IMPACT OF SENSING AND OCCUPANCY PARAMETERS TO ACHIEVE COMFORT AND DEMAND SIDE MANAGEMENT IN BUILDINGS

By

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ABSTRACT

In the United States, the residential and commercial sectors have consumed increasingly more energy over the past 70 years. As the U.S. shifts towards a carbon-neutral electric grid, electrification using fossil fuel-free, renewable energy resources such as wind and solar will help to reduce greenhouse gas (GHG) emissions. To reduce the need for fossil fuels and utilize energy more efficiently, technologies and policies are introduced to help decrease the demand-side intensity of building sectors. Three issues are addressed in this research to support the goals of smart buildings or net energy-zero buildings (NEZB) to achieve human comfort and demand-side management (DSM): sensing technology sensitivity for smart building controls, occupants' patterns and correlations in residential buildings, and appliance use in residential buildings.

First, there has been a lack of studies and guidance on the appropriate placement of various sensors within a building and how this sensor placement impacts building control performance. This research thus first investigates (i) how sensitive controls of buildings are to sensor placement, in particular, sensor location and orientation. Sensor placement impact analysis helps to investigate the impact on energy use and demand for an integrated lighting and shading control system. Second, various studies have shown that occupancy-related factors in energy modeling can create significant differences in building energy consumption. Human-related factors, especially occupants' activities and behavior, are less well understood, especially in the wake of lifestyle changes that have occurred as a result of the pandemic. This research thus (ii) assesses and quantifies the changes to occupancy patterns and the relationship to the socioeconomic factors that have occurred due to the COVID-19 pandemic. Finally, the third topic focuses on demand-side management (DSM), which enables the ability to control the quantity and timing of electricity consumption. Approximately one-third of this consumption is from large appliances, many of which are occupancy-driven loads. Historically, energy use information for estimating the energy

use of individual appliances has originated from a combination of field-collected and simulated data. However, this data originates from sources assessing pre-pandemic energy consumption patterns, thus there is a need to (iii) assess how energy use patterns of appliances have changed during and post-pandemic. This research thus helps to estimate demand reduction opportunities from the use of appliances in DSM applications.

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CHAPTER 1: INTRODUCTION

1.1. Research background and hypotheses

The residential and commercial sectors have consumed increasingly more energy in the United States over the past 70 years (see Figure 1). Based on the U.S. EIA Annual Energy Outlook (AEO) 2023, total floor space will continue increasing, resulting in an estimated energy consumption increase at the rate of 0.3% per year. By 2050, purchased electricity is projected to increase by 20% and 11% in the residential and commercial sector respectively by 2050 as compared to 2022 for reference case as shown in Figure 2 (EIA 2023). As the U.S. shifts towards the carbon-neutral electric grid, electrification using fossil fuel-free, renewable energy resources will help to reduce greenhouse gas (GHG) emissions, such as wind and solar. This has become the focus of energy generation to meet demand growth while minimizing the cost (Perry et al. 2019). The positive perspective is that the demand-side intensity of residential and commercial sectors keeps decreasing due to the support of technology and policy.

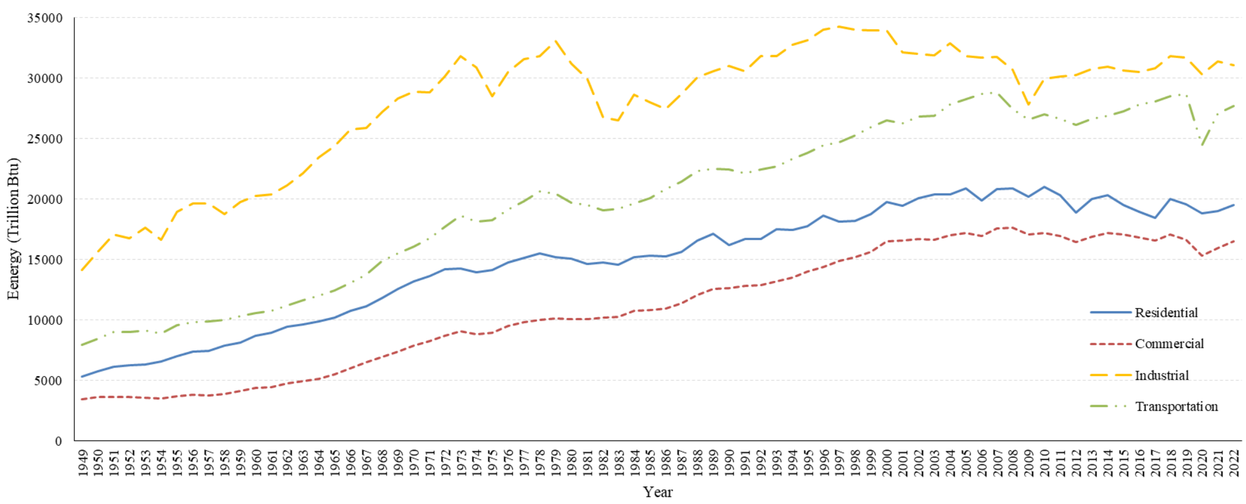


Figure 1. Annual total energy consumed by sectors from 1949 to 2022 (data from: U.S. EIA 2023).

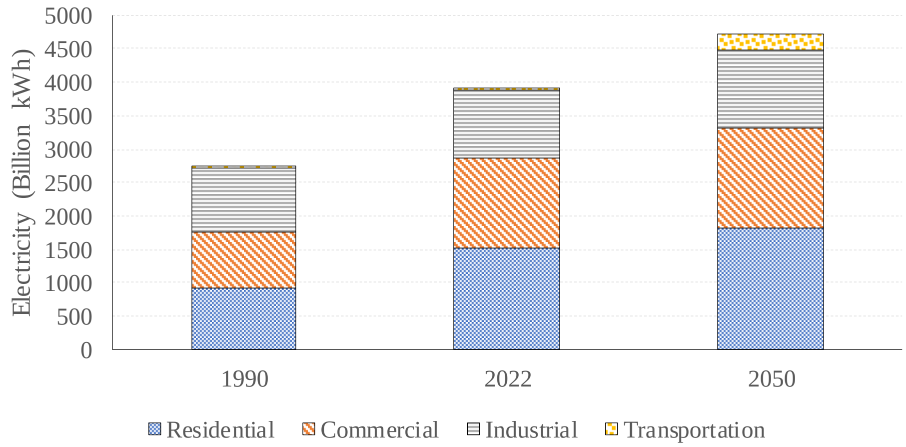


Figure 2. Electricity use by the end-use sectors for 1990, 2022 and 2050 projection (data from: U.S. EIA 2023).

As electrification increases in adoption in an effort to decarbonize the built environment, a common goal is for lighting, heating, and cooling all to use electricity (Goetzler et al. 2019). Particularly for heating in colder climates, which is currently mostly using natural gas, this means greater demand for electricity, especially in winter. In order to minimize the resulting increase in capital investments to support electric grid reliability where electric grid loads increase, various technologies have been subject to efficiency, shedding, shifting, modulating, and generation to provide electricity demand flexibility (Fu et al. 2022) in particular using smarter building controls. Utilizing smart building controls can help to achieve these goals to enable energy cost reduction, support grid services, and meet occupants' comfort expectations (Neukomm et al. 2019). To support these goals, as smart building technology has improved and matured and adoption has increased, an increasing number of buildings have building management systems (BMS) and/or building automation systems (BAS) that help to support the control and smart operation of building systems. Current estimations suggest that about 15% of commercial buildings and 42% of commercial building floor space use BAS to adjust HVAC system operations in the U.S. Similarly, close to 10% of commercial buildings and approximately 18% of commercial floor space use BAS to adjust lighting and/or envelope features (CBECS 2018). Retrofitting commercial buildings with smart connected equipment is estimated to reduce total energy consumption by 8–18% (Perry 2017). The adoption of these and other technologies continues to increase over time. Since buildings are complex systems, three issues are addressed in this study to support the goals of smart building controls: sensing technology sensitivity for smart building controls, occupants' patterns and correlations in residential buildings, and appliance use in residential buildings.

Currently, it is estimated that people are spending more than 90% of their time in indoor spaces (Zomorodian et al. 2016). To further improve building energy efficiency and create occupant-friendly indoor environments, various sensors, such as those that monitor air quality, humidity, indoor illuminance, occupancy, and temperature, have been used. (Sinopoli 2009; Forsström et al. 2021). The sensing technologies deployed in building sectors, such as occupancy sensors, are used in 17% of the commercial buildings along with scheduling, daylighting, multilevel lighting and dimming, and daylight harvesting to reduce lighting energy and demand, as well as to improve occupants' visual comfort (EIA 2018). Studies show that 20-60% lighting energy savings using occupancy sensors can be achieved in open office settings (Pigg et al. 1996; Galasiu et al. 2007; de Bakker et al. 2017). Lighting sensors and dimming technology are estimated to achieve 20% lighting savings (Galasiu et al. 2007). These sensors capture information representing the instantaneous indoor conditions experienced by occupants, which are then used as input to control building system components, such as HVAC, lighting, and shading. Using shading and lighting controls to reduce heating and cooling electricity use (Shen and Hong 2009; Shen and Tzempelikos 2012; Shen et al. 2014) without retrofitting or upgrading the building's HVAC system could reduce upfront costs. It is reported that an estimated 16%-26% cooling energy savings and 52%-72% lighting energy savings can be achieved by utilizing automated shade controls. In addition, such control systems essentially depend on the sensing technology and its captured information. *However, there has been a lack of studies and guidance on the appropriate placement of these various sensors within a building, including how sensitive the sensor placement is to the controls and energy use of the building, especially sensor location, and orientation. In this study, sensor placement impact analysis helps to investigate the impact on energy use and demand for an integrated control system.*

Secondly, studying changes in use has become a necessity in building systems, in particular due to changes in how buildings are used as a result of COVID-19. Occupant's behavior in buildings can be defined as the presence and actions that can impact the building's environmental conditions and energy consumption (Yan and Hong 2014). The occupants' presence creates both latent and sensible heat in indoor space. In addition, their behavior, such as opening/closing windows, turning on/off lights and fans, and using appliances, also impacts total internal loads (Yang et al. 2016). Thus, there is a strong correlation between occupancy use preferences or patterns and building energy consumption. However, occupant-related factors, such as social and economic factors, are lack of knowledge to achieve deep building energy efficiency (Yoshino et al. 2017). Their study pointed out socioeconomic factors, including family information, energy-related attitude and income level should be considered when reporting complex energy use data. (Yoshino et al. 2017) In addition, demand flexibility has been less addressed in the context of assessing the impact of occupancy use on buildings.

Due to the outbreak of COVID-19, the World Health Organization declared a global pandemic (Cucinotta and Vanelli 2020), which marks a global shift in living patterns due to this long-term public health emergency. After three years of travel restrictions, health safety measures, and lockdowns in effect in many countries (CDC 2023), WHO declared COVID-19 were no longer a global emergency in May 2023 (WHO 2023). As of March of 2024, over 7 million reported deaths have been reported due to COVID-19 (WHO 2024). Various studies have shown that occupancy-related discrepancies in energy modeling to estimate total house energy patterns can create a 30% to 100% difference in building energy consumption compared with predicted values in building simulations (Azar and Menassa, 2012). As Yoshino et al. (2017) pointed out, many studies only focus on building envelopes, energy systems, and climate. However, human-related factors such as building operation and maintenance, occupants' activities and behavior, and indoor environmental quality are of less focus. *The COVID-19 pandemic represents an opportunity to assess and quantify changes to occupancy patterns in buildings that have occurred as a result of this event, as well as changes to current and future energy use and demand in buildings.*

Fixed occupancy schedules are currently used in the U.S. DOE prototype (Deru et al. 2010) and reference buildings (Deru et al. 2011). Several approaches have been used to generate such schedules. Common methods include the Markov chain (Page et al. 2008) and cluster analysis (Gu et al. 2018), where the Markov chain method generates the stochastic schedules of occupancy in a building to help simulate the building energy consumption; cluster analysis includes grouping data to group into different occupancy patterns (i.e., like schedule) and using the generated schedule as input to calculate energy consumption. Yan et al. (2015) points out that the adoption of standard schedules to represent occupants' behaviors incorrectly reproduces human-building dynamic interaction. Due to the nature of the stochastic behavior of occupants, using one generalized schedule results in the over-generalization of occupancy patterns. Using time use survey data has become a more common method for generating occupancy patterns and analysis. Previous studies have assessed the impacts based on age groups, household sizes, and income levels (Mitra et al. 2022) in residential buildings using American Time Use Survey (ATUS) data. ATUS is annually collected by the U.S. Bureau of Labor Statistics. The ATUS data is a statistically representative survey of the U.S. population. *Even though various methods have been used to analyze occupancy patterns, it is not clear how, during and in the post-pandemic periods, occupancy patterns in buildings have changed and how this may vary for different demographics. In addition, it is unclear if such changes might impact energy use patterns in these buildings, or the opportunity to support the use of occupancy-based energy savings methods.*

Thirdly, the most important part of the building's electricity usage, beyond space heating, cooling, and lighting, is the use of appliances (e.g., water heater, refrigerator, clothes washer/dryer, dishwasher, cooking range/stove) and miscellaneous electric loads (MELs) such as televisions, computers, and other plug loads. Plug-in loads are expected to continue growing by 20% and 29% in the residential and commercial sectors, respectively, by 2050 compared with 2022 (EIA 2023). Especially in the residential sector, refrigeration, water heating, clothes washing/drying, and electronics are estimated to make up 35% of total and 44% of peak electricity use (Goetzler et al. 2018). In areas with low space heating requirements, domestic hot water (DHW) can correspond to 40%-85% of heating demand in residential buildings (Stene 2008).

Demand side management (DSM) enables the ability to control the quantity and timing of electricity consumption. Prior studies have shown that this can be achieved by utilizing appliances (Assi et al., 2022). Sheppy and Gentile-Polese (2014) discuss that overestimating plug-in loads can result in oversizing electrical infrastructure and cooling systems, increasing capital costs and energy consumption. Thus, the ability to understand the energy use of energy-consuming systems, including appliances, also allows for the ability to assess power use and grid regulation (Li and Just 2018) as well as identify ways to reduce GHG emissions (Berrill et al. 2021).

The appliance energy use profile could be estimated using several methods (Grandjean, Adnot et al. 2012, Kang et al. 2014, Jin et al. 2020). The first is top-down methods where a building is treated as a block, and the cumulative demand of a particular energy-consuming system is based on the linear model considering macro-scale variables such as macroeconomic factors, climate, and building envelope characteristics. The second is the bottom-up method, which is based on analyzing and investigating higher-frequency data to determine energy use patterns. Possible strategies can include statistical, probabilistic-empirical, and time-use (time-use survey or TUS) models. For the first method, the peak energy demand has been found, in some cases, to be overestimated, since such a method can fail to consider the random variability of occupant behavior (Tanimoto and Hagishima, 2010). The second approach may not precisely represent the user's daily activity depending on the time length of collected data, normally one day, which fails to capture the difference in behavior for an extended period and in duration/choice of program (Yilmaz et al. 2017).

Due to the novel coronavirus (COVID-19) pandemic, lockdowns regulated by governments worldwide increased the amount of time that people stayed in their homes and thus indoors in 2020 (Mitra et al. 2022), which posted a new challenge to the existing energy use, appliance use, and occupancy profiles used in energy simulation methods and protocols. There is increased demand for better building energy management technology to meet the requirements of suitable living conditions with lower energy costs. For those loads, the DOE Building American Program developed standard operation conditions for appliances by providing hourly and monthly schedules for house simulation protocols (DOE 2023). However, those schedules were developed years ago and are still commonly used in simulation tools.

Appliances use data has been collected by various studies in recent years by various research efforts across different countries. One of the largest datasets of data for U.S.-based homes includes data collected primarily in Texas and other states, such as California, Colorado, and New

York (Pecan Street Inc. 2023). This dataset includes energy use information for the whole home, as well as for individual circuits. Historically, energy use information for estimating the energy use of individual appliances has originated from a combination of field-collected and simulated data. However, all of this data originates from sources assessing pre-pandemic energy consumption patterns. *Since occupancy patterns and behavior have likely changed, both during 2020 and throughout the aftermath of the pandemic, there is a need to assess if these appliance energy use patterns have changed because of the pandemic and how this has trended over time. In particular, this helps assess how this might impact on the estimated demand reduction opportunities from the use of appliances.*

1.2. Research Objectives

Given the importance of building system components interacting with occupants, this research will improve insights that support the use of sensing technology, smart occupancy-based controls, and smart appliances. These will also support an accurate understanding of energy saving and demand flexibility in residential and commercial buildings, which also supports building electrification and reduced emissions. The schematic for the focus areas of this research is shown in Figure 3.

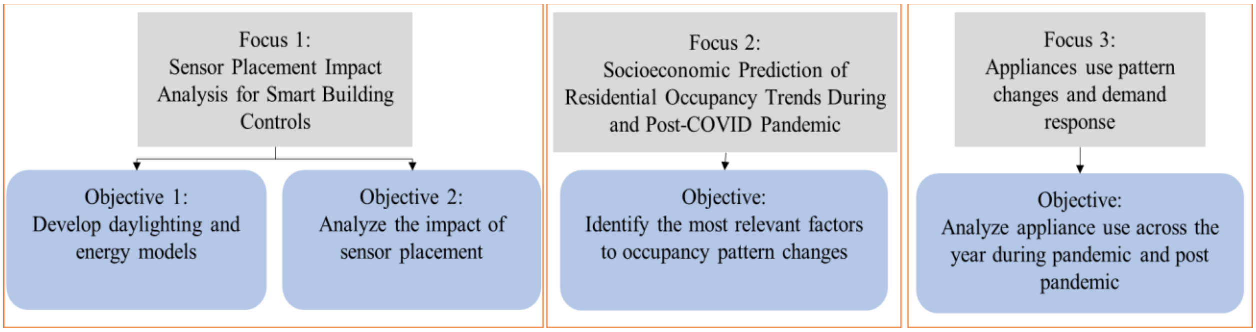


Figure 3. Schematic diagram of research organization.

Focus Area 1: Sensor Placement Impact Analysis for Smart Building Controls

The goal of this focus area is to assess the impact of sensor locations and orientations in obtaining indoor and outdoor environmental parameter inputs for shading and lighting controls when the building system is dynamically controlled. Specifically, it seeks to answer the following questions:

a. What control strategy should be used to smartly adjust lighting and shading in a building to reduce energy and demand?
b. What possible variation in placement (distance and rotation) of sensors used by the identified control strategy is appropriate to consider in evaluating performance sensitivity?
c. How does adjusting the sensor placement impact a building's performance in terms of visual comfort, energy use, and demand?
d. Does this impact vary by zone orientation or climate zone?

To answer these questions, a model needs to be developed to simulate possible scenarios. A literature review of prior research is conducted to determine the possible variation in sensor placement variables and possible control strategies. To determine performance results, a model is developed in EnergyPlus and RADIENCE. Simplified day glare probability (DGPs), illuminance values (lux), shading positions (0-10), energy use (kWh) and demand (W) are used to quantify and visualize results.

Focus Area 2: Socioeconomic Analysis of Residential Occupancy Trends During and Post-COVID Pandemic

The second focus area's objective is to develop a predictive model to determine occupancy patterns and trends of households during and post-COVID-19 pandemic (i.e. primarily targeting

2020-2022). This builds on prior research that suggests that there are differences across different demographics of households. Still, studies have yet to use these factors to predict occupancy, nor have they conducted this analysis across pandemic and post-pandemic periods. The pandemic has significantly impacted how people work and live. Thus, it is important to assess this as new data becomes available. The American Time Use Survey dataset, along with the appropriate mapping of this data to occupancy variables, enables the ability to conduct this study. The following are research questions for this focus area:

a. What socioeconomic factors most impact residential occupancy patterns?
b. What metric(s) should be used to evaluate occupancy pattern impact to enable comparison of socioeconomic factors?
c. What trends in occupancy can be observed during the COVID-19 pandemic across 2020, 2021 and 2022?
d. How do these factors' impacts differ across different years and demographics?

To answer these questions, multiple-year collected surveyed data are used, in particular, 2006-2019 as the pre-pandemic ATUS data and 2020-2022 pandemic/post-pandemic data. Analysis is conducted to evaluate the most significant factors, specifically including the use of correlation matrices and regression analysis are used to select and determine those factors.

Focus Area 3: Appliance Use Pattern Changes and Demand Response During and Post-COVID-19

Appliance use is this focus area's main target, specifically residential buildings. This research focus area complements Focus Area 2. Since appliances are a significant energy consumer in residential buildings and are also impacted by occupants' activity patterns, analysis of appliance uses during, and post-pandemic is also needed. This objective thus focuses on quantifying the impact of the pandemic on appliance use in homes, particularly how this impacts their use potential for demand-side management. The following research questions are addressed:

a. What observable differences in appliance use between pre-, during- and post-COVID can be observed across 2020, 2021, and 2022?
b. How do these differences impact peak demand use and the potential of demand reduction?
c. What is the most suitable time frame for demand response using the studied appliances?

To answer these questions, multi-year data from the Pecan Street database is used, including from 2018-2022. Daily and monthly use profiles are generated and visualize the profiles.

1.3. Dissertation Organization

This research is organized in five chapters and their corresponding publications, as shown in Figure 4. This begins with the introduction (Chapter 1); the three focus areas, as outlined above, are discussed in Chapters 2, 3, and 4. For the first focus area, one journal paper has been published in Science and Technology of the Built Environment, titled "*Sensitivity Analysis of Sensor Placement in Energy-Efficient, Grid-Interactive Ready Small Office Buildings with Dynamic Shading and Lighting Control*" in addition to a conference paper "*Energy and Demand Saving Potential due to Integrated HVAC, Lighting, and Shading Controls in Small Office Building*" published and presented in *2022 Construction Research Congress* and a conference paper "*Energy Use Sensitivity Analysis of Sensor Placement in Small Office Buildings with Dynamic Shading and Lighting*" published and presented in the *2022 ASHRAE Annual Conference*. For the second focus area, one journal paper, "*Socioeconomic Prediction of Residential Occupancy Trends During and Post-COVID Pandemic*" was submitted to a peer-reviewed journal, and a conference paper, "*Trends and Changes in U.S. Residential Occupancy and Activity Patterns across Demographics during and Post-COVID*," published and presented in the *2024 ASHRAE Winter Conference*. For the third focus area, one journal paper, "*Appliance Use Pattern Changes and Demand Response During and Post-COVID*" is ready for submission to a peer-reviewed journal. The final chapter (Chapter 5) summarizes all three focus areas and concludes this dissertation.

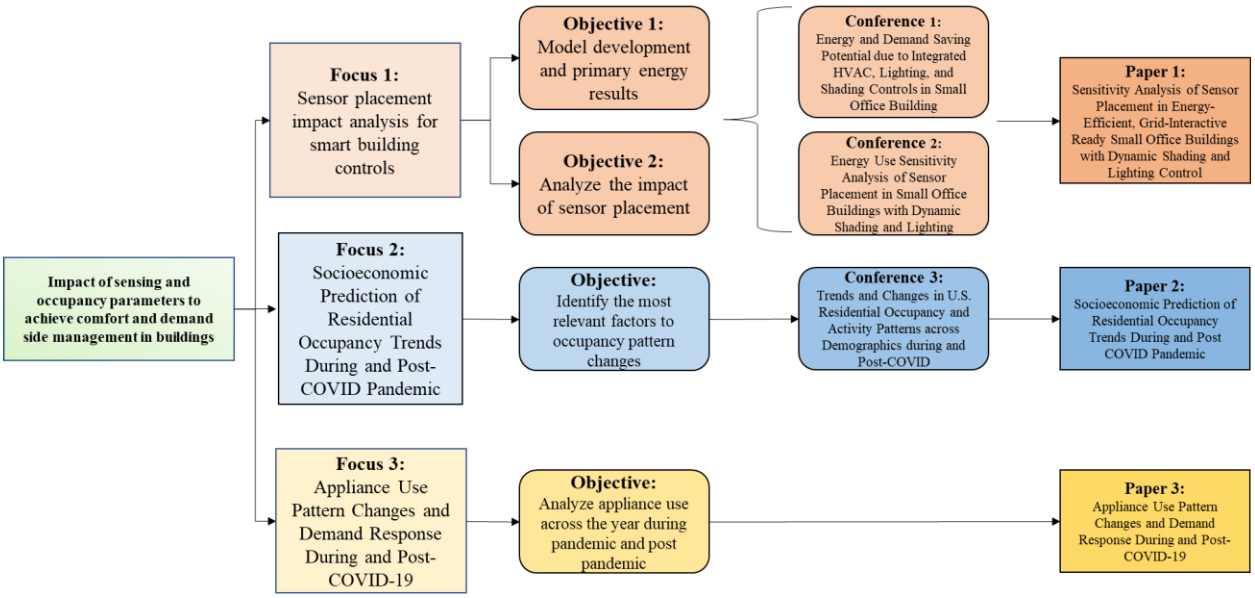


Figure 4. Research organization diagram towards completion of the study.

CHAPTER 2: SENSITIVITY ANALYSIS OF SENSOR PLACEMNET IN ENERGY-EFFICIENT, GRID-INTERACTIVE READY SMALL OFFICE BUILDINGS WITH DYNAMIC SHADING AND LIGHTING CONTROL

Published in "Science and Technology of the Built Environment"

2.1 Introduction

Per the Commercial Buildings Energy Consumption Survey (CBECS), electricity is the largest energy source consumed in over 95% of commercial buildings (U.S. EIA 2018). Among the end uses in the United States overall, space heating, cooling, and lighting are the largest sources of electricity. The specific contributions of each of these end uses vary by region and climate zone. As electrification increases in an effort to decarbonize the built environment, a common goal is for lighting, heating, and cooling, all to use 100% electricity. Particularly for heating in colder climates, which mostly use natural gas, this means greater demand for electricity, especially in winter. To minimize the resulting increase in capital investment to support electric grid reliability where electric grid loads increase, there is a need to reduce the electricity consumption and demand of existing buildings, as well as to support load flexibility. Grid-interactive efficient buildings (GEBs) can achieve this goal by improving building systems' efficiency and performance and their ability to operate dynamically. In particular, this is achieved through the use of smart building technologies such as automated controls, networked sensors, and advanced building automation (King and Perry 2017; Nemtzow 2018; Neukomm et al. 2019).

For commercial buildings, the most common type of commercial building in the U.S. is office buildings based on CBECS. The U.S. has nearly 1 million office buildings, representing approximately 20% of commercial floorspace. Office buildings are among the highest in total floorspace, building numbers, and primary energy consumption contributors within the U.S.

commercial building sector (U.S. EIA 2018). Office buildings generally provide spaces for occupants to work, most commonly using a computer and desk space. Office spaces, as well-occupied spaces in other commercial building types, must provide a comfortable environment for occupants to support occupant productivity. Ideally, a building should provide a visually and thermally comfortable environment while also operating in an efficient manner. To support these goals, as smart building technology has improved and matured, an increasing number of buildings have building management systems (BMS) and/or building automation systems (BAS) that help to support the control and smart operation of building systems. The global smart building market was valued at $80 billion ($32 billion in the U.S.) in 2022, with a projection to reach $408 billion in 2030. (Fortune Business Insights 2022) The U.S. market was the biggest market at a growth rate of 20% annually (Nemtzow 2018). Estimates currently suggest that approximately 15% of commercial buildings and 42% of commercial floor space use BAS to adjust HVAC system operations in the U.S. Similarly, close to 10% of commercial buildings and approximately 18% of commercial floor space use BAS to adjust lighting and/or envelope features as mentioned by CBECS. The adoption of these and other technologies continues to increase over time.

