PERFORMANCE EVALUATION OF HVAC-CONNECTED OCCUPANCY SENSOR SYSTEMS

By

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ABSTRACT

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Occupancy is highly unpredictable and depends on occupants' schedules and their interactions with building systems. Occupancy sensor systems have been deployed in buildings for many years, and many research studies have been conducted that use a range of sensor modalities for occupancy sensing and counting. However, no comprehensive review of occupancy sensor system reliability has been compiled. In addition, there is not currently a universal methodology and metrics to evaluate and report occupancy sensor systems' reliability. There have also been increasing studies on the implementation of occupant-based controls, especially energy savings evaluation in typical office building models. However, although there are many universities throughout the U.S., prototypical academic building models do not currently exist for use in evaluating energy saving potential.

To address these research gaps, in this research, a review of the literature on occupancy sensor systems was completed to develop a comprehensive list of influential variables that may impact occupancy sensor system reliability. Next a survey was developed and distributed to a diversity of stakeholders to obtain a list of the most important factors that may influence occupancy sensor system performance. Then, a methodology was developed to assess the reliability of occupancy sensor systems in residential buildings in a controlled laboratory environment. This includes both "typical" testing, evaluating how reliable and accurate an occupancy sensor system is over time in a typical residential building environment, and "failure" testing, identifying individual influential variables that impact performance. The developed methodology was then

implemented to evaluate a novel occupancy detection sensor system's reliability. For typical testing, results show that on average, the overall accuracy of the tested sensor system ranged from 62.4% to 76.4%. For the failure testing, the number of occupants, presence of large objects, presence of interior light sources, and number of doors were identified as not influential, while lighting level, location of occupants, additional door in the entry/exit area, and having the TV on are variables determined to impact the sensor system performance.

Furthermore, the U.S. DOE reference medium office building model was used as the basis to develop typical academic building models. The model was rezoned to add new spaces based on the space type and functional use data collected from 293 academic buildings across five U.S. universities of different sizes. Four types of typical academic building models were then identified using clustering methods. These include typical "Office-dominated", "Laboratory-dominated", "Study room-dominated", and "Mixed-use" academic building models. Occupant-based controls were then added to the model to evaluate the potential energy savings of these developed models. Results show that among all these four typical academic building models, in ASHRAE Climate Zone 5, the total annual HVAC energy savings ranges from 35% to 51% under "Occupancy presence" scenarios, and a further energy saving increase (3-9%) from "Occupancy presence" scenarios to "Occupancy counting" scenarios.

The proposed methodology for evaluating the reliability of occupancy sensor systems presents an opportunity for use as a standardized method to evaluate residential occupancy sensor systems that currently does not exist. This work also provides typical academic building models with integrated occupancy schedules which can be used to evaluate energy saving measures, and aid building designers and operators in making informed decisions in applying appropriate control strategies to optimize building energy systems, as well as predict energy use and demand.

I dedicate this dissertation to
my family and my beloved husband, Zhengyu
for their constant support and unconditional love.
I love you all dearly.

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CHAPTER 1 – INTRODUCTION

1.1 Research Motivation

Energy consumption throughout the world has significantly increased over the past 20 years, as the population has increased, as well as the use of energy-consuming technologies. Building energy use accounts for approximately 40% of the total primary energy consumption in the U.S. and the E.U., and 27.3% in China (Cao et al., 2016). For end uses in buildings located these regions, space heating and cooling energy make up a large portion of total energy consumption in the residential (46%) and commercial (36%) sectors (Cao et al., 2016). Moving forward, it is projected that total energy demand from heating and cooling will increase in cooling-dominant and less-developed regions (Cao et al., 2016). Therefore, to reduce emissions and energy use overall, in order to reduce climate change impacts and improve grid operations, it is important to develop energy saving approaches to help reduce heating and cooling energy use in buildings.

The energy consumption of buildings and their systems are primarily dependent on outdoor weather conditions, building and system characteristics, and the occupants who utilize them. Data on these parameters is necessary to monitor performance, assess inefficiencies, and identify opportunities for improvements. Among these, weather data is generally ubiquitous and easier to obtain and/or collect using local or regional ground-based weather station or satellite-derived data. Many studies have used such data to demonstrate the relationship between building energy consumption and climate parameters (e.g., Hadley 1993), with outdoor temperature typically being most important. However, even though this information is generally readily available, weather is not a variable that can be adjusted to improve building performance. For individual buildings, data on building systems and their characteristics are relatively available, including assessors and other publicly available information, energy code requirements, and data from the building owners/operators. There are many recent studies focused on the use of this information to assess and improve building performance. For example, for building envelope characteristics, Menyhart and Krarti (2017) applied Dynamic Insulation Materials (DIMs) to replace the traditional, static insulation and found that DIMs can achieve heating and cooling energy savings ranging from 7% to 42%. For energy-consuming building systems, including the heating, ventilation, and air conditioning (HVAC) system, appliances, equipment, and other miscellaneous loads, a broad range of studies have focused on assessing the impact of these systems on energy performance have also been investigated. For example, Anand et al. (2019) investigated the relationship of occupancy with plug and lighting loads energy consumption for several spaces of an institutional building floor, and deep neural network was used to estimate possible energy savings with a rule-based energy-use behavior. Energy efficiency standards for residential and commercial equipment have also been found to be a major source of energy saving in U.S. (U.S. DOE, 2018).

Data, however, on the third above-mentioned influential factor, occupants, is more challenging to collect and less readily available as compared to the other two. Buildings are strongly influenced by the occupants that use them and their energy-consuming behaviors (Hong et al., 2016). There are significant opportunities to better collect and use occupancy related data to inform building controls, to target energy use reductions and efficiency improvements. When there are less occupants, ventilation requirements are lower (ASHRAE 62.1, 2019); when there are no occupants, thermal comfort requirements no longer need to be met (ASHRAE 55, 2017). Therefore, occupancy sensing technologies used in buildings can help to significantly reduce HVAC loads (Jung et al., 2019).

To collect accurate occupancy information, such as occupant presence, counting, location, and tracking (Teixeira et al., 2010), occupancy recognition technologies have been developed and studied in the recent decades. Existing technologies for occupancy information extraction in buildings can generally be classified into two categories: single sensor systems and sensor fusion technology. Single sensor systems utilize one or multiple sensors with the same type to infer occupancy information, while sensor fusion methods combine more than one type of occupancy sensors to compensate the disadvantages of each type of sensor systems. Many of the single sensor technologies have been used to predict the presence and counting of occupants in buildings. Based on a review of 26 recent papers on occupancy sensor systems, the most common types (see Figure 1), are PIR (passive infrared) (Liao et al., 2010), and CO2 (Jiang et al., 2016) sensors, followed by RFID (Liao et al., 2012) and Wi-Fi-based sensors (Zou et al., 2017). Another important, but less commonly used sensor technology is video (Erickson et al., 2009), which is often used to collect ground truth data for occupancy studies. The benefits of the use of single sensor systems is the simplicity of the sensor deployment and data collection, however, edge cases could happen when only one type of sensor is used, for example, the motion sensor could not detect people when a person is static, causing false positive, where sensor fusion technologies could help add more capabilities.

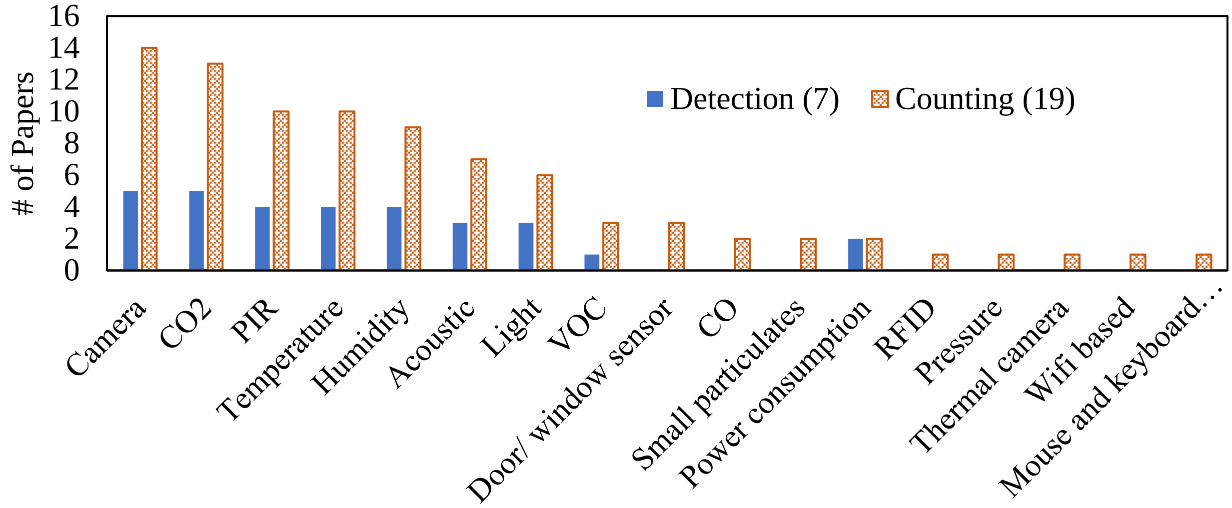

Figure 1 Summary of the most commonly used occupancy sensors

Due to the emergence of machine learning and the big data industry, as well as the significant reductions in cost and size of equipment needed to store data and run computational algorithms, data-driven models have been increasingly used in research to help improve the prediction accuracy of various technologies. These are of particular importance and benefit to the second type of occupancy sensor system - sensor fusion technology. Recent studies using sensor fusion (e.g., Yang et al., 2014; Ryu et al., 2016) have developed low-cost, non-intrusive occupancy sensors systems to predict occupancy in buildings. The data collected from different sensors is pre-processed and fed into a training model. Next, the resulting model is used to predict occupancy (presence or count) based on the provided inputs. In general, the more inputs and diverse data collected as input into the model, the more accurate the models become (Yang et al., 2018).

The challenge with occupants and occupancy data, however, is that occupants are inherently unpredictable, varying both from person to person, and from building type to building type. Factors such as interior building layout and geometry, lighting levels and other physical parameters, depending on the type of sensor(s) used, can significantly impact the ability of a system to detect occupants (Gennarelli et al., 2016; Labeodan et al., 2013; Wang et al., 2017; Yun et al., 2014). This impact varies depending on the type of sensor system used and its corresponding algorithms. Similarly, occupant characteristics, including their physical features and movements, their preferences, and their occupant-building interactions with energy-consuming appliances and systems in buildings, make the accurate detection of occupants challenging due to limited predictability (Yoshino et al., 2017; Yan et al., 2017). The relative importance of these occupant characteristics, similar to physical building characteristics, is also dependent on the sensor system considered. Among the recent literature, while some studies have considered multiple different factors in evaluating their influence on occupancy sensor system performance, *a comprehensive survey gauging of the relative importance of these diverse factors on the performance of occupancy sensor systems has not been conducted.*

In addition, in considering such factors can vary substantially by building type and occupant characteristics, while both single sensor and sensor fusion methods have improved significantly in recent years, these technologies are not 100% accurate. The methodology used to evaluate performance, and the metric used to report it are not uniform across the literature. Sensors can fail under various scenarios and edge cases. For occupancy presence sensors, this can be either as a false positive reading (i.e., the sensor system indicates there is an occupant when there is not), or false negative (i.e., the sensor system does not register an occupant when there is one present). For occupancy counting, the failure would be to incorrectly count the number of occupants in a space. A false positive would result in systems being on (e.g., HVAC, lighting) that do not need to be on since no occupants are present; a false negative would result in a potentially thermally uncomfortable (HVAC) or dark space (lighting). For occupancy counting, an incorrect reading of the number of occupants would result in ventilation rates that could be too high or low for the number of occupants present. In summary, occupancy, while challenging to detect with as strong an accuracy as weather and building characteristics, is of significant importance if the goal of a building is to be both energy efficient and comfortable for the occupants that use it. However, without an established method to evaluate the performance of these sensor systems, it is not possible to objectively evaluate and compare the performance of multiple sensor systems. *Currently there is no standard method to evaluate the reliability of occupancy sensors*. To address these two challenges, *<u>the first focus area of this research is on the development of a universal evaluation methodology to test reliability of occupancy sensor systems in residential buildings.</u>*

Beyond reliability of these sensor systems, among the most important features is their function to support energy savings in buildings. Currently, occupancy sensors detecting the presence/non-presence of people in a space are often used in commercial and in some cases residential spaces to determine whether to turn on/off the lights. In the 2018 International Energy Conservation Code, for some types of buildings occupancy sensors connected to lighting are required (IECC 2018). These sensors are often directly interfaced and integrated with the lighting systems. However, in this research, lighting-connected occupancy sensors are not the focus as this is a more widely used application with significant research. More recently, occupancy sensors, including both occupancy presence and occupancy counting sensors are being considered for HVAC control applications. In residential buildings, smart thermostats with built-in occupancy sensors have been increasing in use (Moon et al., 2011). These thermostats generally include a “home” and “away” mode, depending on whether the sensor detects movement or not. In “away” mode, occupancy is considered to be gone from the home and thus the setpoint temperature is adjusted for the single-zone HVAC system to unoccupied mode, to reduce consumption. Many thermostats, however, do not yet have these occupancy sensors integrated into them. There are various energy saving evaluation methods conducted using modeling, or laboratory/field testing methods related to occupancy information. For example, Jain et al. (2013) examined the impact that information representation has on energy consumption behavior by conducting a one-month empirical study with 39 participants in an urban residential building. Wang et al. (2020) explored a co-simulation platform to assess energy saving impact and economic benefits of occupancy driven thermostats in a residential building. EnergyPlus was integrated into the co-simulation platform to evaluate energy consumption and indoor air temperatures. Qin and Pan (2020) analyzed the energy use of high-rise residential buildings in subtropical climate and examined the impacts of different energy saving measures for developing strategies for achieving very low-energy high-rise buildings by using EnergyPlus software.

