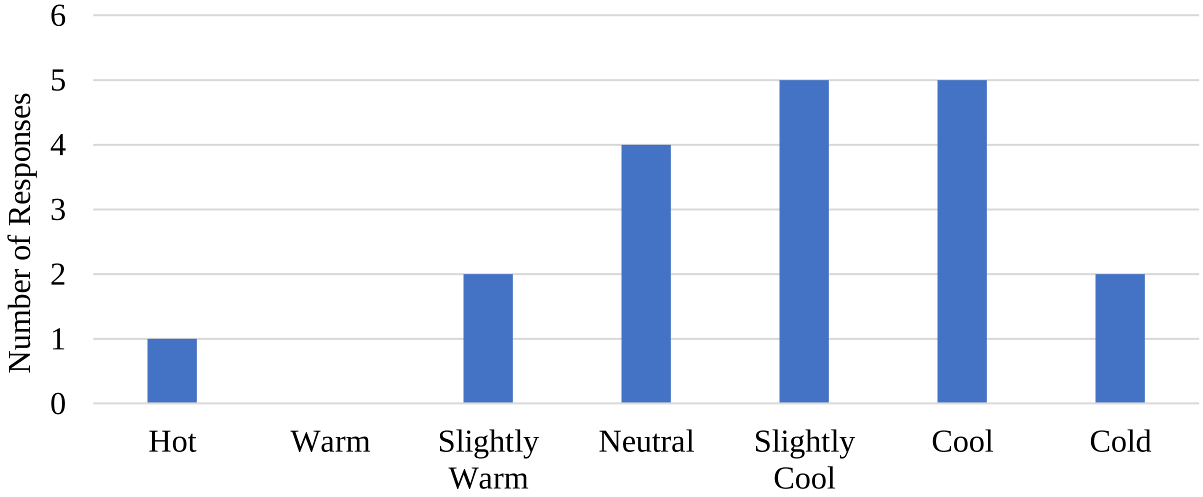

Figure 13. Responses for thermal comfort for the BLCII during test two with an effective cooling setpoint of 76°F (24.4°C).

Figures 14 and 15 show responses for the third test period at a setpoint of 74°F (23.3°C) in which classes were in full session for the Fall semester. Classes at UGA started on August 17th. Based on the capacity of classes offered in the BLCII, approximately 1,519 students may have been in the building at maximum. Professors were requested to distribute surveys to their students. Based on those professors who did pass the survey along, an estimated total of 34 students totaled received the survey. Twelve students responded to the survey, representing 35% of the 34 students who received the survey. Responses specifically from faculty and staff represent roughly 9% of occupants as they were surveyed separately from students. 28% of responses were from Amos Hall while 36% and 36% of responses were from Benson and Moore Rooker Hall. Majority of respondents were not satisfied with the IAT (53%). A plurality of respondents felt the thermal environment was on the warmer side (44%).

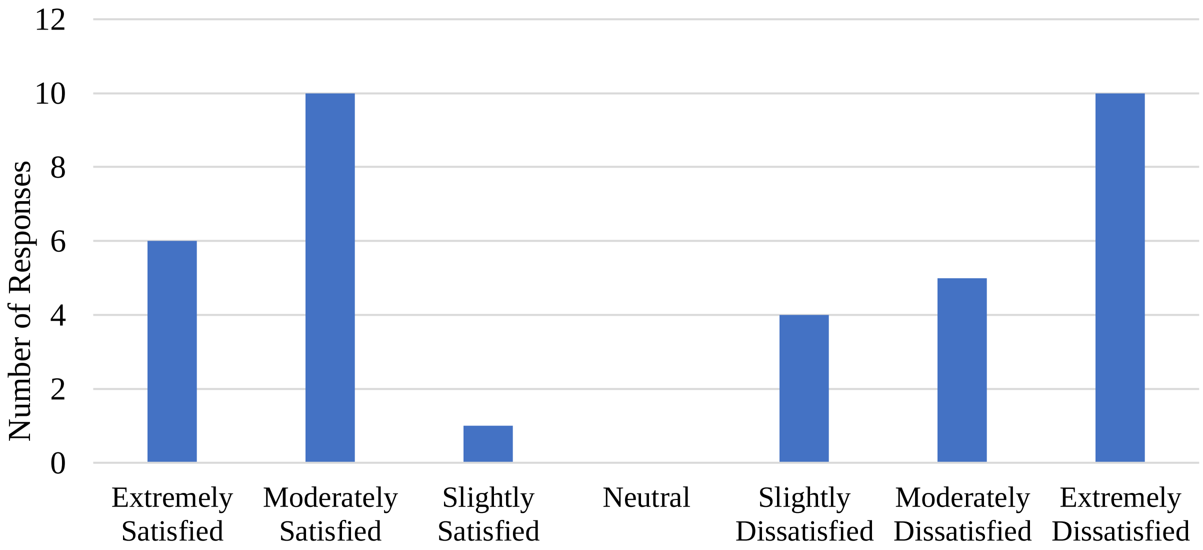

Figure 14. Responses for satisfaction with the IAT for the BLCII during test three with an effective cooling setpoint of 74°F (23.3ºC).

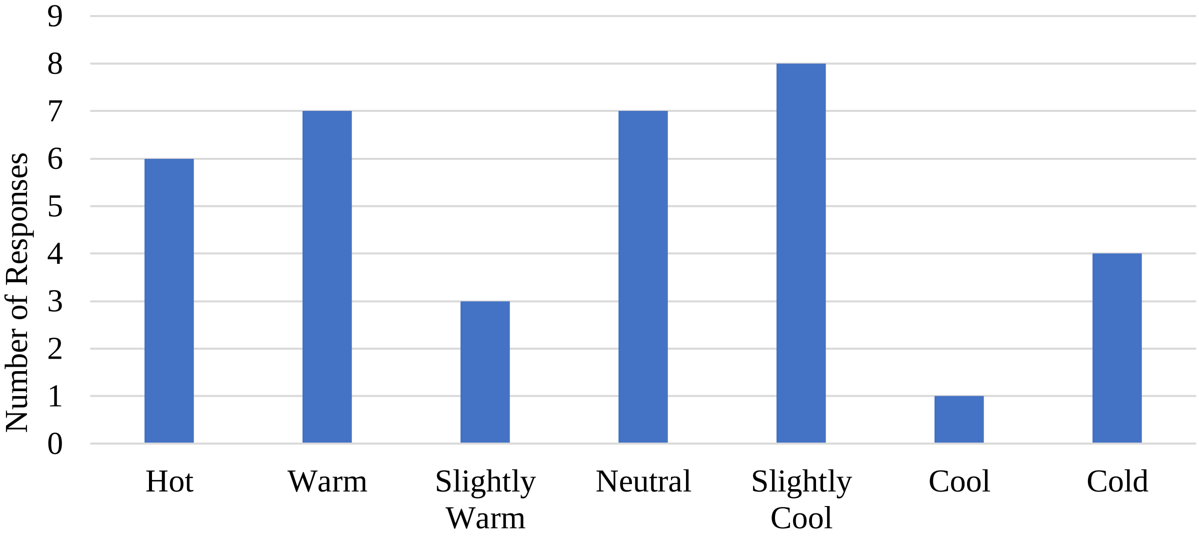

Figure 15. Responses for thermal comfort for the BLCII during test three with an effective cooling setpoint of 74°F (23.3ºC).