As the adoption of these technologies increases, it is important to understand how such smart systems can be ideally controlled and to quantify their sensitivities to various configurations. This can help ensure the systems are configured appropriately in the field to enable the best controls that support occupant comfort and operational efficiency. A smart system uses information and communication technologies to facilitate the building automation operations and controls via interconnected building systems (King and Perry 2017). Commercial buildings can save energy by using advanced sensors and automated controls in plug-in loads, HVAC, lighting, and shading technologies. Internet-connected smart sensors, especially, can collect and stream significant amounts of data to support remote sensing and system automation (Sehrawat et al. 2019). For example, in Chen et al. (2020), illuminance sensors in office buildings were implanted to achieve savings via various lighting controls such as daylight harvesting, lighting dimming, and others. For office buildings, which often have many windows, the advantages of shading control incorporated with lighting control are fulfilling the occupants' expectations for privacy, visibility to the outside view, and ventilation. The latest study also suggests including occupants' cultural backgrounds for adjusting shade, providing new perspectives for shading and lighting control designs besides visual and thermal comfort. (Abdelwahab et al. 2023) Many studies have also incorporated shading along with lighting controls (e.g., Shen and Hong 2009; Shen and Tzempelikos 2012; Shen et al. 2014) to reduce building electricity use.

Technologies such as occupancy sensors are estimated to be used in 17% of commercial buildings, and to a lesser extent, scheduling, daylighting, multilevel lighting and dimming, and daylight harvesting (U.S. EIA 2018). There have been several studies in recent years that utilize illuminance sensors. Shen and Hong (2009) developed and evaluated simulation results to choose optimal window-to-wall ratio, lighting, and shading control combinations. Shen et al. (2014) compared lighting and shading control strategies to identify the best performing. Singh et al. (2015) used a similar approach to determine the glazing and shade fabric combination to achieve visual comfort and energy savings. Suk (2019) conducted glare experiments to define appropriate illuminance thresholds to improve visual comfort. Finally, Kunwar et al. (2020) used illuminance sensors to collect data to control lighting and shading devices for building energy and daylighting saving analysis. In all these studies, a fixed illuminance sensor location was used at an assumed location of about 1 m to 4 m, either close to the exterior window or in the zone center based on the depth. Placing an illuminance sensor used to control shading and lighting close to the window can be more beneficial for reducing potential glare throughout a zone but requires more artificial lighting, while placing an illuminance sensor farther away prioritizes the use of more daylight and less artificial lighting but with increased risk of glare for areas close to the window. This also impacts lighting and HVAC energy use and demand.

However, there is a lack of studies and guidance on the placement of illuminance sensors within a building, including how sensitive the resultant illuminance levels, glare probability, energy use, and electricity demand of a building are to the sensors' placement, including across orientations and climate zones. In practice in occupied buildings, illuminance sensors are typically located on the ceiling, exterior windows, and/or other locations that do not impact occupants and their use of the space. It is not practical to have sensors at the location of occupants (Kent et al. 2022). However, the points of interest that drive the use of sensors in various locations are the illuminance at the work plane and vertically at the human eye level (assuming the occupant is seated). In this research, to simplify the process and reduce the need for additional correlations to be determined between the target points of interest and the location of ceiling and/or window sensor control (Caicedo et al. 2017, Valíček et al. 2014), points of interest at work plane and human's eye level were used for controlling the system in the developed models. This is consistent with previous studies (Galasiu et al. 2004; Goovaerts et al. 2017; Kim et al. 2014; Kunwar et al. 2020; Liang et al. 2018; Reinhart et al. 2006; Tzempelikos and Shen 2013). The light measured at the sensor position accurately represents the ambient illumination available within the indoor zone. In this study, sensitivity analysis is conducted to assess the sensitivity of the performance of integrated shading and lighting control systems to sensor placement. Specifically, the sensitivity of such systems is evaluated for the sensors used as input into the decision-making control algorithm. Because shading and lighting controls are designed and performed differently according to climate conditions (Littlefair et al. 2010; Shen and Hong 2009; Shen and Tzempelikos 2012; Wienold et al. 2011), this study also assesses the impacts and sensitivities of the proposed energy model using selected sensor placements in different climate zones. System-level energy and/or electricity use are used to evaluate energy impacts.

This study assesses the impact of sensor placement on building performance via simulations when implementing dynamic shading and dimmable lighting for the purpose of improving both energy efficiency and demand flexibility. Such effort follows the goal of the U.S. DOE's efforts to support GEBs (Neukomm et al. 2019). This research helps to understand the performance impact of sensor placement at different depths for shading and lighting control, which can help inform field installation based on desired performance targets. The results of this research can help to understand how impactful the placement is on overall system performance and to optimize the design for achieving better energy consumption, demand reduction, and occupant visual comfort. The remainder of this paper is organized as follows. The methodology section reviews the simulation model and control development, sensor placement, and post-simulation analysis and then applies the proposed model in different climate zones. The results include illuminance and DGPs distributions for each perimeter zone, shade operation patterns, and energy and demand comparison at both the zone and building levels. The last section includes the conclusions, limitations, and future work.

2.2. Methodology

2.2.1. Simulation model development

The Department of Energy (DOE) commercial prototype small office building (U.S. DOE 2022) is used as the initial model in this study. The small office prototype building is 511 m² and includes four perimeter zones and one core zone. The ASHRAE 90.1-2004 version was chosen, as shown in Figure 5, because the building characteristics are close to that of a typical office building environment regarding lighting power density (LPD) based on field experience. The LPD of this building is 10.8 W/m^2, representing approximately 100% fluorescent lighting. The perimeter zone depth is 5 m with a window-to-wall ratio (WWR) of 24% for the south facade, 20% for the others, and a floor-to-ceiling height of 3.1 m. Interior roller shades are used for the shading devices. The building is assumed to be fully occupied 8 hours per weekday from 9 am to 5 pm and minimally occupied at other times. The building uses an air-source heat pump for cooling and heating with a backup gas furnace (same for all climate zones).

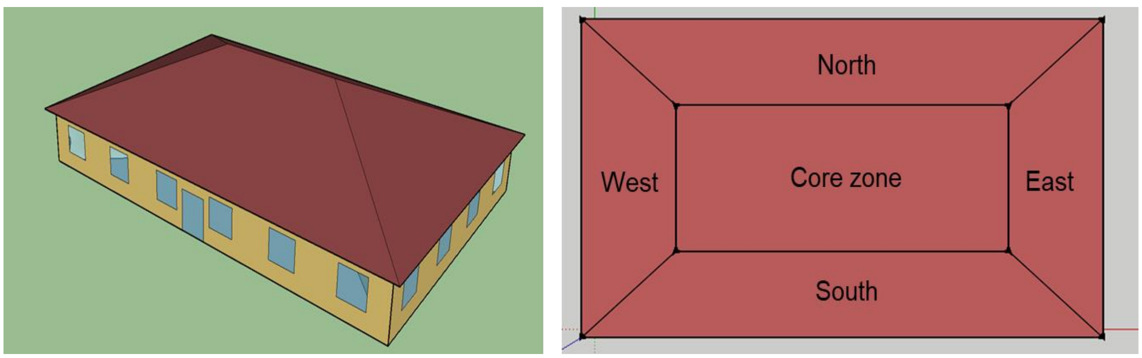


Figure 5. DOE commercial prototype small office building.

Some modifications were made to the prototype building to better represent baseline shading controls. Specifically, manually controlled roller shade was added, where occupants opened the shades in the morning upon arrival and then closed the shade (remained closed until the next day) when direct sunlight exceeding 50 W/m^2 hit the occupants (Reinhart 2004). Different shade types have advantages and disadvantages. In the United States, interior shades are more common than external ones, and roller shades are among the most common (Chan et al. 2015; Tzempelikos and Shen 2013). They also provide the benefit of blocking visual discomfort and features of view that might cause visual privacy concerns, which depend on the characteristics of shading devices and controls (Tzempelikos and Shen 2013; O’Brien et al. 2013). This is considered the “baseline” model, with no smart building or energy-efficient features. Additional modifications were made to the ASHRAE 90.1-2004 model to represent an energy efficiency (EE) building that is more efficient and includes smart building systems, specifically adding more efficient, dynamic lighting and shading. These modifications are made to represent an older building that has recently had energy efficiency retrofits completed. Such a building is likely to be well-placed to support adjustments to operations that enable the building to respond to electric grid needs.

For lighting upgrades, first, LED lighting is assumed to be implemented (based on ASHRAE 90.1-2016 model assumptions). In addition, task tuning (controls that adjust the lighting level for each fixture for a specific task) is assumed using a factor of 0.585 to limit the peak lighting output (DLC and NEEA 2020; Williams et al. 2012). The lighting power density (LPD, W/m²) is thus updated from 10.8 W/m² for the baseline model to 4.4 W/m² to reflect lighting power changes for all hours for task tuning and the LED fixtures retrofit inside all five zones. Then the lighting schedule is updated to adjust lighting power for specific hours to account for daylighting dimming and occupancy-based on-off control except core zone. Since daylight does not affect the core zone, only 15% LPD dimming is applied for fully occupied time to account for occupancy control (ASHRAE 2019) and not affect other hours. In addition, the artificial lighting is dimmed for daylighting such that the target value at the work plane illuminance sensor is 375 lx inside the four perimeter zones. The LPD values are assumed to reduce linearly with a reduction in the illuminance (lx) values. For example, if the available daylight at the work plane sensor is 400 lx at a particular hour, which exceeds the required daylight of 375 lx, the artificial lights will be switched off (schedule value = zero). However, if the amount of available daylight at the work plane is only 300 lx, artificial lighting is set to be on at a dimmed level to provide the remaining illuminance needs.

To control the interior shade position, variables including occupancy, time of day, HVAC condition (heating vs. cooling mode), and sky conditions were considered (Vanage et al. 2022). If a perimeter zone is unoccupied, the lighting schedule is updated to be zero (off) to account for occupancy. The remaining mentioned variables are used to minimize solar irradiation into the zone during the cooling season by closing the shades or to maximize outdoor solar irradiation in winter by opening the shades during the day and closing them at night. In addition, if exterior solar irradiation is above 150 W/m² (Yoon et al. 2009), where the sky condition is considered sunny, the shade position is adjusted to reduce solar irradiation. The control logic for shading and lighting controls implemented in this model is shown in Table 1.

Table 1. Control logic and variables for shading and lighting.

HVAC Mode	Time of day	Occupancy	Sky Condition	Shade control	Vertical illuminance	Lighting control	Work plane illuminance
Cooling	Night	Unoccupied	--	Open shades	--	Switch off	--
Cooling	Night	Occupied	--	Open shades	--	Dim	375 lx
Cooling	Day	Unoccupied	--	Close shades	--	Switch off	--
Cooling	Day	Occupied	Overcast	Adjust (0-10)[1]	2000 lx	Dim	375 lx
Cooling	Day	Occupied	Sunny	Adjust (0-10)[1]	2000 lx	Dim	375 lx
Heating	Night	Unoccupied	--	Close shades	--	Switch off	--
Heating	Night	Occupied	--	Close shades	--	Dim	375 lx
Heating	Day	Unoccupied	--	Open shades	--	Switch off	--
Heating	Day	Occupied	Overcast	Adjust (0-10)[1]	2000 lx	Dim	375 lx
Heating	Day	Occupied	Sunny	Adjust (0-10)[1]	2000 lx	Dim	375 lx

[1] *0 -10 indicates that the shading is in one of 10 possible positions, where 0 is fully open and 10 is fully closed.*

The final model of the small office building with integrated shading and lighting controls is completed following a three-step process, as shown in Figure 6. For daylight simulation, RADIENCE version 5.2.2 (2022) is used; for energy simulation, EnergyPlus Version 8.9 (2022a) is used. To integrate results and variables together, these two model results are connected using Ladybug and Honeybee (Roudsari et al. 2013), which are open-source plugins of graphical algorithm editor Grasshopper (Davidson 2022) integrated with CAD software Rhinoceros (McNeel and Associates 2022).

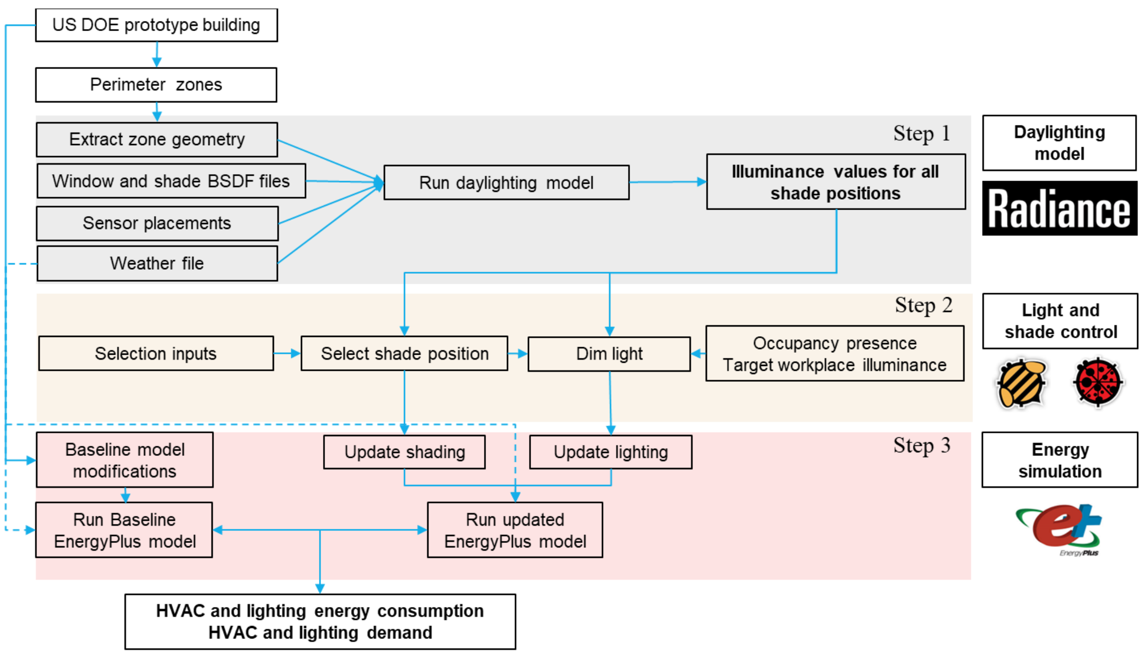


Figure 6. Three-step simulation process to evaluate energy consumption and demand *(adapted from Vanage et al. 2022).*

The first step in the simulation (grey background in Figure 2) is the daylight modeling using RADIANCE (2022) for each perimeter zone, to support obtaining indoor illuminance values using a matrix-based method in the desired locations (Subramaniam 2017). The daylighting model uses various inputs, including zone geometry, Bidirectional Scattering Distribution Function (BSDF) files (.xml) for roller shades and the window, and EnergyPlus (2022b) weather data (.epw). In this model, as a starting point, two illuminance sensors were included, one vertical illuminance sensor at eye-level (1.2 m), and a horizontal work plane illuminance sensor at a height of 0.76 m, to generate illuminance values as the input for adjusting shade position and lighting controls in the next step which would be later used for assessing visual comfort. Further information on sensor placement is included in the next section. The daylight simulation is run across all scenarios throughout a year, for each of 10 different shading positions, resulting in 87,600 values each sensor collected in each zone. Detailed building material properties used in the daylighting model are shown in Table 2 and 3.

Table 2. Surface reflectance used in RADIANCE.

Surface type	**Surface reflectance**
Walls	0.5
Ceiling	0.7
Floor	0.2
Door	0.2
Ground	0.2

Table 3. Glazing and shading devices.

Layers	**Thickness (mm)**	**Visible transmittance**	**Reflectance**	**Emissivity**	**Conductivity**
Glass	6	0.397	0.308	0.84	1
Air gap	6	-	-	-	-
Glass	6	0.909	0.079	0.84	1
Air gap	35	-	-	-	-
Roller shade	1	0.574	0.574	0.828	0.15

The second step (yellow background in Figure 6) is choosing the shade position and artificial lighting level for each timestep in the EnergyPlus model using Ladybug and Honeybee (Roudsari et al. 2013), based on the output illuminance values generated from the daylighting model results. Appropriate shade position and lighting level are selected at each timestep to maintain a vertical illuminance lower than 2000 lx (Kunwar et al. 2020) and a horizontal work plane illuminance of 375 lx (Reinhart 2004). The 2000 lx value is chosen to minimize visual discomfort; the 375 lx threshold for workplace illuminance is chosen to reduce the high probability of switching off the lights (Reinhart 2004). Since the minimum lighting threshold often used in standards (e.g., IES 2020 and EN-12464-1 2021) for paper- and computer-based tasks is 300 to 500 lx, 375 lx falls within the range and will likely provide a better balance between visual comfort and energy utilization. In addition, it should be noted that when reducing lighting levels (assuming dimmable LED lighting is used), such lighting can be reduced to a minimum level to prevent flickering without being turned completely off. This lower limit of lighting level, which depends on the lighting system, will impact the demand response potential.

The third step in the modeling process (red background in Figure 6) includes updating the EnergyPlus building energy model using the identified shade and lighting schedule for each timestep. For this step, the baseline model and EE model are simulated using generated schedules to obtain the heating, cooling, and lighting energy consumption and demand. Both models are used to compare HVAC and lighting energy consumption and demand usage.

2.2.2. Sensor placements and impact analysis

Within the model, the vertical illuminance sensors are placed 1.6 m away from the window in each perimeter zone, at a height of 1.2 m, facing the window. This location serves as the baseline case for the sensor location sensitivity analysis. The horizontal illuminance work plane sensors are placed at a height of 0.76 m, facing the ceiling. The heights for these sensors are based on similar values used in other studies (Heschong and Heschong Mahone Group 2011; Kunwar et al. 2020; Shen and Tzempelikos 2012; Wienold 2009). The position and orientation of these sensors are generally fixed and used in prior studies either for collecting data for daylighting and shading controls to reduce energy use or to mimic human eye position to evaluate visual comfort.

To evaluate sensor location sensitivity, the one-at-a-time (OAT) sensitivity analysis method is followed (Østergård et al. 2020). Following this method, the baseline as a sensor located at 1.6 m from the window and oriented facing the exterior window (0 degrees) is used as a starting point, and then each selected variable was adjusted to evaluate the model sensitivity to this parameter. Several variables were evaluated, specifically vertical and horizontal illuminance sensors' distance from the exterior window, vertical illuminance sensor orientation in each perimeter zone, and climate zone of the building. These were chosen to represent different settings of illuminance placements and system performance at different climate conditions. For the sensor distance from the window (both vertical and work plane illuminance sensors), this was varied incrementally, including 1.6 m at one-third of zone depth, 2.4 m at the center of the zone, 3.6 m at two-thirds of zone depth, and near the interior perimeter zone wall at 4.9 m from the exterior window. Similar distances were used in Kunwar et al. (2020), including 1 m, 2.5 m, and 4 m for the work plane sensor only, in addition to 3 m in Shen and Hong (2009) for both vertical and work plane sensors. In occupied buildings, some dynamic shading and/or lighting controls include the placement of a sensor on the window clerestory. These are used, for example, for controls to prevent daylight from entering the room (Kent et al. 2022) or limit solar radiation onto the window (Tzempelikos and Chan 2016). Following the control scheme utilized in this research, if a sensor is placed at the window rather than deeper into the space, the shades will be lowered more often, resulting in model results that would be more similar to the manual control as used in the baseline model.

To evaluate the sensitivity of the model results to the orientation of the vertical sensors, the first model performance was evaluated with the vertical illuminance sensor facing perpendicular to the window to mimic occupants facing and looking towards the window. The vertical illuminance sensor was then rotated on its vertical axis away from the window from 30 to 90 degrees (i.e., facing the window = 0 degrees, 30 degrees, 60 degrees, and parallel to the window = 90 degrees). The sensor facing parallel to the window mimics a scenario where occupants are working on their paperwork or looking at the computer and not looking directly toward the exterior window; such orientation is used in occupant visual comfort and glare studies (e.g., Park et al. 2011; Wienold and Christoffersen 2006). These variables are evaluated in perimeter zones in four orientations, including north, south, east, and west, in order to understand how orientation impacts these results. The climate zone is discussed in a later section.

2.2.3. Post simulation results assessment

For visual comfort evaluation, daylight glare probability (DGP) is used to quantify the sensitivity of sensor placement inside the zone since the DGP method demonstrates high accuracy and correlation with users' responses (e.g., Wienold and Christoffersen. 2006). For daylighting model results, the obtained vertical illuminance values are used to calculate simplified daylight glare probability (DGPs, Equation 1) (Wienold 2007) to expedite the simulation process as a measure of indoor visual comfort in each perimeter zone.

$$DGPs = 0.184 + 6.22 * 10^{-5} * E_v \qquad (1)$$

where E_v is the estimated vertical illuminance value (lx) obtained from the model simulation. As Wienold (2007) mentions, this equation does not consider luminance contrast. Since the model used in this study had no other glare source except the daylight entering the zone space, DGPs is thus used in this study. DGPs is categorized into four bins, including imperceptible glare (less than 0.35), perceptible glare (from 0.35 to 0.4), disturbing glare (from 0.4 to 0.45), and intolerable glare (greater or equal to 0.45). The controls (see Table 1) were designed to maintain an indoor vertical illuminance level below 2000 lx, equating to a DGPs value of less than 0.31 (imperceptible glare). The energy modeling results are assessed to determine annual lighting energy use (kWh), annual cooling energy use (kWh), and summer (June, July, and August) cooling and lighting electricity demand (kW) in each of the four perimeter zones, as well as for the whole building (all perimeter and core zones combined).

2.2.4. Climate zone performance

Energy use and demand are analyzed across different climate zones to assess performance under different climate conditions. The chosen locations include ASHRAE climate zones 2A (hot humid; Tampa, FL), 2B (hot dry; Tucson, AZ), 4A (mixed humid; New York, NY), 4B (mixed dry; Albuquerque, NM), 5A (cool humid; Lansing, MI), 6A (cold humid; Rochester, MN), and 6B (cold dry; Great Falls, MT). These are chosen to capture both humid and dry conditions in heating- and cooling-dominated climates as well as mixed climates. For those selected locations, each corresponding prototype building model is used for daylighting and energy simulations (U.S. DOE 2022).

2.3. Results and Discussion

The results include first a demonstration that the EE model, with sensors located at 1.6 m facing the window, achieves energy and demand savings as compared to the baseline model. Next, for the EE model, the sensor location is varied, including distance from the exterior windows in all orientations and rotation of the sensors. The sensitivity analysis results include, first, an analysis of illuminance and glare and, second, an analysis of energy and demand associated with lighting and space conditioning. These results are summarized and discussed as follows.

2.3.1. EE Model Results

When comparing the performance of the EE model with the baseline model across climate zones, energy savings originate mostly from lighting for colder climate zones 6A (cold humid) and 6B (cold dry), including a total of 84% energy savings for both locations shown in Figure 7. For hotter climates, zones 2A (hot humid) and 2B (hot dry), energy saving is achieved more from a combination of cooling and lighting savings (41% and 47%, respectively). In this scenario, lighting achieves savings of 18,398 kWh (85%) and 18,464 kWh (85%), respectively, and cooling reaches 13,563 kWh (24%) and 9,414 kWh (25%) respectively. Across all the climate zones, there is a net annual decrease in cooling and lighting energy ranging from 41-71%, where the smallest saving (20,914 kWh) is for CZ 6B (cold dry) and the maximum (31,960 kWh) saving from CZ 2A (hot humid). In terms of peak demand reduction throughout a typical day (7 am to 9 pm), the results in Figure 8 quantify the ability of this building to reduce demand during peak hours as a grid-interactive building system. The greatest cooling demand reduction includes a decrease of 6.5 kW (23%) in CZ 2A (hot humid), and the least cooling demand reduction is 5.5 kW (23%) from CZ 4B (mixed dry). The demand reduction of peak lighting uses is nearly the same (64%) for all climate zones due to the same lighting and shading control strategy. Across all the climate zones, the demand reduction of peak cooling use ranges from 21-26%, and the combined peak use of lighting and cooling demand reductions range from 28-33% (9-10 kW) across climate zones, where the least saving is in CZ 4B (mixed dry) and greatest saving for CZ 2A (hot humid). In summary, these results demonstrate that the use of the outlined control strategy can achieve energy and demand savings across the climate zones but that these results vary somewhat by climate condition.

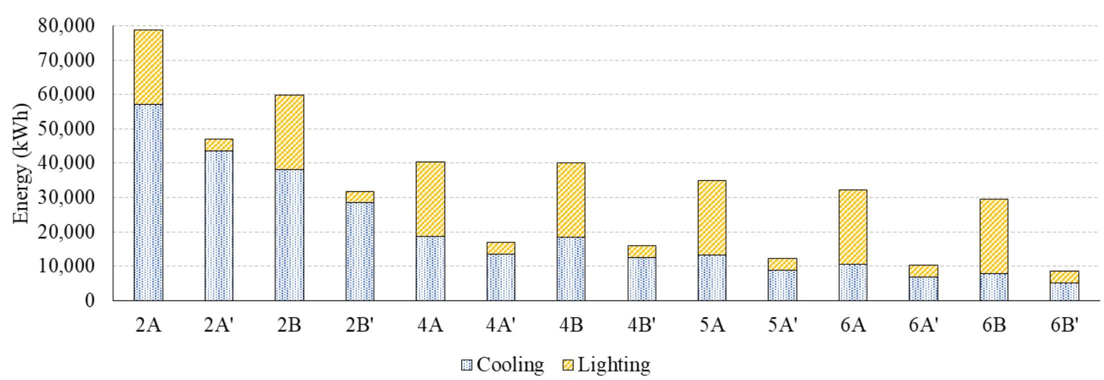


Figure 7. Annual energy (kWh) for ASHRAE climate zones using fixed sensor placements *(2A for baseline model, 2A' for EE model at sensor location 1.6 m and facing window).*

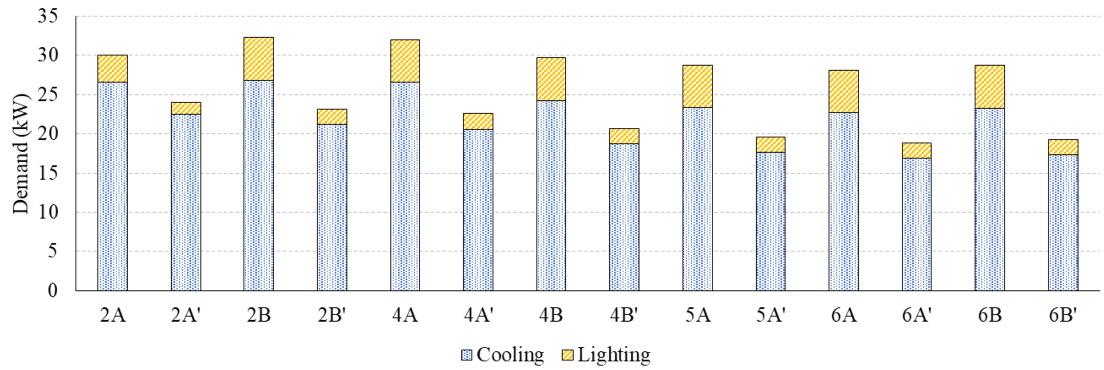


Figure 8. Peak demand (kW) for ASHRAE climate zones using fixed sensor placements *(2A for baseline model, 2A' for EE model at sensor location 1.6 m and facing window).*

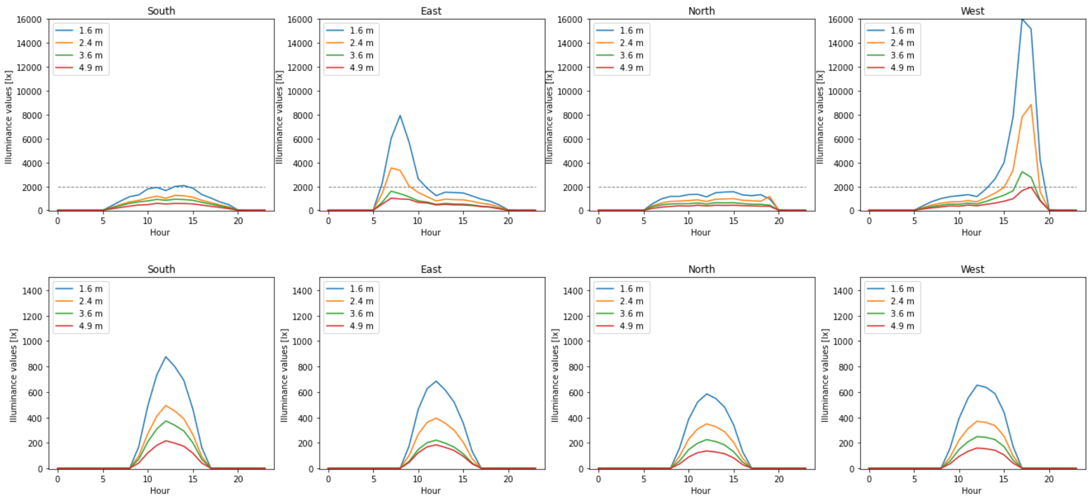
2.3.2. Sensitivity Analysis

Taking Climate Zone 5A, which has moderate cooling and lighting use, the following discusses the sensitivity of the model results to changes in sensor placement. The first sensitivity of illuminance values is discussed, followed by glare (DGPs), shading operation, energy use, and electricity demand. It is noted that regardless of climate zone, the resulting illuminance, glare, and shading operation are similar; the energy use and demand, in particular for HVAC, is the main result that varies somewhat by climate zone, as shown in the previous section.