In commercial buildings, HVAC systems are generally more complex than residential buildings since there are typically multiple thermal zones with a variety of space types. In addition, modern commercial buildings require mechanical ventilation per energy code requirements, thus outdoor air is required to maintain acceptable levels of indoor air quality. The energy consumption associated with ventilation accounts for approximately 50% of the total HVAC energy use in commercial buildings in U.S. (CBECS, 2012). Based on ASHRAE Standard 62.1-2019 (ASHRAE 2019), the outdoor air flow depends on the number of occupants in commercial buildings, thus adjusting outdoor air intake based on real-time number of occupants could significantly improve energy saving. In addition, GPC 36 (High Performance Sequences of Operation for HVAC Systems) within ASHRAE (ASHRAE, 2018) in recent years has also included consideration for occupancy sensing technologies. Given these recent developments in state-of-the art controls, including GPC there is a need to evaluate the level of energy savings that can be achieved in commercial buildings using such controls.

There are two main methods which can be used to evaluate energy savings, including laboratory/field testing, and energy simulation. For energy modeling, while some recent efforts within the past year have considered office building types (i.e., Pang et al., 2020), none have considered academic buildings, which is a primary building type of interest to ARPA-E/DOE and this research (ARPA-E SENSOR FOA, 2017). In academic buildings there are significant transient populations, thus there is a significant opportunity for energy savings from occupancy sensor systems. However, currently there is *no established prototypical building model for academic building types which is able to be used to evaluate energy savings from occupancy sensors*.

The U.S. Department of Energy Prototype (U.S. DOE, 2018) and Reference (Deru et al., 2011) building models were created, in part, to represent the most common types of buildings and their associated energy-impacting characteristics. These can be used with the energy simulation engine, EnergyPlus (Crawley et al., 2000), to assess the building energy performance of such typical building types in different climate zones, for different age buildings (Deru et al., 2011) and/or buildings built to different energy codes (U.S. DOE, 2018). Despite the substantial effort made to validate these and other building energy models, there is, however, typically a discrepancy between the predicted building energy use, and the energy used during actual operation. This is due in part to the unpredictable nature of occupants and their energy-related impacts. Various related studies have been conducted to improve the occupant-related energy efficiency in buildings. In particular, occupant-based control has been the subject of increasing research interest in recent years. Zhang et al. (2018) summarized that the energy saving potential from the use of occupant-based controls is 10%-25% for residential buildings, and 5%-30% for commercial buildings. However, the occupant-based control used in existing studies varies substantially from the perspective of occupant sensing, ranging from simple presence-based switching of lighting systems to full model predictive control. Energy savings estimates vary substantially for these technologies as well (Naylor et al., 2018).

Commercial buildings can be classified into 15 different types according to their principal activity, as outlined in the CBECS (Commercial Buildings Energy Consumption Survey) dataset (Michaels and Leckey, 2012). Based on these, Commercial Reference building models were developed (DOE Commercial Reference Buildings) to represent nearly 70% of the commercial buildings in the U.S. (Deru et al., 2011), including offices, schools, restaurants, hotels, etc. The reference office building models have been widely used in energy simulation efforts in research projects to assess the potential energy savings of typical office buildings in U.S. Buildings used for educational purposes are among the subgroups of commercial buildings in the U.S. that consume a large amount of HVAC energy (U.S. EIA, 2012). Academic buildings at universities are included among these and can vary substantially from typical office buildings in their space use, occupancy patterns, and energy use. However, despite substantial energy use, *there are few studies which have considered occupant-based control in academic buildings*.

In summary, *the second portion of this research focuses on developing typical academic building models and assessing the influence of occupant-based control strategies on energy efficiency improvement in the developed typical academic building models.* Figure 2 summarizes the two focus areas of this research and the associated above-mentioned challenges.

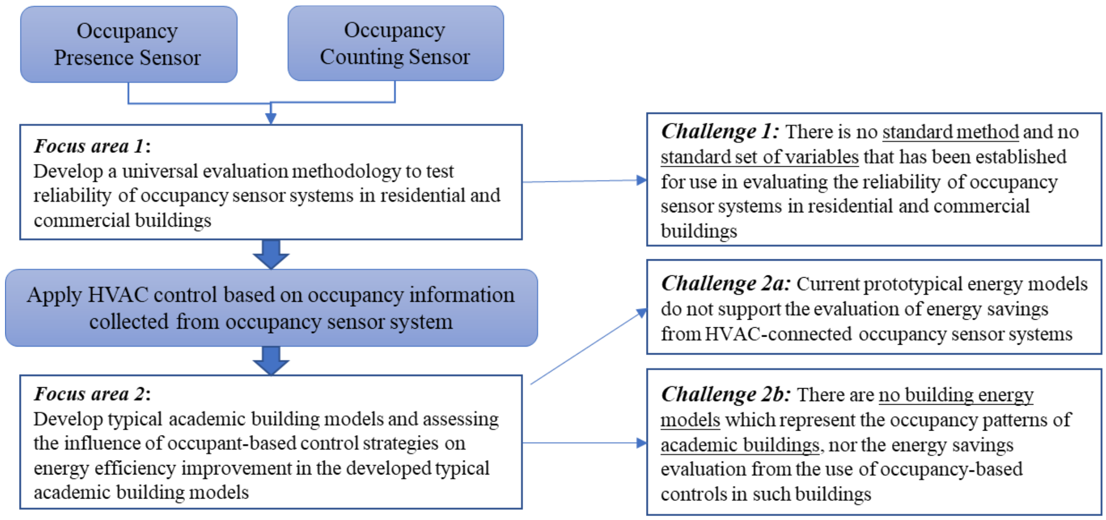

Figure 2 Diagram of challenges associated with the reliability and energy savings evaluation of occupancy sensor systems

1.2 Research Objectives and Research Questions

Based on the above-described challenges, the overarching purpose of this research is to evaluate the reliability of occupancy sensor systems and HVAC energy saving from occupancy sensor systems in residential and commercial buildings. More specifically, the scope of this research includes the development of a systematic test procedure to access the reliability of sensor systems based on a stakeholder consensus on the most important variables to evaluate, development and use of a methodology to evaluate laboratory energy saving from occupancy sensors in buildings, and development of typical academic building models and HVAC energy saving evaluation using occupant-based control. Figure 3 represents the relationship of these aspects of this research and how they relate to the overarching purpose. The details of each objective are described below, where each objective aims to address several major research questions.

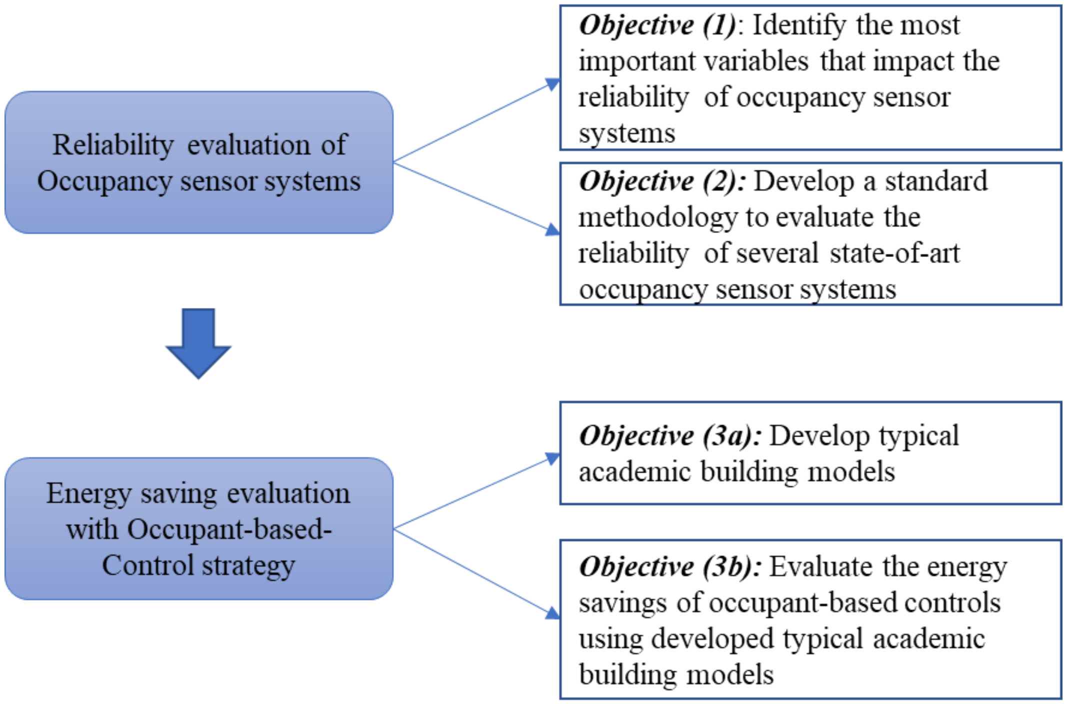

Figure 3 Schematic diagram of research objectives

To develop a systematic testing protocol to evaluate the reliability of the occupancy sensor systems using experimental method, and provide feedback to manufacturers and researchers, this research addresses two major issues identified as Objectives 1 and 2. For the evaluation of energy savings of HVAC systems using occupant-based control, including both the development of typical academic building models, and the implementation of occupancy-based controls for developed typical academic building models, this research focuses on two major and related issues designated as Objective 3a and 3b.

1.2.1 Objective 1: Identify the most important variables that impact the reliability of occupancy sensor systems

Occupancy sensor systems are sensitive to different types of variables based on their operational characteristics and types of sensors used. If sensitive to variations in such variables, this would limit an occupancy sensor system's ability to accurately determine the occupancy of a building. Thus specifically, this objective aims to answer the following research questions:

a) For each occupancy sensor/sensor system type, what are the influential variables that are likely to cause failures?

b) What is the relative impact of variations in these variables on different occupancy sensors/sensor system types?

c) What do diverse stakeholders agree are the most and least important variables for use in a standard methodology of evaluation of occupancy sensor system reliability?

d) Are these most important variables the same for residential and commercial building settings?

In this research, the comprehensive evaluation of potential influential variables that may cause sensor failures are summarized based on literature review, the results from a workshop with the occupancy sensor stakeholders, and the results of a survey of diverse stakeholders on the most and least important variables that affect occupancy sensor performance for commercial and residential building applications.

1.2.2 Objective 2: Develop a standard method to evaluate the reliability of several state-of-art occupancy sensor systems

This objective focuses on the development of a testing protocol to evaluate the robustness of sensor systems in a range of "typical" and "challenging" scenarios, in order to identify areas in need of improvement for the system being tested. The following questions will be addressed in this objective related to the reliability evaluation:

a) Should a standard set of variables be used to test all types of occupancy sensor systems, or should variations in different variables be evaluated, depending on the sensor system type?

b) What experimental methodology should be used to test the identified variables from Objective 1?

c) What evaluation methods should be used to analyze the experimental results?

d) What reliability evaluation metric should be used for the occupancy sensor systems?

In this research, typical testing and failure testing are defined based on the results of research conducted for Objective 1 which identify the potential sources of issues and/or failures for different sensors. Typical testing is defined as the "typical" conditions that are expected to occur on an everyday basis in the residential or commercial setting. Failure testing is the "challenging" conditions that may be less common and/or more extreme than what might occur under a "typical" scenario (e.g., someone running quickly, very dark/bright lighting conditions, etc.), which are helpful in determining what (extreme) conditions will elicit a system failure. Several experimental design methods are considered, and one is chosen for the method development. These test methods are then used for laboratory testing of the reliability of occupancy sensor systems.

1.2.3 Objective 3: Typical academic building energy model development and energy saving evaluation

This objective focuses on the development of a prototypical academic building energy model, which can be used to evaluate energy savings from the use of occupancy sensor system in academic buildings, using occupant-based control (OBC) strategies. Academic buildings are a combination of various space types with different functional uses based on the Postsecondary

Education Facilities Inventory and Classification Manual (FICM). The following questions will be addressed:

a) What is the typical composition of space types for typical academic buildings?

b) How many prototypical academic building models are needed to sufficiently represent typical academic buildings in the U.S.?

c) What modifications should be made to existing prototypical building models in order for them to represent the features of typical academic buildings, and to allow for the use of occupancy-based controls?

d) What are the potential energy savings for the developed typical academic buildings using occupancy sensor systems to control the HVAC system?