Figures 16 and 17 show responses for the fourth test period, which was run when classes were in full session at a setpoint of 76ºF (24.4ºC). Professors were again requested again to distribute surveys to their students. The only professors who passed surveys along had classes located in Correll Hall, thus, it is unsure what portion of the population the responses for test period 4 represent. Of those who received the survey, only 2 students responded. Responses specifically from faculty and staff represent roughly 10% of occupants as they were surveyed separately from students. 28% of responses were from Amos Hall while 36% and 36% of responses were from Benson and Moore Rooker Hall. Majority of respondents were satisfied with the IAT (67%) and felt the thermal environment was on the cooler side (63%).

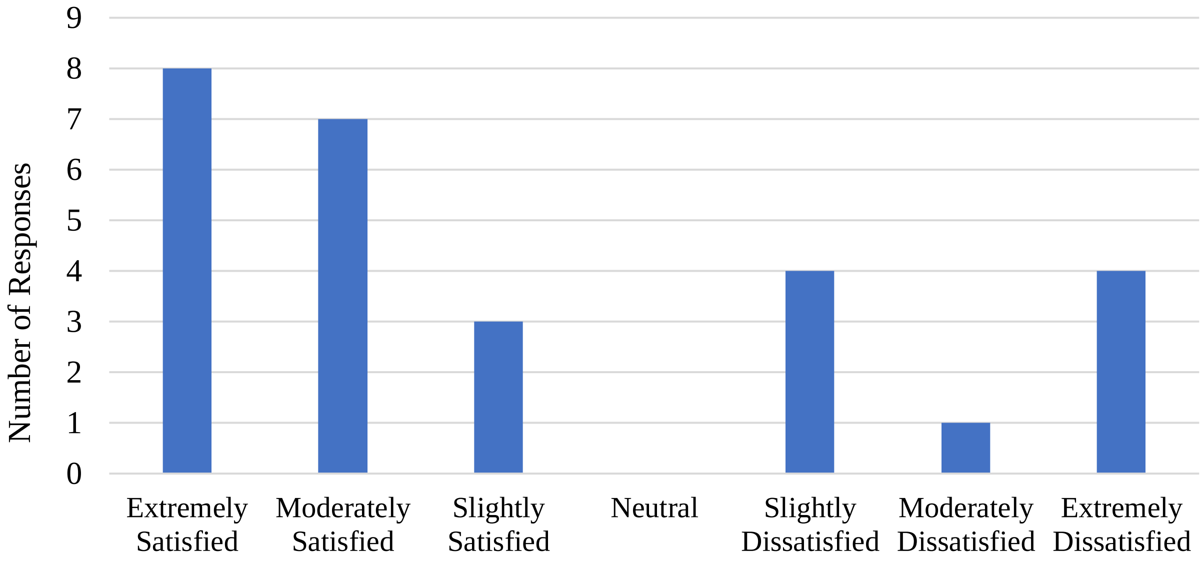

Figure 16. Responses for satisfaction with the IAT for the BLCII during test four with an effective cooling setpoint of 76°F (24.4ºC).

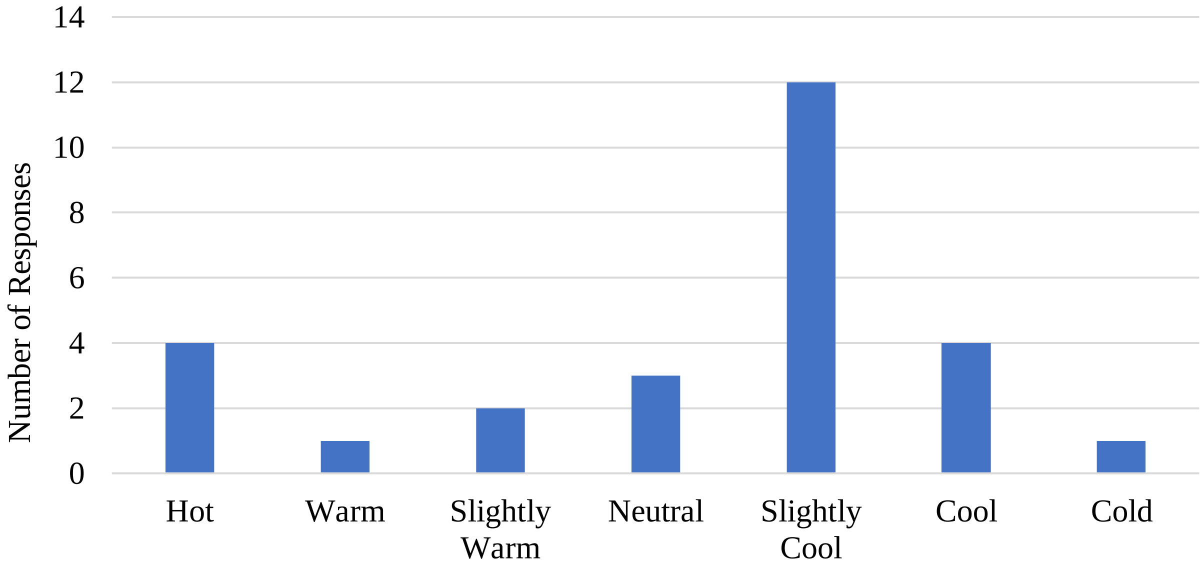

Figure 17. Responses for thermal comfort for the BLCII during test four with an effective cooling setpoint of 76°F (24.4ºC).

4.6 CATEGORIZING THE UGA CAMPUS BY PROGROMMATIC USE

Table 31 summarizes the UGA main campus building square footage by the five programmatic uses recognized within the University System of Georgia. General uses spaces are spaces that have more than one designated use. An example of this on UGA's campus is the Tate Student Center which has offices, food services, study spaces, print and copy areas, and large event spaces. Lab Type One is for building purely used for research purposes. Lab Type Two is for buildings that have lab spaces as well as classroom spaces such as the Science Learning Center. Studios are for buildings with nontraditional student work spaces such as the Thomas Street Art Studio or Ceramics building. Miscellaneous spaces are spaces that were not identified in the campus building index or not present on campus GIS maps and thus were not able to be assigned a programmatic use.

Table 31. Known program area distribution for representative campus buildings.

Building Type	Area (ft^2)	% of Total Area	Total by type (ft^2)
Academic Spaces			5467178
Classrooms	2899333	18%	
Office	721734	4.5%	
Study	442481	2.8%	
General Use	1234661	7.7%	
Special Use	168969	1.1%	
Laboratory Spaces			4071164
Lab Type One	929995	5.8%	
Lab Type Two	1283522	8.0%	
Studio	72291	0.45%	
Athletic	1163460	7.3%	
Veterinary Medicine	509966	3.2%	
Greenhouse	111930	0.70%	
Auxiliary Spaces			3460553
Parking Deck	2621030	16%	
Mechanical	66600	0.42%	
Storage	5822	0.036%	
Services	580442	3.6%	
Healthcare	79930	0.50%	

Dining Hall	106729	0.67%	
Residential			2612687
Housing	2612687	16%	
Misc.[1]	355813	2.2%	2612687
Total	15967395		

[1] The total UGA main campus area is 15967395 ft^2. Buildings which were not identified or were not present on campus GIS maps are labeled as miscellaneous. Buildings outside of the main Athens campus area were not included.