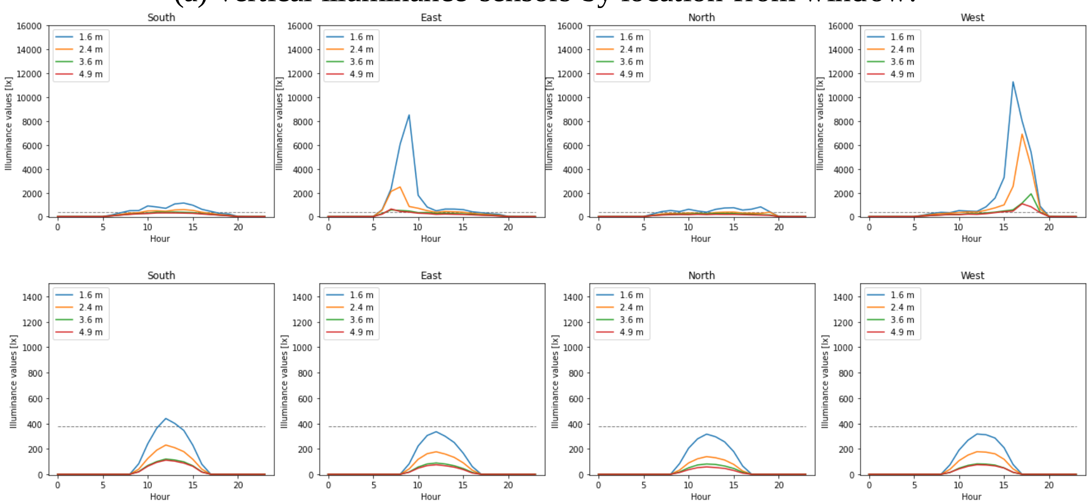
The illuminance values resulting from the RADIANCE model (Step 1) are shown for both summer (June 21st) and winter (December 21st) in Figure 9 for distances from the window ranging from 1.6 m to 4.9 m, and sensor rotation from parallel to perpendicular to the window. The two days shown are the summer and winter solstices, the longest and shortest days of the year. Vertical illuminance shows how much daylight enters occupants' vision at eye level when they are sitting or working, so no excessive light causes harm to their physical condition. Work plane illuminance reflects the daylight and lighting level on the desk surface to meet the requirement of adequate light provided in the space.

For vertical illuminance shown in Figure 9, most detectable vertical illuminance occurs from 5 am to 8 pm during the summer solstice and 8 am to 7 pm during the winter solstice, so the shading control will be deployed most during the periods. During this period, the illuminance values are more sensitive to sensor distance from the window at closer distances (i.e., 1.6 m to 2.4 m) as compared to farther away. Increasing the sensor distance to 3.6 m and 4.9 m further decreases the detected illuminance values; no illuminance values higher than the 2000 lx threshold occur except for a few hours in the west zone, so less shade control will occur. For the winter solstice, the detected vertical illuminance values at all sensor locations are lower than 2000 lx for all four perimeter zones, causing no shading to be lowered. For the work plane illuminance sensor, changing the sensor distance to 3.6 m and 4.9 m further decreases the detected illuminance values, which means that increased periods of artificial lighting occur. However, there are still a considerable amount hours higher than 375 lx in the south, east, and west zones.

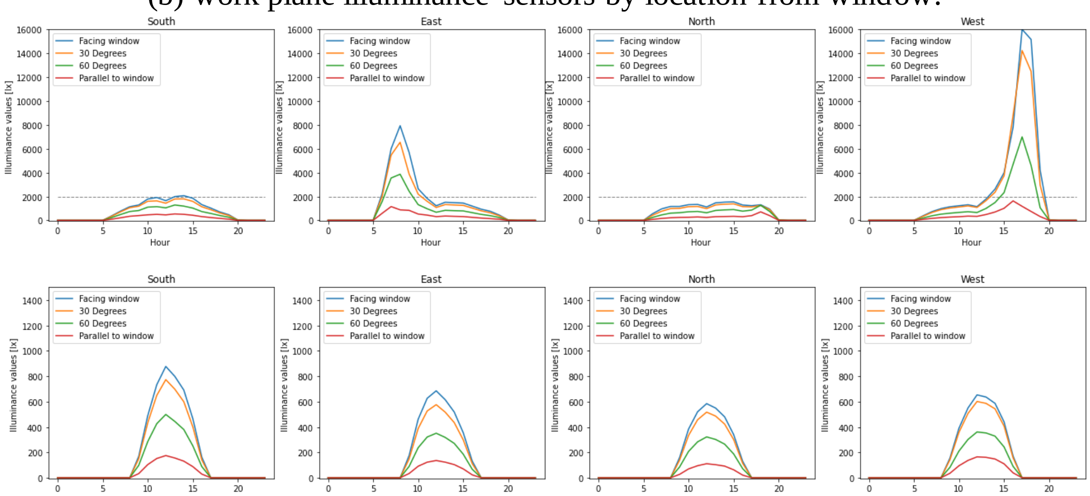
For the winter solstice, moving the sensor between 1.6 and 2.4 m or further decreases the illuminance value below 375 lx in all perimeter zones, resulting in additional lighting needs. Small degrees of rotation (30 degrees and less) appear to impact the sensed illuminance values less than larger angles for both summer and winter solstices, which have a greater change in illuminance values for the same amount of additional rotation. Thus, less shade operations occur for these larger rotation angles. Sensor locations deeper inside the zone space (2.4 m, 3.6 m, and 4.9 m) are also observed to be less sensitive than locations closest to the window. The further the sensors are from the exterior windows, the less available daylighting is detected by those sensors, so additional lighting needs to be provided, and less shade operation.



(a) vertical illuminance sensors by location from window.



(b) work plane illuminance sensors by location from window.



(c) vertical illuminance sensors by rotation.

Figure 9. Illuminance values during the summer (top row) and winter (bottom row) solstices (*horizontal dashed line for control threshold*).

Using the results from Step 1, the annual frequency of DGPs values is compared across sensor distances and rotations in Figure 10 and Figure 11, respectively. When the illuminance sensors are placed at 1.6m and facing the exterior window shown in Figure 10, despite the high frequency of no glare and imperceptible glare, there are considerable amounts of perceptible, disturbing, and intolerable glares (DGPs value above 0.35), with frequencies of 671, 490, and 733 hours per year for the south, east, and west zones (and negligible glare in the north zone). If the distance is increased to 2.4 m, the amount of time that the DGPs above 0.35 is decreased by an average of 69%, 50%, and 42% for the three perimeter zones compared to placing sensors at 1.6 m. For 3.6 m, the DGPs values are decreased by an additional approximately 20% across the three zones. When moving the sensor near the interior wall at 4.9 m, no glare is detected by the sensors except slightly in the east and west zones. There are approximately 76 hours of DGPs values above 0.35 for west zone and 4 hours of perceptible glare in east zone compared with 1.6m.

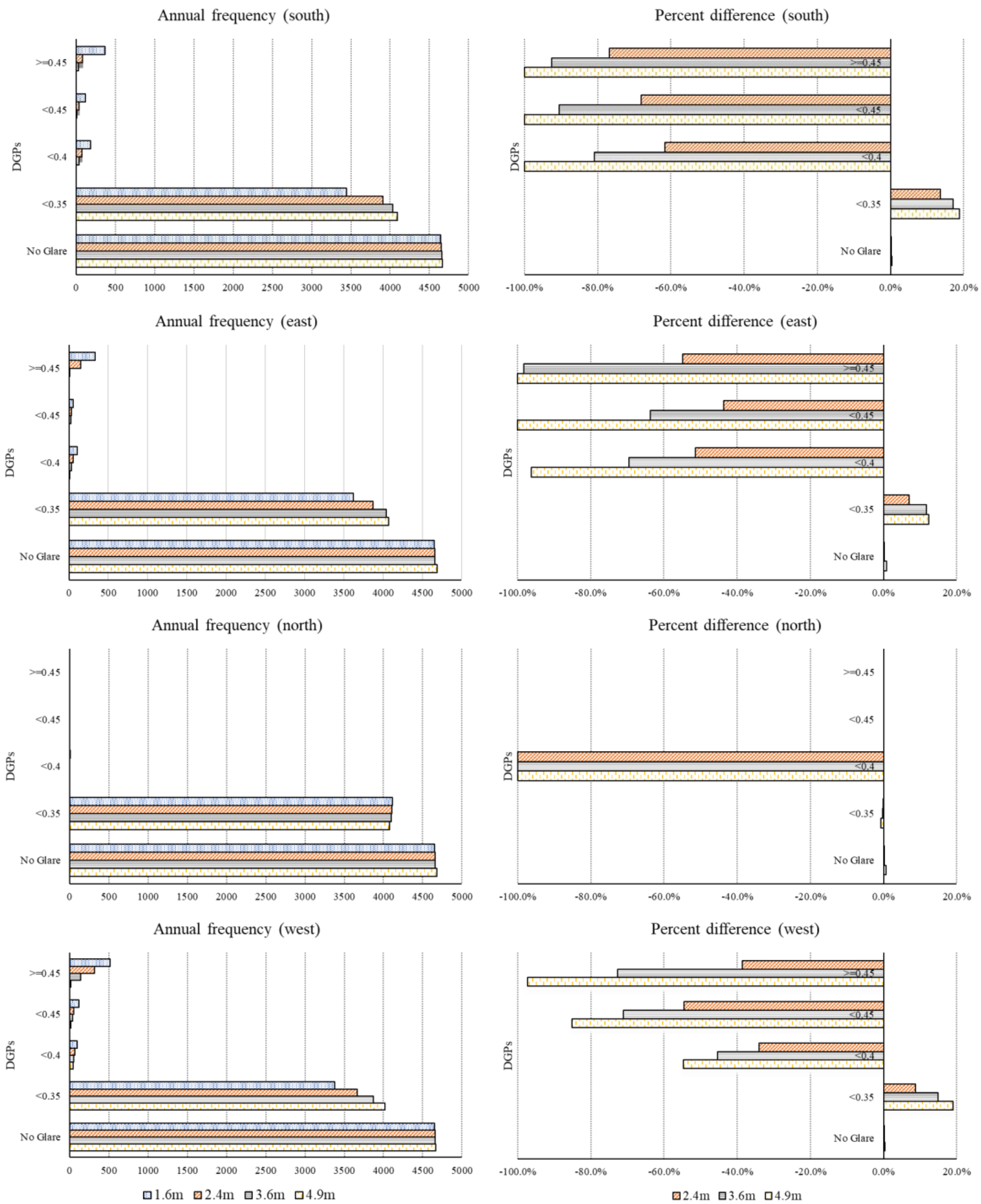


Figure 10. Annual DGPs frequencies at different sensor locations from the exterior windows (left), and changes (%) in DGPs as compared to sensor located 1.6 m from the windows (baseline case) (right); each row of figures shows one perimeter zone orientation (south, east, north, west).

For sensor rotations, as shown in Figure 7, rotating the sensor 30 degrees away from the window decreases the overall detected glare in all perimeter zones. However, this also increases perceptible glare (2%) and disturbing glare (7%) in the east and west zones and 2% perceptible glare for 60 degrees in the west zone. This is because the illuminance sensor receives direct daylight at certain hours during the day in the east (sunrise) and west (sunset) and is impacted by the reflectance from the interior wall, which has less impact on the south and north zones. On average, 21%, 24%, and 9% less glares are detected compared with when the sensors are facing the exterior windows in the south, east, and west zones despite the increase of perceptible and disturbing glares in east and west zones. Rotating to 60 degrees, a decrease in high DGPs of 31%, 27%, and 29% is achieved in the south, east, and west zones despite the increase of perceptible glare in the west zones. While placing the sensor parallel to the window, there are still 35, 16, and 127 hours of DGPs values (above 0.35) across these three zones compared with the sensor facing window.

Overall, in summary, placing the sensor(s) further from the windows and rotating away from the exterior window at chosen locations will result in increasing the detected occurrence of no glare and imperceptible glare (DGPs values less than 0.35) at the location of the sensor, while decreasing the frequency of detectable glare (DGPs values exceeding 0.35). Occupants located at other depths besides where the sensor(s) is located will be impacted differently.

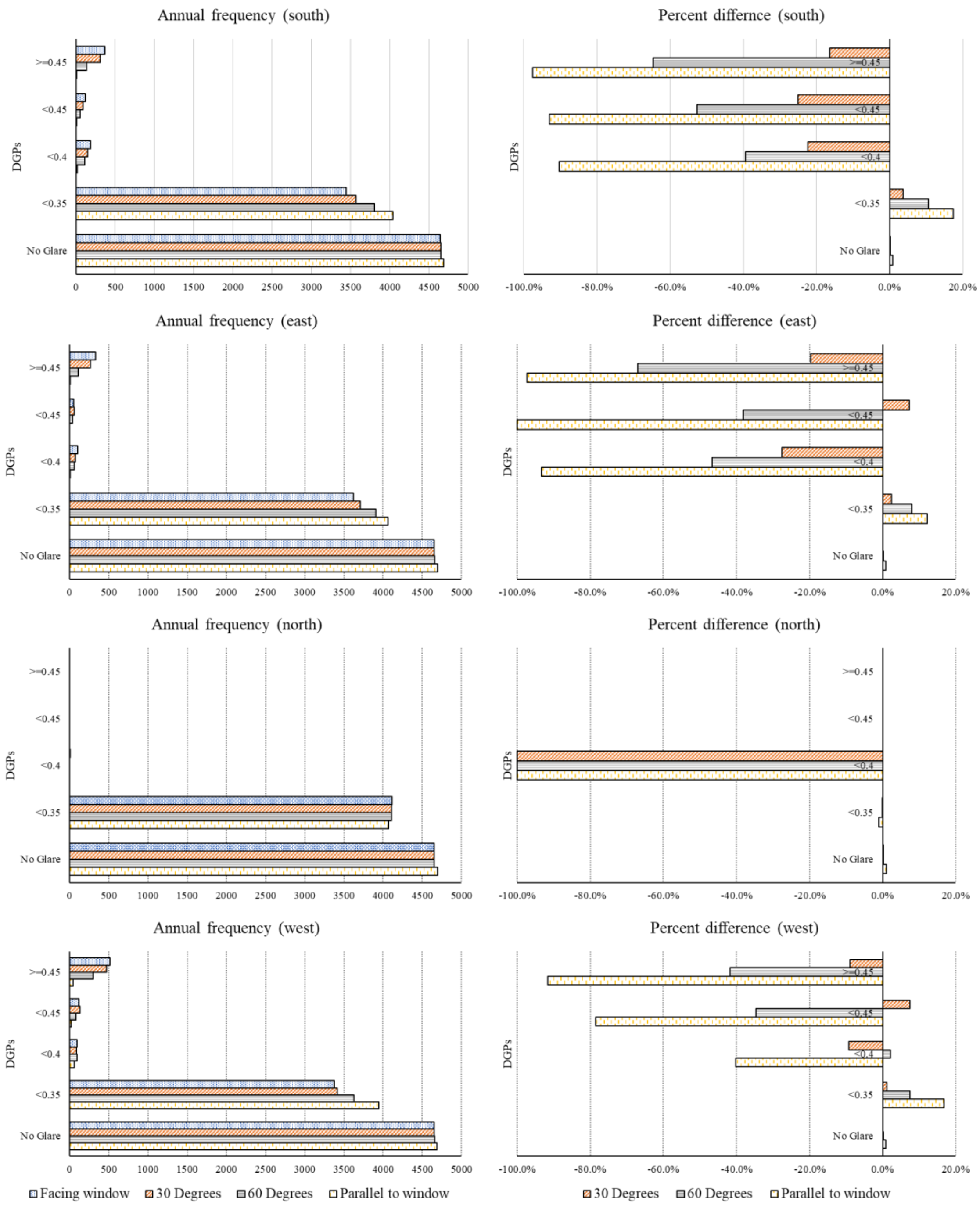


Figure 11. Annual DGPs frequencies at different sensor orientations (left), and changes (%) in DGPs as compared to sensor facing the windows (baseline case) (right); each row of figures shows one perimeter zone orientation (south, east, north, west).

Based on the changes in sensor location and orientation, the shade operation pattern also changes, as shown in Figure 12 and Figure 13. These show daily shade position operations on a scale of zero to ten, where 0 (light green) indicates the shade is fully open and 10 (grey) indicates the shade is fully closed. During occupied times, the shade tends to stay open more, per the specified control scheme, to allow more daylight to enter the space. When the illuminance sensor is moved further from the exterior window or turned away from the window, all perimeter zones increase the amount of time that shades are raised. One exception is the north zone since this zone does not have significant daylight.

The south, east, and west zones are most impacted by sensor placement. Compared with a sensor distance of 1.6 m, moving the sensor location to 2.4 m decreases the number of hours for closing the shade, which is shown in the figures as more hours of green color. For a sensor location of 4.9 m, the shading is more in the open position in the south, east, and west zones, which results in more natural light entering the zones compared to the amount of natural daylight if the sensor location is at 1.6 m. Comparing sensor location results with sensor rotation, changing location has more impact on the shading operation than rotation until a certain rotation degree is achieved. In this case, more hours of lowering the shade can be seen for 30- and 60-degree sensor rotations as compared to increasing the distance from the window to 2.4 m and 3.6 m. The shade operation patterns are similar when comparing the sensor location at 4.9 m with rotation parallel to the window. In other words, if the sensor distance from the exterior window is increased or the sensor is rotated away from the window, people sitting near the windows experience more glare and incoming daylight due to opening shade. Previous studies point out that productivity can improve by 5-15% in companies moving into buildings with more daylight (Romm 2014; Thayer 1995).

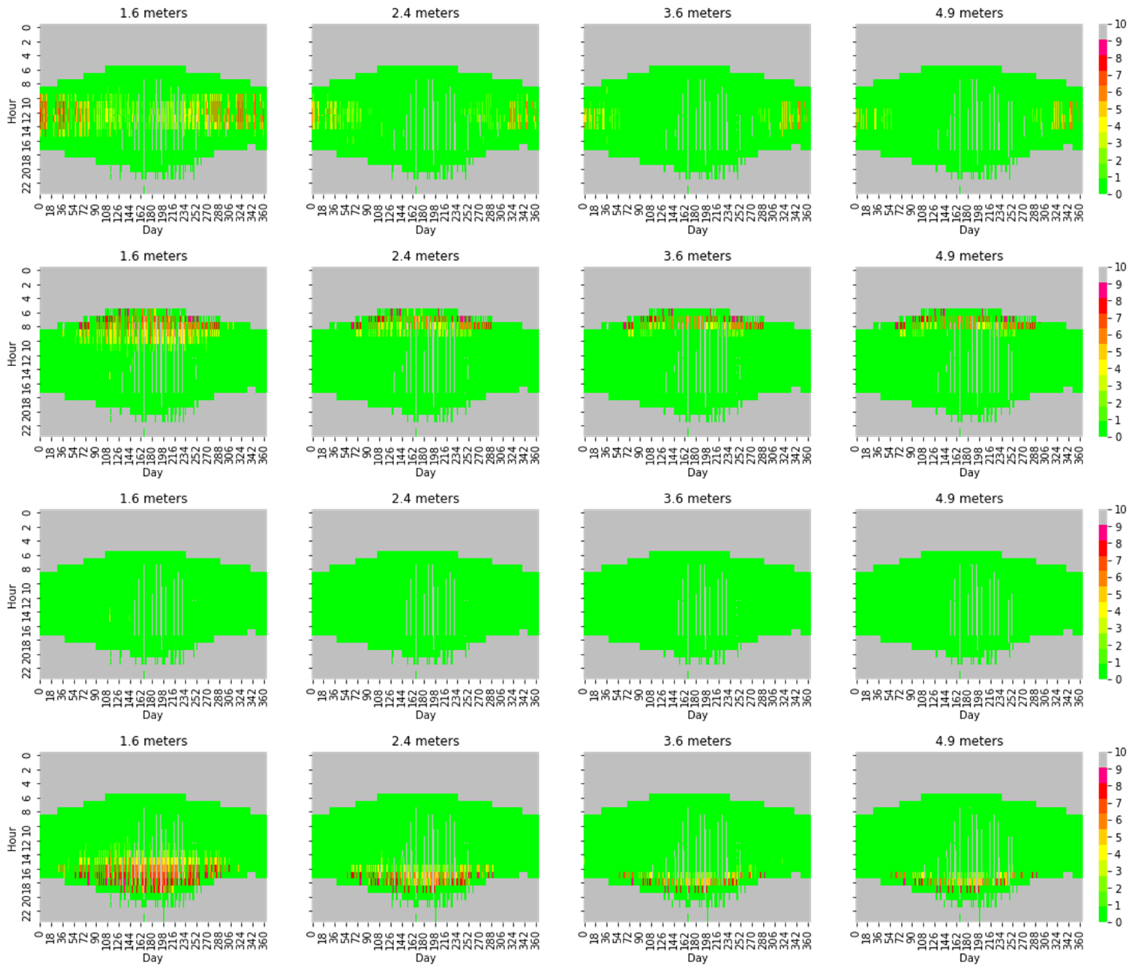


Figure 12. Daily shade position for sensor locations (From the top: south, east, north, and west zones). *Note: shade position 0 = open; 10 = closed.*

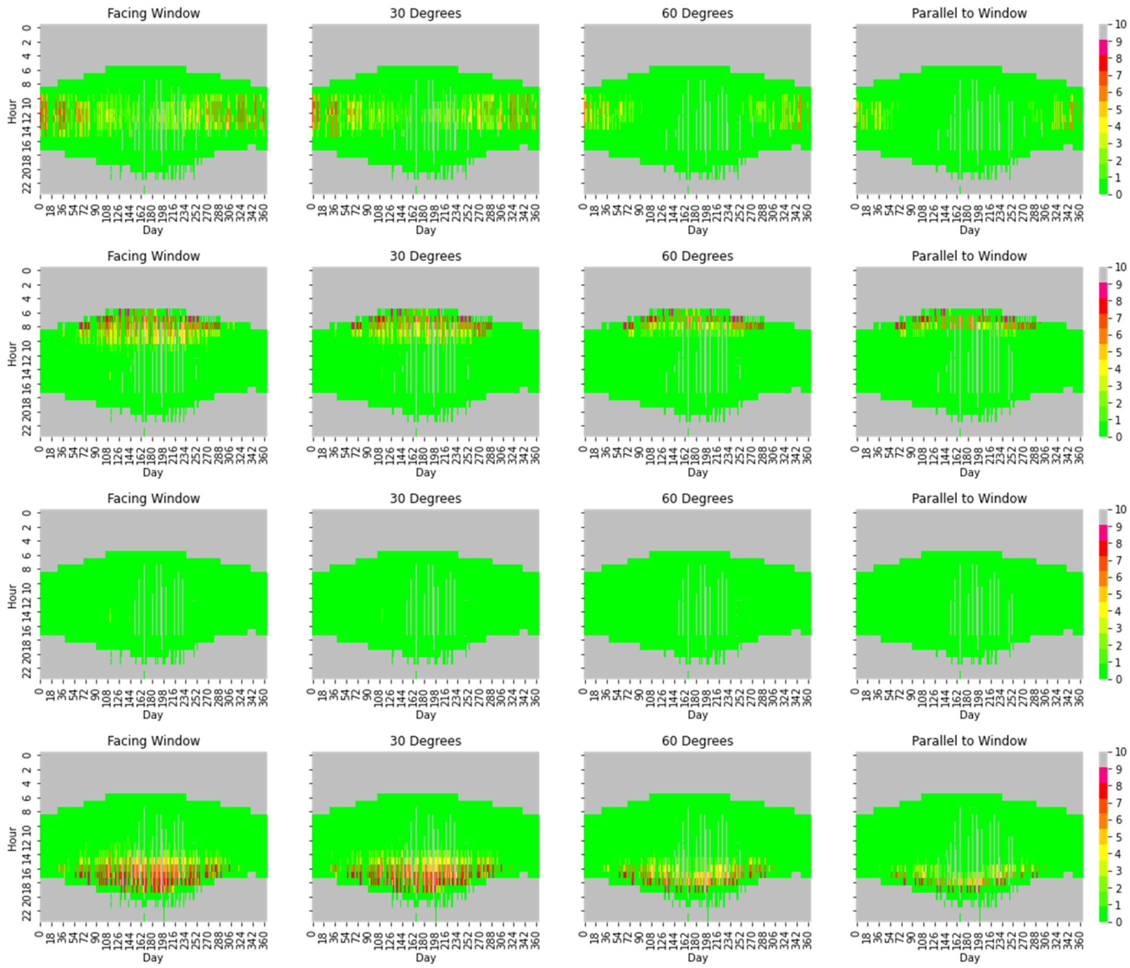


Figure 13. Daily shade position for sensor rotations. (From the top: south, east, north, and west zones). *Note: shade position 0 = open; 10 = closed.*

If the sensors are closer to the windows, then the shade positions are also likely to change more frequently based on previous results Figure 12 and 13, particularly in the south zone throughout the day (47%), the east zone in the morning (35%), and west zone in the afternoon (35%) along with north zone the lowest 10%, as shown in Figure 14. Selecting the appropriate sensor location will help to reduce the frequency of adjusting shade positions and cause less disturbance to occupants. In addition, the shade position controls could also be adjusted to be less sensitive. Based on previous research, if shading is not automated, occupants would likely keep the shade positions to a particular level, then leave this in the same position regardless of illuminance level (Ding et al. 2020). Placing the sensors' location from 1.6 m to 2.4 m and 4.9 m will reduce 13% to 21% of shade operation frequencies during fully occupied time (9am to 5pm) for the south, east, and west zones. The north zone is not impacted since shade operation is not significantly affected by daylight. Similarly, rotating the sensor away from the window achieves the same effect as placing the sensor further inside the zone.