To determine typical academic building models, data from different size universities was collected, as designated by the Carnegie Classification of Institutions of Higher Education (CCIHE). This system provides university size categories according to the FTE-based enrollment (FTE = Full-Time Headcount plus 1/3 part-time headcount). Iowa State University data, as well as data from the Texas Higher Education Data (THED) was used. THED provides, under the Facilities Inventory and Audit portal, detailed building, and relevant space information for all Texas-based campuses. This includes the predominant purpose and function of a building and corresponding spaces in that building, the functional use of each room in a building, following the FICM (Facilities Inventory and Classification Manual) code, and the size of each room, and other details. For these universities, FTE-based Enrollment data was obtained from the Integrated Postsecondary Education Data System (IPEDS) under the National Center for Education Statistics. Ultimately, based on this analysis, four universities are chosen from the THED system, in addition to Iowa State University (ISU), to support a diversity of university sizes. To define typical scenarios of space use, the percentage of the area of each space type is used to define the typical academic buildings. A medium office DOE Reference building (U.S. DOE, 2020) was used as the basis of design, then conditioned zones were further divided into different types of rooms with corresponding sizes based on functional uses by using EnergyPlus and Sketchup. The resulting model is used to evaluate energy savings compared to a baseline without the use of OBC.

1.3 Research Organization

This research is organized into one review paper, and several journal papers and associated conference papers (Figure 4). The citations for the papers indicated in this figure are listed in Section 1.4 (Chu et al. 2021, 2022). Chapter 2 includes a review of the literature on occupancy sensor systems focusing on influential variables that may cause systems to incorrectly represent occupancy and developed a survey to attain the most influential variables. Chapter 3 proposes a standard performance evaluation methodology to assess the reliability of occupancy sensor systems in residential buildings. Chapter 4 discuss a novel methodology of developing typical academic building models and potential energy savings evaluation based on occupant-based control. The conclusions, limitations, research contributions, and future work are described in Chapter 5. The details of each of the corresponding publications are including the following Chapters 2, 3 and 4.

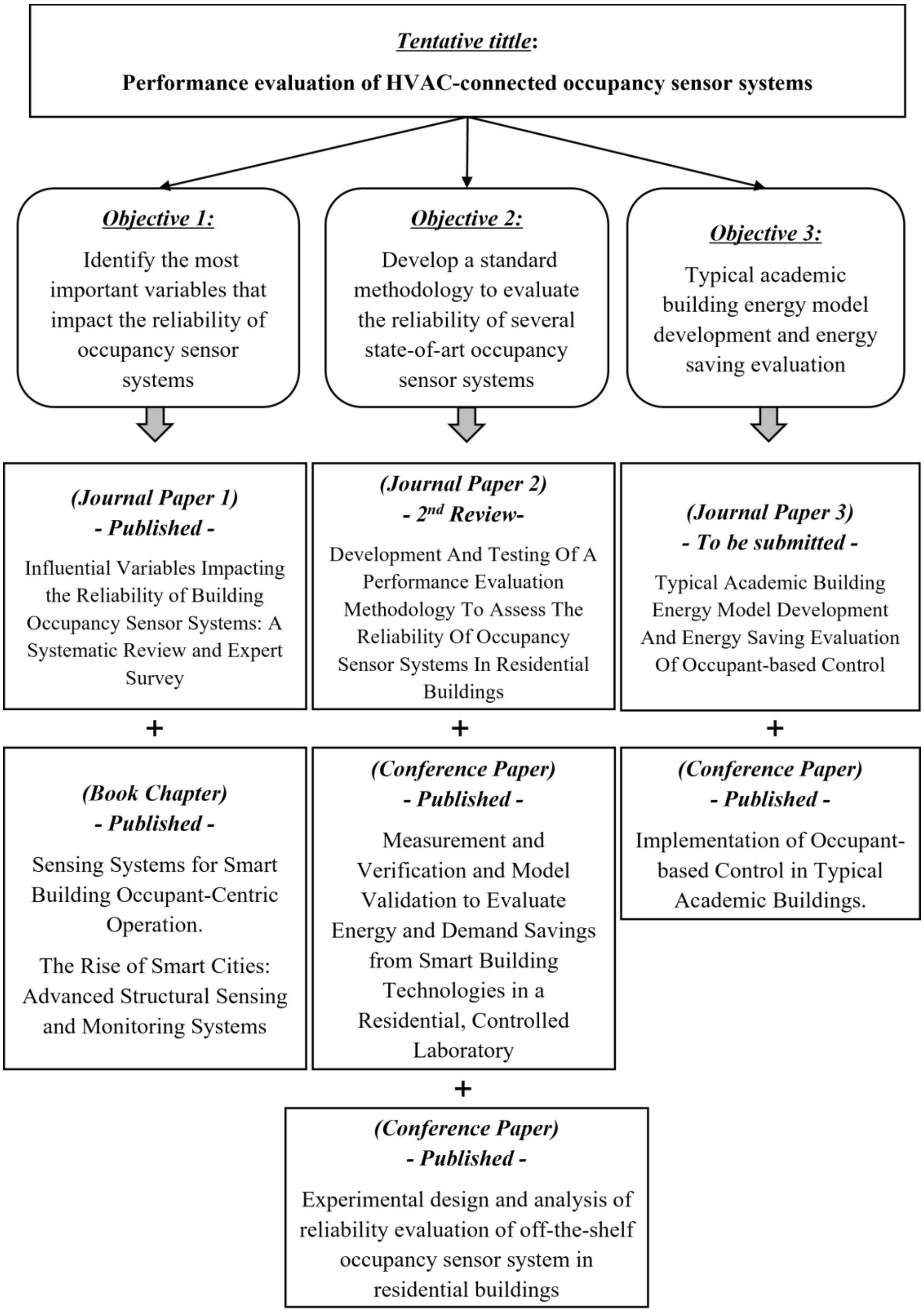

Figure 4 Research Organization by Published and Submitted Papers ***(Note: (Chu et al. 2021, 2022) are references for these papers)***

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CHAPTER 2 – INFLUENTIAL VARIABLES IMPACTING THE RELIABILITY OF BUILDING OCCUPANCY SENSOR SYSTEMS: A SYSTEMATIC REVIEW AND EXPERT SURVEY

2.1 Abstract

Occupancy information is critical for buildings, as it can substantially impact energy consumption. However, occupancy is highly unpredictable, and depends on occupants' schedules and their interactions with building systems. Occupancy sensor systems have been deployed in buildings for many years, using a broad range of sensor types, most typically for lighting control. Similarly, many research studies have been conducted that use a range of sensor modalities for occupancy sensing. These studies have assessed reliability considering diverse variables, testing methods, and evaluation metrics. However, no comprehensive review of occupancy sensor system reliability has been compiled. In this research, a review of the literature on occupancy sensor systems is presented, focusing on influential variables that may cause systems to incorrectly represent occupancy. Next, a survey was developed and completed by researchers, practitioners, and other stakeholders, ranking the most influential variables. The results of this effort provide a tiered list of what both literature and experts suggest the most influential factors are on occupancy sensor system performance. Future work includes the development of a standard methodology to evaluate the reliability of different occupancy sensor systems based on these efforts.

Keywords: Building occupancy; Occupancy sensor systems; reliability testing; influential variables

2.2 Introduction

Energy consumption throughout the world has significantly increased over the past 20 years, as the world population has increased, as has the use of energy-consuming technologies.

Building energy use accounts for approximately 40% of the total primary energy consumption in the U.S. and in the E.U., and approximately 27% in China (Cao et al., 2016). For end uses in buildings located these regions, space heating and cooling energy make up a large portion of total energy consumption. In the U.S., heating and cooling consumes approximately 51% of the total energy use in the residential (U.S. EIA, 2019) and 33% in commercial sectors (U.S. EIA, 2019). Moving forward, it is projected that total energy use from heating and cooling will increase in cooling-dominant and less-developed regions throughout the world (Cao et al., 2016). Therefore, in an effort to reduce greenhouse gas (GHG) emissions and energy use overall to limit climate change impacts and improve electric grid operations, it is important to develop energy saving approaches to reduce, in particular, heating and cooling energy use in buildings.

The energy consumption of mechanically conditioned buildings and their systems are primarily influenced by outdoor weather conditions, building and system characteristics, and the occupants who utilize them. Data on these parameters are necessary to monitor performance, assess inefficiencies, and identify opportunities for improvements. Weather data are generally easier to obtain and/or collect using local or regional ground-based weather station or satellite-derived data. For individual buildings, data on building systems and their characteristics are sometimes available, most typically through building owners and/or operators, with more data being available if the building has a building management system (BMS) or building automation system (BAS). Occupancy data, however, are more challenging to collect and less readily available as compared to the others.

Buildings are strongly influenced by the occupants that use them and their energy-consuming behaviors (Hong et al., 2016). There are significant opportunities to improve the collection and use of occupancy-related data to inform building controls, to target energy use reductions and efficiency improvements (Wang et al., 2017). When there are less occupants in commercial buildings, ventilation requirements are lower (ASHRAE, 2019); when there are no occupants, thermal comfort requirements no longer need to be met (ASHRAE, 2017), thus enabling adjustments to setpoint temperatures without impacting occupants. Therefore, through both mechanisms, occupancy sensing technologies used in buildings can help to significantly reduce HVAC use, also resulting in reduced energy demands of buildings (Jung et al., 2019).

To collect accurate occupancy information, such as occupant presence, counting, location, and tracking (Teixeira et al., 2010), occupancy recognition technologies have been developed and studied in the recent decades. Existing technologies for occupancy information extraction in buildings can generally be classified into two categories: single sensor systems and sensor fusion technology. Single sensor systems utilize one or multiple sensors of the same type to infer occupancy information, while sensor fusion methods combine the use of multiple types of sensors and sensing modalities to detect occupancy.

The benefit of the use of single sensor systems is the relative simplicity of the sensor deployment and data collection, however, edge cases can occur where the utilized single sensor type determined occupancy incorrectly. For example, a motion-based sensor may not be able to detect occupants who are not moving, causing a false negative, the sensor provides “unoccupied” as its output when there are occupants in the space. Sensor fusion technologies that have multiple sensor modalities can help to compensate for known weaknesses of single sensor systems, by adding other sensor systems that work better where others have weaknesses. These then typically use a data-driven model which is developed based on the data collected from the different sensor system modalities, to determine occupancy. In general, the more inputs and diverse data collected as input into the model, the more accurate the models become (Yang et al., 2018).

The challenge with occupants and occupancy data, however, is that occupants are inherently unpredictable. Occupants and their schedules vary both from person to person, and from building type to building type (Gu et al., 2018). While there are "typical" occupancy schedules and activities that represent the most common behaviors (e.g., Mitra et al., 2020), even the most "normal" people can deviate from these typical scenarios, creating edge case occupancy scenarios. In order to create the most reliable occupancy sensor systems possible, they should perform well under both typical scenarios and edge cases, and thus in a range of building scenarios, indoor environmental conditions, and occupancy scenarios.

To evaluate if occupancy sensor systems perform well across this range of scenarios, what characterizes "typical" must be defined, such that system performance can be tested and evaluated under these conditions following a standardized methodology. The results from the use of such a methodology would enable comparison of occupancy sensor system performance, to determine their relative reliability. Currently, however, there is no standard method of testing, nor a standard definition of "typical" occupancy scenarios and typical building conditions under which to test. There are occupancy schedules commonly used in energy modeling software (Christensen et al., 2005; Deru et al., 2011), however these define only the occupancy fraction (percent of total occupants in a space), and not their activities, locations, building interactions, and other variables. There are also prototypical building energy models developed to represent typical residential (Mendon et al., 2014) and commercial buildings (Deru et al., 2011). However, when considering these typical buildings for use in defining an appropriate setup for a controlled laboratory environment for sensor system testing and evaluation, translating the buildings' setup to a space-limited environment for controlled laboratory testing can present challenges. Similarly, edge cases must be defined. Edge cases occur when occupants, building systems or other factors deviate from “typical” conditions. Therefore, to determine what type of normal and edge cases may occur, it is necessary to define what specific variables may influence the performance of occupancy sensor systems, how these variables are likely to vary under normal and extreme scenarios.

There are many factors that may influence building occupancy sensor system performance. These can generally be classified into four categories, including building-related, environment-related, occupant-related, and others. For building-related and environment-related characteristics, factors such as interior building layout and geometry, and lighting levels can significantly impact the ability of a system to detect occupants (Gennarelli et al., 2016; Labeodan et al., 2013; Wang et al., 2017; Yun et al., 2014). This impact varies depending on the type of sensor system being evaluated, its corresponding algorithms, and how the sensor system is deployed in a particular location. Similarly, occupant-related characteristics, including their physical features and movements, their preferences, and their occupant-building interactions with energy-consuming appliances and systems can make the accurate detection of occupants challenging (Yoshino et al., 2017; Yan et al., 2017). The relative importance of these occupant characteristics, similar to physical building characteristics, is also dependent on the sensor system considered. Other variables include those that do not fit into the other three categories, such as presence of pets.

Among recent literature, while many of sensor testing studies have considered multiple different factors in evaluating their influence on the occupancy sensor system performance, these papers follow different methods and test different sets of variables. The current gap in the literature is that 1) there is no comprehensive assessment gauging the relative influence and importance of these diverse factors on the performance of occupancy sensor systems; 2) there has been no attempt to develop a standard method to evaluate sensor system performance, including defining what influential factors to consider for typical and edge case scenarios. Therefore, to address these challenges, the objectives of this paper are to 1) conduct a comprehensive literature review on the variables that impact occupancy sensor system performance, including what variables are likely to vary under normal and extreme scenarios; 2) obtain expert feedback from occupancy sensor system stakeholders regarding the most and least important variables influencing occupancy sensor performance for commercial and residential building applications, in order to evaluate the relative importance of these variables. The development of a standard methodology to evaluate sensor system performance is the focus of ongoing efforts.