Figure 16 is a tree-map of the campus area distribution with each color representing a programmatic use. Academic spaces compromise the largest portion of the UGA campus at approximately 34.2%. This is primarily due to the large amount of spaces used as classrooms at UGA (18%). This is not unexpected, as there are approximately 38,000 students at UGA. Laboratory spaces are approximately 25.5% of campus area distribution. Auxiliary spaces account for 21.8% of the campus. Residential spaces account for 16.4%. Miscellaneous spaces account for 2.2%.

As described earlier, it was estimated that 228 million Btu to 476 million Btu of chilled water consumption could have been avoided throughout the entire cooling season in the BLCII alone if the cooling setpoint changes had been changed to anywhere from 74°F (23.3ºC) to 76°F (24.4ºF). This is equivalent to 1,562 to 3,268 Btu/ft^2. Given that the academic spaces such as classroom, office, and study are similar to the building type of the BLCII, the total savings if the cooling temperature setpoints changes had been made is estimated for all buildings of these types. The total square footage of such buildings on UGA's campus is 4,063,548 ft^2. An estimated savings of 6,348 million Btu to 13,281 million Btu of savings could have occurred if setpoint changes had been made in all classroom, office, and study spaces (Table 32). Table 33 lists estimates for emissions reductions and the avoided SCC for chilled water consumption. It should be noted that this may not be possible for all buildings, given that not all UGA facilities are on a BAS system. Also, certain spaces may have restrictions that affect the ability to change temperature setpoints in certain parts of the building, such as labs which have to be maintained at certain temperatures. Estimates for hot water consumption are not included given evidence that does not support a relationship between increased cooling setpoints and reduced hot water consumption.

Table 32. Avoided utility costs for implementing effective cooling setpoint changes for all classroom, office, and study spaces on the UGA campus for the entire cooling season for chilled water consumption.

	Consumption (million Btu)	**Utility**
Low Scenario	6348	$52,903
High Scenario	13282	$110,680

Table 33. Avoided emissions and SCC for implementing effective cooling setpoint changes for all classroom, office, and study spaces on the UGA campus for the entire cooling season for chilled water consumption.

	SO_2 (lb)	**NO_x (lb)**	**CO_2 (lb)**	**SCC (lb)**
Low Scenario	25.82	225.90	305282	$7,327
High Scenario	54.01	472.60	638690	$15,329

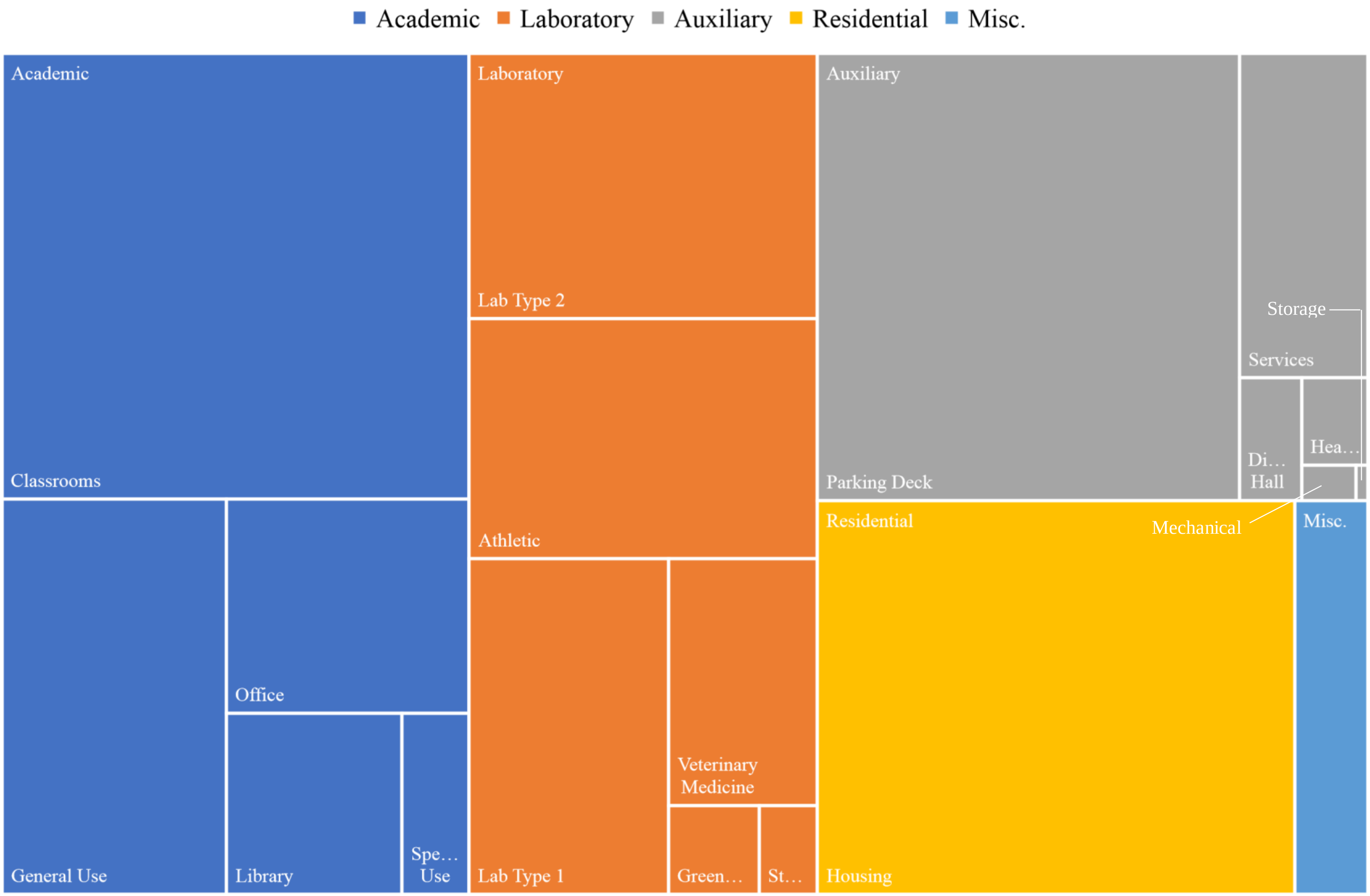

Figure 18. Campus floor area distribution by programmatic use.

CHAPTER 5

DISCUSSION

The main goal of this paper is to analyze the impact of increased cooling temperature setpoints on building energy consumption during the cooling season. The discussion aims to answer the five central research questions which underpin this goal. Any of other relevant discoveries are also discussed.