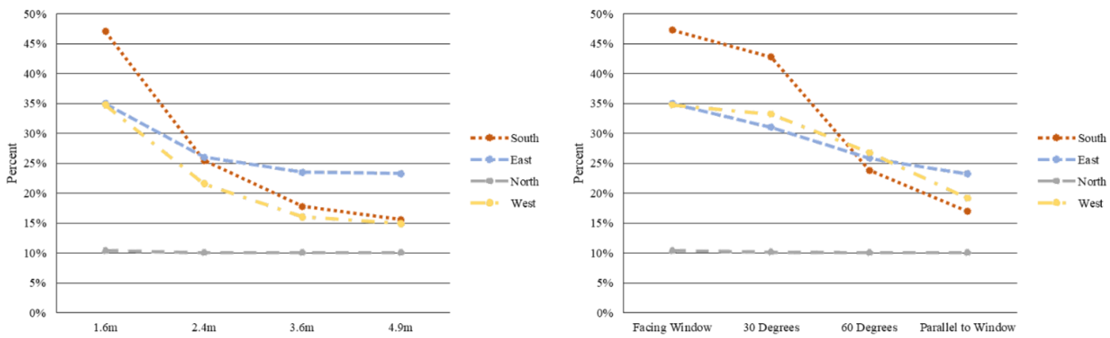


Figure 14. Occupied time (9AM to 5PM) annual shade operation frequency probability (Left: sensor location; right: sensor rotation).

For daily energy demand (kW), the summer solstice day (June 21st) is selected to reflect how much lighting and cooling energy is required each hour of the day for the four perimeter zones at climate zone 5A (cool humid) (Figure 15 and 16). These results are similar to that of other summer days in terms of pattern.

Regarding sensitivity to sensor distance away from the windows shown in Figure 15, the lowest lighting and cooling demands occur at a sensor location of 1.6 m. Peak use of demand mostly happens from 7 AM to 9 PM. When the sensor is placed at 1.6 m from the exterior window, the shading is generally lowered more than when placed deeper into the zone. Because the sensor is closer to the exterior window, this area generally receives more natural light detected by the horizontal work plane illuminance sensor during the day. However, the shading may not be fully closed at this placement location, so there may still be natural light entering the zone. If the shade is fully closed, the shading is not completely opaque and thus will allow some natural light. If this occurs, the horizontal sensor may still detect light either from the natural light transmitted or reflectance from the wall, resulting in reducing the artificial lighting used and its emitted heat into the zone. For maximum case, sensor location at 4.9 m, the peak use of lighting demand is increased to 0.22 kW (38%) in the south zone, 0.16 kW (71%) in the east zone, 0.26 kW (63%) in the north zone, and 0.18 kW (84%) in the west zone; the peak use of cooling demand is increased by 0.08 kW (2%) in south zone, 0.32 kW (9%) in the east zone, and 0.42 kW (14%) in the north zone. In the west zone, the cooling demand is decreased by 0.57 kW (17%), likely due to fewer occupants and shade operation to prevent excessive solar heat. For certain hours, areas farther away from the window require more lighting than the areas near the window, thus increasing the demand for lighting and resulting in increased lighting energy needs. Increasing lighting also creates more internal loads, which results in increased cooling needs. In addition, since increasing sensor distance from the exterior window causes the shading to be open more, more cooling energy is needed to offset the temperature increase due to solar radiation through the windows.

For sensor rotation (Figure 16), there is a more minimal impact on energy demands for lighting and cooling as compared to sensor distance. The cooling hourly energy demand is essentially the same, with only minor changes. Lighting energy is also not significantly impacted, with only slight changes seen in demand across each hour evaluated. Slightly less lighting is needed during the day for certain hours because the sensor may receive direct daylight or reflectance from the interior wall, especially for the east and west zones, which could cause cumulative lighting and cooling savings throughout the year.

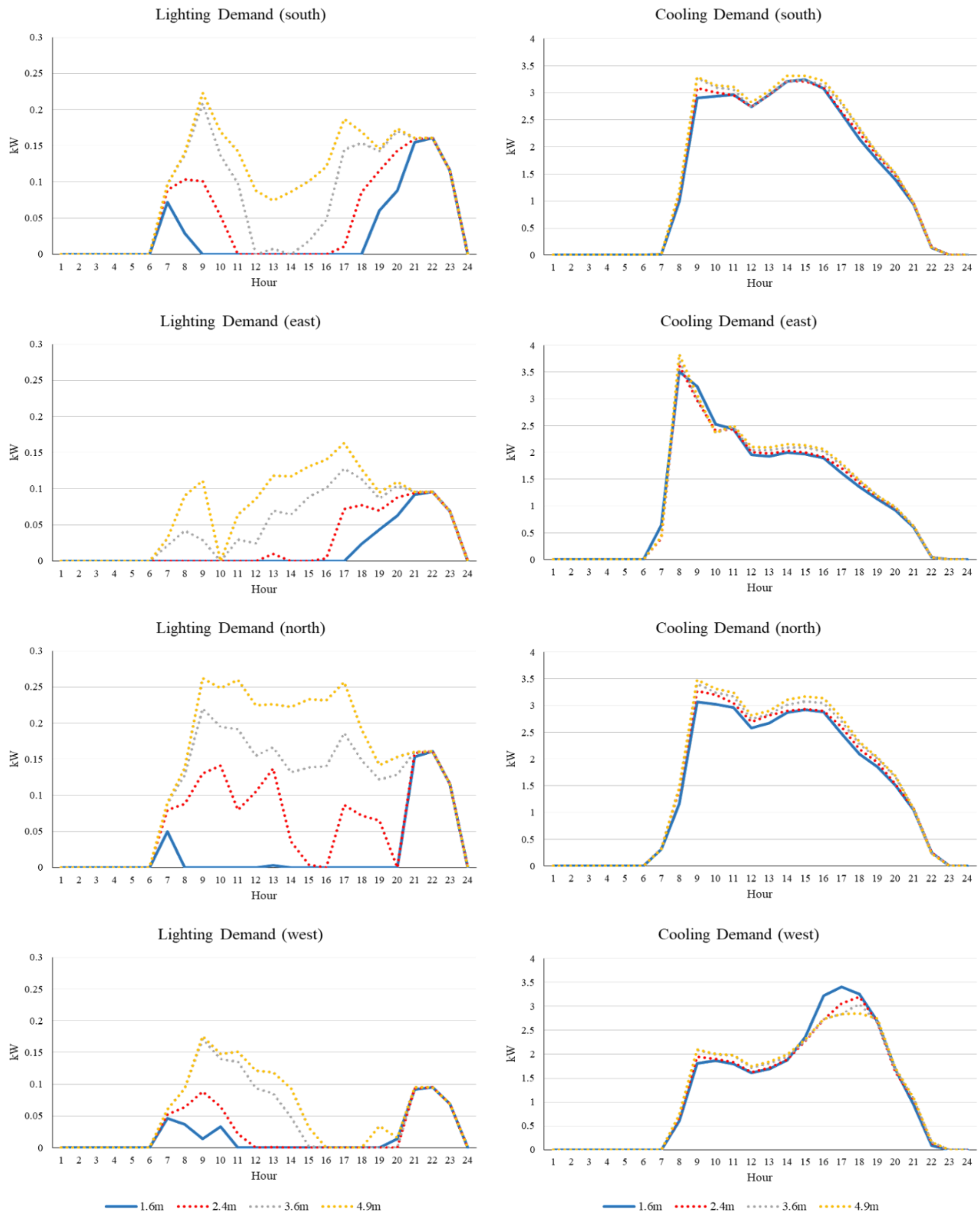


Figure 15. Summer solstice lighting (left) and cooling (right) energy demand based on sensor distance from the exterior window, for each perimeter zone (from the top: south, east, north, west).

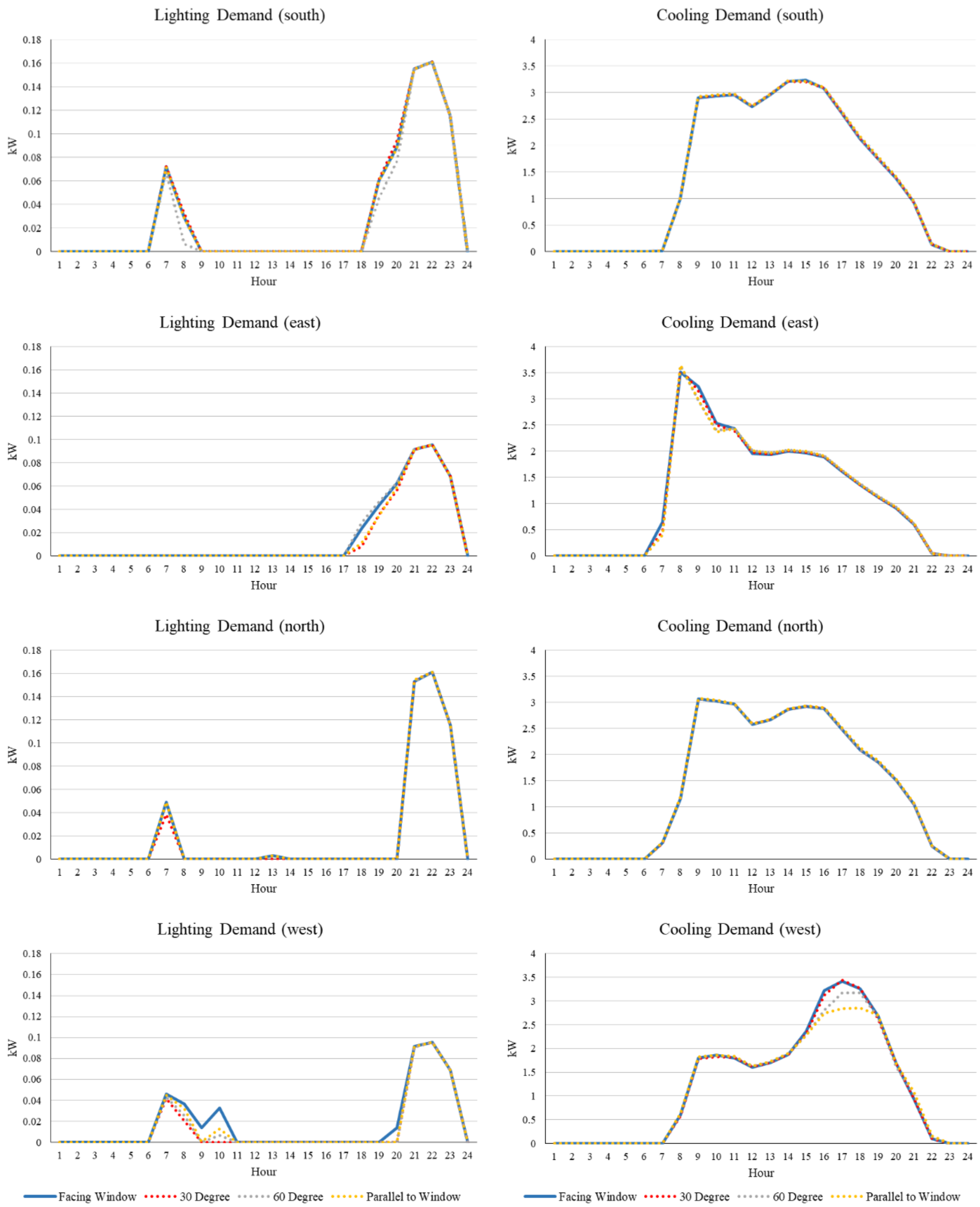


Figure 16. Summer solstice lighting (left) and cooling (right) energy demand based on sensor orientation, for each perimeter zone (from the top: south, east, north, west).

Based on simulating energy use throughout the entire year, placing the sensors farther away from the exterior windows increases lighting energy use by an average of 34% at 2.4 m for the south, east, and west zones as shown in Table 4. For the north zone, 73% more lighting energy is needed at 2.4 m (same for south zone at 3.6 m), and more than double lighting energy consumed at 3.6 m and 4.9 m compared with 1.6 m (same for the east and west zones). This also increases the annual cooling energy use in all four zones, as shown in Table 5 and 6, by 1.4-13.4% (maximum for north) and summer cooling demand up to 2.6-11.2% (maximum for north) due to more lighting use and open shades. Based on these results, the sensor location at 1.6 m results in overall less energy and demand requirements as compared to other locations, for this climate zone. For sensor rotation, as compared to facing the window, 30 degrees results in the lowest lighting energy use in the east (-3.9%) and west (-8.4%) zones because of sensor receiving more daylight as mentioned previously. For certain rotations, including 30 degrees in the south zone, 60 degrees in the west zone and parallel to window in the north zone increases the lighting energy use as compared to facing the window because the sensor may face the corner of the zone where less daylight is received by the sensor. And sensor rotation parallel to window results in the lower cooling energy for east (-0.8%) and west (-2.4%) zones, and summer cooling demand for east (-0.6%) and west (-1.7%) zones due to cumulative less lighting needed which sensor receives direct daylight or reflectance from the interior wall. There is less impact on annual lighting, annual cooling energy uses and summer cooling demand for sensor rotation compared to sensor distance from the window.

Table 4. Annual lighting energy use (kWh) change (%) by sensor distance from the exterior windows and rotation compared to a baseline of 1.6 m facing the windows.

Zone	2.4 m	3.6 m	4.9 m	30 Degrees	60 Degrees	Parallel to Window
South	34.3%	72.3%	85.7%	1.8%	-3.9%	0.0%
East	37.5%	90.7%	113.4%	-3.9%	1.8%	-2.8%
North	73.3%	115.7%	141.6%	-0.8%	-2.9%	6.2%
West	30.5%	90.7%	100.3%	-8.4%	-6.2%	-3.1%

Table 5. Annual cooling energy use (kWh) change (%) by sensor distance from the exterior windows and rotation compared to baseline of 1.6 m facing the windows.

Zone	2.4 m	3.6 m	4.9 m	30 Degrees	60 Degrees	Parallel to Window
South	1.1%	3.6%	5.0%	0.0%	-0.7%	-0.4%
East	0.7%	3.7%	5.8%	-0.4%	-0.6%	-0.8%
North	5.6%	10.4%	13.4%	0.0%	0.5%	1.1%
West	-1.3%	0.8%	1.4%	-0.7%	-1.7%	-2.4%

Table 6. Summer cooling demand (kW) percent change (%) by sensor distance from the exterior windows and rotation compared to baseline of 1.6 m facing the windows.

Zone	2.4 m	3.6 m	4.9 m	30 Degrees	60 Degrees	Parallel to Window
South	1.8%	4.4%	5.8%	0.1%	0.0%	0.4%
East	0.9%	3.5%	5.2%	-0.3%	-0.4%	-0.6%
North	4.4%	8.6%	11.2%	0.1%	0.5%	1.0%
West	-0.2%	2.0%	2.6%	-0.5%	-1.2%	-1.7%

2.4. Conclusions

This study focuses on assessing the impact of sensor placement in a small commercial office building on illuminance, DGPs, shade operations, energy demand, and annual energy use in each perimeter zone. Sensitivity analysis has also been conducted at the building level to assess the magnitude of buildings in different ASHRAE climate zones. The key findings are as follows:

- Compared to the baseline model, for the energy efficient model that implements shading and lighting controls, energy savings originate more from lighting (18,230 kWh, 84%; 18,222 kWh, 84%) for colder climate zones 6A (cold humid) and 6B (cold dry), and combined cooling and lighting (31,960 kWh, 41%; 27,878 kWh, 47%) for hotter climate zones 2A (hot humid) and 2B (hot dry). The cooling and lighting energy savings range from 41-71% (minimum savings from CZ 6B and maximum savings from CZ 2A) using a sensor location at 1.6 m and rotation facing window.
- For demand reduction of peak use (7 am to 9 pm), the greatest cooling demand saving is from CZ 2A and the least from CZ 4B, where the lighting demand reduction of 3.5 kW (64%) is similar for all climate zones. The cooling demand savings range from 21-26%

(5.5-6.5 kW) across climate zones, and combined cooling and lighting demand reduction ranges from 28-33% (minimum reduction is 9 kW in CZ 4B and maximum reduction is 10 kW in CZ 2A).

- The measured vertical and work plane illuminance are more sensitive to sensor distance from the exterior window at closer distances to the exterior window as compared to farther away for all zones. For sensor rotation, small degrees of rotation (30 degrees and less) appear to impact the sensed illuminance values less than larger angles. A sensor location of 4.9 m (farthest from the window) or rotation parallel to the exterior window results in the lowest detected illuminance values throughout the day.
- Placing the sensor(s) further from the windows or rotating away from the exterior window at chosen locations will result in increasing detected occurrence of no glare and imperceptible glare (DGPs values less than 0.35) at the location of the sensor while decreasing detected frequency of glare (DGPs values exceeding 0.35). Placing the sensor(s) at 4.9 m from the exterior windows, as chosen in this study, results in no glare detected at this location, except in the east and west zones. 30 and 60 degrees increase perceptible and disturbing glares detected in east and west zones. However, since occupants can be in other locations besides the chosen sensor location, glare may still be present at locations closer to the exterior windows.
- Occupants sitting near the exterior window will see more glare and be exposed directly to the incoming daylight if the sensor distance is increased or rotated away from the window because the shading is increasingly open. Placing the sensors further or rotating the sensors away from the window reduces the shade operation frequency by 13% to 21% during fully

occupied times from 9 AM to 5 PM in the south, east, and west zones. There is no notable difference in the north zone.

- Placing the sensors at 4.9 m (farthest away) from the window increases the peak use (7 AM to 9 PM) by 38%-84% (most in west zone) and 2-14% (most in north zone) for lighting and cooling demands respectively, on the summer solstice day for CZ 5A (cool humid). The increase in cooling demand is mostly due to heat from lighting and radiation transmitted through the open shades. Placing the sensors nearer to the window at 1.6 m reduces peak use of lighting demand by half and summer cooling demand by 2.6-11.2% in perimeter zones.
- Placing the vertical illuminance sensor rotation parallel to the window results in lower cooling energy use (0.8%, 2.4%) and summer cooling demand (0.6%, 1.7%) for the east and west zones due to receiving more direct daylight or reflectance from the interior wall compared with facing window for CZ 5A. Sensor rotation has less impact on annual lighting, annual cooling energy use, and summer cooling demand compared to sensor distance.

2.5. Limitations and future works

There are several limitations of this study. The vertical illuminance sensor used in each zone was rotated in one direction. This could also be compared in both directions in the 180-degree horizontal plane to determine if there is any differential impact. Simplified DGP was used to compare the glare from daylight. Moving forward, given consideration of the complexity of shading control, in which this study does not vary shade position based on glare prediction, more factors can be used, such as visual privacy, view to the outside, and precise glare prediction due to the low accuracy of DGP at certain circumstances (Kent and Jakubiec 2021). For climate zones, including more climate zone locations could provide a more comprehensive understanding of the impacts of the proposed controls scheme and sensor placement changes on the energy performance of commercial buildings across the U.S. Future studies could also consider evaluating how indoor thermal comfort level is affected by adjusting sensor placements and the proposed energy model.

2.6. Acknowledgments

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CHAPTER 3: SOCIOECONOMIC FACTORS INFLUENCING RESIDENTIAL OCCUPANCY TRENDS DURING AND POST-COVID PANDEMIC

"Submitted in Science and Technology for the Built Environment"

3.1. Introduction

Due to the outbreak of Coronavirus 2019 (COVID-19), the World Health Organization (WHO) declared a global pandemic in March 2020, marking a global shift in lifestyle due to this long-term public health emergency (Cucinotta and Vanelli 2020). As of December 2023, there have been over 7 million reported deaths due to COVID-19 globally and 1.1 million in the United States (WHO 2023). Travel restrictions and health safety measures implemented in 2020 were still in effect in many places in early 2023 (CDC 2023). However, in May 2023, WHO declared COVID-19 was no longer a global health emergency but still a health threat. This 2020-2023 period marks a significant change compared to pre-pandemic life.

Due to the strict measures and lockdowns in 2020 in particular, residential electricity demand and resulting emissions increased, while overall annual electricity demand on the electric grid decreased in countries like China and the U.S. (IEA 2020). People spent more time at home, while other grid-impacting sectors, particularly commercial buildings, were being used less (Balemi et al. 2021). This has continued to be the case since 2020. January 2024 reports note that office building vacancies throughout the U.S. were at their highest since 1979 (Putzier 2024). Other research suggests that residential building use has continued to increase, including 8% higher electricity operational costs after adjusting for inflation (U.S. EIA 2023). These findings suggest that it is also important to note that despite reductions in residential energy consumption per capita due to increased energy efficiency, factors such as the occurrence of a pandemic can dominate such improvements in terms of the relative impact on the overall electric grid, emissions, and total energy use (Anand 2023; Jiang et al. 2021; Moutuzienė et al. 2022).

Conventional methods to improve energy efficiency can also ignore the complexities of households' roles (O'neill and Chen 2002) in which the savings can be offset by demographic changes such as income and age (Brounen et al. 2012). As such, other factors in addition to efficiency, including occupancy and activity schedules, are critical components that can help to describe homes' energy use patterns and behaviors. Future projections of shifts in lifestyle patterns such as hybrid and work-from-home options continue to be made in the wake of the pandemic (Gagné et al. 2022), however, a consensus on which changes to people's lifestyles will be permanent versus return to pre-pandemic "normalcy" are still somewhat unclear.

Occupant behavior in buildings can be defined as the presence and actions of occupants that can impact the building's environmental conditions and energy consumption (Yan and Hong 2018). Occupants' presence creates both latent and sensible heat in space; their behavior, such as opening/closing windows, turning on/off lights, and using appliances, also impacts total internal loads (Yang et al. 2016) and the need for heating and air conditioning. However, while many studies focus on building envelopes and energy systems, less attention is given to human-related factors such as building operation and maintenance, indoor environmental quality, and especially occupants' behavior (Yoshino et al. 2017; Hong et al. 2017). A limited number of studies have considered such impacts on occupant behavior. During the start of shelter-in-place orders in March of 2020 in California, Zanocco et al (2021) found a significant spike in occupancy was observed for homes with minors, higher income occupants, and/or individuals with a bachelor's degree or higher. By contrast, fewer changes were observed in occupancy among smaller households, single-family units, and young individuals. Recent research (e.g. Mitra et al. 2022) suggests that the time spent at home in the U.S. increased 1.2 to 1.9 hours per household in 2020 in office and kitchen spaces for households with 2 or more members. However, no research has looked at multi-year longer terms trends of occupancy in the U.S. in the wake of the pandemic, nor has such research included consideration of how socioeconomic factors may influences such trends and changes.

Other research on the impact of socioeconomic and demographic factors on residential energy consumption also points to the need for further information on post-pandemic occupancy, particularly as they relate to energy equity and energy justice. Household (demographics, socioeconomic factors) and housing (size, age, type, ownership, duration of residence) characteristics have been found to have significant effects on per-capita residential energy use in the U.S. (Estiri 2015; O'neill and Chen 2002; Palani et al. 2023; Ramírez-Mendiola et al. 2017). Analysis of Census data has shown that low-income, African American, and Hispanic households were highly correlated with high energy use intensity (EUI), especially heating (Bednar et al. 2017). In addition, energy accessibility has been a long-term issue and unevenly distributed in the U.S., primarily affecting low-income, racial/ethnic minority households (Lewis et al. 2020). The pandemic has also worsened the housing energy burden in low-income, African American, and Hispanic households, as well as households requiring medical devices or having young children (Memmott et al., 2021). One case study found that working from home could increase annual residential household utilities in the city of Phoenix, Arizona, by $1,100 per household (Anand 2023). It also found that shifting to working from home compared with the pre-pandemic level increased utility bill costs up to 60%. However, various demographic and socioeconomic characteristics restrict the flexibility of working from home. For instance, only 28.6% of lower-wage workers can telecommute compared with 67.9% of higher-wage workers; this gap is even larger when comparing education levels (Yasenov 2020). These studies further emphasize the importance of not generalizing findings using averages across the entire U.S. population. Rather, they suggest the importance of understanding if there are significant social factors influencing residential building use and the implications of this moving forward.

This study aims to understand how, during (2020) and in the post-pandemic (2021 and 2022) periods, occupancy patterns in residential buildings have changed. This is accomplished using American Time Use Survey (ATUS) data from 2018 to 2022, including socioeconomic factors and time use data translated into residential occupancy data. Specifically, it seeks to understand changes in the amount of time spent at home, and when this time occurs, and which factors most greatly influence such values. It also seeks to understand trends in occupancy patterns to understand which populations have arrived at a post pandemic "normal" which others are still several years out from stabilizing household occupancy patterns to the minimal variations seem across years pre-pandemic.

The remainder of this research is organized as follows. The methodology details the use of ATUS data and how the socioeconomic variables are selected along with results generated for the profiles at home. The results section presents the relationship of selected socioeconomic variables with hours at home, average hours, daily profiles across different socioeconomics, as well as the use of specific areas within homes. The conclusion section summaries the significant findings, as well as limitations and future work to extend this research further.

3.2. Methodology

In this research, first, American Time Use Survey (ATUS) data from 2018 to 2022 was converted into home occupancy data. At the time of this research, 2022 was the most recently available ATUS data available for use, as the ATUS data is made publicly available approximately 6 months after the end of the prior year. Next, socioeconomic variables were selected using the correlation method. Next, selected variables were tested using regression analysis to determine the significance level in predicting time spent at home. The following summarizes the datasets used, socioeconomic factors selected, and the analysis method of such data.

3.2.1. American Time Use Survey Data

The use of time-use survey (TUS) data collected using various methods across many countries has been used for generating information on people's behavioral patterns in buildings (Collins et al. 2021; Mitra et al. 2021; Mitra et al. 2022; Mo and Zhao 2022; Song and Gao 2020). The American Time Use Survey (ATUS) data has been collected annually since 2003 by the U.S. Bureau of Labor Statistics (BLS) and includes data for the U.S. population. Starting in 2006, the same data collection and methods that are still in use today have been used. The sampling method used is meant to produce a statistically representative sample of the U.S. via the use of weighting factors (BLS 2023). ATUS data is collected via in-person, phone calls and mail interviews to include information on how people in the U.S. spend their time over a typical day (24-hour period); it includes data collection for all days of the week and months of the year. Demographic and socioeconomic information, such as age, household income, and the activities the participants have participated in are then compiled. This data is subdivided into six files made publicly available annually. The ATUS data is also linked to the Current Population Survey (CPS) data, as some CPS participants also participate in the ATUS data collection (U.S. Census Bureau and U.S. BLS 2023). This data provides the labor force statistics for the U.S. population.

When downloading ATUS data, a folder of data files is provided for each year. Within these data files, the following files have been used in this research: "Respondent", "Roster", "Activity", "ATUS-CPS" and "Who", each of which contains different information on the participants. All data files are linked together via the household identification number

(TUCASEID), which is present in all files for each year of data. The “Respondent” file has only one record of each ATUS respondents; the “Roster” file includes age, gender, and relationship to the survey respondent for all other household members. The “ATUS-CPS” provides additional socioeconomic information for all people involved in ATUS, as provided by the linked CPS dataset (BLS 2023; Census Bureau 2023). The “Activity” file includes a set of activity codes for each participant, associated with a set of timestamped periods, location during each activity, and duration of the activity. The “Who” file contains information on if the respondent and/or others in the household are present during the activity. The sizes of the ATUS dataset for the past five years, from 2018 to 2022, are shown in Table 7.

Table 7. Characteristics of ATUS data for recent years.

Year	Households (people)	Recorded Activities
2018	9,594 (65,501)	184,103
2019	9,436 (64,285)	182,980
2020	8,782 (64,783)	155,109
2021	9,087 (63,645)	164,581
2022	8,136 (62,896)	146,393

3.2.2. ATUS and CPS socioeconomic factors considered

In total, across the variables that are available for use within the ATUS data, 14 socioeconomic variables and 1 time variable (time of the week) (Table 8) were considered for use in this study. These socioeconomic variables include age, gender, employment status, employment status of spouse, high school/college enrollment status, enrollment level, highest education level, marital status, income (annual), household sizes, number of children, race, ethnicity, and house tenure (own or rent). These variables are considered in related studies (Bednar et al. 2017, Estiri 2015, Lewis et al. 2020, Memmott et al. 2021, O'Neill and Chen 2002, Palani et al. 2023, Ramírez-Mendiola et al. 2017). Overall, as these studies discussed, such variables have strong potential for connections with energy use and behaviors. The statistical weight of data (TUFINLWGT) was also used, following the guidance from the US BLS reference documents, to ensure each participant's data reflects the appropriate portion of the U.S. population. Therefore, the results discussed in later sections can effectively represent the U.S. population.