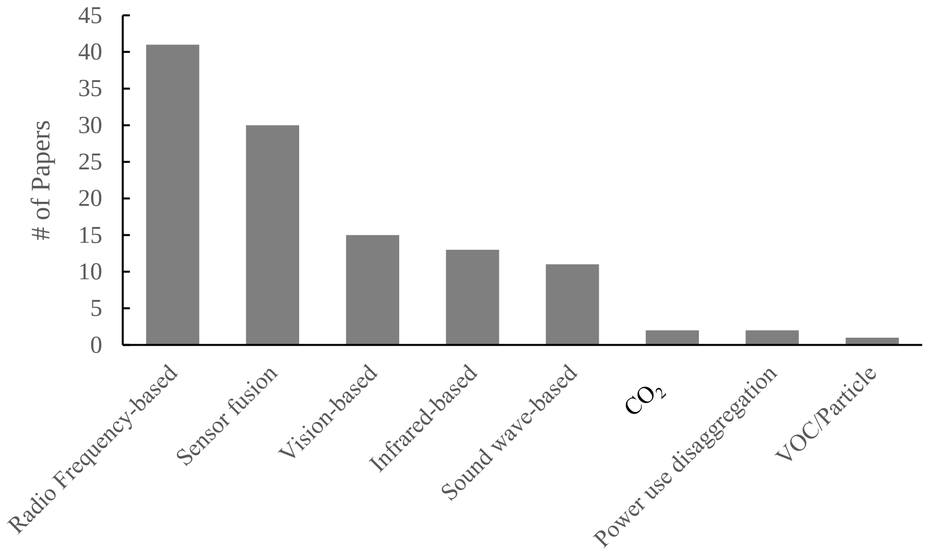
The next section describes a general review of the commonly used occupancy sensor systems, to summarize the influential variables that could cause sensor failures. Section 3 presents the expert workshop, expert survey, and their results that were used to identify, based on stakeholder feedback, the most important variables to evaluate for sensor system reliability.

2.3 Literature Review

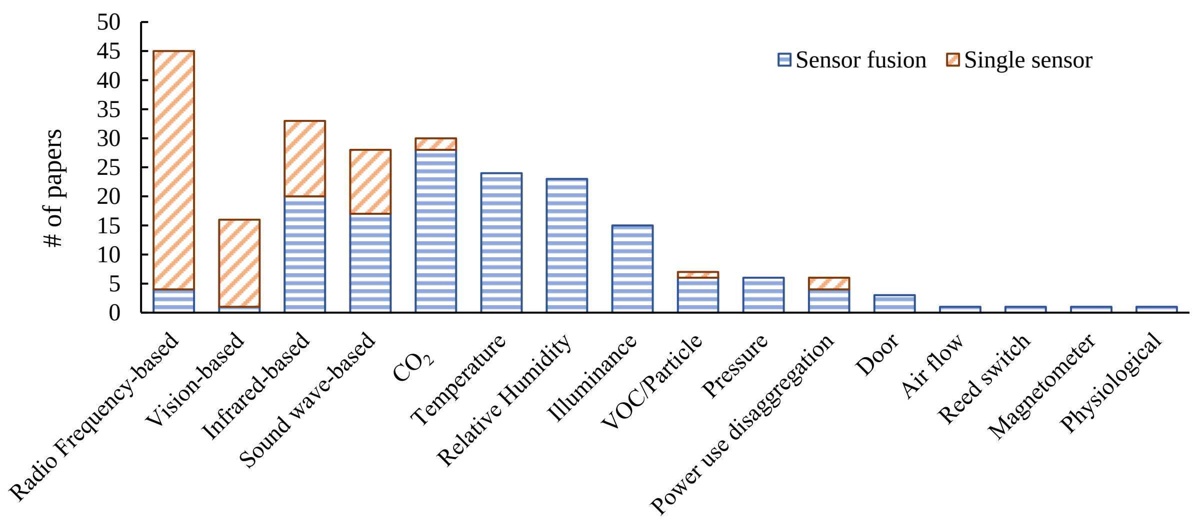
Human-sensing technologies can be divided into five categories: presence, counting, location, tracking, and identification (Teixeira, et al., 2010). From the perspective of building energy performance, whether or not there are people is significant for lighting control in both residential and commercial buildings. For HVAC system control, the presence/non-presence of people is of significance in residential buildings, while how many people in each thermal zone of a building is critical in commercial buildings, particularly for ventilation controls. The specific location, tracking of occupants and their identification have more limited impact on the energy use of a building. Thus, in this research, the main focus among these categories is occupant presence and counting.

Many sensor technologies have been used to assess the presence and counting of occupants in buildings. Of the 120 recent papers published between 2003 and 2020 on occupancy sensor systems identified based on keywords search in Google Scholar, such as "occupancy sensor", "occupancy detection", and "occupancy counting", including both single sensor systems and sensor fusion systems, 80 focused on either occupancy detection (presence/non-presence) and occupancy counting (number of people). These are used in this paper.

Figure 5 (a) and (b) summarizes the number of papers where each of the occupancy sensor technologies appear. From Figure 5 (a), the most commonly used sensor technologies include both single sensor systems, which are radio frequency-, vision-, infrared-, sound wave-based sensors, and sensor fusion systems. Sensor fusion is generally a combination of one or more of the single sensor systems' sensing modalities and one or more environmental sensors. Figure 5 (b) further subdivides the sensor modalities' sensor fusion systems into each of the single sensor systems as well as each of the environmental sensors and provides the number of papers in which each appears. For those papers that use sensor fusion systems, each is included in the count for each of the single sensor systems and environmental sensors. From Figure 5 (b), it is also noted that there are some other types of sensors that were used in sensor fusion methods, such as door sensors, reed switches, and pressure mats, which have not been discussed in detail as a single sensor system in this research since it was not found to be common for these sensor types to be used as a single sensor system, as compared to others.



(a)



(b)

Figure 5 Frequency of occupancy sensor modalities used in recent literature from 2003 to 2020, for occupancy detection and counting, including (a) types of single sensor system modalities and sensor fusion, and (b) types of single sensor system modalities, with sensor fusion subdivided into single sensor system modalities with other environmental sensors

This literature review is discussed by sensor type. A literature review of 80 relevant peer-reviewed research articles on occupancy sensor systems in buildings, focusing on occupancy detection and occupancy counting, resulted in five types of sensor technologies that were most commonly used (Figure 5 (a)), including single sensor systems (radio frequency-, soundwave-, infrared-, vision-based sensors), and sensor fusion, which are discussed herein. For the single sensor systems, the focus is on the potential sensor failures for each type of sensor modality. For sensor fusion technologies, which are typically a combination of one or more of the single sensor systems sensing modalities and environmental sensors, the potential sensor failures include failures caused by not only the above single sensor modality, but also the environmental sensors, as well as the system's interpretation and use of this information. Table 1 shows each of the types of sensors for each sensor category.

Table 1 Most common types of occupancy sensor types used in single sensor and sensor fusion applications in residential and commercial buildings

Sensor Category	Sensor type
Radio frequency-based	Normal Doppler Radar
	Ultra-wide band (UWB) Radar
	Radio-frequency Identification (RFID)
	Wi-Fi
	Bluetooth low energy (BLE)
Sound wave-based	Acoustic
	Ultrasonic
Infrared-based	Active infrared (IR)/Passive infrared (PIR)
Vision-based	Video/camera
Sensor fusion	Combination of environmental sensors (e.g., temperature, relative humidity, CO_2, VOCs) and the above-listed single sensor types

In the following section, a literature review is discussed, and a summary table provided for each of these five sensor technologies, including the type of occupancy information each paper studied (presence/counting), the building type where this occurred (residential/commercial), the sensor type (single/sensor fusion), and the influential variables (building-related, environment-related, occupant-related, others) that either have been tested and shown to impact occupancy detection/counting, or were mentioned as variables that may cause sensor failure.

Across these studies, most of the goals are to develop an occupancy sensor system and test it in a controlled environment to evaluate the performance of the system. Several also combined the developed occupancy sensor system with HVAC control to evaluate the level of energy savings that can be achieved with occupancy-based control. Data collection periods, in general, ranged from 1 min to four months, where the shorter ones focused on assessing specific variables, while the longer ones were to assess the performance of the occupancy sensor system over a longer period of time, coving a range of scenarios such as workdays, weekend, and holidays, and different weather conditions. Most of the data collection periods are several days to several weeks in length. Ground truth data (e.g., data from the camera system) was also collected across these studies to be compared with occupancy data attained from occupancy sensors to assess their reliability. Different performance metrics were used in these papers, including accuracy, confusion matrix (true positive, true negative, false positive, and false negative), F-score (calculated based on confusion matrix), and other statistical methods (e.g., mean average error, mean absolute error, root mean square error, normalized root mean square error, standard deviation, and root mean square deviation**).**

2.3.1 Radio frequency-based sensors

Radio frequency-based sensors utilize radio waves as media for signal transmission, ranging from approximately 20 kHz to around 300 GHz (Basnayaka et al., 2017), and detect occupants based on a change in the characteristics of the radio signals. Doppler-shift sensors operate on the principle that radio waves reflected from a moving object will result in a frequency shift that is related to the radial component of the object’s velocity. Generally, such a sensor will register as detecting occupancy as long as it is able to detect motion. There are four main classifications of motion levels, including major (e.g., people walking), minor (e.g., people extending arms), fine (e.g., sitting and typing), and no motion (e.g., sleeping), as defined in National Electrical Manufacturers Association (NEMA) WD 7 Occupancy Motion Sensors Standard (NEMA, 2011). The level of motion that occurs at a particular instance could influence the performance of sensors. At the finer levels of motion, it may be more difficult for such a sensor to detect occupants, and thus may elicit a failure (Yavari et al. 2013).

There are two main categories of Doppler sensors, including normal Doppler radar sensors, and ultra-wide band (UWB) radar sensors. Compared to UWB radar sensors, normal Doppler radar sensors can more easily experience interference with other parallel signatures, such as from nearby systems generating electromagnetic interference in the same frequency range (Diraco et al., 2017). UWB sensors, however, use a radio signal with a fractional bandwidth equal to or greater than 0.20 or at a frequency greater than 500 MHz (Wilzeck et al., 2010). UWB also uses the Doppler-shift effect to detect occupants. It is also able to operate over a larger bandwidth and wider range of frequencies, resulting in submillimeter range resolution and high penetration power, supporting detection of small objects even through obstacles (Diraco, et al., 2017). In addition, UWB sensors can penetrate walls and other obstacles with relatively low power consumption compared to normal Doppler radar systems (Kim et al., 2016).

Table 2 summarizes recent research using Doppler radar sensors in occupancy sensing technologies. Of the listed studies in Table 2, the influential variables that appeared multiple times in multiple studies are building-related (presence of large metal objects), and occupant-related (motion level, number of occupants, location of occupants, posture of occupants) variables.

Table 2 Influential variables evaluated in recent literature using Doppler sensors for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
Normal Doppler Radar	(Yavari et al. 2013)	Presence	-	Motion level of occupants
	(Yavari et al., 2014)	Presence	-	1. Number of occupants; 2. Multiple occupants walking at similar speeds; 3. Non-human periodic motion; 4. Number of sensors; 5. Direction of arrival of sensors.
	(Sekine et al., 2012)	Presence	-	1. Presence of large metal objects (fan, microwave, oven, washing machines); 2. Environmental noise.
UWB Doppler radar	(Kilic et al., 2013)	Presence	Commercial	1. Motion level of occupants; 2. Range of sensor system; 3. Measurement duration.
	(Kim et al., 2013, Yarovoy et al., 2006, Ossberger et al., 2004)	Presence/ Location	Commercial	1. Location of occupants (Occupants behind walls); 2. Distance between the sensor and occupants; 3. Body shape of occupants.
	(Gulmezoglu et al., 2014)	Presence/ Tracking	Commercial	1. Number of occupants; 2. Occlusion.
	(Rane et al., 2016, Mabrouk et al., 2014)	Presence	-	1. Location of occupants (Stationary occupants behind the wall); 2. Posture of occupants.
	(Singh et al., 2011)	Presence	Commercial	1. Wall type (drywall, wooden door, brick wall, load bearing concrete wall); 2. Motion level of occupants; 3. Presence of large metal objects; 4. Posture of occupants.
	(Yavari et al., 2018)	Counting	Commercial	1. Size/shape of the test space; 2. Number of occupants; 3. Location of occupants; 4. Location of sensors; 5. Clustering of occupants.

Another type of RF sensor is RFID (radio-frequency identification). RFID sensors identity and track tags attached to occupants or other item. An RFID tag receives signals from a nearby RFID reader, then transmits digital data back to the reader. The reader recognizes the received information from each of the tags to decide whether a person is in this space. RFID is an identification technology designed to provide data on the location and the testing occupants itself. RFID sensors have several advantages, including that they do not require line of sight conditions, and that they can have on-board storage capacity, making it more flexible for data collection. RFID sensors are truly real-time, and thus do not have accumulated errors like vision-based sensors. RFID sensors, however, can be highly impacted by noisy environments due to noise interference and the sensitivity patterns of anisotropic antennas (Li et al., 2011). One of the main disadvantages is the needed network density, i.e., a larger number of sensors are needed as compared to other sensor types (Wang et al., 2017). RFID sensor systems require a complex infrastructure of beacon nodes, which can be expensive and cumbersome to install and manage. It also requires calibration once the built environment has been changed, such as chairs or furniture being in different positions.