5.1 IMPACT OF INCREASED COOLING TEMPERATURE SETPOINTS ON BUILDING ENERGY CONSUMPTION AND EXTERNALITIES OF ENERGY CONSUMPTION (RQ1)

Total savings generated from setpoint changes for the cooling season could range from \$1,898 to \$3,970 for chilled water consumption only. While this cost is small relative to the total utility costs at UGA, these savings could be generated from other buildings of similar type as well. As shown in Table 27, savings could be anywhere from \$52,903 to \$110,680 if applied throughout all campus classrooms, offices, and study spaces. Emissions savings were mainly in the form of CO_2. CO_2 emissions were reduced by a total of 0.05 lb/ft^2 for chilled water consumption over the course of the testing periods. If applied to the entire cooling season, emissions could have been reduced anywhere from 0.075 lb/ft^2 to 0.16 lb/ft^2. If applied to all buildings with a type of classroom, study, or office space at UGA, a total reduction of 138 to 294 metric tons of CO_2 could be avoided in a single cooling season alone. The utility costs and emissions reduction demonstrate the large opportunity for savings at UGA by implementing temperature setpoint changes. The feasibility of cooling temperature setpoint control on such a scale is explored further in Section 5.3.

5.1.1 IMPACT OF DIFFERENCES IN OCCUPANCY LEVELS

As demonstrated in Table 9, the cooling setpoint changes from normal operating conditions of 73°F (22.8°C) to 74°F (23.3°C) and 76°F (24.4°C) improved building level energy efficiency. It was expected that the setpoint of 76°F (24.4°C) would generate larger energy savings than 74°F (23.3°C). Upon looking at the normalized energy consumption for each testing period, the lowest energy consumption occurred during test one at a setpoint of 74°F (23.3°C) and test four at a setpoint of 76°F (24.4°C). Given that classes started full session on August 17th, the difference in occupancy levels of the BLCII may explain such results. Summer months experience much lower levels of occupancy given that the student population is lower and that faculty and staff may not be occupying their offices as frequently as the traditional Fall and Spring sessions. Given this lower level of occupancy, this may explain why the normalized energy consumption for the 74°F (23.3°C) is the same as that of the 76°F (24.4°C). Also, a holiday, July 4th, occurred during the first testing period. This is a recognized holiday at UGA. While the HVAC controls for cooling setpoints were not adjusted to an unoccupied state on this day (since the setpoint was essentially in an override position for testing), it is assumed that the building occupancy was much lower (approaching zero) than even that of normal summer levels which may explain why the normalized consumption is the same as that of the 76°F (24.4°C) setpoint in test period 4.

5.1.2 IMPACT OF DIFFERENCES IN DAILY CDDS

The average amount of daily CDDs which occurred over test period one is roughly 1.14 times higher than the average daily CDDs for May through August. The higher the amount of daily CDDs in a testing period, the lower the expected normalized energy consumption. Thus, this contributes to the lower normalized energy savings for test one even though the cooling setpoint is 74°F (23.3°C). Outside of the anomalies in this section and Section 5.1.1, the 74°F (23.3°C) setpoint change in test three generated less energy savings than the either of the other 76°F (24.4°C) setpoint changes in tests two and four, as expected.

5.1.3 CORRELATIONS IN REGARD TO CHILLED WATER CONSUMPTION

Overall, the normalized energy consumption demonstrates that significant reduction in energy consumption may be achieved during the cooling season by increasing cooling temperature setpoints, even if only for short periods of time. The correlation between IAT and chilled water consumption is low (R = -0.029, P = 8.87E-137). This suggests that other variables outside of IAT alone are influencing consumption for chilled water, which is generally an understood fact within the industry. The relationship between OAT and the ΔT of initial cooling setpoint and what occupants may have changed it to is significant (P = 7.98E-126) with a weak negative correlation (R= -0.34). This insinuates that as the OATs become higher, the ΔT between the initial cooling setpoint and changes made by occupants becomes more negative, indicating more manual decreases in thermostat setpoints. This suggests that OAT does directly impact IAT, although there is almost no direct correlation between OAT and IAT (R = -0.02, P=5.67E-33).

Not all the rooms indicated that the setpoint was changed. There is some possibility that the building is isolated from the outdoor thermal environment given that there is no correlation between OAT and IAT. This is not supported by the correlation between chilled water consumption and CDDs (R = 0.6, P = 8.86E-137) given that CDDS are determined by OAT. This theory is also not supported by the correlation between OAT and chilled water consumption

(R=0.45, P = 8.87E-137). This is also not supported by the increase in energy consumption seen during the cooling season as indicated in Figures 6 and 7. Also, all temperature values used in this study are based on averages from 9 rooms located in each of the three halls in the BLCII and thus these averages are not a full representation of setpoints in the BLCII, only estimates. It is assumed though, that the influence of other room setpoints would not be that large given that setpoints can only diverge from the cooling by +/- 2°F (1.1°C).

This may also explain why there appears to be no direct correlation between IAT and chilled water consumption. It is possible that the data was not granular enough to capture the variability in IAT to adequately correlate it to energy consumption. This is supported by the correlation between IAT and chilled water consumption including weekend and weekdays and all 24 hours of building operation each day. The correlation coefficient between IAT and chilled water consumption is -0.88 in this case, which is a strong negative relationship. The reason this relationship is more extreme than that of the IAT and chilled water consumption for occupied schedules on weekdays only is because the chilled water consumption in this data set captures the chilled water consumption differences between occupied (~73°F, 22.8°C) versus non-occupied (~80°F, 26.7°C) setpoints. This supports the theory that there is a relationship between IAT and chilled water consumption that was not expressed through the metered data from the BAS given the minimal variability in temperature setpoint data from 7AM-7PM on weekdays as seen in the low standard deviations for average hourly temperature setpoints for testing periods 1 through four in Tables 16 through 18.

The literature also supports a relationship between IAT and energy consumption, as multiple studies have linked manipulation of IAT with impact on building energy consumption [271, 273, 328]. Results from this study concur with such studies, as comparisons between normalized energy consumption during testing periods shows impact on building energy consumption from setpoint changes. Correlations between OAT, ΔT (which is based on IAT), and chilled water consumption also demonstrate that HVAC cooling demand, OAT, and IAT are related to one another, although there may be other variables that are also related which are not included in this study.