Table 8. Selected variables and meanings from the American Time Use Survey (ATUS).

Variables	Meaning
TUCASEID	Respondent individual (identification code)
TUFINLWGT	Weight of the data
TEAGE	Age
TESEX	Gender
TELFS	Employment status
TESPEMPNOT	Employment status of spouse or unmarried partner
TESCHENR	High school/college enrollment status
TESCHLVL	High school/college or university enrolled level
PEEDUCA	Highest level of education degree received
PEMARITL	Marital status
HEFAMINC	Household income (annual)
TRNUMHOU	Family size
TRCHILDNUM	Number of children younger than 18
PTDTRACE	Race
PEHSPNON	Hispanic/non-Hispanic
HETENURE	House tenure (own or rent)
WEEKEND	Weekday or weekend
TEWHERE	Location
TRCODE	Activity

3.2.3. Calculating Occupancy based on ATUS and CPS

To determine the amount of time spent at home, this was calculated based on first converting the activity reported as located in a residential building based on the TEWHERE variable. For all entries in which the location was in a home, a "1" was used, while a "0" was used when reporting being elsewhere. If no location was reported, the previous timestep's location was used. The total hours at home were then calculated by summing the time spent during all activities at home, i.e., where a "1" was used to define that activity's location as being in a home. Average total hours at home on weekdays or weekends were weighted average values to represent the hours spent at home for the U.S. The occupancy fraction was then calculated as the percentage of the total time spent at home and plotted over a 24-hour period.

3.2.4. Socioeconomic groups and data segmentation for analysis

Among the socioeconomic variables considered, several adjustments were made to the representation of the variables including age, income level, and household size for ease of analysis. For age, the analysis the ATUS age code (TEAGE) was used to divide the participants into five groups: <25, 25-35, 35-45, 45-55, 55-65, 65-75, and 75+, to be consistent with methods used in related research (Unnikrishnan and Figliozzi 2020; Mitra et al 2021). Second, income level (HEFAMINC) was defined in three groups: low, middle, and high. This is determined based on household size (HRNUMHOU), as shown in Table 9, by considering the average thresholds of federal poverty guidelines for different household sizes from the past five years, from 2018-2022 (HHS 2023). Finally, for household size, since 90% of households were either 1-, 2-, 3- or 4-member households, the 5+ member households were not included since the total number of household members varied across all households in this category (U.S. Census 2023). Other variables were assigned integer numbers and were able to be grouped without modifications, including gender, employment status, employment status of spouse or unmarried couples, high school/college enrollment, enrollment level, highest education level received, marital status, number of children, race, Hispanic/non-Hispanic, and house tenure.

Table 9. Household sizes and corresponding income levels define categorization as low-, middle-, or high-income ranges.

Household member #	Annual income range (low; middle; high)
1	<$15,000; $15,000-$60,000 >$75,000
2	<$20,000; $20,000-$100,000; >$100,000
3	<$25,000; $25,000-$150,000; >$150,000
4	<$30,000; $30,000-$150,000; >$150,000

3.2.5. Variable Correlation & Regression Analysis

Statistical analysis methods were then used to identify the variables that were the most significant predictors of occupancy. First, across the 14 socioeconomic variables considered, the Pearson correlation method was used to assess how closely related each variable was to one another. Pearson correlation values range from -1 to 1, where the absolute value of 0 to 0.3 was considered uncorrelated, low correlation from 0.3 to 0.5, moderate correlation from 0.5 to 0.8, and high correlation 0.8 to 1. When a correlation coefficient was 0.8 or higher, one of the two variables was eliminated (Guo et al., 2023), thus leaving a set of variables without high levels of correlation for the next steps in the analysis.

Regression analysis methods (Hothorn et al. 2022) in R (Version 0.9-34, R Core Team 2023) were then used to determine the significance level of each considered variable on time spent at home. This method tested the null hypothesis, which signifies relations between the fitted regression model's predictor and response variable. To differentiate the significance level, the p-value was set as above 0.001 (99.9% confidence level), but also evaluated at other levels of significance. The selected recorded socioeconomic variables were chosen using the backward selection or elimination regression method, which iteratively selected the most contributory variables to the results (Barrett and Gray 1994, Al-Subaihi 2002). The final variables were significant variables impacting time spent at home.

The resulting coefficients for the variables in the model are either negative or positive. A positive coefficient indicates an increase in the time spent at home with the dependent variable; similarly, a negative coefficient indicates a decrease in the time spent at home with an increase in the dependent variable. The coefficient also helps to measure the strength of the impact of a change in the variable, in which a larger absolute value means a larger impact and a smaller value suggests a lesser impact.

3.3. Results and discussion

3.3.1. Changes in time spent by location

Using the ATUS data classification, people can be considered as indoors, outdoors, in transit via some form of transportation, and unknown (including non-reported locations). Prior to analysis of time spent at home, it is helpful to first understand the over location trends. As shown in Figure 17, prior to the pandemic people spent approximately 94% of their time in indoor locations, 0.7-0.9% outdoors, and 5.0-5.2% in some form of transportation. During the pandemic (2020), time spent in indoor spaces increased by 1.3%, to 95.3%, while time in transportation decreased to 3.7%, thus time spent indoors went up by approximately the amount of time participants previously spent in transportation. This trend makes sense since many people worked from home during the pandemic and did not commute and thus did not spend time in various modes of transportation as frequently. Furthermore, there was also a surge in the adoption of virtual processes, including e-commerce, food delivery, and streaming services, particularly for remote meetings and entertainment supporting working and schooling remotely (Auxier and Anderson 2020; De' et al. 2020; Wang et al. 2021).

Interestingly there was also a slight increase of time spent outdoors in 2020 which may indicate people were tired of being in their homes but unable to go to indoor places with other people due to social distancing restrictions, so instead they spent this time outdoors (Wagner 2022). This approximately 1% of time spent outdoors has continued to be the same in 2021 and 2022, suggesting that this slightly higher level of time spent outdoors may remain at this level in future years. Given that wellbeing has been linked to time spent outdoors (e.g. Sadick and Kamardeen

2020, Leobach et al. 2022), and that there has been an increased focus on workplace wellbeing in the post-pandemic periods (Business Group on Health, 2022), such a trend appears to make sense.

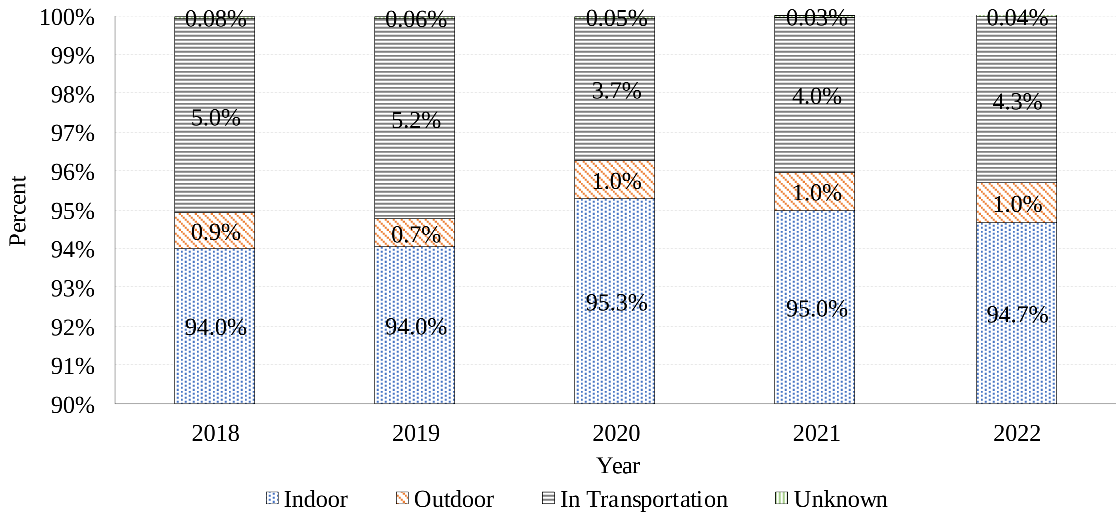


Figure 17. Annual time spent (%) based on location, using ATUS data from 2018-2022.

Another trend observed is that in 2021 and 2022, compared to 2020, the 1% uptick that occurred in time spent indoors decreased by 0.3% per year, slowing being replaced again by time spent in transportation. Based on these trends, it appears that changes in time spent indoors versus in transportation have not yet found a leveling point and continue to change. Analysis of 2023 data would help to understand if this change has continued or is beginning to level off.

3.3.2. Changes in time spent at home

Next, the average amount of time per day that people spent at home each year from 2006 to 2022 is investigated to evaluate how this trend has changed over time, including on both weekdays and weekends (Figure 18). From 2006 to 2019, the average time remained nearly constant, at 17.1 ± 0.14 hours on weekdays and 19.4 ± 0.24 hours on weekends. However, in 2020, this average increased by 1.8 hours on weekdays (18.9 hours total) and 1.4 hours more on weekends (20.8 hours total) at home respectively compared to the pre COVID-19 period. In 2021, the time spent at home decreased by 12 minutes on weekdays and 24 minutes on weekends. During this time lockdowns and restrictions were loosened, as the first vaccines were produced and began to be administered (FDA 2020). By 2022, the decrease in time spent at home dropped by 42 minutes on weekdays and 36 minutes on weekends, compared to 2020. However, this average time at home did not return to pre-pandemic levels in 2021 and 2022. Time at home has continued to decrease, but in 2022, it still remains 1.1 hours more per day on weekdays and 48 minutes more per day on weekends than the averages before the pandemic.

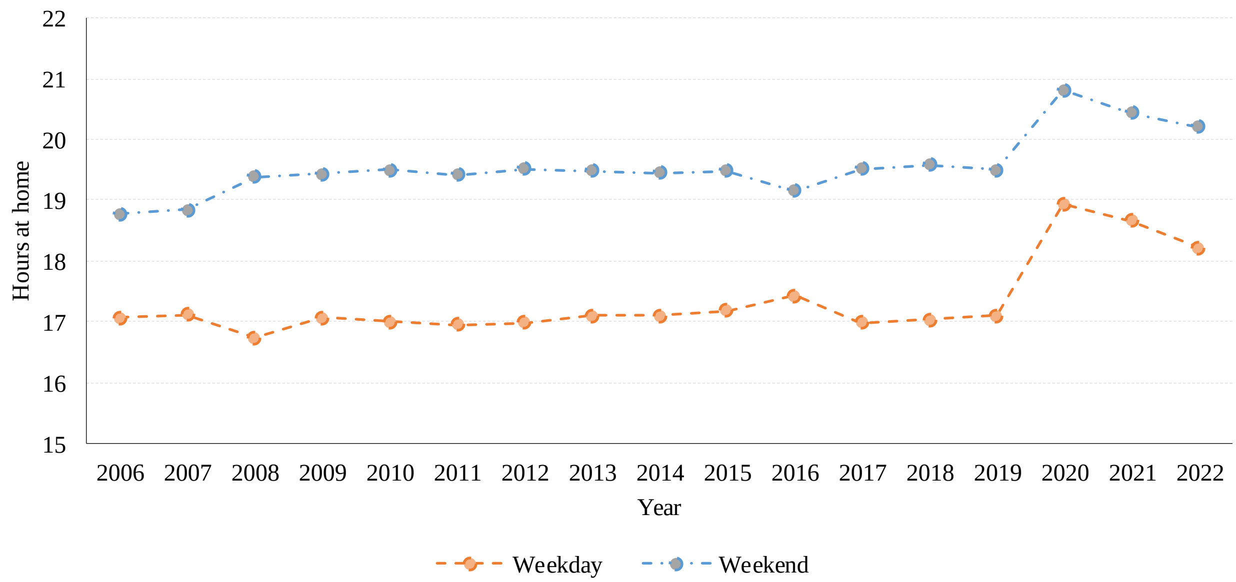


Figure 18. Average hours spent at home per day from 2006 to 2022 for U.S. households.

Analysis of future years of data (2023 and beyond) will help to understand if these trends continue or will level off. Recent discussions have focused on whether return-to-office (RTO) efforts effectively support employee productivity and wellbeing. Such debates originate from many companies asking formerly complete remote employees during the pandemic to be required to return to the office one or more days per week in 2023 and 2024 (Pandita et al. 2024, Stelson et al. 2023). And how this debate ultimately settles will likely impact what the future amount of time-at-home trends look like.

3.3.3. Variables most influencing time spent at home

Next, Pearson's correlation coefficients were determined for the selected socioeconomic variables for the years of ATUS and CPS data that were evaluated (2018 to 2022), to assess the strength and relationship between the considered variables (Table 8). In this analysis only 2018 to 2022 are used since the 2006-2019 data is highly similar in overall trends. Among the 14 variables considered, most have no or poor correlation with one another, with absolute values less than 0.5. A correlation matrix among these variables for the year 2020 is shown in Figure 19. For the other years, although the correlation coefficients are slightly different, the level of correlation remains the same, i.e. those that are strongly correlated continued to be strongly correlated; those that are poorly correlated continued to poorly correlated.

		TEAGE	TESEX	TELFS	TESCHENR	TRNUMHOU	WEEKEND	PTDTRACE	PEHSPNON	HEFAMINC	TESCHLVL	TESPEMPNOT	TRCHILDNUM	PEMARITL	PEEDUCA	HETENURE
Age	TEAGE	1.00	0.06	0.41	-0.82	-0.46	-0.02	-0.10	0.15	-0.18	-0.38	0.10	-0.45	-0.29	0.05	-0.20
Gender	TESEX		1.00	0.13	-0.04	-0.02	0.00	0.00	-0.01	-0.09	-0.01	-0.09	0.03	0.01	0.02	0.02
Employment	TELFS			1.00	-0.37	-0.16	0.00	-0.03	0.04	-0.33	0.02	-0.05	-0.15	0.01	-0.22	-0.03
Enrollment status	TESCHENR				1.00	0.43	0.03	0.09	-0.12	0.17	0.12	-0.02	0.50	0.15	0.05	0.17
Family size	TRNUMHOU					1.00	0.00	0.04	-0.12	0.27	0.16	0.33	0.83	-0.24	-0.06	-0.11
Weekday/weekend	WEEKEND						1.00	0.02	-0.02	-0.01	-0.01	0.00	0.00	0.02	-0.02	0.01
Race	PTDTRACE							1.00	0.05	0.00	0.05	-0.05	0.03	0.06	0.03	0.08
Hispanic/non-Hispanic	PEHSPNON								1.00	0.14	-0.05	0.04	-0.09	-0.10	0.25	-0.18
Income level	HEFAMINC									1.00	0.02	0.29	0.14	-0.27	0.39	-0.34
High school/college or university enrolled level	TESCHLVL										1.00	-0.16	0.11	0.25	-0.12	0.07
Employment status of spouse	TESPEMPNOT											1.00	0.14	-0.76	0.16	-0.24
Number of children	TRCHILDNUM												1.00	-0.14	-0.04	-0.01
Marital status	PEMARITL													1.00	-0.19	0.30
Highest education received	PEEDUCA														1.00	-0.14
House tenure	HETENURE															1.00

Figure 19. Correlation matrix for selected variables using 2020 ATUS data.

Several pairs of variables are highly correlated, including age (TEAGE), school/college enrollment status (TESCHENR), household size (TRNUMHOU), and number of children (TRCHILDNUM). Age is negatively correlated with school/college enrollment status since older people are less likely to attend school; household size is positively correlated with the number of children, suggesting a larger household is likely to have one or more children. Based on this, school/college enrollment status (TESCHENR) and children number (TRCHILDNUM) were removed, leaving the remaining variables for consideration, all of which have absolute correlation coefficients lower than 0.8 across all years of data. Most are well below this threshold.

Regression analysis was then used to evaluate the level of significance and relative impact of the remaining 12 socioeconomic variables on time spent at home across all years of data (2018-2022). The results of backward stepwise regression suggested the use of 10 socioeconomic variables, as shown in Table 10. This includes the coefficient resulting from the regression analysis, where a positive value indicates a positive relationship with the amount of time spent at home. The significant level is also provided; coefficients are provided in the table only if the variable was significant (p-value < 0.05) for a particular year; variables with p-values greater than 0.05 are not shown.

Table 10. Regression analysis coefficients and level of significant of socioeconomic variables predicting amount of time spent at home.

	2018	2019	2020	2021	2022
Age (TEAGE)	0.0161**	0.0136**	-	-	0.009
Gender (TESEX)	-	-	-	0.312**	0.208
Employment (TELFS)	0.792**	0.809**	0.832**	0.737**	0.699**
Income (HEFAMINC)	-0.115**	-0.079**	-0.043	-0.033	-0.051*
Household size (TRNUMHOU)	-	-	-	-0.092	-
Education (PEEDUCA)	-	-0.068*	0.093**	0.066*	-
House Tenure (HETENURE)	-	-	0.216	-	-
School/ college enrolled level (TESHLVL)	-0.231	-0.265*	-	-	-0.297*
Race (PTDTRACE)	-	-	0.108	0.115	0.133
Hispanic (PEHSPNON)	0.337	0.408	-	0.458*	0.478*
Weekend (WEEKEND)	2.44**	2.34**	1.69**	1.66**	1.81**
R-squared	*0.232*	*0.221*	*0.171*	*0.163*	*0.168*

*Note: Values shown are significant, P<0.05. * Significant for P<0.001; **Significant for P<0.0001.*

Results suggest that employment status (TELFS; 0 for employed, 1 for unemployed), household income level (HEFAMINC), and time of the week (WEEKEND; 0 for weekdays, 1 for weekends) were statistically significant across all years (p-value < 0.05) in predicting time spent at home. This suggests that it was significantly more likely for a person to have spent time at home if they are unemployed, and lower income, and if it is a weekend compared to a weekday, regardless of whether the year was impacted by the pandemic. Other variables, including age (TEAGE) and school/college or university enrolled level (TESCHLVL) were statistically significant pre-pandemic (2018-2019), became insignificant during the pandemic in 2020, 2021 and became significant again in 2022. School/college or university enrollment level (TESHLVL) is negatively correlated with hours spent at home, suggesting that students enrolled in a college or university spent less time at home than high school students.

Age positively correlates with time at home, suggesting older people spent more time at home pre-pandemic. Age being a less important variable during and post-pandemic (2020 and after) is likely due to the significantly larger population still of working age and their children spending a more similar amount of time at home to those older. This is not surprising; however, the uptick in age significance in 2022 suggests that those working and/or going to school outside of the home are returning more to pre-pandemic levels of leaving home, at least compared to the older population.

A similar trend is seen for household income (HEFAMINC). Income is more strongly negatively correlated with hours spent at home pre-pandemic. In 2020 and 2021 it was not significant, and then in 2022 was statistically significant again but to a lesser extent than pre-pandemic. Previous research found that high-income groups were more likely to spend more time away from home on weekdays pre-pandemic (Mitra et al. 2021). The change in significance of household income suggests that the middle- and high-income groups' occupancy patterns became closer to low-income groups occupancy patterns during the height of the pandemic, and have returned to being somewhat different, but still not to pre-pandemic levels. This is likely due to the significant increase in work-from-home jobs available, particularly to middle- and high-income groups or those working in higher-tech industries (Baker 2020).

The highest education received (PEEDUCA) variable became significant during the pandemic, with a positive correlation to the time spent at home. This means that the higher the degree a person completed, the more time they spent at home, with more time being dedicated to working at home. Gender (TESEX; 0 for male, 1 for female) was positive and significant in 2021. This suggest that females were spending more time at home, however it is unclear why it is only significant in 2021. This may be partly due to the increased number of females that either left the workforce in the wake of the pandemic or continued to work at home (Azcona et al. 2020; Fisseha et al. 2021). Household size (TRHUMHOU) and race/ethnicity (PTDTRACE/PEHSPNON) also influenced time spent at home but were less significant than the previously mentioned variables. In particular, those who identified as Hispanic (PEHSPNON) were statistically significantly more likely to spend more time at home during and post-pandemic, as compared to pre-pandemic. In addition, those who identified as minorities also spent more time at home. This may be in part related to trends that suggested that minority groups were more likely to lose their jobs during the pandemic (Fan and Moen, 2023).

3.3.4. Trends in time at home for most significant variable predictors

After the initial regression analysis, trends of time spent at home were evaluated by subdividing the sample population by the most significant variables. The hours spent at home by employment status and income level are shown in Figure 20 for weekdays and weekends. Age and race/ethnicity are also shown. These were chosen as recent research suggests that those who are elderly and minorities were more likely to lose jobs and thus be at home more (Bednar et al. 2017, Lewis et al. 2021, Memmott et al. 2021, Zanocco et al. 2021).

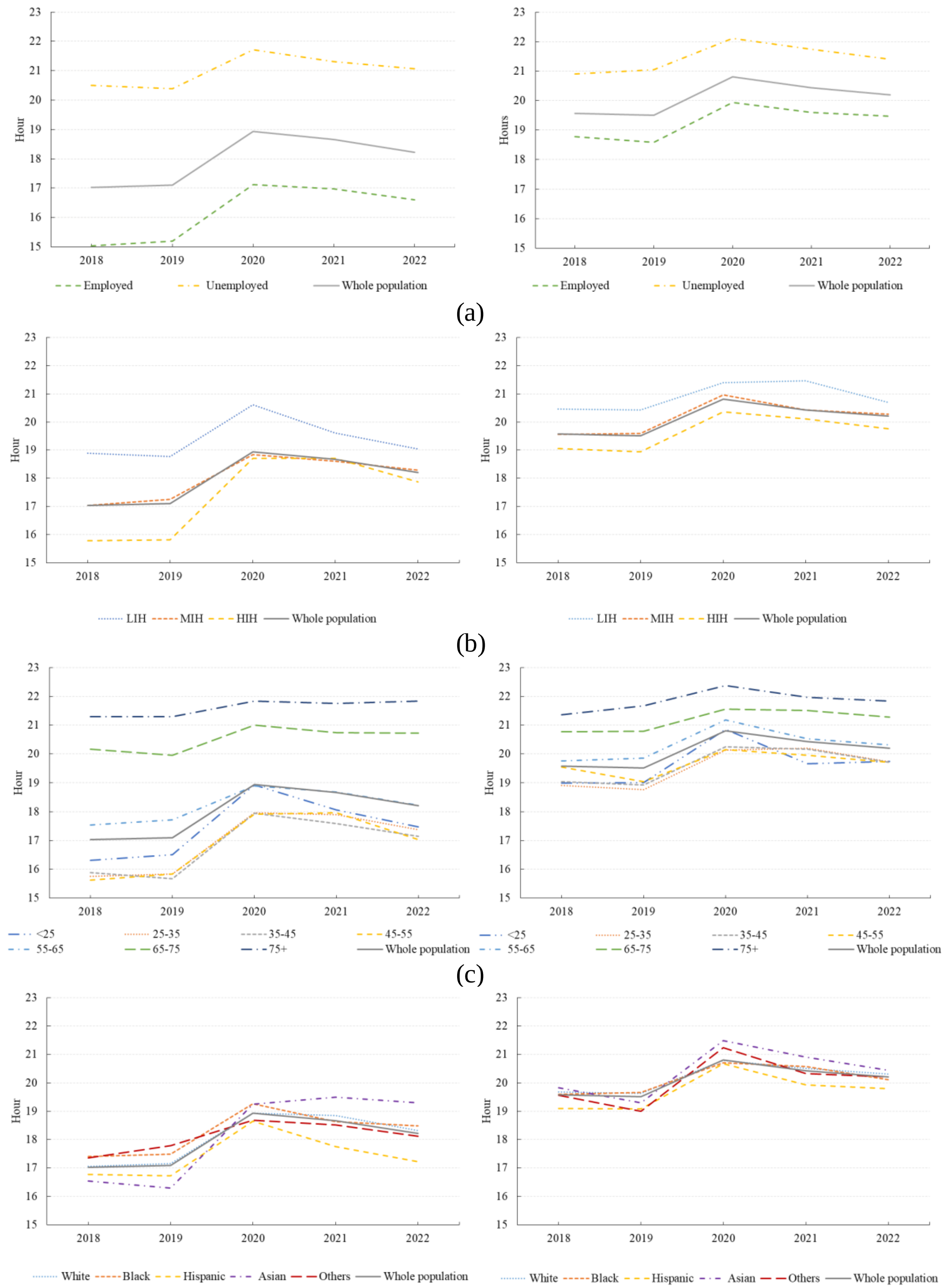


Figure 20. Hours spent at home for weekdays (left) and weekends (right) based on (a) employment, (b) income, (c) age, and (d) race/ethnicity between 2018 and 2022. *Note: LIH = low-income household, MIH = middle-income household, HIH = high-income household.*

The biggest differences in time spent at home across the studied years are seen associated employment (Figure 4a), with unemployed households spending close to five hours more at home per day on weekdays and two more hours per day at home on weekends. While the pandemic clearly impacted the amount of time spent at home, interestingly, the jump in time spent at home followed similar trends for both those employed and unemployed.

Compared with the pre-COVID period, those employed during the pandemic spent an additional 2 hours at home on weekdays and 1 hour on weekends in 2020; this is similar for those unemployed, who spent approximately 1.1 more hours on weekdays and weekends at home. It is important to note in considering these trends that in March and April 2020, 26 million workers in the U.S. filed for unemployment benefits (DOL, 2020; Czeisler et al., 2020), suggesting that some households likely bounced between the "employed" and "unemployed" groups. Thus, it is important to keep in mind that a single household may not have followed only one of these trends, but a combination of both. In 2021 and 2022, hours at home decreased on weekdays and weekends for employed and unemployed households. Those employed saw a slightly higher rate of decrease in time spent at home on weekdays, suggesting that return-to-office trends may influence this. Those employed also saw a lower rate of decrease in time spent at home on weekends.

For income, low-income households spent the most time at home across all years, followed by the middle-income, and high-income households, on both weekdays and weekends. The middle-income households closely followed the overall population trend across all years studied. In terms of the impact of the pandemic, in 2020, low-income households spent additional 1.8 hours at home on weekdays (20.6 hours total), middle-income increased by about same (18.8 hours total), and high-income households increased the most, by about 2.9 hours (18.7 hours total). The pandemic also brought the amount of time that mid- and high-income households spent at home together, with both groups spending a similar amount of time (about 18.7 hours) at home on weekdays in 2020 and 2021. Since this time, the amount of time at home has decreased for all income levels; however, in 2022, high-income households' time at home on weekdays decreased more than middle-income households for the first time, suggesting high-income earners may be subject to more return-to-office trends or leisure activities than middle-income earners (Morasae et al. 2022). In 2022, middle- and high-income households' time at home is still lower than low-income households (0.8-1.1 hours less in 2022), but compared to pre-pandemic (1.8-3 hours less in 2018/2019) the gap between income groups in time spent at home is substantially smaller (1-1.9 hours less in 2022 than 2018/2019). Also important to note is that low-income households' time at home on weekdays returned to pre-pandemic levels in 2022, while middle- and high-income households were still 1.1-2.1 hours more than the pre-COVID period. This is likely due partly to the reduced likelihood that lower-income households have jobs that allow for working from home (Yasenov 2020). For weekends, the differences in amount of time at home across income groups is smaller, and trends have generally been similar across 2018-2022.

For age groups, those 55-65 most closely followed the overall population trend on both weekdays and weekends. People younger than 55 were most affected by COVID-19, with all groups under 55 spending an additional approximately two hours at home in 2020 on weekdays. Following the pandemic, for those under 55, the rate of decrease in time spent at home between 2020 and 2022 was also greatest on weekdays, while particularly those 65 and older time spent at home did not change more than 0.3 hours in 2021 and 2022.

Considering trends across different races/ethnicities, this is particularly important since minorities were more affected by the pandemic due to their household characteristics (Lewis et al. 2020; Memmott et al. 2021); this could explain some of the differing trends seen in this analysis.