Table 3 provides a list of recent research efforts that have evaluated the use of RFID sensor systems. Of the listed studies in Table 3, the variables that appeared multiple times in multiple papers include occupant-related variables (motion level, number of occupants, location of occupants).

Table 3 Influential variables evaluated in recent literature using RFID sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
RFID	(Li et al., 2012)	Counting	Commercial	1. Number of occupants; 2. Motion level of occupants; 3. Location of occupants (occupants walk close to the boundary of thermal zones); 4. Response time of the sensor.
	(Li et al., 2011)	Counting/ Location	Commercial	1. Motion level of occupants; 2. Size/shape of test area; 3. Number of occupants; 4. Location of occupants; 5. Environmental noise.
	(Ranjan et al., 2012)	Presence	Residential	1. Different locations of sensor (RFID tags such as attached to hat, shoes, belt, shirt, pants, wrists, and ankles, antennas placed on diff. appliances); 2. Configuration of antennas.
	(Wang et al., 2017)	Counting	Commercial	1. Awareness of occupants wearing tags.
	(Xu et al., 2021)	Counting/ Location	Commercial	1. Location of occupants; 2. Environmental noise; 3. Number of tags; 4. Protocol reconfigurability; 5. Tag read rate; 6. Allowable operational bandwidth.

Note: The “location of occupants” can influence the sensor performance when occupants are at a boundary (e.g., corners), as occupants may not be sensed or detectable by the sensor system in this location.
The “size/shape of test area” refers to the size, interior layout, and geometry of a space, which may influence sensor system configuration, number of sensors needed and their ability to cover the test area.

A third type of RF sensor uses Wi-Fi communication. Wi-Fi describes a local wireless network that uses radio waves to communicate data, typically originating from the Internet. To be considered Wi-Fi, the radio signal must use the IEEE 802.11 standard (2016) to communicate. Multiple versions of Wi-Fi are defined in the IEEE specifications, including common ones such as 2.4 GHz and 5 GHz frequency radio waves. Wi-Fi infrastructure is widely available in most buildings along with mobile devices (e.g., smart phones, tablets, laptops) with Wi-Fi connectivity carried by occupants. The data packets are transmitted in existing Wi-Fi traffic, and both received signal strength (RSS), and, in some cases, the MAC address of each occupant's mobile device connected to Wi-Fi can be extracted to estimate occupancy, including either presence/non-presence or number of occupants. The MAC address of each device serves as a unique identifier for each of the occupants. Some of the main advantages of the use of Wi-Fi include the use of a common and widely implemented network, especially in residential and commercial buildings. In addition, the cost of using this technology is negligible in comparison to some other sensor types (Ouf et al., 2017), particularly when Wi-Fi is already available. Disadvantages include that it requires occupants to carry their mobile devices (Zou et al., 2018) and higher power consumption compared to some other sensor types (Mahmoud et al., 2015). In addition, there may be privacy concerns for occupants since the personal MAC addresses and other universally unique identifiers (UUIDs) need to be monitored and collected (Wagner et al., 2018).

Table 4 includes a summary of recent studies which have used Wi-Fi-based sensors systems to evaluate occupancy. Of the listed studies, the influential variables that appeared in multiple papers include building-related variables (size/shape of test area, presence of large metal objects), environment-related variables (electromagnetic interference), occupant-related variables (number of occupants), and others (distance between occupants and sensors).

Table 4 Influential variables evaluated in recent literature using Wi-Fi sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
Wifi-based	(Ravichandran et al., 2015)	Presence	Residential	1. Distance between occupants and sensors; 2. Orientation of the antennas; 3. Motion level of occupants; 4. Posture of occupants; 5. Presence of large metal objects (refrigerator, computer monitor, large furniture).
	(Xi et al., 2014)	Counting	Commercial	1. Number of occupants; 2. Clustering of occupants; 3. Walking speed of occupants; 4. Spatial distribution of occupants.
	(Palipana et al., 2016)	Presence	Commercial	1. Distance between occupants and sensors.
	(Wang et al., 2017, Wang et al., 2018, Ouf et al., 2017)	Counting	Commercial	1. Wi-Fi device not turned on by occupants; 2. Phone in sleep mode if not in use; 3. Occupant(s) has multiple devices (phones, laptops, wireless printers); 4. Presence of large metal objects (interior metal separations); 5. Size/shape of test area; 6. Electromagnetic interference;
	(Balaji et al., 2013)	Counting	Commercial	1. Phone in sleep mode if not in use; 2. Occupant leaves space without carrying their phone; 3. Electromagnetic interference.
	(Lu et al., 2016)	Counting	Commercial	1. Presence of large metal objects; 2. Data collection timestep.
	(Vasisht et al., 2016)	Presence	Residential	1. Signal strength of sensors
	(Petrovic et al., 2018)	Counting	Residential/ Commercial	1. Size/shape of test area; 2. Number of occupants; 3. Response time of sensor(s)
	(Vattapparamban et al., 2016)	Counting	Commercial	1. Electromagnetic Interference

Note: Occupant posture was found to impact the ability of some technologies to detect respiration rates for use in occupancy detection. For moving occupants, the spatial distribution of occupants and their movements was found to influence occupancy count accuracy, where randomly moving and distributed occupants reduced estimate errors.

A fourth RF wireless sensor technology is Bluetooth, which uses short-wavelength radio transmissions in the range of 2400-2480 MHz, standardized in IEEE 802.15.1 (2005), to exchange data within short ranges from fixed and mobile devices. Using Bluetooth, smart devices need to be in discoverable mode for an initial registration to be connected. As long as the Bluetooth capability is enabled, there are no subsequent actions needed to change Bluetooth settings. One example is an iBeacon, which uses Bluetooth low-energy (BLE) wireless technology to provide location-based information. There are three main components used in the detection of occupancy using Bluetooth: beacon transmitters, which send uniquely identified beacon packets with a Universally Unique Identifier (UUID), receivers who install a client mobile application on their smartphones to periodically scan signals to detect beacons in a building, and remote servers which gather and implement algorithms to identify whether there is a person in the space based on the information that the client mobile application receives from occupants' smart phones. The main advantages of the use of Bluetooth sensor technologies include much lower power consumption compared to standard Bluetooth and Wi-Fi devices (Putra et al., 2017). However, a main disadvantage would be the potential interference this system with Wi-Fi, which may disturb the connection if multiple Bluetooth devices are running at the same time.

Table 5 summarizes recent research using Bluetooth and/or BLE-based sensors systems to evaluate occupancy. Of the listed studies, the variables that appeared multiple times in multiple papers are building-related variables (size/shape of test area).

Table 5 Influential variables evaluated in recent literature using Bluetooth/BLE-based sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
BLE-based	(Conte et al., 2014, Corna et al., 2015)	Presence	Commercial	1. Cyclic behavior of beacons; 2. Humidity; 3. Occupant(s) have multiple devices.
	(Filippoupolitis et al., 2016)	Presence	Commercial	1. Size/shape of test area; 2. Location of sensor(s); 3. Distance between occupants and sensors.
	(Shen et al., 2016)	Presence	Commercial	1. Occupant leaves space without carrying their phone; 2. Occupants go beyond the Bluetooth range; 3. Response time of sensor(s).
	(Park et al., 2018)	Counting	Commercial	1. Size/shape of test area.
	(Longo et al., 2019)	Counting	Commercial	1. Size/shape of test area; 2. Number of occupants.

2.3.2 Sound wave-based sensors

There are two main types of soundwave-based sensors, including acoustical sensors and ultrasonic sensors. Acoustic wave sensors are named because their detection mechanism is a mechanical or acoustic wave using a piezoelectric material. For this application such sensors detect only human audible sound with frequency of 20 Hz–20 kHz (Launer et al., 2016). Ultrasonic sensors measure distances based on transmitting and receiving ultrasonic signals, which detects these sounds that are inaudible to humans. An ultrasonic sensor is generally made up of piezoelectric material, where the ultrasonic transmitter transmits an ultrasonic wave, when then travels through a medium of air until it is intersected by a material. The wave is reflected back when it detects a person, which can then be detected by the ultrasonic receiver. By analyzing the time and distance that the reflected ultrasonic wave is received, it can infer whether there is a person in the space. Compared to other sensors, the main advantages of the use of sound wave-based sensor technologies is that it can include an increased range of sensitivity for minor movement. However, the disadvantage would be that certain materials absorb sound waves, such as cloth or foam, causing problems when a person is covered in multiple layers of clothing and the sensor would not detect motion consistently, and they are highly sensitive to reflective materials such as glass or plastic (Yavari et al., 2014).

Research focused on sound wave-based sensors for occupancy detection is provided in Table 6. Of the listed studies, the variables that appeared multiple times in multiple papers include: building-related (size/shape of test area), occupant-related (number of occupants, motion levels, walking speed of occupants), and other (location of sensors, distance between occupants and sensors, number of sensors) variables.

Table 6 Influential variables evaluated in recent literature using sound wave-based sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
Acoustic	(Khan et al., 2015)	Counting	Commercial	1. Number of occupants; 2. Location of sensors; 3. Distance between occupants and sensors; 4. Environmental noise; 5. Noise level of occupants.
	(Xu et al., 2013)	Counting	Commercial	1. Number of occupants; 2. Location of sensors; 3. Presence of non-occupant sounds; 4. Characteristics of sound (utterance length of sound).
	(Yavari et al., 2014)	Presence	-	1. Different wall materials (cloth, foam) absorption of sound waves; 2. Presence of reflective materials (glass, plastic); 3. Motion levels of occupants.
	(Shih et al., 2015)	Counting	Commercial	1. Size/shape of test area; 2. Performance over time of the sensor; 3. Number of sensors.
	(Shih et al., 2016)	Presence/ Counting	Commercial	1. Size/shape of test area; 2. Number of occupants; 3. Distance between occupant and sensors; 4. Blind spots where sensor cannot see.
	(Khalil et al., 2018)	Presence	Commercial	1. Body shape of occupants (height, width, girth, hand-waist distance, and bounce); 2. Motion level of occupants; 3. Location of sensors; 4. Angle between occupants and sensors; 5. Number of occupants walking simultaneously; 6. Occupant(s) with a purse; 7. Walking speed of occupants; 8. Occupant in a wheelchair; 9. Location of the door frame (corner); 10. Door size; 11. Number of sensors.
	(Hnat et al., 2012)	Presence	Residential	1. Occupant height; 2. Walking speed of occupants; 3. Number of sensors; 4. Posture of occupants; 5. Presence of large metal objects; 6. Occupants wearing hats; 7. Occupants standing in doorways; 7. Movement of furniture over time; 8. Opening and closing of doors and windows; 9. Presence of household objects (bags, laundry baskets).

2.3.3 Infrared-based sensors

PIR (passive infrared) sensors, which are among the most common types of occupancy sensors used, are passive in that they do not generate or radiate energy for detection purposes. Instead, they function through the detection of infrared radiation emitted by or reflected from objects. Active IR sensors require both an emitter and receiver, where the IR emitter emits a beam of light, facing an in-line receiver. If nothing is in the way, the receiver sees the emitted signal. If the receiver fails to see an IR beam, it detects that a person is between the emitter and the receiver, and therefore present in the monitored area. Low-resolution IR arrays are based on thermopile technology, of which the thermopile element is sensitive to a motionless object. The main advantages of the use of infrared-based sensor technologies is that it is the most commonly used technology for occupancy presence sensing. However, the disadvantage would be that they cannot detect static occupants, and the sensitivity of this sensor type drops off drastically with distance and requires line of sight (Santra et al., 2018). There have been studies focusing on the improvement of motion sensors to detect static occupants. For example, Wu et al., (2019) developed an optical shutter based on a PIR sensor, which indicated an accuracy of 97% in unoccupied and occupied scenarios. Ma et al., (2019) also proposed an active PIR sensing system to actively detect static thermal targets.

Research using IR-based sensors for occupancy detection is provided in Table 7. Of the listed studies, the variables that appeared multiple times in multiple papers include occupant-related variables (location of occupants, body shape of occupants, number of occupants, motion level of occupants, clustering of occupants).

Table 7 Influential variables evaluated in recent literature using infrared-based sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
Infrared-based sensor	(Dodier et al., 2006)	Presence	Commercial	1. Location of occupants.
	(Kuutti et al., 2014)	Counting	Commercial	1. Differences among multiple individual sensor; 2. Response time of sensor; 3. Height of sensor; 4. Body shape of occupants; 5. Clustering of occupants; 6. Air flow (e.g., from HVAC vents).
	(Yun et al., 2014)	Presence	-	1. Number of occupants; 2. Different walking directions of occupants (back and forth); 3. Motion level of occupants; 4. Distance between occupants and sensors; 5. Number of sensors; 6. Location of sensors.
	(Zappi et al., 2007)	Counting	Commercial	1. Number of occupants; 2. Clustering of occupants.
	(Raykov et al., 2016)	Counting	Commercial	1. Location of occupants; 2. Number of occupants; 3. Data collecting frequency.
	(Chowdhury et al., 2016)	Presence	-	1. Body shape of occupants; 2. Location of occupants.
	(Liu et al., 2017)	Presence	-	1. Motion levels of occupants.