5.1.4 CORRELATIONS IN REGARD TO HOT WATER CONSUMPTION

IAT and hot water consumption has a moderate positive relationship (R = 0.61, P = 2.60E-45). Thus, as cooling temperature setpoints increase, hot water consumption increases. The SAT remains at 55ºF (12.8°C) to maintain humidity control even though the cooling temperature setpoint is increased during testing periods. Thus, more reheat is needed to reach the higher cooling temperature setpoints, as demonstrated in the relationship between IAT and hot water consumption. Looking at normalized energy consumption for hot water in Table 8, hot water consumption is highest during the May baseline. These results do not support the positive correlation between IAT and hot water consumption, given that cooling temperature setpoints were lowest during the May baseline. A partial explanation for why the hot water consumption is higher during the May baseline is because there is a moderate negative relationship between hot water consumption and OAT (R = 0.-43, P = 2.6E-45). A negative relationship with OAT is logical, as it is expected that the occupants will try to set IATs lower when OATs increase, requiring less reheat given the lower the cooling temperature setpoints. This is based on the relationship between chilled water use and outdoor air temperature (R = 0.4) which suggests that chilled water use increases (and thus space cooling needs increase) as OATs increase. Thus, based on the correlation between OAT and hot water consumption it would be expected that hot water consumption and reheat needs would increase as OAT decreases and May had lower average OATs than June, July, or August per Table 8. This may explain why the May baseline had the highest hot water consumption even though the cooling temperatures were lowest, and thus OATs may have offset the reductions for hot water consumption that would have been expected from the lower cooling temperature setpoints. Based on these correlations, it should not be assumed that increased cooling temperature setpoints caused the decreased hot water consumption, but that most likely increased OATs caused decreased reheat needs. It should also be noted that while increased cooling setpoints can cause additional energy consumption for reheat needs, this does not negate savings generated for chilled water consumption in the results of this work. Increased cooling temperature setpoints are still a viable method to improve energy efficiency in buildings but energy consumption for reheat should be monitored throughout periods of increased cooling temperature setpoints to ensure increased energy consumption for reheat does not exceed energy consumption reduction from setpoint changes.

5.2 THERMAL COMFORT (RQ2)

Thermal comfort was not jeopardized during any of the testing periods except test period 3 in which a majority of respondents were not satisfied with the thermal environment. When questioned regarding thermal comfort for test 3, most occupants felt as though the thermal environment was slightly cool to cold. This is also in line with majority of thermal comfort votes in which occupants generally expressed in the May baseline as well as test periods that their thermal comfort leans toward the cooler side of the seven-point scale. This contrasts with complaints the building manager received about the building being too hot. Concern was specifically raised during test period two in which the building manager mentioned that numerous complaints were received, and a work order was placed to improve the thermal environment of the building. This is supported by the average ΔT from each building located in the BLCII during the testing periods. The largest negative deviations from cooling temperature setpoints are for temperatures setpoints of 76°F (24.4°C). This is opposite of results listed in thermal comfort surveys, as results indicate that the building would be perceived as too cold before too hot. It is recognized, though, that the thermal comfort results represent a very small sample of the population of the building and that it is possible that this skewed results in favor of the cooler side of the 7-point scale.

It should also be noted, though, that such thermal comfort results are consistent with a previous study at UGA in which results revealed that temporarily increasing cooling temperature setpoint by at least 3.6°F (2.0°C) did not jeopardize thermal comfort [329]. It is also important to emphasize the variable nature of thermal comfort, given that there is not any one specific point in which occupants start to feel thermal discomfort and may experience thermal comfort at a variety of different temperature and humidity levels [330-332]. This helps explain differences between complaints received by the building manager and responses in the thermal comfort survey.

Results also indicate the difference in metrics used to evaluate thermal comfort. If analyzing only thermal comfort votes alone, one may assume that majority of occupants would not be satisfied with their thermal environment given that most occupants voted their thermal comfort is on the cooler side of the 7-point scale. Upon analyzing the votes with the level of thermal satisfaction experienced by occupants, all periods (except test three) experienced a thermally satisfactory environment. It is possible that increased levels of occupancy and internal sensible and latent loads resulting from such occupancy caused increased levels of discomfort. It would be expected, though, that this would cause majority of respondents to feel as though the environment is on the warmer side of the thermal comfort sensation scale, which is not the case. Also, majority of respondents experience a satisfactory thermal environment in test period 4 which has a higher cooling temperate setpoint at assumed same occupancy levels. Thus, it is inconclusive as to why majority of occupants in test period three were not satisfied with the IAT. Thus, the assumption that occupants experience comfort at only a vote of neutral on the 7-point scale may not be true. This is supported by the same previous study at the UGA as well as a conference paper published by the same author which evaluates the difference between continuous and categorical thermal comfort scales [330, 333]. Thus, it is also important to consider the impact that the type of thermal comfort evaluation metric can have on results.

Given that complaints were received during the test period in which the cooling setpoint temperature was 76°F (24.4°C), 74°F (23.3°C) is most likely a more realistic cooling temperature setpoint. It may be ok to have setpoints at 76°F (24.4°C) as long as it is not for extended periods of time, as no complaints were received during the fourth testing period which only lasted 5 days whereas the testing lasted 12 days when the complaints were received. Thus, such setpoints may be good for demand response events when energy prices spike, and then setpoints can be changed back to baseline once the demand response event is over.

5.3 FEASABILITY OF SETPOINT CHANGES THROUGHOUT THE UGA CAMPUS (RQ3)

There is significant opportunity for utility savings and emission reductions if such changes were implemented campus wide. This would only be possible for systems which are already set up on a BAS system so setpoints may be changed globally, thus limiting current options on the UGA campus. Such changes are also made at the building level and cannot be made for individual rooms. Thus, if there were specific rooms inside a building which could not have temperature setpoint changes, this would limit the applicability of such strategies. This would apply in cases such as rooms that are required to be maintained a certain temperature in order to store chemicals, maintain ongoing research, etc. A specific example would be rooms located in the UGA Veterinary Medicine buildings where animals are kept or operated on.

Also, such retrofits may not be well suited for older buildings, as it may be more difficult to retrofit HVAC systems in older buildings [334, 335]. Installing BAS systems in all campus building would also require a large upfront cost which would not be possible. Also, if occupants are able to change setpoints outside of a range of +/- 2°F (1.1°C), savings are not guaranteed as cooling setpoints may revert back to original operating setpoints or to more extreme setpoints [169, 336, 337]. Thus, individual building should be evaluated to determine not only what buildings are most suitable to have a BAS, but also to identify those that are most suitable for setpoint changes if a BAS system was implemented. For buildings that already have BAS systems, the cooling setpoints of 74°F (23.3°C) and 76°F (24.4°C) should be considered for normal building operating conditions or for use during demand response events to reduce utility costs when the price per kilowatt of energy consumption is high. Not all UGA buildings are technically on a real-time energy pricing system. This is because most buildings on UGA's campus are fed by a central substation. 50% of the substation is priced based on dynamic pricing and 50% is based on a controlled baseload. In 1992, UGA was offered a real-time energy pricing program by Georgia Power. Anything newly built after 1992 or built prior to 1992 that had renovations (such as lighting, chillers, etc.) could move a certain amount of power demand to the real-time energy pricing program. The real-time energy pricing is on average four cents per kilowatt over a year whereas the controlled baseload pricing is on average six cents per kilowatt over a year (50% at CBL and 50% at RTP). UGA also has internal pricing in addition to the rate charged by Georgia power to allow for distribution costs within the campus. This cost is on average three cents per kilowatt. This amount of energy charged via dynamic pricing has increased by 5% over the last 12 years. Thus, the BLCII is assumed to be part of the real-time energy pricing portion of the substation given that its construction was implemented after 1992. Regardless, such setpoints should still be evaluated to generate energy savings.

Given that setpoint changes may not be applicable in all buildings, there should be an educational campaign to explain to occupants the benefit of conservative thermostat setpoints, as studies show that such informational campaigns can be effective in changing occupant behaviors [338-340]. This would help improve cooling setpoint control in buildings that do not have a BAS or where a BAS installation is not possible. Results from this study and other studies could be presented to occupants to improve understanding on impact of setpoint controls on building energy consumption. "Green" buildings are also shown to have a positive impact on the perception of the indoor environment and could lead to increased positive impact on occupant experience in building [341, 342]. Such an educational campaign could be conducted by the UGA Office of Sustainability.