Those that identify Asian saw the biggest jump in time spent at home in 2020, jumping from 16.4 to 19.3 hours per day on weekdays; this same group continued to spend the most time at on weekdays and weekends in 2021 and 2022, differentiating themselves from other racial/ethnic groups. Those identifying primarily as White follow similar trends to those identifying as Black and Hispanic. Each saw an increase in time spent at home in 2020 and a similar level of decrease each year through 2022.

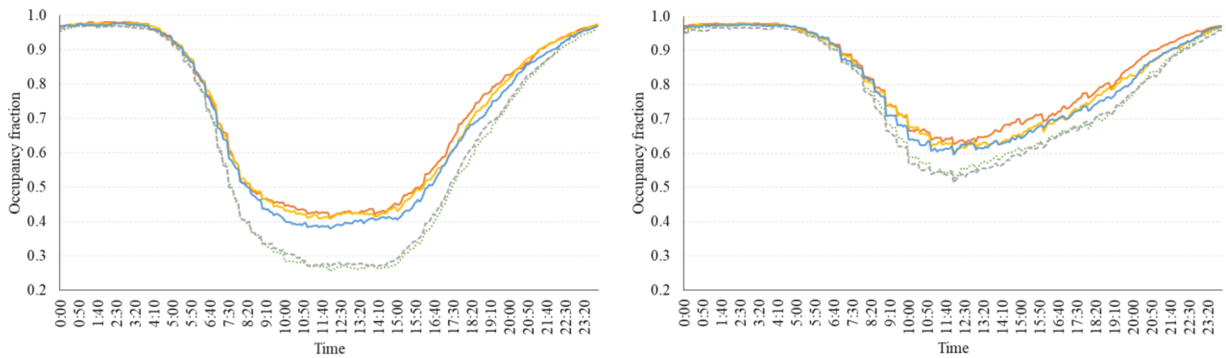
The main difference between these groups is that those identifying primarily as Black generally spent slightly more time on average at home on weekdays, and those identifying as Hispanic generally spent slightly less time at home. Other races/ethnicities including non-Hispanics (e.g. American Indian, Native Hawaiian, Native Alaskan) followed slightly different trends, with a slightly smaller increase in time spent at home in 2020 on weekdays, but slightly higher increase on weekends. On weekdays, those identifying as Hispanic have been the quickest to return to pre-COVID levels. In contrast, all other races/ethnicities had not yet returned to similar levels by 2022, particularly those identifying as Asians. For weekends, those identifying as Asian, Hispanic, and Other decreased their time at home in 2021 compared to 2020, while those identifying as Black and White maintained a similar amount of time at home. Hours spent at home decreased for all races/ethnicities on weekends in 2022, with Asians having the highest amount of time at home (20.4 hours) by a small amount.

3.3.5. Occupancy profile variations across most significant variable predictors

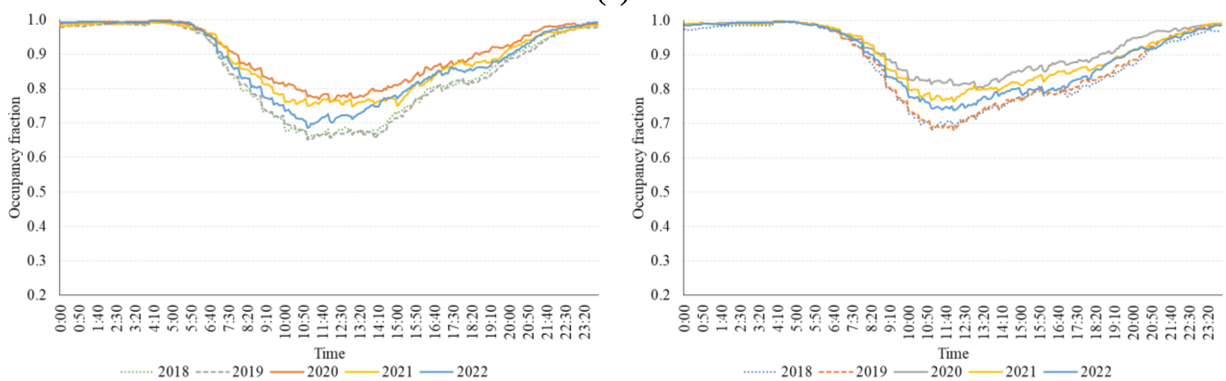
Related to total time at home, occupancy profiles are also influenced by various socioeconomic variables. Occupancy profiles are important in the context of energy and sustainability of buildings as they have been shown to affect overall energy consumption and carbon footprint of households (Dubois et al. 2019, Estiri 2015, Memmott et al. 2021, O'Neill and

Chen 2002). Occupancy profiles also impact the potential for demand response, particularly for large appliances such as HVAC systems and other occupant-driven large appliance loads (e.g., washers, dryers, dishwashers, water heaters, etc.). A higher occupancy fraction indicates a higher likelihood of being at home (1 = home; 0 = absence). In this case, the middle of the day is generally considered as, for most households, the likelihood they are away from home in the middle of the night is very low compared to during the day (i.e., the greatest variations in occupancy patterns are seen during the day).

This analysis used employment status to compare occupancy fractions for employed versus unemployed during the study period. This was chosen because it was one of the most significant factors influencing occupancy in the previous section. For the pre-COVID period, the occupancy fraction for those employed remained at approximately 0.28 at noon on weekdays and 0.55 at midday on weekends (Figure 21). Higher occupancy fractions are observed at midday for those who were unemployed, including 0.66 and 0.70 on weekdays and weekends, respectively. In both cases, occupancy fractions increased by about the same during the pandemic, including 0.15 (weekdays) and 0.1 (weekends). In 2021, this trend was similar to 2020 on weekdays, but in 2022, the occupancy fraction decreased, particularly for unemployed people. Those who were employed continued to do some work from home in 2022, but to a lesser extent, those who were unemployed followed an occupancy pattern more similar to pre-COVID.



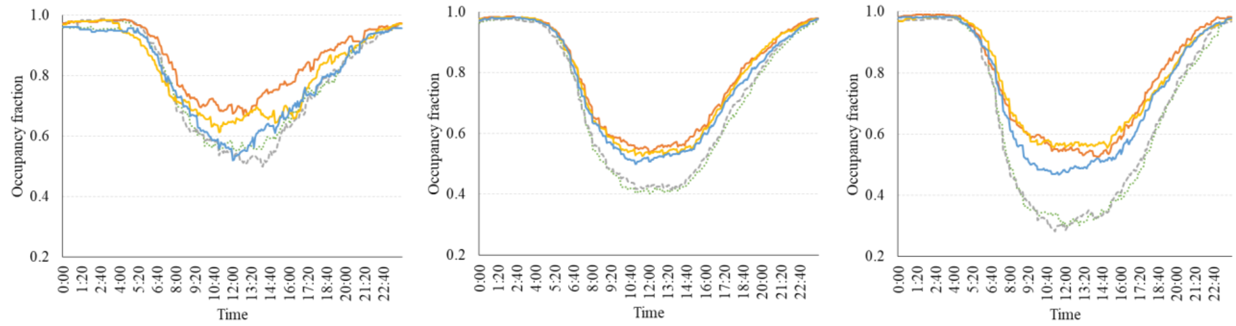
(a)



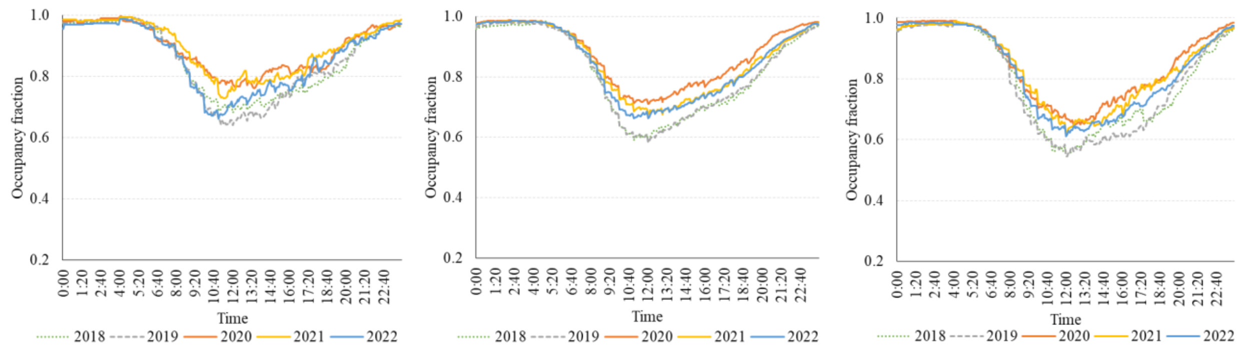
(b)

Figure 21. Occupancy fraction at home for (a) employed and (b) unemployed on weekdays (left) and weekends (right).

As household income level was also found to significantly impact occupancy, this variable is also used to compare occupancy fractions (Figure 22). In pre-COVID periods, low-income households (LIH) had the highest occupancy fractions during the day, followed by middle-income households (MIH) and then high-income households (HIH) on both weekdays and weekends. On weekdays, low-income households spent more time at home, with an occupancy fraction of 0.50 midday. This is aligned with literature suggesting low-income households are more likely to be unemployed and/or have childcare responsibilities and thus need to be at home (Carlin 2019). Middle-income households had an occupancy fraction of 0.40 pre-COVID but spent more time away from home; high-income household members spent the most time away from home, with an occupancy fraction of 0.3 midday.



(a)



(b)

Figure 22. Occupancy fraction at home for low- (left), middle- (center), and high-income (right) households on (a) weekdays and (b) weekends.

During and post-COVID, similar trends emerged with some distinct differences, particularly for middle- and high-income earners. For weekdays, 2021 and 2020 were nearly identical for middle- and high-income households, with an occupancy fraction of 0.53 and 0.55 midday, respectively. This changed from the pre-COVID period when these occupancy schedules were significantly different. In 2022, middle- and high-income household members were less likely to stay home during the day but were still much more similar in occupancy fraction compared to pre-COVID. High-income households saw a slightly larger drop in occupancy fraction (0.03) at midday. On weekends, all income groups have increasingly been away from home, particularly in 2022 compared to 2021 and 2020.

Low-income households have been the quickest to return to the pre-COVID period patterns for weekdays and weekends in 2022. However, middle- and high-income households have not yet returned to the pre-pandemic level for weekdays and weekends, especially on weekdays. This may be partly due to the higher likelihood that middle- and higher-income households have jobs that enable them to work at least partly from home. Also of importance to note in terms of implications of such trends is the varied impact that participation in programs such as demand response using adjustments in setpoints could have on different income households (Wilson et al. 2019). While closer in occupancy schedule across income groups than pre-pandemic, lower income households are still more likely to be at home than middle- and high-income groups, and thus may be potentially more impacted in terms of comfort, from participation in demand response programs.

3.3.6. Variation in location within home

By using the recorded activities (used as TRCODE in ATUS) and the duration time, the daily home locations were assigned to the bedroom, bathroom, dining area (including kitchen), living room, office/study, garage, and "other" (all other locations). For example, sleeping was assigned to the bedroom, and work-related activities are associated with office/study. Please see Mitra et al. (2022) for more details on this methodology. This was completed for all years of study, then compared to assess trends in time spend in different areas of the home across 2019-2022 (Figure 23). Note, in Figure 23, a positive number indicates an increase in hours spent in that particular home area compared to 2019; a negative indicates a decrease in hours spent in an area.

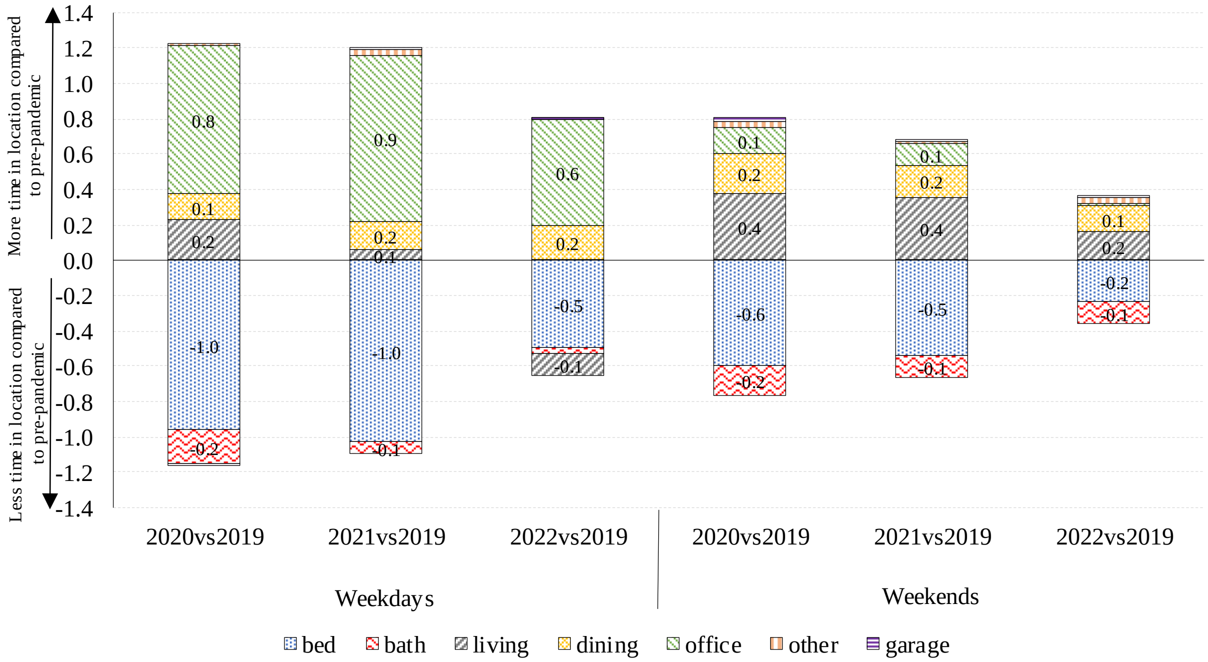


Figure 23. Hours spent at home based on locations for both weekdays and weekends compared to pre-pandemic (year 2019). *Note: a positive number means increase in hours in a particular location compared to 2019; a negative number indicates a decreased hours spent in a particular location.*

The greatest increases in locations spent compared to pre-COVID, across all years, is in the office/study (working from home, schoolwork, etc.) and dining area (cooking, eating, etc.), on both weekdays and weekends. The greatest decreases in time spent in various locations include a decrease in time spent in the bedroom (sleeping) and bathroom on both weekdays and weekends. Interestingly, these trends across categories remained similar on weekdays and weekends and across 2020, 2021, and 2022 compared to 2019. However, the amount of difference changes, particularly in 2022 compared to 2020 and 2021.

In particular, on weekdays, 2021 was similar to 2020 in time spent in the office/study and bedroom; however, in 2022, there was a 0.6-hour decrease in office/study time and a 0.5-hour increase in the bedroom (sleeping) time compared to 2021 and 2020. The notable shift that differentiates 2022 and the other years is the shift in the living room use, where people spent 30 minutes less in 2022 compared to 2019, but 30 minutes more than in 2020 and 2021. For weekends, people spent 0.6 hours less in the bedroom (sleeping) in 2020 compared to 2019, then have steadily increased back this time. They also spent 0.4 hours more hours in the living room in 2020 and 2021. By 2022, people stayed 0.4 hours more in the bedroom and 0.2 hours less in the living room compared to the hours in 2021. For the dining/kitchen area, there was an increase of 0.1 hour during 2020 and 0.2 hour for 2021 and 2022 on weekdays, and 0.2 hour (2020 and 2021) and 0.1 hour (2022) on weekends.

Regarding implications from a building energy perspective, these trends provide some potential clues as to why residential building energy use changed since pre-pandemic. Due to the increased use of dining/kitchen areas, people are likely to spend more time cooking using ranges/stoves and washing dishes using dishwashers. The 0.8-hour increase in the office/study area suggests longer use of laptops, desktops, and other plug-in electronics/appliances. The increased use of the living room could mean more use of electronics such as televisions, video games, living area cleaning, lighting, and other related activities. More time in the office/study area and the increased use of video and audio would lead to more plug load use and internal heat generation (De' et al. 2020). An increase in hours spent at home also suggests an increase in heating and cooling energy needs and other factors that would benefit from further investigation. Conversely, the decrease in bathroom time compared to 2019 suggests less use of water heaters and other bathroom appliances.

3.4. Conclusions

This study examines the impact of the global pandemic due to COVID-19 in 2020, considering residential households' socioeconomic characteristics, using the ATUS data. The study evaluates the importance of 14 possible variables, such as age, race/ethnicity, employment status, and income levels, on the time spent at home across five years, from 2018 to 2022. The findings of this study are summarized as follows:

- The time in indoor spaces increased by 1.3% during the pandemic (95.3%), shifting mostly from the time in transit to another location. From 2021 to 2022, the 1% increase in the indoor portion gradually decreased by 0.3% each year and was added back to the time spent commuting to other locations.
- By 2022, the decrease in time spent at home dropped by around 40 minutes for both weekdays and weekends compared to 2020. However, both had not yet returned to pre-COVID levels compared to the average values from 2006 to 2019.
- Employment status (TELFS), income level (HEFMINC), and time of the week (WEEKEND) for weekdays and weekends were the most statistically significant variables for total time spent at home across the five years studied. In 2020, employment status (TELFS), highest education received (TEEDUCA) and time of the week (WEEKEND) were most significant, while others were not as significant during the pre-COVID period. Age (TEAGE) and school/college or university enrollment level (TESHLVL) became less significant in 2020 and 2021, while race/ethnicity appeared to be becoming more important during and post-pandemic.
- Across different races/ethnicities on weekdays, those identifying as Hispanics were the quickest to return to the pre-COVID levels of home occupancy, while all the others have not yet returned to pre-COVID levels, especially those identifying as Asian (highest 19.3 hours). Those identifying as White most closely follow the overall trend for weekdays; those identifying as Black most closely follow the overall trends on weekends.

- The midday occupancy fraction increase by approximately 0.15 (weekdays) and 0.1 (weekends) in 2020 for those that were employed and a similar amount for those unemployed. In 2021, this trend was similar to 2020, but in 2022, the occupancy fraction decreased, particularly for unemployed people. This suggests that those employed continued to do some work from home in 2021 and 2022 but the unemployed individuals returned to pre-COVID pattern.
- In 2022, low-income households returned back to nearly pre-COVID occupancy profiles for both weekdays and weekends. However, middle- and high-income households decreased in occupancy, did not return to pre-COVID levels, and have remained similar in occupancy profiles compared to pre-COVID when their profiles were quite different.
- Across 2020, 2021 and 2022, people spent more in the office/study, living (2020 and 2021) and dining areas of their home on weekdays, but less time in the bedroom and bathroom. And similar trend was observed on weekends for those three years as compared with 2019.

In terms of future work, it is clear that for many household types and specific demographics, occupancy patterns are still changing in the wake of COVID. Occupancy patterns have not returned to pre-pandemic levels for many, and it is not clear if they will ever do so, or if they will level off and remain the same as the previous year in 2023 and moving forward. Therefore, continuous investigation is necessary to understand the still dynamic situation. Also, of importance to note is that this study focuses on the residential sector, but similar approaches could be applied to the commercial sector based on selected locations. Additionally, the hours spent at home and occupancy fraction are the metrics used in this study, but other factors could also be considered in the future analysis to determine the frequency of certain activities.

3.5. Acknowledgments

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CHAPTER 4: APPLIANCE USE PATTERNS CHANGE AND DEMAND RESPONSE DURING AND POST-COVID-19

4.1. Introduction

Many studies on residential building energy consumption focus opportunities to reduce energy use from space heating and cooling (Amonkar et al. 2023, Colelli et al. 2023, Harrye et al. 2023, Zhang et al. 2021). However, the energy consumption from the use of large appliances (e.g., water heaters, refrigerators, clothes washers/dryers, and dishwashers) and miscellaneous electric loads (MELs) such as televisions and computers can also have significant impact on consumption. Given that many of these appliances and MELs are occupant-dependent and thus highly stochastic, they also are important to consider when targeting operation of net zero-energy buildings and grid-interactive buildings (Jin et al. 2020, Hischier et al. 2020, Lee et al. 2023, Yilmaz et al. 2019, Yamaguchi et al. 2020).

In the residential sector, refrigeration, water heating, clothes washing/drying, and electronics are estimated to make up 35% of total consumption and 44% of peak electricity use (Goetzler et al. 2018). In areas with low space heating requirements, domestic hot water (DHW) can correspond to 40%-85% of heating demand in residential buildings (Stene 2008). In addition, plug loads are expected to grow by 20% and 29% in the residential and commercial sectors by 2050 compared to 2021 (U.S. EIA). Based on projections, household appliance sales will increase by 25% globally and 15% in the U.S. in 2028 compared with 2022 (Statista 2023 a, b). Recent research has also suggested that in the U.S., one of the critical pathways to decarbonize residential building operations is to focus on appliances (Zhang et al. 2023).

Demand side management (DSM), introduced by the American Electric Power Research Institute (EPRI) in the 1980s, enables the ability to control the quantity and timing of electricity consumption (i.e. the “demand” side, rather than the electricity production side of the grid). Recent studies have shown that this can be achieved by utilizing advancements in controls capabilities of appliances (Assi et al. 2022, Chen et al. 2014, Mathur et al. 2023). For instance, a building energy management system integrated with smart appliance controls can help to meet the requirements of better living conditions with lower energy costs (Zhai et al. 2018). Responsive loads, including clothes washers, dishwashers, pool pumps, and electric vehicles that are sensitive to electricity prices can be shifted from peak hours to reduce utility costs and reduce grid burdens. Such shiftable loads can be arranged to operate during price valleys or flat-rate hours (Ma et al. 2021). Sheppy and Gentile-Polese (2014) found that overestimating these loads also results in oversizing electrical infrastructure and cooling systems, increasing capital costs and energy consumption.

As an effective DSM control strategy, demand response (DR) of home appliances provide quick response (on/off) to grid needs, demand reduction potential, and relatively minimal influence on occupant convenience (Mathur et al. 2023). For instance, Lundstrom et al. (2018) experimented with a proposed fast grid response framework for household appliances (refrigerator, range/oven, plugin-heater, lighting) finding a coordinated response time within 143 milliseconds. By participating in the incentive-based DR program, appliances can be controlled in response to grid signal to ease the burden of the grid (Adeyemo and Amusan, 2021). Understanding the energy use of energy-consuming systems, especially appliances, allows for the ability to assess power use and grid regulation (Li and Just 2018), as well as to identify ways of reducing greenhouse gas (GHG) emissions (Berrill et al. 2021).

Due to the novel coronavirus disease 2019 (COVID-19) pandemic, lockdowns regulated by governments worldwide increased the amount of time that people stayed in their homes and thus indoors in 2020 (Mitra et al. 2022). Various studies have investigated the changes in the residential sector during the pandemic. Qarnain et al. (2020) found that social distancing, home quarantine, and home transformation (i.e., work from home) were the primary factors that affected energy consumption at home. Dai et al. (2023) indicated that residential energy consumption was impacted by government policies in the U.S. One study in Turkey found that the use of dishwashers, refrigerators, clothes washers, and dryers was shifted from other times of the day to midday, increasing the grid burden during the pandemic (Tanugur and Zehir 2022). Another study found that in Australia, the UK, and the U.S, during the lockdowns, HVAC and appliance uses caused 11%-32% more energy demand in the residential sector (Krarti and Aldubyan 2021). Furthermore, a recent study conducted in China indicates the need for analysis of residents' space use and behavior changes in the post-pandemic period, which shows an increase in online activities at home and outdoor activities with a decrease in indoor public use and traveling (Tu and Reith 2023). Such changes have posed a new challenge to the existing energy use and occupancy profiles used in energy simulation methods and protocols. For appliance loads, the DOE Building American (BA) Program developed standard operation profiles for appliances based on historically connected data from the 1980s and 1990s (DOE BA 2023, Wilson et al. 2014). Such schedules are still commonly used in simulation tools, yet research suggests that changes in how residential buildings and their corresponding appliances are used post-2020 should be considered as lifestyles have changed.

Appliance energy use profiles can be estimated using several different methods (Fisher et al. 2020, Grandjean et al. 2012, Jin et al. 2020, Kang et al. 2014, Osman et al. 2023). The first is top-down methods, where a building is treated as a block, and the cumulative demand of a particular energy-consuming system is based on a model considering macro-scale variables such as macroeconomic factors, climate, and building envelope characteristics. However, for this method, the peak energy demand has been found, in some cases, to be overestimated since such a top-down method can fail to account for the random variability of occupant behavior, particularly if it is not captured in training data (Tanimoto and Hagishima, 2010). The second common method is the bottom-up method, which is based on analyzing and investigating higher-frequency data to determine energy use patterns. Possible strategies include statistical, probabilistic-empirical, and time-use (time-use survey or TUS) models. The second approach may not precisely represent users' daily activity depending on the time length of collected data, usually one day. As a result, this method can fail to capture the differences in behavior and corresponding energy consuming systems use for an extended period (Yilmaz et al. 2017).

Appliances use data has been collected by various studies in recent years by numerous research efforts across different countries, such as the UK (Yilmaz et al. 2017) and the U.S. (Cetin et al. 2014). Historically, energy use information for estimating the energy use of individual appliances has originated from a combination of field-collected and simulated data. Such a modeling approach benefits greatly from the use of larger, highly detailed metered datasets (Ramírez-Mendiola et al. 2017). However, for nearly all studies, the utilized appliance use data originates from sources that assessed energy consumption patterns during the pre-pandemic period (pre-2020).

Since occupancy patterns and behavior have changed, both during 2020 and throughout the aftermath of the pandemic, this study seeks to determine if these appliance energy use patterns have changed because of the pandemic and how this has trended over time. This is accomplished using submetered appliance use data for homes across consecutive years from 2018 to 2022. Specific appliances studied include dishwashers, refrigerators, clothes washers, dryers, and water heaters. The objective of this paper focuses on quantifying the impact of the pandemic on appliance use in homes, and in particular, how this impacts their use potential for use in DSM. The remainder of this research is organized as follows. First the dataset characteristics are discussed, then in the methodology, how the data is processed, cleaned, and analyzed is discussed. The results and discussion include analysis of trends and patterns across the years of study of appliance use data. The conclusions summarize the findings, as well as limitations and future work.

4.2. Dataset Characteristics

The dataset utilized in this research is extracted from a broader dataset of 1930 homes of disaggregated energy use data, collected between 2012 and 2024 (Pecan Street Inc. 2023). Data is collected in this dataset using eGauge energy monitoring systems that allow for the collection of energy use of the entire home, as well as individual circuits of data. Given that most larger appliances each have their own dedicated circuit within a home, the energy use of specific appliances can be obtained without the need for disaggregation algorithms. In this research the data utilized includes appliance use from 2018 to 2022. Table 11 provides the high-level characteristics of all households, such as housing type, size, and year of construction, as well as similar data for the overall U.S. The households included in this study were only a portion of the entire dataset extracted for the five years because some families were withdrawn in a particular year or missing data for studied appliances. Overall, there were 527 households included in this study; 95% were single-family homes. The median year of construction was 1998 (average, 1980), with an average area of 210 square meters. The most common locations for homes in the studied data include the following: Texas (348), New York (98), Colorado (26), Delaware (20), California (18), and Michigan (14).

Table 11. Summary of the dataset.