2.3.4 Vision-based sensors

Vision-based sensors include camera and video technologies. These sensors are used to collect video/camera frame data to infer occupancy information. Methods include background subtraction, where the foreground elements are separated out from the background by generating a foreground mask to be used for differentiating frames before and after a person appears, and pattern matching approaches, where Haar-like features and a cascade of classifiers are constructed. Other methods include HOG (Histogram of Oriented Gradients), SVM (Support Vector Machine), SIFT (Scale-invariant feature transform)-inspired features, to detect and locate occupants in a video frame, frame-differencing (subtracting consecutive frames pixelwise), and optical flow (i.e. measuring the motion gradient of each pixel over a number of frames). The advantage of vision-based sensors is that video is considered as the most accurate occupancy sensing technology, and thus is usually used as a ground truth method (Shen et al., 2017). The disadvantage of the traditional RGB cameras is the passive vision problems due to brightness variations, shadows, and occlusions (Kwolek et al., 2015). In addition, the privacy concern is also a concern when using vision-based sensors. Recently, 3D depth-based cameras have been increasingly implemented, which use structured light to measure distances from every point to the camera, such that it can work in a completely dark environment, and the privacy concern could also be addressed by using only the depth data (Diraco et al., 2015, Munir et al., 2017).

A summary of the variables that have been tested for vision-based sensor is presented in Table 8. Of the listed studies, the variables that appeared multiple times in multiple papers include building-related (presence of large metal objects), environment-related (lighting levels, presence of direct sunlight), and occupant-related (clustering of occupants) variables.

Table 8 Influential variables evaluated in recent literature using vision-based sensor systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Influential variables mentioned/tested
Vision-based	(Zou et al., 2017)	Counting	Commercial	1. Lighting levels; 2. Presence of interior lighting sources; 3. Presence of direct sunlight; 4. Age of occupants; 3. Hairstyles of occupants; 4. Posture of occupants; 5. Motion level of occupants; 6. Presence of large metal objects; 7. Clustering of occupants.
	(Teizer et al., 2007)	Presence	-	1. Presence of large metal objects; 2. Objects located in the shadow; 3. Blind spots where sensor cannot see; 4. Lighting levels; 5. Air temperature; 6. Presence of direct sunlight.
	(Tomastik et al., 2008)	Counting	Commercial	1. Door sizes (Multiple entrances/exits).
	(Ahmad et al., 2018)	Counting	Commercial	1. Number of occupants.
	(Yang et al., 2018)	Counting	Commercial	1. Lighting levels; 2. Presence of cobweb on the camera; 3. Clustering of occupants.

Note: Age was found to influence occupancy detection abilities as age influence the shape and size of occupants' heads used as a target for occupancy detection.

2.3.5 Sensor fusion

Sensor fusion methods usually combine the use of environmental sensors, such as temperature, relative humidity, lighting, and CO_2, with other types of sensors, such as those discussed in the previous portions of this research, to indicate occupancy information. Compared to sensor systems than only use one sensor type, sensor fusion methods have the advantage of multiple sensing modalities. With the appropriately developed data processing algorithms, this can help to reduce the occurrence of false positives and negatives through the use of multiple sensor systems' data to check the agreement among sensor data output to largely improve accuracy. However, the limitation of sensor fusion is that models can differ largely in terms of their predictive accuracy; additionally, the model formalism chosen, and its complexity can substantially influence the model accuracy (Hobson et al., 2019).

A summary of recent sensor fusion research efforts to detect occupancy is included in Table 9. Of the listed studies, the variables that appeared multiple times in multiple papers include building-related (size/shape of test area), occupant-related (number of occupants), and other (short-term transition, number of sensor types, locations of sensors, response time of sensors) variables.

Based on the literature review, a comprehensive list of variables that may impact the occupancy sensor systems is compiled (Table 10). This compiled list was also used to determine variables that should potentially be considered when evaluating the performance of the sensor systems. The number of times each of the variable was discussed in this literature review is also shown in Table 10. It is noted that among the variables that appear multiple times in multiple papers for each of the sensor systems, several variables appear in these lists for two or more of the five sensor system types, including size/shape of test area, presence of large metal objects, motion level of occupants, number of occupants, and location of occupants. The variables were arranged based on the categories they belong to, the order for each variable within each category was random, to limit bias for discussion of stakeholders when ranking the most/least important variables.

Table 9 Influential variables evaluated in recent literature using sensor fusion systems for occupancy sensing

Sensor type	Reference	Occupancy Information	Building type	Sensor type	Influential variables mentioned/tested
Sensor fusion	(Hailemariam et al., 2011)	Presence	Commercial	Sensor fusion (CO2, current, lighting, motion, sound)	1. Short term transition (a person just arrived or left their office).
	(Ekwevugbe et al., 2013)	Counting	Commercial	Sensor fusion (sound, case temperature, CO2 and motion)	1. Size/shape of test area.
	(Yang et al., 2014)	Presence/ Counting	Commercial	Sensor fusion (temperature, relative humidity, CO2, lighting, motion, door switch)	1. Number of sensors; 2. Interrupted Wi-Fi connection; 3. Loss of electricity; 4. Physical damage to sensors; 5. Data corruption; 6. Location of sensors; 7. Size/shape of test area; 8. Presence of large metal objects.
	(Chen et al., 2016)	Counting	Commercial	Sensor fusion (temperature, relative humidity, CO2, VOCs, noise, PIR)	1. Number of occupants; 2. Size/shape of test area; 3. Short term transition; 4. Response time of sensors; 5. Air temperature; 6. Presence of direct sunlight.
	(Zikos et al., 2016)	Presence/ Counting	Commercial	Sensor fusion (door counter, acoustic, PIR, CO2)	1. Size/shape of test area; 2. Noise level of occupants; 3. Motion level of occupants; 4. Door sizes; 5. Number of sensor types.
	(Zikos et al., 2016)	Presence	Residential/Commercial	Sensor fusion (temperature, humidity, CO2, pressure)	1. Number of occupants; 2. Short term transition; 3. Response time of sensors.
	(Meyn et al., 2009)	Counting	Commercial	Sensor fusion (CO2, PIR, video, access control)	1. Size/shape of test area; 2. Number of sensor types; 3. Location of sensors.

Table 10 Compiled list of influential variables from literature review and expert stakeholder feedback

Category	All variables	Frequency
Building-related	A1. Glass walls & mirrors (reflective surfaces)	1
	A2. Size (length/width) and shape of test area	6
	A3. Location/characteristics of windows	0
	A4. Number of doors (entrances/exits)	1
	A5. Door sizes (i.e., single vs. double, other)	3
	A6. Wall, floor, and ceiling color/characteristics	1
	A7. Height of ceiling	0
	A8. Building envelope type (e.g., brick, siding, EFIS, batt vs. continuous insulation)	1
	A9. Presence of large objects (especially metal objects) within or near a space	9
	A10. Electromagnetic interference	1
	A11. Ventilation rates	0
	**A12. Other building-related variables (please specify)	0
Environment-related	B1. Lighting level (regardless of source of light) (lux)	1
	B2. Spectral distribution of light	0
	B3. Presence of interior lighting sources (non-overhead)	1
	B4. Indoor humidity	1
	B5. Indoor temperature	2
	B6. Mean radiant temperature (indoor)	0
	B7. Presence of sunlight - direct	2
	B8. Presence of sunlight - diffuse	0
	**B9. Other environment-related variables (please specify)	0
Occupant-related	C1. Number of occupants (including 0)	10
	C2. Age of occupant(s)	1
	C3. Metabolic rate	0
	C4. Spatial location of occupant(s)	5
	C5. Level of motion of occupant(s)	10
	C6. Noise level of occupant(s)	3
	C7. Clustering of occupants (distance between occupants)	5
	C8. Speed of occupant (e.g., walking vs. running)	2
	C9. Speed of occupants relative to one another	1
	C10. Number of occupants entering/exiting a room at the same time	1
	C11. Speed of occupants entering/exiting a room at the same time	0
	C12. Presence of occupants in adjacent spaces	0
	C13. Clothing color/contrast/patterns (including images on clothing) of occupants	0
	C14. Occupant clothing level (clo)	0
	C15. Skin color of occupant(s)	0
	C16. Body shape of occupant(s)	4
	C17. Occupants wearing heavy winter coats with a cold surface temperature	0
	**C18. Other occupant-related variables (please specify)	0
Others	D1. Presence of pets	0
	D2. Motion characteristics of pets (if present)	0
	D3. Size/type of pets	0
	D4. Use of robots	0
	D5. Presence of mylar balloons/party items	0
	D6. Ability to communicate with thermostat	0
	D7. Initial performance/performance over time	1
	D8. Range of devices (related to electromagnetic interference)	0
	D9. Repeatability of performance of system	0
	D10. Presence of heat sources such as a heat lamp	0
	D11. Presence of wheelchairs, strollers, shopping carts, etc.	4
	D12. Vibrations in spaces	0
	**D13. Other variables (please specify)	0

*Note: The content with "**" indicates that these variables are not from the literature review or stakeholder feedback but are shown because in the survey this was an option for participants to provide in the case that they want to suggest other variables. The "0" represents variables that were identified based on discussion with stakeholders.*

2.4 Expert Survey on Most and Least Important Influential Variables

Using the results of the literature review, the influential variables tested in previous literature were compiled into a comprehensive list. An expert workshop was held on June 26, 2019 with a diverse set of 50+ stakeholders from academia, consultants, utility workers, manufacturers, and building owners. Four facilitated discussions were completed during the workshop, the first of which included a discussion of influential variables impacting the reliability of occupancy sensor systems. The question posed during this session is as follows:

"Which variables that may affect the performance of a sensor system should be included in a test standard/guideline for occupancy recognition sensor systems? Which are most critical?"

The compiled list of influential variables was provided to attendees for discussion. Throughout the discussion, additional variables were suggested by stakeholder attendees, which were added into a final list of potential influential variables (Table 10). The final list of variables was then divided into four categories, including (a) building-related variables, (b) environment-related variables, (c) occupant-related variables, and (d) other variables.

Using this list of variables, an online survey was developed to determine which influential variables were "most important" and "least important" for use in the development of a standard method of testing of occupancy sensor systems. The participants chose to answer the questions for residential building applications or for commercial building applications. Next, the participants were presented with the list of variables in Table 10 divided into one question for each of the four categories. For each question, the participants consider one category of variables, and were asked to categorize which they would consider the most and least important in evaluating the reliability performance of occupancy sensor systems. Respondents were limited to the choice of the top 6 most and top 6 least influential variables. Within each of the "most" and "least" influential groups, participants were also asked to rank the order of importance. Participants were not required to select a certain number of variables, however a suggested amount in each category was provided in the survey. Not all variables in each question (each category) were required to be selected, thus the variables that were not selected as most or least important were not used in the survey analysis.

Following the four questions on the four variable categories, a final question provided a list of all variables across all categories and asked participants to select the most and least important variables. This allowed for the comparison of responses from the categorial rankings (Questions 1-4) and overall rankings of variables (Question 5).

The survey was sent to all ARPA-E SENSOR teams (2017), members of Annex 79 (Occupant-Centric Building Design and Operation) (O'Brien et al., 2018), and all workshop attendees. 54 survey responses were gathered in Fall 2019. 24 expert stakeholder responses were complete responses, including 9 focused on residential buildings, 15 focused on commercial building applications. This number of responses is similar to other expert surveys in terms of number of collected responses from experts (e.g., Constenla et al. 2015).

2.5 Survey Results

Two methods were used to evaluate the survey data results. The first method ("Method 1") was a count of the number of times that participants selected each variable, regardless of how it was ranked among the "most" and "least" important categories. In this case, the higher the count, the more important the variable; and the lower the count, the less important the variable. The second method ("Method 2") incorporated the rankings of participants' responses using a weighing factor. In this method, for each of the first four questions, the first six variables selected in the "most" and "least" important variables were considered. In the case of the most important variables, the variable that was ranked first received a weightage factor of 6, the second received a factor of

5, etc. The same method was applied for the least important variables. For both methods, the final count or score was summed across all participants. Two methods were used as a way to double check the results, to make sure that results from the two methods used to ask stakeholders to rank these variables are consistent. All variables were divided into different categories and then combined together to see if these two methods identified the same or similar set of important influential variables.

Natural breaks in the summed count or score were used to determine the tier of importance of each variable. If the resulting count (from Method 1) for each variable was larger than half of the total responses from the data for that category of variables, then the variables were categorized as Tier 1 (i.e., the most/least important variables). Following Method 2, similar results were obtained. Thus, with this data, the Tier 1 variables were then ordered based on their count.

2.5.1 Most important and least important variables by category

Figure 6 (a) shows the results of the count of variables under each category for residential buildings using Method 1. The red columns are the variables where the count value is larger than half of the total responses, which is classified as Tier 1 – the most important variables. Weightage distribution is also provided (Method 2), showing that the variables designated as Tier 1 based on the first method also have higher weightage value, as seen in Figure 6 (b), which shows the results are consistent between these two methods. Figure 7 (a) and (b) present the count and weightage results for commercial buildings.