5.4 COMPARISON TO CURRENT BUILDING ENERGY CODES (RQ4)

Table 34 estimates current site EUIs for all building types as well as classroom and offices spaces specifically based on current building stocks and building designed according to various ASHRAE standards and technology scenarios. Based on the metered power, chilled water consumption, and hot water data from the BAS, the current site EUI for the BLCII is 37.3 kBtu/ft^2-yr for 2018. The BLCII EUI indicates that this building is fairly energy efficient, compared to the current building codes (more discussion on this below). If the cooling temperatures setpoint changes were made for the entire cooling season, this could have a reduction of 1,562 Btu/ft^2 to 3,268 Btu/ft^2 each year considering chilled water consumption in the BLCII only. Given that one cooling season occurs each year, this could reduce building site EUI by 1.56 kBtu/ft^2 to 3.27 kBtu/ft^2 each year for chilled water consumption reduction.

Table 34. Comparison of existing building stock and current energy codes for site EUI. It is assumed that study spaces are captured by office and classroom building types.

Site EUI for all Commercial Building Types (kBtu/ft^2-yr)	**Site EUI for Office/Classroom Building Types (kBtu/ft^2-yr)**	**Building Code**	**Reference**
90		Existing commercial buildings	[304]
79.2		Models of existing stock	[343]
72.3	52.0	ASHRAE Std 90.1 - 2004	[344]
69	49.5	ASHRAE Std 90.1 - 2007	[344]
58.5	49.7[1]	ASHRAE Std. 90.1 - 2010	[345]
54.1	46.0	ASHRAE Std. 90.1 - 2013	[345]
50.4	41	ASHRAE Std. 90.1-2016	[346]
43		ASHRAE Std. 189.1-2017 with renewable energy	[347]
40.3		Max technology energy efficient scenario	[347]
12.2		Max technology energy efficient scenario with solar PV	[347]

[1] Overall EUI is higher in this case given an increase in EUI for large office spaces.

The current Georgia State Minimum Standard Energy Code for commercial buildings is based on the 2009 International Energy Conservation Code (IECC) referencing ASHRAE Std. 90.1-2007. Thus, most new commercial buildings built in Georgia would be expected to have an average site EUI of 69 kBtu/ft^2-yr. There were are also Georgia specific amendments to this minimum code in 2011 which aimed to strengthen the code [343]. Regarding specific building codes at UGA, all new constructions are designed to be at least 20% more efficient than state minimum code. Thus, buildings at UGA are designed to be 55.2 kBtu/ft^2-yr which is 13.8 kBtu/ft^2-yr better than the Georgia minimum code. In regard to classrooms and office type spaces specifically, the Georgia minimum code would be 49.5 kBtu/ft^2-yr and UGA standards would be 39.6 kBtu/ft^2-yr, a 9.9 kBtu/ft^2-yr improvement over the Georgia minimum. The BLCII currently performs roughly 32% better than UGA design standards for building energy efficiency for all commercial building types. If looking at classroom and office space EUIs specifically, the BLCII performs roughly 6% better than UGA design standards. The cooling temperature setpoint change during the cooling season alone could help complete the UGA design standard reduction of 13.8 kBtu/ft^2-yr by 11% to 24% for all commercial building types. If looking specifically at classroom and office spaces, cooling setpoint change could help reach the 9.9 kBtu/ft^2-yr reduction by 16% to 33% to meet UGA design standards. Thus, HVAC control strategies, such as improved temperature setpoint control, should be strongly considered when designing new buildings in order to reach UGA's construction code.

5.5 POTENTIAL IMPACT ON THE UGA CAMPUS SUSTAINABILITY PLAN (RQ5)

UGA emitted roughly 249,000 net tons of CO_2 in 2014. This is an 8% decrease from 2010 levels (270,000 net tons). The campus sustainability plan outlines a goal of reducing CO_2 emissions by 40% by 2040 with carbon neutrality by 2060 from the 2010 baseline. UGA has already reached its first reduction goal of 20%. Given that CO_2 reduction resulting from setpoint changes are estimated to be roughly 0.075 lb/ft^2 to 0.16 lb/ft^2 for the entire cooling season for chilled water consumption based on the BLCII data, a total reduction of 138 to 294 metric tons of CO_2 emissions could be avoided in a single cooling season alone. This is only 0.051% to 0.12% of the 2010 baseline scenario for one year.

Estimates for the impact on campus energy consumption only analyze the emissions from site energy alone. If looking at emissions from source energy, the impact on the campus sustainability for classrooms, offices, and study spaces is larger. Accounting for source emissions, the total avoided emissions could be anywhere from 0.21 to 0.44 lb/ft^2. If applied to all campus classrooms, offices, and study spaces, a total reduction of 387 tons to 811 metric tons of CO_2 would be expected. This is 0.14% to 0.30% of the campus sustainability goals. This emphasizes the impact that inefficiencies and transmission and distribution losses play regarding building efficiency. If building performance was evaluated based on source instead of site ratio, the overall energy performance of buildings would decrease and emphasize the importance of conservative energy consumption habits to improve building performance. Accounting for source energy consumption will be crucial to truly evaluate the impact building energy consumption has on society and the environment. Impacts on the use of source energy as the reference for the SCC are also not analyzed because it is evaluated based on site energy as well.

Prior estimates do not include potential impact of climate change. The average temperature is expected to continue to rise by 3.6ºF (2°C) over the next century even with significant reduction in emissions [3]. This will subsequently increase the amount of CDDs that occur throughout the cooling season and increase the use of space cooling in buildings. Building energy consumption already increases during the cooling season, as seen in Figures 6 and 7, and thus energy consumption for space cooling needs is expected to be even larger with the influence of climate change. This is supported by multiple studies which identified that climate change may have significant impact on building cooling loads [348-350]. This is supported by evidence in Figures 8 which establish that chilled water consumption increases as CDDs increase. While the R-squared value is low ($R^2 = 0.37$) the overall correlation coefficient suggests a moderate positive relationship ($R = 0.6$) between chilled water consumption and CDDs. The low R-squared value is due the noisiness of the data given that this is real-time metered data with a high standard deviation ($\sigma = 1338716$). Such variation most likely occurred due to unpredictability of occupant behavior as well as data gaps that occurred during failure of the BAS system which had to be filled in with estimated consumption. This data does not provide a strong predictive model for what energy consumption would look like as a result of increased CDDs, but it does indicate that the increase in CDDs will subsequently increase the cooling load of the BLCII and energy consumption, concurring with the current literature. Climate models have predicted that the U.S. Southeast is particularly susceptible to climate change compared to other states, with temperature changes in Georgia reaching 2ºF (1.1°C) above historical levels (79ºF, 26.1ºC) in the next 20 years [351]. This will lead to increased utility costs and downstream emission from energy consumption, emphasizing the importance that improved cooling temperature setpoints will have as climate change increases the length and severity of the cooling season.