	This study*	U.S. homes**
Number of households	527	143,772,895
Single-family house	95%	68%
Median constructed year	1998	1979
Average floor area (m^2)	210	163

**Based on available recorded data, **2018-22 American community survey, 2021 American Housing survey (U.S. Census Bureau 2024 a, b).*

By comparison with the overall U.S. homes, the homes in this dataset are newer, larger and more heavily single-family home dominated. This does not necessarily mean that the appliance use patterns and consumption would be substantially different than the U.S. population. Current simulation protocols for appliances assume the same use profile regardless of home type or characteristics (Pratt et al. 1989, Wilson et al. 2014). This suggests that the time of day during which appliances are used may not vary by house type. However, these same simulation protocols also base total consumption of each appliance on empirically developed equations, with dependent variables including the number of bedrooms and/or floor area of the home (Wilson et al. 2014) This previous research suggests that the size of the home impacts the magnitude of energy use. Consequently, based on these assumptions, it can be assumed that the appliance use profiles established from this research may not be impacted by utilized sample, but the total consumption values may be. This will be discussed further in the results and discussion sections.

4.3. Methodology

This study follows a three-step procedure, as shown in Figure 24. The specific appliances considered include the dishwasher, water heater, refrigerator, clothes washer, and dryer. For the first step, the data of all analyzed appliances was downloaded for five consecutive years. In later sections, this study refers to the years of 2018 and 2019 as the pre-COVID period, 2020 as the year of the pandemic, and 2021 and 2022 as the post-COVID period. For the second step, the raw dataset was quality controlled to detect erroneous readings, which were either error readings (high value spikes) or null values, and then remove them from the dataset. This was completed using the object-relational database management system (ORDBMS) software PostgreSQL version 15 (2023). Then, the remaining processes were coded using Python version 3.8.3 (2023) programming language. Negative values (most homes this was 0% of the data, and up to 1% maximum of data per home) were also converted to zeros.

The dataset was then queried to determine across 2018-2022 (five years) each year, which homes have more than 85% of available 1-hour data for each appliance across each year. The 85% threshold was adjusted based on the percentage of data removed as mentioned in the previous process. Then, the percentage of date availability for each home for each year was used in the third step to generate the daily and monthly use profiles. For each appliance, in order to form consistent trends for comparison from pre- to during- to post-COVID, only common homes with enough available data across the five years were used. This reduces the sample size for each appliance but allows a more easy and consistent comparison across the years studied.

The third step was to calculate the average daily and monthly use profiles for a detailed comparison, where those profiles provide information on peak and minimal use periods as compared with the pandemic and post-COVID period. This includes total consumption per home across each hour of a 24-hour day, and the normalized load profiles, which is represented as a percentage of total daily use. Based on the time of the week, weekday and weekend profiles were also analyzed to show the peak demand periods and changes throughout the day for all five years. The normalized monthly profiles are also developed following methods in the Building America (BA) simulation protocols and simulation tool ResStock developed by NREL (Wilson et al. 2017), and compared for any suggestions to be made.

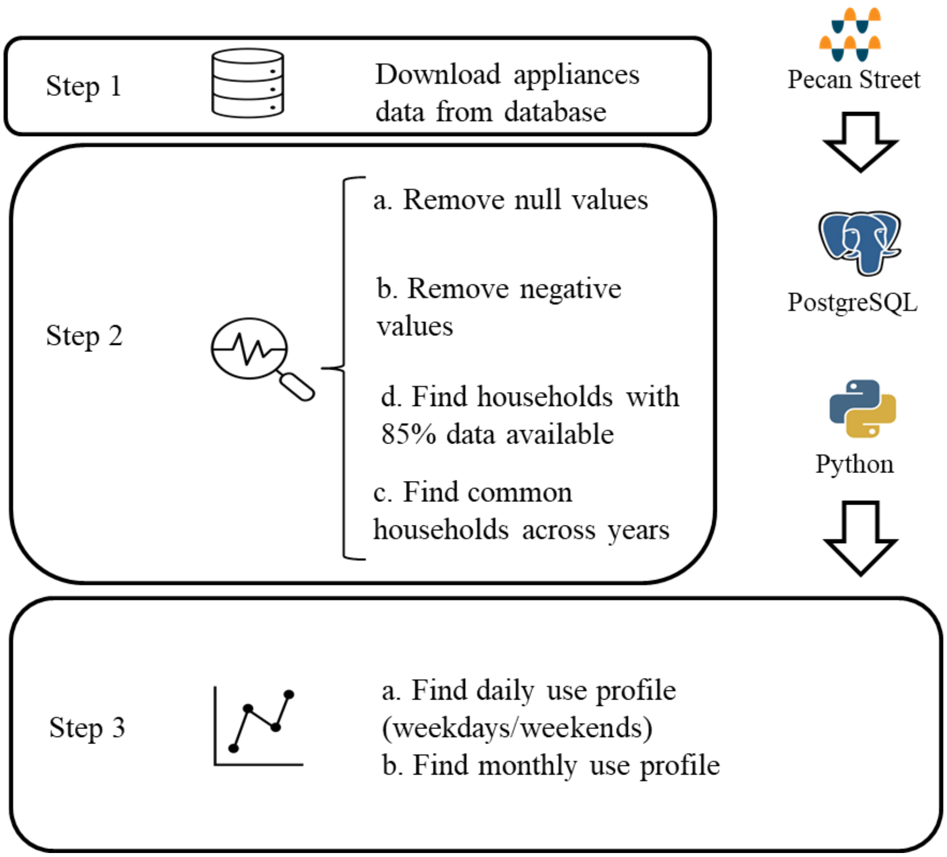


Figure 24. Schematic procedures used in this study.

4.4. Results

The summary of post-processed data of all four household appliances from 2018 to 2022 is shown in Table 12. Approximately 45,000 data points per year per appliance for each appliance remained after cleaning and filtering process discussed in the methodology section (see Figure 24). Overlapping households were those that had consistently recorded appliance use data across the five years. Approximately, 16% of initial households in the original dataset remained, because many households have single year of data or less available instead of multiple year data. As such, 54 to 62 households per appliance were kept after the cleaning and filtering process as mentioned in the methods section. Water heaters were considered, but ultimately excluded from the results because there were only 13 households that had all 5 years of data (less than 13% of all households that had water heater data available), thus this data was determined to be insufficient and excluded from further analysis.

Table 12. Final annual hourly dataset counts used for analysis after cleaning.

	Dishwasher	Refrigerator	Clothes Washer	Dryer
2018	517,320	493,168	463,435	536,957
2019	499,275	476,202	450,705	518,404
2020	521,162	496,940	468,467	538,788
2021	518,528	493,430	467,956	535,041
2022	518,141	490,568	464,301	532,291
Households used	60	57	54	62
Total household	314	361	310	356
% used	*19%*	*16%*	*17%*	*17%*

4.4.1. Appliance Annual Consumption and Energy Use Profiles

Table 13 shows the median annual consumption and standard deviation (kWh) for each of the studied household appliances across the five years. This table also shows the Building America (BA) simulation protocol-based values assumed for a three-bedroom home (Wilson et al. 2014) and 2022 ANSI/RESNET/ICC 301 Standard (American National Standards Institution 2022) for Energy Rating Reference Home. This reference home is a hypothetical home that meets 2006 IECC Standards. A three-bedroom home was chosen due to the average of 2.6 bedrooms in the homes in this study.

In general, in the studied data, clothes washers had the lowest annual energy use (kWh), followed by dishwashers, and dryers; refrigerators consistently had the highest annual consumption (kWh). During and post-COVID, an increase in total consumption is seen across refrigerators, dishwashers, and clothes washers, but not for dryers. Given that more people spent time at home between 2020-2022 (Dong et al. 2024), the increase in use of appliances is not surprising. However, it is surprising that dryers do not appear to follow this trend in parallel with the other appliances. The standard deviation shared similar characteristics across appliances, with this value becoming larger during, and post-pandemic compared with the pre-COVID period, including a 3-15%, 4-11%, 11-65%, 1-8% increase for dishwashers, refrigerators, clothes washer, and electric dryers, respectively. This signifies the differences in consumption patterns both within and among households increased due to the pandemic. Interestingly 2022 data does not show a decrease in standard deviation, suggesting that there are still higher levels of variability in appliance use than the pre-pandemic levels of variability in appliance use.

It is also interesting to note that the refrigerator energy use is substantially higher (6-77%) across all years in this dataset than the values assumed in the BA or ANSI standard homes; by contrast across all years studied the dishwasher, clothes washer and dryer are substantially lower, including pre- and post-pandemic. In the case of the electric dryer, the values in this dataset are less than half the annual consumption suggested by the BA or ANSI standard homes.

Table 13. Median and standard deviation of each household's annual consumption (kWh).

Appliances\Year	BA*	ANSI**	2018	2019	2020	2021	2022
Refrigerator	434	691	732 (233)	734 (238)	769 (247)	754 (259)	736 (248)
Dishwasher	175	171	124 (90)	124 (88)	150 (93)	142 (95)	137 (101)
Clothes washer	78	68	40 (27)	43 (26)	47 (30)	46 (32)	48 (43)
Dryer	1076	979	418 (277)	423 (259)	415 (271)	413 (281)	405 (281)

*Note: Value in the parenthesis is standard deviation. *Benchmark values for three-bedroom house from BA simulation protocols. **2019 ANSI/RESNET/ICC 301 Standard for three-bedroom Energy Rating Reference Homes.*

Based on these trends and two-tail test results comparing 2020, 2021, and 2022 to 2018 appliance energy use are provided in Table 14. These results suggest that the energy use of dishwashers and clothes washers continue to change through 2022, but the use of refrigerators and dryers appear to be similar to the 2022 of data, and thus are less likely to be changing further in terms of total energy use. The specific profiles of use are discussed further in the remainder of this section.

Table 14. Two-tailed t-test for the mean of the total daily energy use.

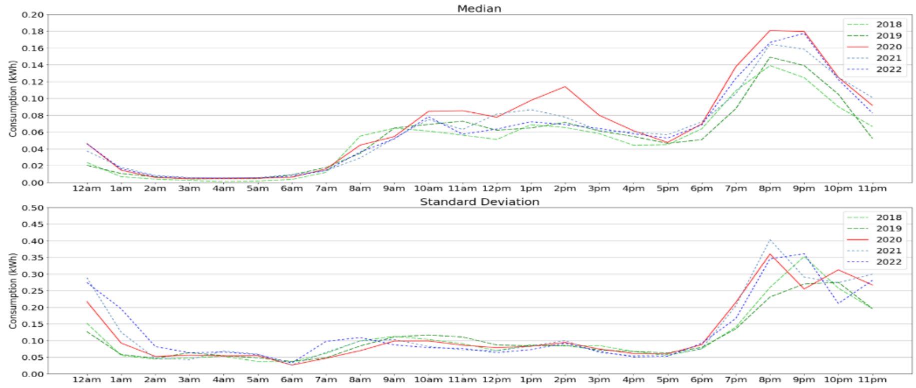
Appliances\Year	2020 vs 18	2021 vs 18	2022 vs 18
Refrigerator	**1.29E-8**	**1.39E-9**	5.10E-2
Dishwasher	**2.30E-4**	**7.00E-3**	**2.10E-2**
Clothes washer	**1.20E-4**	**2.91E-6**	**2.50E-6**
Dryer	7.85E-1	5.51E-1	2.63E-1

Note: bolded values for p-value<0.05, which means the daily profile is different.

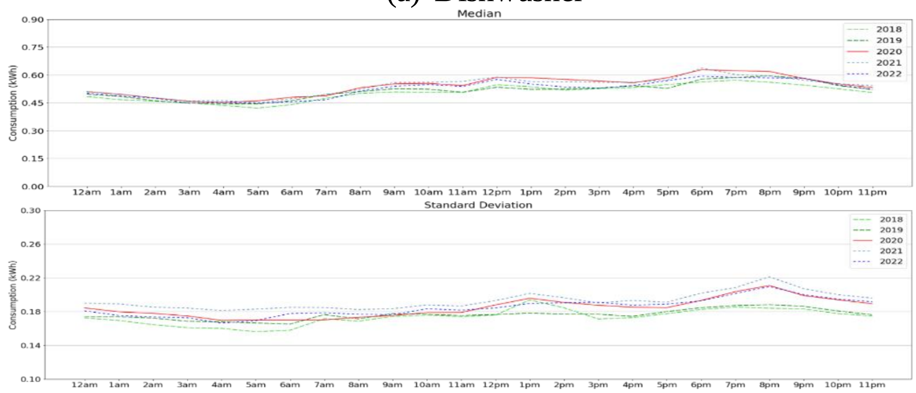
For analysis it is helpful to understand the total energy use profile trends across the studied appliances (Figure 25), to complement the total energy use values shown in Table 14. Specifically, this figure shows the daily profile of median consumption and standard deviations for each hour across each household.

Across all appliances, the median values in 2020 were observed higher than the other years in certain periods of the day, while lower in others. In addition, across all appliances, higher standard deviations were seen from noon to 5:00 pm (especially 1:00 - 2:00 pm, and also at 5:00 pm) and at night (8:00 pm). Across the 5-year period, 2:00 am to 5:00 am was the minimal use period for all the studied appliances, as shown by the lowest medians and standard deviations across the day. In terms of potential for supporting demand side management, if load shedding were to be needed, appliances could potentially be turned on during this period without impacting typical use patterns. However, other than refrigerators, there is not substantial opportunity to reduce load during this time. During the peak use periods, which vary by appliance, the appliances used could be reduced or moved to the other periods of the day, especially to the minimal use periods, to support demand response needs. The following paragraphs discuss specific observations by appliance.

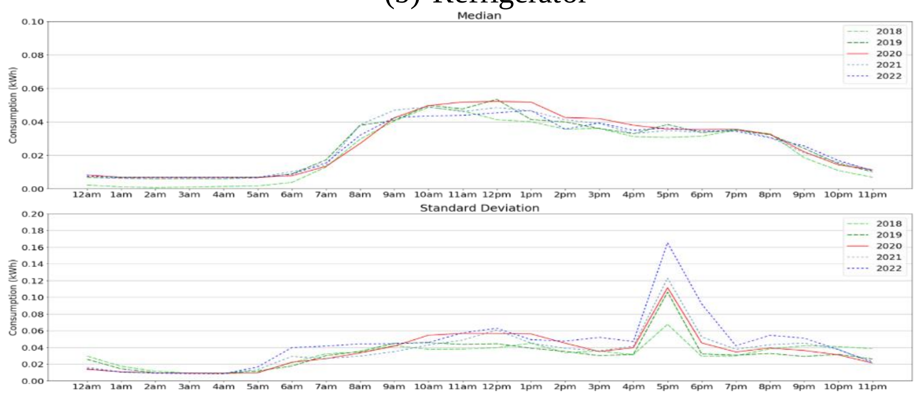
For the dishwasher, 2020, in comparison to pre- and post-pandemic years, has higher overall median energy use most of the day. The post-pandemic energy use trends suggest that this use has decreased throughout the day than the pandemic and is now closer to but still higher than pre-pandemic level, with the greatest differences occurring in the late evening at around 9:00 pm. The highest median (0.18 kWh) and standard deviation (0.36 kWh) of dishwasher use occurred at 8:00 pm during the pandemic, and with similar values in the post-COVID period. These medians were higher than the pre-COVID period from 7:00 pm to 1:00 am and similarly for standard deviations.



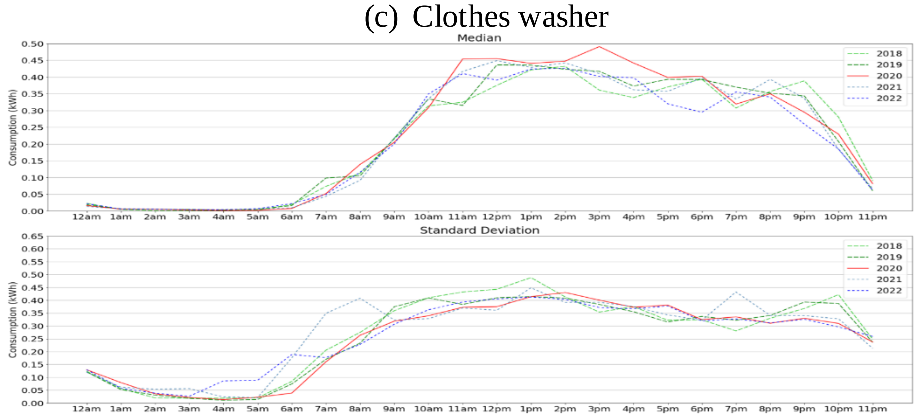
(a) Dishwasher



(b) Refrigerator



(c) Clothes washer



(d) Dryer

Figure 25. Median consumption (top) and standard deviation (bottom) by hour for each appliance.

For refrigerators, the difference in the median appliance use per hour is quite a bit less than that of other appliances. Similar to dishwashers, refrigerator use is higher after around 5:00-6:00 am, and continues to be higher in the pandemic and post-pandemic compared to the pre-pandemic. The peak median (0.63 kWh) occurred at 6:00 pm and the standard deviation (0.21 kWh) at 8:00 pm during the pandemic and similar values in the post-COVID period. One noticeable trend was that medians and standard deviations for 2020-2022 were generally higher than in the pre-COVID period. This suggests higher use but also variability in use across and within homes.

For clothes washers, median total energy use, the pre-, and post-COVID trends are less clear and do not show a consistent increase or decrease in trend. In 2020, an increase was seen from 10:00 am to 4:00 pm. All five years shared a similar period of high median values lasting from 10:00 am to noon and notably extended to 1 pm for 2020-22, while the highest standard deviations occurred at 5:00 pm. An increased standard deviation value was seen at 5:00 pm from 2020 to 2022, especially in 2022 at 0.17 kWh. For dryers, the median values were similar to the pre-COVID period but above other years in the period from 10:00 am to 6:00 pm, with the highest of 0.49 kWh at 3:00 pm during the pandemic. The higher standard deviations happened in the afternoon after 2:00 pm (highest of 0.43 kWh) during the pandemic and were higher than in the pre-COVID period. However, both the medians and standard deviations were lower after 8:00 pm for the years from 2020 to 2022 as compared with the pre-COVID period.

4.4.2. Appliance Percent Daily Use Percentage Profiles

It is next helpful to understand how appliance use patterns pre-, during- and post-pandemic may differ from appliance use profiles assumed to occur for use in building energy modeling based on the BA Simulation Protocol (Wilson et al. 2014). Figure 26 shows the average percent (%) of daily use of each appliance per hour of the day, for each year of the studied data; the BA simulation protocol profiles are also shown, titled the “standard” profile.

For dishwashers, the standard use profile is similar to those values observed across the study period for dishwashers, with the most noticeable difference occurring from 9:00 to 11:00 am (0.5% for the pre-COVID period; 1% for 2020 and after). Comparing the percent daily use across the years of study, during the pandemic, dishwashers were used 1% less in the morning (9 am to 11 am), on average, as compared with the pre-COVID period. This decreased even further in the post-COVID period. There was slightly increased use (0.2%) of dishwashers from 1:00 pm to 3:00 pm in 2020, but not in the post-COVID period. This is likely due to more people eating at home due to restaurants being closed or having limited hours during this period, and/or due to more people working from home and/or attending school remotely. This increased use was seen during the pandemic and more in the post-COVID period from 11 pm to 2 am compared with the pre-COVID period. Overall, however, all profiles shared a similar peak use of approximately 11% at 8:00 pm.

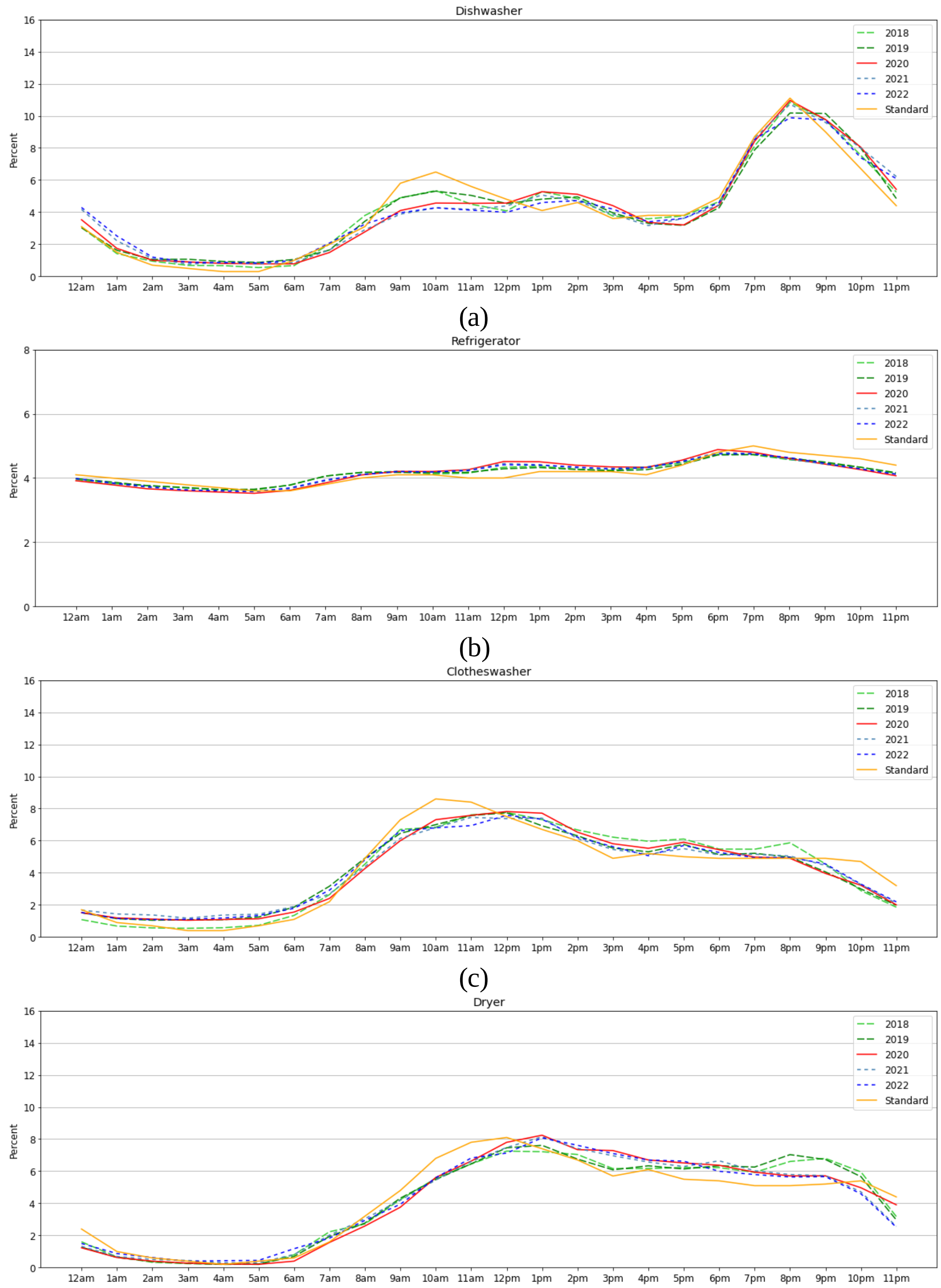


Figure 26. Hourly average percent of daily year for each appliance (a) dishwasher, (b) refrigerator, (c) clothes washer, (d) dryer. *Note: "Standard" profile from BA simulation protocol.*

The refrigerator profiles were remarkably similar across the studied years and similar to the standard profile. However, the use pattern of the studied data appears to be shifted one hour earlier, peaking at about 4.8% at 6:00 pm, compared with the standard refrigerator profile (peak of 5%, at 7:00 pm). There are not many other major differences in use patterns other than this slight shift, including between the standard use profile assumption, and between different years of studied data. This is consistent with other studies which have analyzed refrigerator use data (Kawka et al. 2021, Cetin et al. 2014).

For clothes washers, larger differences in percent use are observed compared to the standard profile, with the most remarkable being higher percent use from 8:00 am to 12:00 pm and from 9:00 pm and 11:00 pm, and lower percent use in the other time throughout the day. This pattern is consistently different regardless of year of study. Compared with the standard clothes washer profile peak use (around 8.6%), the five years of data was about 0.6% less on average. In addition, the peak use is around 12:00 pm across all year of the studied data, whereas peak use from the standard profile is at 10:00 am. Comparing different years of data, in 2020, there was a slight increase in the percentage use of clothes washers at 10:00 am (0.4%) and 1:00 pm (0.6%) compared with the pre-COVID period. Another slight increase was seen for the post-COVID period at night, especially from midnight to early morning.

For electric clothes dryers, similar to clothes washers, there are more substantial differences in use percentages compared to refrigerators and dishwashers. For dryers, similar to washers, the standard use profile appears to overestimate dryer use in the morning from 8:00 am to noon (up to 0.3%) and underestimate the percent use from the afternoon 2:00 pm to early evening 9:00 pm (up to 0.3%) across nearly all years of data. However, while these precent use values across the studied years are more similar in the morning, the larger differences occur in the afternoon and evening. In terms of peak use, compared with the standard dryer profile which peaks in use at noon, a 1-hour shift when the same peak use (8%) occurs at 1:00 pm is observed for 2020 and the post-COVID period. A higher percentage of use (up to 1% per hour) continued from 1:00 pm to 5:00 pm but for the hours after, dryers were used less during and post-COVID compared with the pre-COVID period. This may be related to adjustments in the use of clothes washers, as dryers are typically used directly after the clothes washers. For 8:00 pm to 10:00 pm, a peak (1.2% higher) was seen for pre-COVID profiles but not seen during the pandemic and post-COVID period.

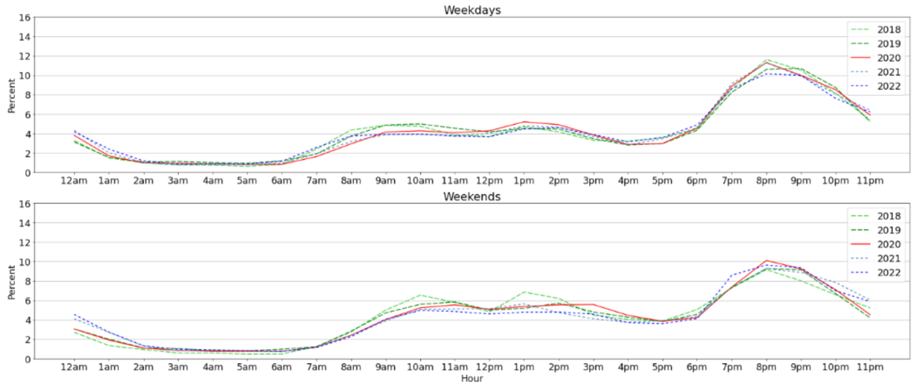
4.4.3. Comparison of Weekdays and Weekends

Based on the time of the week, Figure 27 includes the plots of average daily use on weekdays and weekends for all the appliances. For average daily consumption, the increased use can be seen for all four appliances during the pandemic as compared with the pre-COVID levels. On weekdays, there was a decrease (up to 1.4%) in the use of dishwashers in the morning but a slight increase (up to 0.7%) for the interval of noon to 3:00 pm in 2020 as compared with the pre-COVID period. The dishwashers were used less (1%) during the daytime for 2021 and 2022 compared with pre-COVID period and 0.2-0.7% less than 2020. The peak of around 12% occurred at 9:00 pm to 8:00 pm in 2020 and 2021. A 0.7% increase occurred at night from 11:00 pm to 1:00 am in 2020, specifically up to a 1.2% increase in the post-COVID period compared with the pre-COVID period. For weekends, the trend was similar to weekdays in 2020. The use of dishwashers was still up to 2.1% less during the daytime for 2021 and 2022 as compared with the pre-COVID period, but an increase (up to 1.8%) in the use of dishwashers occurred especially from 11:00 pm to 1:00 am for the post-COVID period, similar to the weekdays. Such an increase may be due to decreased use during the daytime since many people were working from home or completing other activities, and thus may have chosen to run the dishwasher late at night.