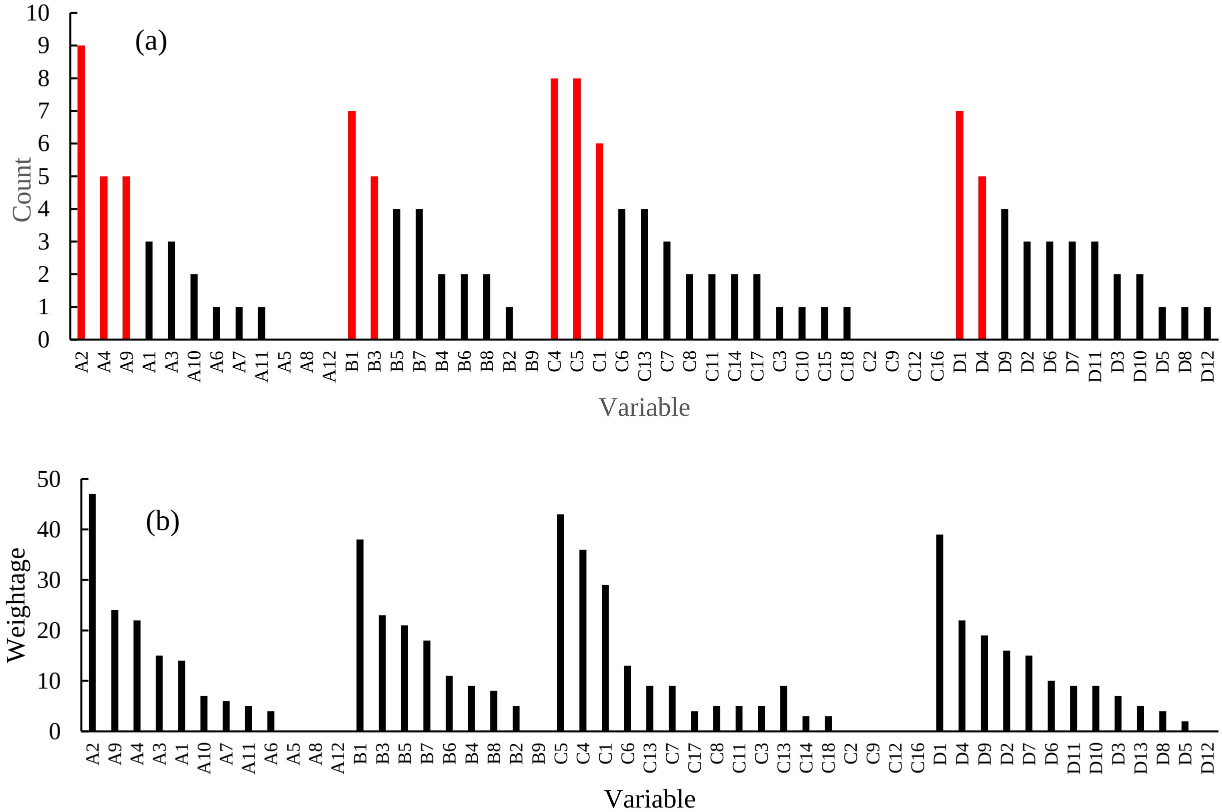


Figure 6 (a) Count value (Method 1) and (b) weightage value (Method 2) for most important influential variables for residential building applications. ***(Note: Red columns indicate where more than half of responses include this variable for Method 1)***

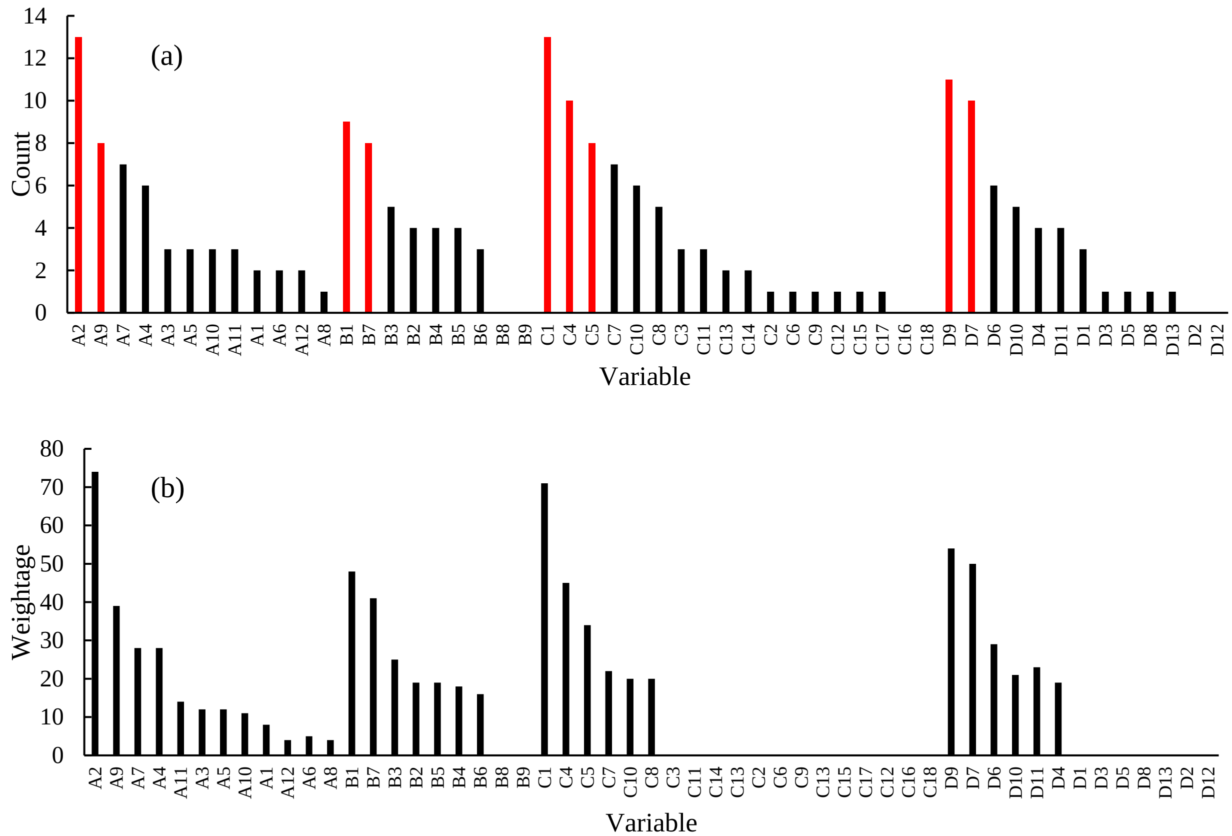


Figure 7 (a) Count value (Method 1) and (b) weightage value (Method 2) for most important influential variables for commercial building applications. ***(Note: Red columns indicate where more than half of responses include this variable for Method 1)***

Table 11 shows the survey results for the most important and least important variables and variables that are never mentioned as most or least important for residential buildings. The order in the table represents the importance of these variables. The other variables not presented here are considered in-between variables, being neither most nor least important. Half of the most important variables are never mentioned as the least important variables, and one third of the least important variables are also never mentioned as the most important variables, which shows the results are consistent with each other. In addition, there is no overlap between the most and least important variables. Table 12 summarizes the results of the most important and least important variables in commercial buildings, parallel to Table 11.

Table 11 Most and least important variables for residential buildings, and those never chosen as most/least important

Most Important	Least Important
A2. Size (length/width) and shape of test area	A8. Building envelope type (e.g. brick, siding, EFIS, batt vs. continuous insulation)
C5. Level of motion of occupant(s)	A6. Wall, floor, and ceiling color/characteristics
D1. Presence of pets	B6. Mean radiant temperature (indoor)
B1. Lighting level (regardless of source of light) (lux)	B4. Indoor humidity
C4. Spatial location of occupant(s)	C15. Skin color of occupant(s)
C1. Number of occupants (including 0)	C2. Age of occupant(s)
A9. Presence of large objects (especially metal objects) within or near a space	C16. Body shape of occupant(s)
B3. Presence of interior lighting sources (non-overhead)	C3. Metabolic rate
A4. Number of doors (entrances/exits)	D5. Presence of mylar balloons/party
D4. Use of robots	D11. Presence of wheelchairs
Never Chosen as Most important	Never Chosen as Least Important
A5. Door sizes (i.e., single vs. double, other)	A2. Size (length/width) and shape of test area
A8. Building envelope type (e.g., brick, siding, EFIS, etc..)	A12. Other building-related variables (please specify)
A12. Other building-related variables (please specify)	B1. Lighting level (regardless of source of light) (lux)
B9. Other (please specify)	C1. Number of occupants (including 0)
C2. Age of occupant(s)	C4. Spatial location of occupant(s)
C9. Speed of occupants relative to one another	C5. Level of motion of occupant(s)
C12. Presence of occupants in adjacent spaces	C8. Speed of occupant (e.g., walking vs. running)
C16. Body shape of occupant(s)	D9. Repeatability of performance of system (i.e., does it provide the same results consistently)

Table 12 Most and least important variables for commercial buildings, and those never mentioned as most/least important

Most Important	Least Important
A2. Size (length/width) and shape of test area	A8. Building envelope type (e.g., brick, siding, EFIS, etc.)
C1. Number of occupants (including 0)	B4. Indoor humidity
D9. Repeatability of performance of system (i.e., does it provide the same results consistently)	B5. Indoor temperature
D7. Initial performance/performance over time (e.g., does it take a while for the system to learn/work well)	C6. Noise level of occupant(s)
B1. Lighting level (regardless of source of light) (lux)	C16. Body shape of occupant(s)
C4. Spatial location of occupant(s)	C2. Age of occupant(s)
A9. Presence of large objects (especially metal objects) within or near a space	D1. Presence of pets
C5. Level of motion of occupant(s)	D8. Range of devices (related to electromagnetic interference)
B7. Presence of sunlight - direct	D4. Use of robots
--	D5. Presence of mylar balloons/party items
--	D11. Presence of wheelchairs, strollers, shopping carts,
Never Chosen as Most important	Never Chosen as Least Important
B8. Presence of sunlight - diffuse	A2. Size (length/width) and shape of test area
C12. Presence of occupants in adjacent spaces	A4. Number of doors (entrances/exits)
C16. Body shape of occupant(s)	C1. Number of occupants (including 0)
D2. Motion characteristics of pets (if present)	C4. Spatial location of occupant(s)
--	C7. Clustering of occupants (distance between occupants)

Comparing the most important variables for residential buildings with that of commercial buildings, approximately 2/3 of variables are the same, including the size and shape of test area, lighting level, spatial location of occupant(s), presence of large objects, number of occupants, and the level of motion of occupant(s). Similarly, for the least important variables, approximately half are the same for both residential and commercial buildings, including building envelope type, indoor humidity, age of occupant(s), presence of mylar balloons, and presence of wheelchairs. These variables are either difficult to adjust in an existing building, such as the building envelope type, or in most applications, are a rare occurrence, such as balloons that typically are only present during a party. The presence of wheelchairs is also not common, except in specific building types. Indoor humidity in mechanically controlled commercial buildings is typically controlled within a certain range and is generally a variable that sensor system types are not impacted by.

For the other important variables, there are differences between residential and commercial buildings. For example, the presence of pets is important for residential buildings but not for commercial, which makes sense given pets are much more likely to be in a home than a commercial building. Commercial buildings are also more likely to have overhead lighting sources as compared to residential which likely include a broader diversity of lighting sources. The use of robots is also a variable that is also more common in homes, specifically sweeping/vacuum robots. The presence of direct sunlight appears to be ranked more importantly for commercial buildings, likely because there are typically more windows in commercial buildings compared to residential, and that a visually comfortable work environment is important.

2.5.2 Most important variables across all variable categories

The last question in the survey asked participants to, regardless of the type/category of variables, identify and rank the most/least important variables. Figure 8 shows the weightage values calculated for each variable based on the ranking of respondents in (a) residential buildings, and (b) commercial buildings, indicating that there are large jumps/breaks in rankings among the variables. Approximately half of the variables were not chosen by respondents and thus not shown. In addition, for residential buildings, for 85% of the variables, their weightage values were less than 10, compared to the five most highly ranked variables with a weightage value larger than 22 (shown in red). For commercial buildings, 92% of variables had a weightage value of less than 15, whereas the four top variables had a weightage value of more than 36.