5.6 OTHER RELEVANT FINDINGS OUTSIDE OF THE CENTRAL RQS

The following section discusses other relevant information outside discoveries in relation to the central research question. Findings are subdivided into relevant sections. Topics discussed are lack of variability in room setpoints, accuracy of the BLCII building sensors, and the impact of the social cost of carbon.

5.6.1 LACK OF VARIABILITY IN COOLING TEMPERATURE SETPOINTS

Realized energy savings and subsequent utility savings from the setpoint changes also emphasizes the important of occupancy sensors in buildings to reduce cooling load when rooms are not occupied. This is mentioned given the lack of variability in temperature setpoints each hour from 7AM-7PM. Standard deviations of these temperatures for Amos Hall, Benson Hall, and Moore Rooker Hall are in Tables 6 through 8. The standard deviation of setpoint for all 27 rooms is not higher than 0.46. This suggests that once setpoints are changed by occupants, they typically do not deviate from this change over the course of the scheduled occupancy cooling temperature setpoints. While this is expected for office spaces in which occupants are most likely there from 7AM-7PM, this is not expected for more transient spaces such as conference rooms or classrooms. Specific examples include rooms B220A and B331 in Amos hall which are a conference room and work room/kitchen. The average setpoint of these rooms over the May baseline were 72ºF (22.2°C) and 73ºF (22.8°C). The same issue also occurred during the May baseline for rooms A112 and A101 in Moore Rooker Hall in which setpoints were on average 72ºF (22.2°C) and 70ºF (21.1°C). A112 is a conference room and A101 is a print/copy room. Benson Hall did not have any rooms with setpoints left at relatively low temperatures. Occupancy sensors in rooms of these types would help reduce cooling load by changing to unoccupied setpoints when the rooms are no longer occupied. The sensors would also help account for holidays in which buildings may be either empty or have a much lower occupancy. This is based on the cooling setpoint changes in all rooms remaining at normal occupied settings on July 4th even though this is recognized as a UGA holiday.

This emphasizes the need for occupancy sensors in order to increase the cooling temperature setpoints when rooms are no longer occupied. Typical occupancy sensors are CO_2 sensors which measure the level of CO_2 in a room to determine occupancy. This would be a great tool in order to account for variability of occupancy of buildings such as the BLCII, especially over summer months when occupancy is more intermittent that Spring and Fall semesters. Such sensors would be best used in spaces that may not be occupied throughout the entire course of the day, such as classrooms, breakrooms, kitchens, print/copy rooms, and other similar transient spaces. Studies have proven that use of occupancy driven setpoints can decrees energy consumption [352, 353]. These particular studies demonstrated energy savings ranging from 23% to 38%. While this may generate energy savings, there is also potential it may lead to occupant thermal discomfort, as rooms would not be pre-cooled. Thus, it would be fair, based on this study, to at minimum have setpoints revert back to a setpoint of 76ºF (24.4°C) when unoccupied, as thermal comfort results did not indicate a significant impact on thermal comfort. Occupants would also only have to experience thermal discomfort for a short period of time until the sensors detect occupancy and adjust cooling setpoints accordingly. Sensors can also be overridden by manual change of a thermostat.

5.6.2 BUILDING SENSORS

Facilities management division has the choice of using the Chicopee building weather station or building sensors to regulate the HVAC system for outdoor air conditions at the BLCII. Facilities management mentioned that while the current system operates based on the building sensors, there is potential they may switch to the Chicopee weather station readings. Giving that there was a significant relationship and correlation between OAT and the BLCII chilled water consumption mentioned in Section 5.1, the accuracy of the BLCII sensors was investigated in order to determine if the switch is necessary. Based on results in Section 4.1, the BLCII building sensors temperature readings align more closely with readings from a nearby weather station (Athens Ben-Epps Airport) than the Chicopee weather station located at Facilities Management division. Thus, it is suggested that the BLCII sensors continued to monitor OA conditions for the BAS system. Use of inaccurate weather data may cause bias in energy consumption, as one such study showed that using weather data from different weather stations within the same region can cause load bias in energy models of 20-40% [354]. It is also suggested that the accuracy of the Chicopee weather station be checked, as other campus HVAC systems may be operating a BAS using such readings.

5.6.3 THE SOCIAL COST OF CARBON

The SCC is used to estimate the long-term damage done by a ton of CO_2. It is meant to represent damages due to climate change including net agricultural productivity, human health, property damages from increased flood risk, and changes in energy system costs (such as reduced costs for heating and increased costs for air conditioning), although current modeling limitations constrain the parameters that are included and results in some physical, ecological, and economic impacts that would most likely increase the SCC [129]. These parameters are left out due to lack of precise information on the nature of such damages. The SCC is used to analyze the CO_2 impacts of various rulemakings, mostly in relation to car and truck standards. Avoided SCC for the entire cooling season could range from $263 to $550 for the BLCII alone. If applied throughout the entire campus, avoided damages may range from $7,327 to $15,329. The SCC is used throughout this paper to represent the benefits of emissions reductions into a single metric that is easy to understand. This emphasizes the positive impact that emission reduction through setpoint change can have outside of reduced utility rates, as there are other economic benefits that society would experience outside of UGA alone. It should be noted though, that other studies have SCC estimates that are higher than the U.S. estimate, as these estimates are closer to $200 per ton [355, 356]. This emphasizes the variability of the SCC given the large number of parameters that must be evaluated and the lack of data that often surrounds such parameters. The SCC still needs more research in order to eliminate such uncertainty to be more useful in the policymaking process, but it does help to emphasize other societal benefits of energy consumption reduction. In future building code scenarios, it could prove to be a valuable asset to help to evaluate building performance and impacts larger than the building level alone such as reduced utility rates and emissions. This also is a better way to explain to the public the benefit of certain building design scenarios, as it emphasizes an economic benefit that society would experience versus building operators and tenants only, expanding the range of affected stakeholders.

CHAPTER 6

LIMITATIONS AND FUTURE WORK

Sections 6.1 and 6.2 discuss the limitations of this work and future work required. Main limitations include low responses to thermal comfort surveys, malfunctioning of the BAS system, and inability to determine a strong correlation between chilled water consumption and IATs. Given results and limitations of this study, future work should focus on determining buildings most suitable for cooling temperature setpoint change, long-term effects of cooling temperature setpoint change, impact of an educational campaign on building energy consumption, and the divers of reheat use in buildings.

6.1 LIMITATIONS

A limitation of this study was the lack of responses to the thermal comfort surveys. The relatively low sample sizes may not be an accurate representation of actual majority thermal comfort votes of occupants in the building given that Facilities Management division received a request by the building manager to decrease the cooling temperature setpoint during testing. A low response rate was expected as this was not a controlled lab situation where all test subjects were aware of the testing going on and 'required' to give a survey response.