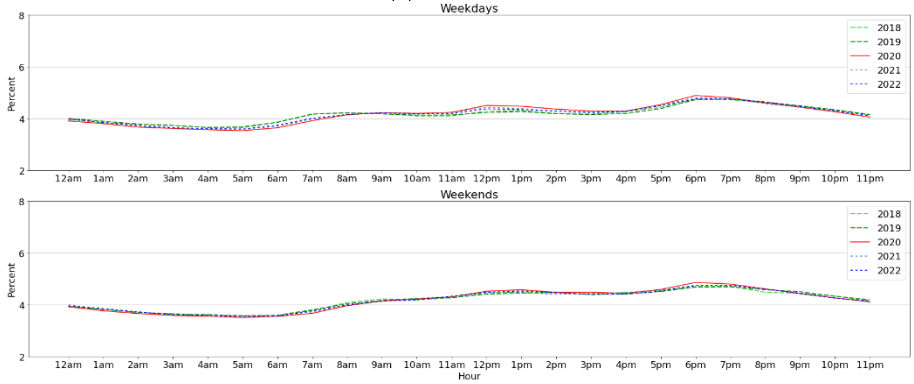
For refrigerators, the changes were less noticeable than the other appliances. On weekdays, a slight increase in usage (0.3%) was seen from noon to 7:00 pm (peak use of 4.8% at 6:00 pm) in 2020. On weekends, there is also a slight increase in use at 1:00 pm and 3:00 pm followed by a more noticeable one at 6:00 pm (peak use of 4.8%) to 8:00 pm, in 2020. Since people were spending more time at home, they were also likely cooking and eating more at home than in the pre-COVID period (Mitra et al. 2022, Dong et al. 2024); this may have caused the increased use of refrigerators. The years 2021 and 2022 followed the trends of 2020, but gradually have returned to the pre-COVID trends.

For clothes washers, the use increased by 1% to the peak of 8% during the pandemic at 11:00 am on weekdays and to 9% at noon on weekends. For 2020, clothes washers were used less in the early morning. There were also certain periods of higher use that occurred as compared with the pre-COVID period, including, on weekdays: 10:00 am to 2:00 pm for 2020, and 1 pm for the post-COVID period; on weekends: 10:00 am to 6:00 pm for 2020, and noon for 2022. For other times, the trends in the post-COVID period were similar to the to pre-COVID period on both weekdays and weekends. The increased amount of clothes washer use may indicate that people were spending more time at home cleaning and taking care of others (Memmott et al. 2021) who needed to change clothes more frequently.

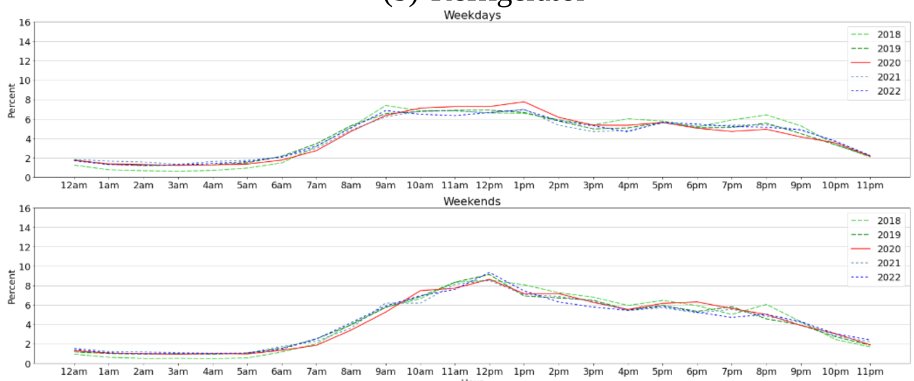
There was an increased use of dryers by 1.5% during the daytime (peak use of 8.1% at 1:00 pm) in 2020 on weekdays, and 1:00 pm till night around 9:00 om (peak use of 8.2% at 3:00 pm) on weekends. In the post-COVID period, there was still around 1.4% higher use across the daytime as compared with the pre-COVID period for both weekdays and weekends. However, there is also less use at night after 8:00 pm across 2020-2022, especially the post-CVOID period, compared to the pre-COVID period for both weekdays (up to 2%) and weekends (up to 1.2%). Since there is an increase in use during the daytime, this is likely part of the reason there is less use at night.



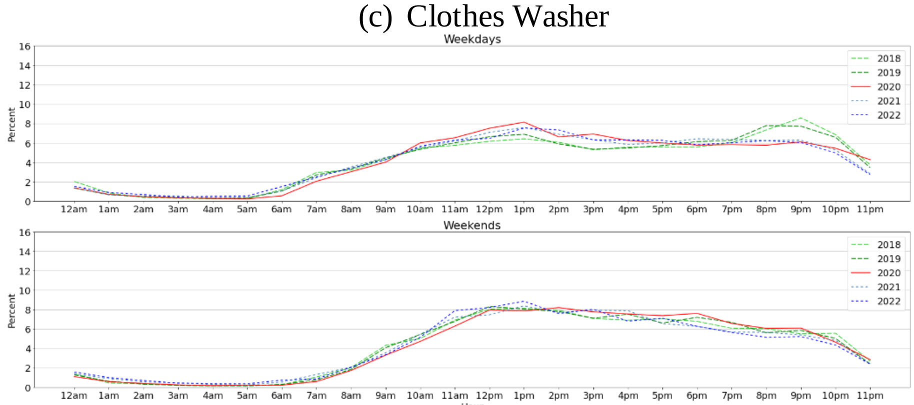
(a) Dishwasher



(b) Refrigerator



(c) Clothes Washer



(d) Dryer

Figure 27. Daily consumption profile for weekdays and weekends.

4.4.4. Monthly Variation in Energy Use

Due to the pandemic, there were up to 1% increases in monthly consumption in April-July and December for dishwashers, May-July and November for refrigerators, March and July-October for clothes washers, and March for dryers compared with the pre-COVID period, as shown in Figure 28. In certain months of 2021 and 2022, higher use of those appliances can also be seen, especially during August of 2021 and December of 2022. Over these years, the overall monthly profiles appear to be consistent for refrigerators and dryers. This can be seen in the comparison to the monthly use of dishwashers and clothes washers, which fluctuated more due to the pandemic. Over the five years, dishwashers, similar to dryers, were more often used when the outdoor temperature got colder (peak in January), with more than 9% usage during the winter months. The high use of refrigerators exceeding 9% happened during the summer months (July-September; peak in August). Conversely, the use of dryers reached the lowest use at around 7% in June during the summertime and exceeded 9% in the winter months (peak in January). The use of clothes washers fluctuated around 8% to 9% across the year.

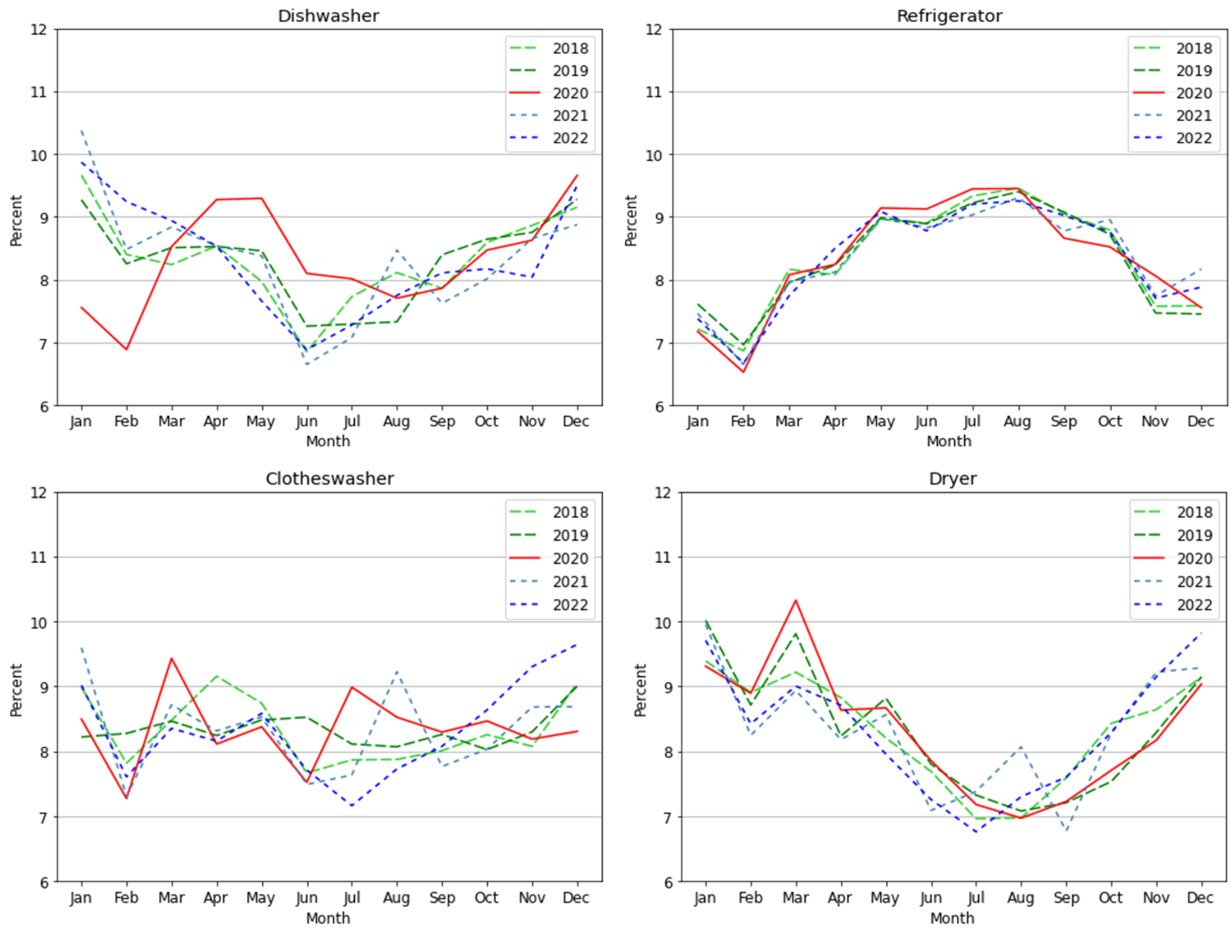


Figure 28. Monthly energy consumption for all the appliances.

To enable comparison with currently assumed values for residential building energy modeling, all the households' consumption were next normalized using the monthly average value, as shown in Figure 29. The "standard" profiles also shown in this figure are from the same BA program simulation protocol's monthly scaled factors. Another monthly scale factor considered for comparison was from the NREL simulation tool ResStock (Wilson et al. 2017). ResStock robustly simulated representative archetype homes to provide baseline energy consumption. For analyzed households, the use increased by 0.03-0.15 for dishwashers (April to July), 0.01-0.07 for refrigerators (May to July and November), 0.11-0.14 for clothes washers (March and July), and 0.07-0.13 dryers (March) in 2020 as compared with the pre-COVID period. For the post-COVID period, the use of appliances stabilized and generally returned back to the pre-COVID level with some slight variations higher or lower than pre-COVID levels. For certain months in the post-COVID period, the use of dishwashers and clothes washers is more different (±0.1) than the previous years. This suggests that further analysis in future years would be beneficial.

By comparing the monthly trends, some potential modifications are suggested to the standard profiles based on the trends across the five years. For dishwashers, the standard profile values are consistently close to 1 instead of 1.1 in February and October and 0.85 in September. For refrigerators, the values are also suggested to be 1 instead of 1.1 in March and April, and 1.05 instead of 0.93 in October. For dryers, 1.2 is suggested in January, and 1.1 for February and March instead of 1.15 and 1.14.

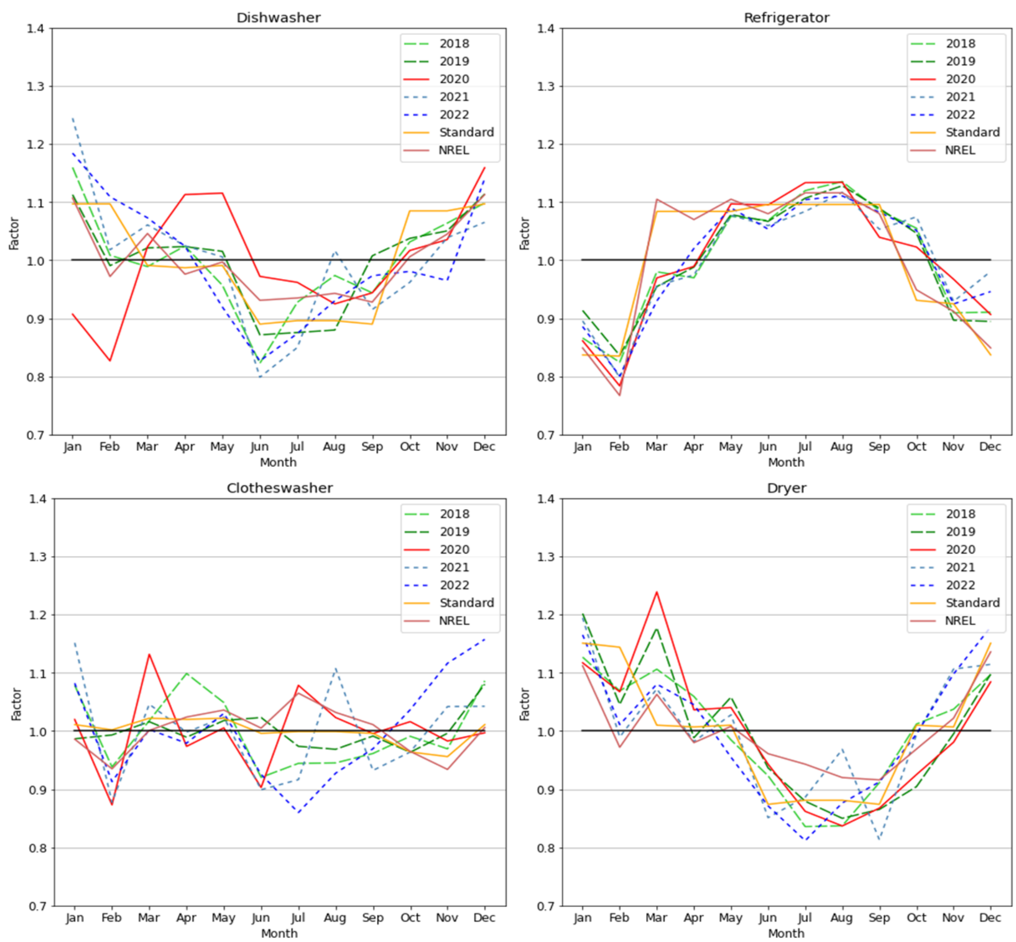


Figure 29. Monthly energy uses relative to the mean monthly value (Top: Refrigerator, clothes washer; bottom: dryer, dishwasher). *Note: Horizontal line is the ideal average monthly factor*.

Finally, since not all the possible large appliances utilized in a home are analyzed in the previous sections, in this final section, the overall usage of non-HVAC loads (all household electricity end uses that are not HVAC) has changed across the five years. This can help provide a more broad understanding of the electricity use trends. This non-HVAC usage profile is shown in Figure 30. In the pre-COVID period, non-HVAC use peaked for a 2-hour period (around 5.4% per hour) in the evening from 6:00 pm to 8:00 pm before starting to decrease. In 2020 this trend changed slightly, with two peak times at noon (5.2 %) and 6:00 pm (5.4%). In addition, non-HVAC equipment was used more during the daytime from 8:00 am to 5:00 pm (0.1-0.6%) as compared to the pre-COVID period but used less (up to 0.6%) from 7:00 pm to 7:00 am. For the post-COVID period, the profiles were very similar in 2021 and 2022.

Similar to the pandemic period, two peaks occurred at 12:00 pm (5.1%) and 6:00 pm (5.1%). From 8:00 pm to 7:30 am, the usage during the post-pandemic period was very similar to the pre-COVID pattern. However, from 7:30 am to noon, the post-COVID period's use patterns have increased by generally remained much closer to 2020 than the pre-COVID periods. After noon, it began to decrease until it overlaps with pre-COVID pattern at around 4:30 pm. And then till 8:00 pm, the usage was less than in all the previous years (0.4% less than the pre-COVID level; 0.2% less than the pandemic) and then followed the same usage pattern as the pandemic through midnight. This trend shows that between 5:00 pm and midnight, people were using less non-HVAC appliances, likely due to the increased use during the daytime. Based on the observation of post-COVID period, the non-HVAC load seems stabilized and different from the pre-COVID pattern, which may suggest a new norm has formed.

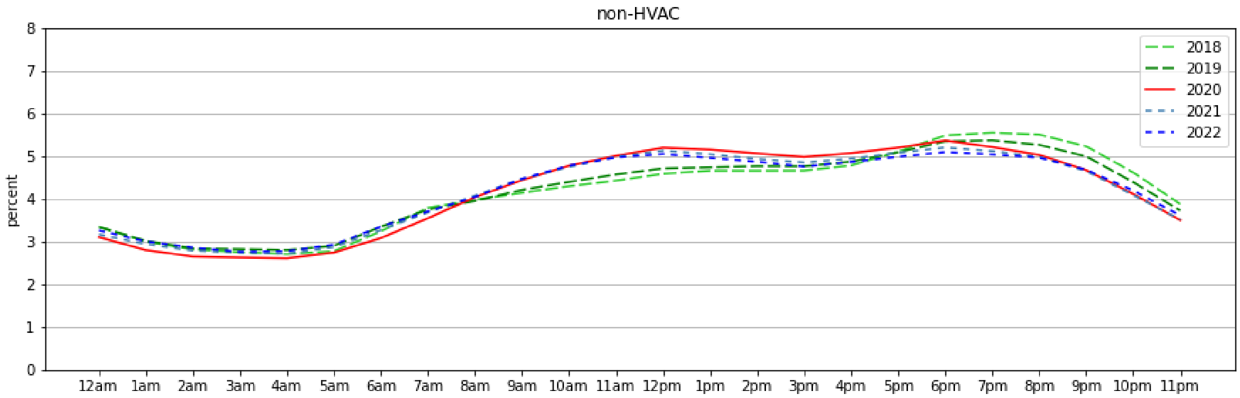


Figure 30. Average daily non-HVAC usage profile.

4.5. Conclusions

This study investigates residential appliance use patterns and changes for the period of 2018 to 2022, which includes 2020 as the year of the COVID pandemic, and the two years that follow. Previous studies have identified that COVID impacted home energy use patterns, thus this study focused on the assessing trends in the years after the pandemic using the latest data available. Based on the results of this study, daily and monthly energy uses of four residential appliances, including dishwashers, refrigerators, clothes washers, and dryers, and well as all non-HVAC end uses combined, were analyzed to show the overall trends and changes during (2020) and post (2021, and 2022) pandemic. The most significant findings are as follows:

- The highest median (10.9 kWh) Based on the standard deviation of total energy use, the differences in consumption patterns both within and among households have increased due to the pandemic. In addition, across all appliances in 2020, higher standard deviations were seen from noon to 5:00 pm (especially 1:00 - 2:00 pm, and also at 5:00 pm) and at night (8:00 pm). The most recent 2022 data suggests that variability is still higher than the pre-pandemic levels in appliance use. Statistical results suggest that the total energy use of dishwashers and clothes washers continue to change through 2022, but the use of refrigerators and dryers appears to be more stable.

- Across all appliances, the median values in 2020 were higher than the other years in certain periods of the day. For the dishwasher, 2020, in comparison to pre- and post-pandemic years, has higher overall median energy use most of the day. For refrigerators, the difference in the median use is quite less than other appliances. For clothes washers, the pre-, and post-COVID trends are less clear and do not show a consistent increase or decrease in trend. In 2020, an increase was seen from 10:00 am to 4:00 pm. For dryers, the median values were above other years from 10:00 am to 6:00 pm during the pandemic, but were lower after 8:00 pm from 2020 to 2022 compared with the pre-COVID period. Across the 5-year period, 2:00 am to 5:00 am was the minimal use period for all four appliances with the lowest medians and standard deviations across the day.
- Across the appliances studied, while the "standard" profile is similar to the measured data, there are also some notable differences. For dishwashers, the "standard" use profile is similar to those values across the study period; they also both share a similar peak use at 8:00 pm. The refrigerator profiles were the most similar, among the studied appliances, to the standard profile across the studied years. However, the measured data peaks at 6:00 pm rather than 7:00 pm for the standard profile. The standard clothes washer profile peaks at 10:00 am whereas the measured data peaks at noon. For the dryer, the standard profile peaks at noon, whereas the measured data peaks at 1:00 pm for 2020 and the post-COVID period.
- Considering changes in use in the COVID and post-COVID period as compared to pre-COVID, across all appliances, each appliance had slightly different trends. The dishwashers were used slightly less during the daytime and on weekends for the post-COVID period compared with pre-COVID period; on weekends in the post-COVID period

use increased nearly 2% between 11:00 pm and 1:00 am. For refrigerators, there was an increased use in 2020, and similar but slightly less use post-COVID. For clothes washers and dryers, use increased during the pandemic during the day on weekends, and less use at night. There are smaller periods of higher use for washers and dryers post-COVID as compared with the pre-COVID period, where other times, the trends in the post-COVID period were similar to the to pre-COVID.

- The monthly profiles appear to be most consistent for refrigerators and dryers across the 5 years of study. The monthly use of dishwashers and clothes washers fluctuated more due to the pandemic, and post-COVID. For the normalized monthly use factors, the use increased in all the studied appliances across many months in 2020 as compared with the pre-COVID period. For the post-COVID period, the use of appliances stabilized and generally returned back to the pre-COVID level with some slight variations than the pre-COVID levels.
- The non-HVAC load appears to have stabilized across 2021 and 2022, in a slightly different pattern than pre-COVID, suggesting a new norm of housing end-use energy consumption. In terms of differences, the key differences in the post-COVID periods as compared to pre-COVID are two peaks that occurred at 12:00 pm and 6:00 pm. From 8:00 pm to 7:30 am, the usage during the post-pandemic period was very similar to the pre-COVID pattern. However, from 7:30 am to noon, the post-COVID period's use patterns have increased much closer to 2020. After noon, it began to decrease until it overlaps with pre-COVID pattern at around 4:30 pm. Till 7:00 pm, the usage was less than in all the previous years, and then followed the same pattern as the pandemic through midnight.

Households used in this study are only based on the data collected from Pecan Street, and potentially biased concluded results are shown in the study. Thus, to validate the conclusion of this study, future studies will be necessary for further investigation. The continuous study is worthwhile for the post-COVID period when the latest data becomes available because changes in the use of appliances are still dynamically changing from time to time. The next step could consider the average use profile by considering different demographics of the households, such as income levels, family member numbers, and house types. In the future, the time of the profiles will be divided into more granular timesteps, such as different times of the week and seasons.

4.6. Acknowledgment

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CHAPTER 5: CONCLUSIONS

5.1. Summary

Research has been completed for all three focus areas. This study investigated the impact of variations in sensing technology, human-related socioeconomic variables and occupancy, and appliance use on building use, energy consumption and demand. The first study assesses the impacts of adjusting vertical and work plane illuminance sensor location and rotation for different zone orientations across different climate zones on illuminance levels, glare, energy demand, and consumption. An integrated system of automated shading and lighting controls was created using the most common control variables.

Further, in the second study, the socioeconomic factors that most impact occupants' time in residential spaces were identified. This research examines the impact of the pandemic and post-pandemic on hours at home across different household demographics, using the American Time Use Survey (ATUS) data. The results of this research help support understanding the changing trends in occupancy among different groups of people, especially during the post-pandemic period. They also show that occupancy trends different for different socioeconomic groups and cannot be all treated as homogeneous. Findings also suggest that in the wake of the pandemic, that some socioeconomic groups' occupancy patterns continue to change while others have returned to a steady state. Such conditions must be monitored moving forward as they continue to evolve. Another important aspect of the second study is that it helps to provide insight on the changes in housing use in the event a future catastrophic or pandemic-like events occurs. These results are also critical to help support the ongoing electrification of homes and decarbonization of the electric grid.

Finally, the third study investigates the use of appliances and how they have changed post-pandemic (2018-2022). This specifically helps to understand peak demand use periods and how such devices can support participation in demand side management. Similar to the second study, the importance of this third study is to help predict the appliance use trend and peak use hours during possible catastrophic events in the future. These results are also critical to help support ongoing electrification and development of demand-side management in the residential sector, in particular it helps to identify which appliances are the best fit to support demand side management.

5.2. Significant Findings and Contributions

For the first study, this research demonstrates that dynamic shading and lighting can support significant demand reduction (due to lighting and cooling demand reduction) in commercial buildings. However it also importantly notes that the placement of sensors can significantly impact the performance of a smart building, its systems, and its controls, and thus should be considered and assumptions should be explicitly stated when conducting such analyses. In particular using the sensor locations of 1.6 m and facing the window (typical assumption), the lighting and cooling energy savings range from 41% to 71% across both heating and cooling-dominated climate zones using the integrated shading and lighting control sequences. The greatest cooling peak use demand reduction of 6.5 kW (23%) is achieved. The combined cooling and lighting demand savings range from 28 to 33% (9-10 kW). Results suggest that, among the factors studied, adjusting the sensor distance from the window has a greater impact on illuminance levels, glare, and lighting and cooling energy use in all climate zones as compared to sensor rotation.

The second study's results demonstrate the importance of considering the impacts of the pandemic and post-pandemic on occupancy assumptions in residential buildings. In particular this study evaluates the importance of 14 possible variables, such as age, race/ethnicity, employment status, and income levels, on the time spent at home across five years, from 2018 to 2022. Results suggest that employment status and household income level are the most significant variables predicting hours a home is occupied. Results also suggest that those under 25, low-income households, and those identifying as Hispanic have most quickly returned to pre-pandemic (2018-19) occupancy patterns. They also indicate that based on the most recently available data in 2022, occupancy patterns continue to change for those under 55, middle- and high-income groups and 3+ member households, and thus require continued study to understand further changes.

The third study's results demonstrate that among the appliances studied, all energy use patterns shifted somewhat compared to pre-pandemic, as did the variability in the use of these appliance. Refrigerators and clothes dryers have leveled off in terms of use pattern changes in the wake of the pandemic, whereas dishwasher and clothes washer use have continued to change. Results of this research also suggest the need for changes in the standard assumptions for appliance use profiles in building energy modeling protocol and software. This research also found higher standard deviation in appliance energy use in the afternoons (especially 1 pm to 2 pm and 5 pm) and at night (8 pm), when peak demand periods typically occur, implying that availability of appliances for demand response events may be less consistent in the wake of the pandemic.

5.3. Future work

The next steps for the first focus area are to apply the proposed control sequence and sensor placement for a test site and validate the results using the data collected. This is important, although time consuming and costly, as modeling can present ideal conditions while some scenarios are less ideal in the real-world environment. As a part of a broader collaborative research effort, field testing of the developed controls is being tested in two buildings in the U.S.

The next step of the second study would be to investigate how much of the changes in occupancy patterns are associated with working from home. This is important given that this can have a significant impact on demand response potential (i.e. those working from home may be less flexibility in what loads could be adjusted during a period where demand response is needed). An additional next step would be due to the finding from this research that occupancy patterns have not returned to pre-pandemic levels for many specific demographics. It is unclear if they will ever do so, or if they will level off and remain the same as the previous year in 2023 and moving forward. As such, future investigation is necessary, specifically conducting similar analysis for 2023 and beyond, as data becomes available, to determine if and when occupancy patterns have returned to more consistent levels over time.

Future research on appliance use patterns would also be beneficial, for similar reasons to those cited in the second study. Specifically, continuous study is worthwhile for the post-COVID period when the latest data becomes available because the use of appliances are still changing. The use profiles across different days of the week and across demographics of the households would also be helpful to quantify variability. Both the second and third study have implications from an energy justice lens as well, which would be beneficial to explore further. Specifically, because different demographics have different occupancy and appliance use patterns, this makes their ability to participate in and/or benefit from demand response and other decarbonization efforts different. It would be beneficial to assess the relative benefits of demand response participation due to these changes across demographics to understand if all household types can realize the monetary benefits of such programs equally.

CHAPTER 6: PUBLICATIONS

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