There were also issues with the BAS that occurred over the summer which affected the length and timing of testing periods, as it was desired to have at minimum two weeks of cooling temperature setpoint change for each testing period. The variation in length of testing may have affected thermal comfort responses as different cooling temperatures were experienced for different lengths of time. Another limit is the inability to determine a strong correlation between

IAT and chilled water consumption. This is due to a lack of hourly temperature variations in the consumption data, which makes it difficult to associate a change in temperature with a percent energy savings. There is a potential that longer periods of testing would be able to better distinguish the relationship between stepwise cooling temperature changes and chilled and hot water consumption by the BLCII, but the timeline of this work and issues with the building BAS over the summer did not allow extended periods of testing.

6.2 FUTURE WORK

Future work should analyze the current UGA building stock to determine which exact buildings would be best suited for temperature setpoint changes and then have implementation of such setpoints changes, as this current study only assumes classrooms, offices, and study spaces would be suitable. There is potential that more buildings outside of these types have potential for improved setpoint control. This would allow better comparison to determine how effective cooling setpoint changes are for a variety of buildings versus just the BLCII alone. Comparisons could be made between buildings of similar and different types to indicate performance. This would also offer an opportunity for UGA to perform energy benchmarking for its own building stock in order to which buildings are least energy efficient and of highest need for improvements through comparison of site EUI.

Future work should also evaluate the long-term effects of temperature setpoint change in order to better determine drivers of chilled and hot water consumption for HVAC. Other parameters outside of IAT should be analyzed such as air speed and indoor humidity levels and their impact on chilled and hot water consumption. Analyses should also focus on the relationship between the variables individually and together on chilled and hot water consumption, as it may be that no one variable drives chilled and hot water consumption alone.

Such studies should also include thermal comfort testing in order to identify the range of thermal comfort experienced at the UGA campus using various metrics to measure thermal comfort. This could help identify if student’s thermal preference is different than that of neutral as assumed by the ASHRAE 7-point scale as well as analyze how different occupants interpret different scales used to measure thermal comfort.

Impacts of an educational campaign on temperature setpoints and building energy consumption should also be evaluated. Campaigns would be targeted for buildings with a BAS system to see if overall temperature setpoints change in response to information about the energy consumption of HVAC systems and relationship between cooling setpoints and energy consumption. Thermal comfort testing should be done in conjunction with this campaign to see if overall thermal preference and the range of thermal comfort is impacted by such information. Results from this study could be used to justify a campus wide energy efficiency campaign and cooling temperature setpoint policy to improve overall campus sustainability.

The uncertainty of factors influencing hot water consumption for reheat emphasizes the need for future studies on the drivers of reheat. Currently, there is very limited literature on factors that influence use of reheat in buildings. Future work should aim to determine if factors such as OAT and IAT drive reheat use, if so, to what extent. Research should also be done to see if internal sensible and latent loads are larger drivers of reheat use, such as heat emitted from lights, computers, people, etc. It is also possible that each of these factors alone cannot predict needed reheat, and thus research should look at how the combination of these variables impacts reheat use and subsequent energy consumption. This would be beneficial in order to reduce use of reheat in buildings, especially given that the boilers at UGA are natural gas fired and have much larger CO_2 emissions that electricity consumption by the chillers.

CHAPTER 7

CONCLUSION

The goal of this study is to analyze the impact of cooling temperature setpoint change on building energy consumption. The cooling temperature setpoint changes were increased from an average baseline of 73°F (22.8°C) to 74°F (23.3°C) and 76°F (24.4°C) over four different testing periods in the BLCII at UGA. Results from the field testing are used to estimate the impact changes have throughout the entire cooling season as well as the impact on all buildings of similar type to the BLCII. Findings estimated the temperature setpoint changes improved energy efficiency of the HVAC system regarding chilled water consumption from the baseline by 19.2% to 40.2 % with estimated CO_2 emissions reductions of 0.05 lb/ft^2. If applied throughout the entire cooling season, utility costs could be reduced by $1,898 to $3,970 and CO_2 emissions could be reduced by 10,951 lbs to 22,911 lbs in just one cooling season. This would improve site EUI by 1.56 kBtu/ft^2-yera to 3.27 kBtu/ft^2-year. If applied throughout all building types like the BLCII during the entire cooling season, savings could be $52,903 to $110,680 with CO_2 reductions ranging from 305,282 lbs to 638,690 lbs. Thus, results from this study identify that increasing the cooling temperature setpoints during the cooling season improve overall HVAC efficiency and subsequently, building energy efficiency, without severely jeopardizing thermal comfort. Given the onset of climate change and increase of future CDDs, these findings emphasize the impact conservative cooling temperature setpoints have on energy consumption. Future work should further analyze the potential for large scale implementation of such setpoint changes and a campus wide temperature setpoint policy in order to ensure conservative setpoints and efficient operation of HVAC systems in buildings given that roughly have of energy consumption by buildings is for indoor space cooling and heating. Drivers of reheat use should also be explored. Such results could have large financial benefits for the University through avoided utility costs which could be used to invest in other energy efficiency and sustainability projects. This would also further the completion of 40% emissions reductions from the 2010 baseline as outlined in the UGA Campus Sustainability Plan.

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APPENDICES

A THERMAL COMFORT SURVEYS

Category 1: Relevant building information

Q.1 Which of these buildings did you enter most recently? Please answer all following questions in regard to this building.

Scale of possible answers: 1 – Correll Hall, 2 – Moore-Rooker Hall, 3 – Amos Hall, 4 – Benson Hall, 5 – I have not entered any of these buildings

Q.2 What was the last date you were in this building? Please type below using this format xx/xx/xx.

Category 2: Assessment of thermal environment

Q.3 Indoor Environmental Quality (IEQ) refers the quality of a building's environment in relation to health and wellbeing of those who occupy the space. IEQ is determined by many factors, such as temperature, lighting (artificial and natural), air quality, and humidity. Please estimate how your performance in regard to work, study, research, etc. is increased or decreased by the IEQ of this building.

Scale of possible answers: 1 – 20%, 2 – 10%, 3 – 5%, 4 – 0%, 5 – -5%, 6 – -10%, 7 – -20%

A series of questions asked how satisfied occupants are in regard to the following factors:

- Overall lighting, including daylighting
- Level of humidity
- Temperature
- Indoor air quality
- Acoustics

Q.4 How satisfied with you with the…?

Scale of possible answers: 1 – extremely satisfied, 2 – moderately satisfied, 3 – satisfied, 4 – neither satisfied nor dissatisfied, 5 – slightly dissatisfied, 6 – moderately dissatisfied, 7 – extremely dissatisfied

Q.5 How do you feel in regard to the temperature in this building?

Scale of possible answers: 1 – Hot, 2 – Warm, 3 – Slightly Warm, 4 – Neutral, 5 – Slightly Cool, 6 – Cool, 7 – Cold

Q.6 What is your clothing level? Please choose the combination which matches what you most frequently wear in the building.

1 – Short sleeved shirt, shorts, shoes; 2 – short sleeved shirt, shorts, jacket or sweater, shoes; 3 – short sleeved shirt, pants, shoes; 4 – short sleeved shirt, pants, jacket or sweater, shoes 5 – skirt with short sleeve shirt or dress, shoes; 6 – skirt with short sleeved shirt or dress, jacket or sweater, shoes; 7 – I prefer not to answer

Category 3: Demographic Information

Q.7 The following demographic information was elicited: Gender, Age, Ethnicity