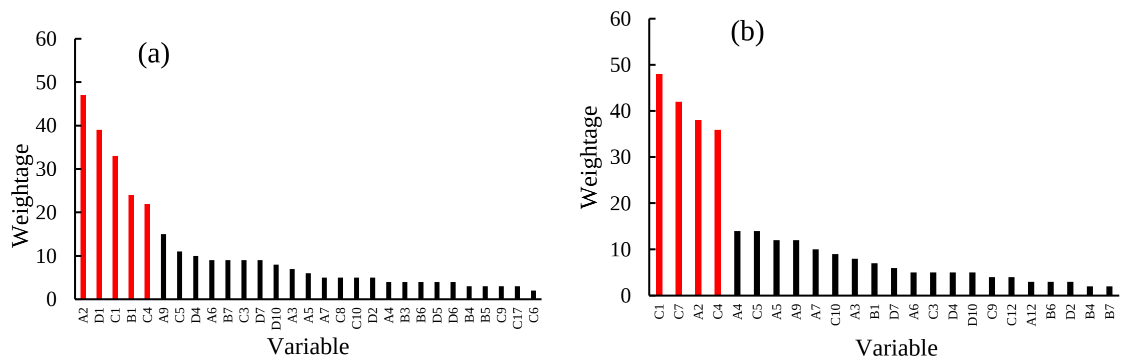


Figure 8 Weightage value for variables considered as the most important in (a) residential and (b) commercial buildings based on the final survey question

The final question in the survey asked responders to indicate, across all variables, regardless of category or type, what variables are most important, in rank order. This was used as a check of the above-mentioned variables which were evaluated by category of variable. Figure 9 shows the average ranking across all responses for each of these variables for both residential (Figure 9 a) and commercial (Figure 9 b) buildings. The variables, where none or only one responder provided a ranking, are not included in the analysis. Among the variables with more than one ranking, if a person did not rate that variable, we assume the remaining unrated variables are the next rank after their last rank. For example, if one person rated four variables 1 to 4, the rest were rated are considered as 5. Error bars indicate standard deviation. From the results, we can see that the standard deviation is similar across the different variables. In addition, the average rankings for the most important variables determined in Figure 8 are smaller compared to the others, indicating that they are more important than others.

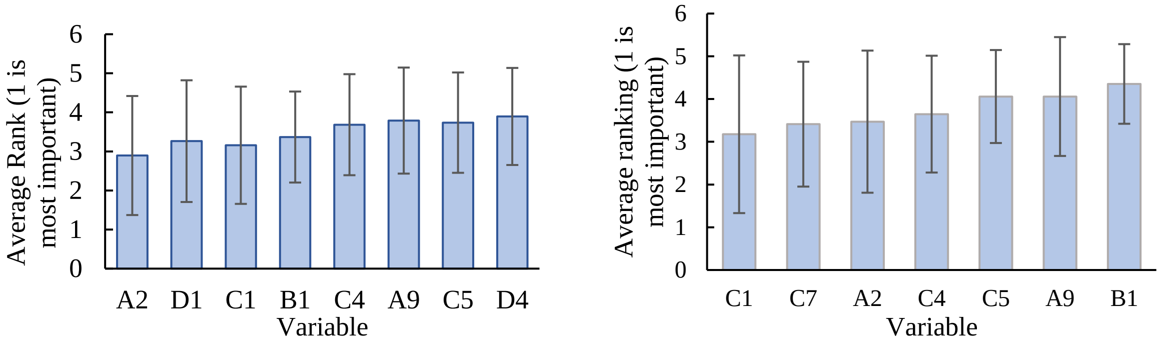


Figure 9 Average ranking and standard deviation of variables considered as the most important in (a) residential buildings and (b) commercial buildings based on the final survey question

Considering the top variables from Figure 8, the results of this final survey question are very close to the results shown in Table 11 and 12, with the exception of variable C7, Clustering of occupants, for commercial buildings. As such, the most important variables for standard testing and evaluation of occupancy sensor systems for residential and commercial buildings are summarized in Table 13.

Table 13 Most important variables for residential and commercial buildings

Building type	Most important (Tier 1)
Residential buildings	A2. Size (length/width) and shape of test area
	C5. Level of motion of occupant(s)
	D1. Presence of pets
	B1. Lighting level (regardless of source of light) (lux)
	C4. Spatial location of occupant(s)
	C1. Number of occupants (including 0)
	A9. Presence of large objects (especially metal objects) within or near a space
	B3. Presence of interior lighting sources (non-overhead)
	A4. Number of doors (entrances/exits)
	D4. Use of robots
Commercial buildings	A2. Size (length/width) and shape of test area
	C1. Number of occupants (including 0)
	B1. Lighting level (regardless of source of light) (lux)
	C4. Spatial location of occupant(s)
	A9. Presence of large objects (especially metal objects) within or near a space
	C5. Level of motion of occupant(s)
	B7. Presence of sunlight - direct
	C7. Clustering of occupants (distance between occupants)

2.6 Conclusions and Future Work

This paper reviewed existing occupancy sensor technologies and summarized the potential influential variables that may cause sensor failures. Using the results of the literature review, the influential variables tested in previous literature were compiled into a comprehensive list, and additional variables were suggested by stakeholder attendees. Then an expert survey was conducted across a diversity of stakeholders on the most and least important variables impacting occupancy sensor performance based on this comprehensive influential variable list. A final list of most and least important variables was determined for both residential and commercial buildings. The results of this work provide insights for sensor manufacturers on what variables industry stakeholders care about most when assessing the performance of occupancy sensor systems, and also provide initial results for use in considering a standard set of variables by which to test occupancy sensor systems for comparative performance evaluation.

The limitations of this work include that there are many different influential variables and combinations of variables that can impact occupancy sensor systems, some of which may be more important in some building scenarios as compared to others. It was not attempted to rank the order of importance for different building types, such as hospitals versus schools. It is anticipated that they may be variations in these ranking among building types, as well as the frequency of occurrence of various variables. However, this effort was an attempt to define the most and least important variables for residential and commercial building applications overall. The stakeholders that participated in the survey were also mostly based in the U.S., which may influence results.

Moving forward, as climate change challenges becoming increasingly important to address, significant efforts are and will continue to be made to improve the efficiency of buildings, as one of the largest consumers of energy and electricity. Occupancy sensor systems used to more efficiently control the lighting, HVAC, and other systems in a building represent a strong opportunity for energy savings compared to most building operations today. The results of this work will support the development of a standard methodology to test these systems. By having a standard set of variables that a diversity of representative stakeholders suggests are most important to use, the next step is to develop associated methods of testing to evaluate the performance of occupancy sensor systems, which will help to provide a standard method for comparative performance evaluation, to determine which sensor systems work best and where these systems can be improved. Additionally, it is also important to consider that if a reliability issue is identified for a certain type of occupancy sensor system, further efforts are needed to mitigate these to improve the sensor's reliability and performance. For example, if a sensor system is determined to be sensitive to natural daylight, it may be recommended to not install this sensor system near exterior windows, or additional changes to the sensor system may be made to reduce the sensitivity to daylight. The reliability challenges, however, vary depending on each sensor type, therefore, the specific methods to address each of these issues are also unique to the sensor system and need to be address individually.

APPENDIX

Appendix: "Occupancy Sensor System Evaluation Methodologies - Stakeholder Feedback" survey

Q4: Please categorize the **building-related variables**, including those that you believe would be **<u>most and least</u>** important to test for **Occupancy presence sensing systems**:

A1. Glass walls & mirrors (reflective surfaces)
A2. Size (length/width) and shape of test area
A3. Location/characteristics of windows
A4. Number of doors (entrances/exits)
A5. Door sizes (i.e., single vs. double, other)
A6. Wall, floor, and ceiling color/characteristics
A7. Height of ceiling
A8. Building envelope type (e.g., brick, siding, EFIS, batt vs. continuous insulation)
A9. Presence of large objects (especially metal objects) within or near a space
A10. Electromagnetic interference
A11. Ventilation rates
A12. Other building-related variables (please specify)

Q5: Please provide any additional comments or suggestions for building-related variables (e.g., any additional variables/situations that should be considered)

Q6: Please categorize the **environment-related variables** including those that you believe would be **<u>most and least</u>** important to test for **Occupancy presence sensing systems**:

B1. Lighting level (regardless of source of light) (lux)
B2. Spectral distribution of light
B3. Presence of interior lighting sources (non-overhead)
B4. Indoor humidity
B5. Indoor temperature
B6. Mean radiant temperature (indoor)
B7. Presence of sunlight – direct
B8. Presence of sunlight – diffuse
B9. Other environment-related variables (please specify)

Q7: Please provide any additional comments or suggestions for environment-related variables (e.g. any additional variables/situations that should be considered):

Q8: Please categorize the **occupant-related variables** including those that you believe would be **<u>most and least</u>** important to test for **Occupancy presence sensing systems**:

C1. Number of occupants (including 0)
C2. Age of occupant(s)
C3. Metabolic rate
C4. Spatial location of occupant(s)
C5. Level of motion of occupant(s)
C6. Noise level of occupant(s)
C7. Clustering of occupants (distance between occupants)
C8. Speed of occupant (e.g. walking vs. running)
C9. Speed of occupants relative to one another
C10. Number of occupants entering/exiting a room at the same time
C11. Speed of occupants entering/exiting a room at the same time
C12. Presence of occupants in adjacent spaces
C13. Clothing color/contrast/patterns (including images on clothing) of occupants
C14. Occupant clothing level (clo)
C15. Skin color of occupant(s)
C16. Body shape of occupant(s)
C17. Occupants wearing heavy winter coats with a cold surface temperature
C18. Other occupant-related variables (please specify)

Q9: Please provide any additional comments or suggestions for occupant-related variables (e.g., any additional variables/situations that should be considered):

Q10: Please choose **other variables** that you believe would be the **<u>most/least important</u>** to evaluate for **Occupancy presence sensing systems**:

D1. Presence of pets
D2. Motion characteristics of pets (if present)
D3. Size/type of pets
D4. Use of robots
D5. Presence of mylar balloons/party items
D6. Ability to communicate with thermostat
D7. Initial performance/performance over time (e.g., does it take a while for the system to learn/work well)
D8. Range of devices (related to electromagnetic interference)
D9. Repeatability of performance of system (i.e., does is provide the same results consistently)
D10. Presence of heat sources such as a heat lamp
D11. Presence of wheelchairs, strollers, shopping carts, etc.
D12. Other variables (please specify)

Q11: Please provide any additional comments or suggestions for other variables:

Q12: Above you selected important variables for environment, building, occupant, and other categories. Of those that you felt were the most important, please list below the **topmost important** variables across all categories that should be tested for occupancy **presence sensor systems** used in **residential buildings** AND occupancy **counting systems** used in **commercial buildings**

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CHAPTER 3 – DEVELOPMENT AND TESTING OF A PERFORMANCE EVALUATION METHODOLOGY TO ASSESS THE RELIABILITY OF OCCUPANCY SENSOR SYSTEMS IN RESIDENTIAL BUILDINGS

3.1 Abstract

With the emergence of advanced occupancy sensor technologies to better detect occupancy in buildings, a universal methodology and metrics are required to evaluate and report sensor systems' reliability and compare the performance across multiple sensor systems. This research presents a methodology to assess the reliability of occupancy sensor systems in residential buildings in a controlled laboratory environment, including both "typical" and "failure" testing scenarios. The developed methodology was then implemented to evaluate a novel occupancy detection sensor system's reliability. "Typical" testing evaluates the overall accuracy of the sensor system, which suggest how reliable the occupancy sensor system is over time. Results show that on average, the precision and recall are 0.75 and 0.70, indicating similar numbers of false positives and false negatives across the dataset. The overall accuracy of the tested sensor system was 62.4% to 76.4%. Failure testing results indicate whether there are influential variables impacting the sensor performance. For the tested sensor system, the number of occupants, presence of large objects, presence of interior light sources, and number of doors are not influential, while lighting level, location of occupants, additional door in the entry/exit area, and having the TV on are variables determined to impact the sensor system performance.

Keywords: Sensor reliability; Standard testing methodology; Typical testing; Failure testing; Performance metrics; Occupancy sensor systems

3.2 Introduction

Buildings account for approximately 40% of the total energy use in the U.S. (U.S. EIA, 2021). In residential buildings, heating and cooling energy consumption consists, on average, of more than 50% of this energy use among the different energy end uses (RECS, 2015). Therefore, it is of importance to develop energy saving approaches to help reduce heating and cooling energy use in residential buildings.

Energy consumption in residential buildings is strongly impacted by occupants and their energy use patterns (Hong et al., 2016). There have been an increasing number of studies focusing on the development of more advanced occupancy sensor systems to better collect occupancy information such that this occupancy related data could be used to inform building controls. For example, Razavi et al. (2019) proposed a genetic programming approach to predict the present and future home-occupancy status of households based on high-frequency meter data. Tan et al. (2022) used an ensemble method to combine sensor data from different data modalities, including environmental sensors (temperature, humidity, and illuminance), image sensors, and acoustic sensors to predict occupancy information in residential buildings. Such controls can help to target opportunities to reduce energy use and improve operational efficiency. For example, occupancy sensors may be connected to lighting systems to detect the presence/non-presence of people to determine when to turn lights on or off (Nagy et al., 2015). More recently, occupancy sensors have been considered for HVAC (heating, ventilation, and air conditioning) control applications. Turley et al. (2020) proposed non-probabilistic occupancy models developed based on occupancy data derived from occupancy sensors incorporated in smart thermostats to provide occupant-based controls in residential buildings in Colorado. These thermostats generally include a “home” and “away” mode, depending on whether the sensor detects movement or not. In “away” mode, occupants are considered to be outside of the home and thus the setpoint temperature is adjusted to unoccupied mode, to reduce energy consumption. These thermostats generally include a "home" and "away" mode, depending on whether the sensor detects movement or not. In "away" mode, occupants are considered to be outside of the home and thus the setpoint temperature is adjusted to unoccupied mode, to reduce energy consumption. Esrafilian-Najafabadi and Haghighat (2021) used deep learning algorithms to provide dynamic estimations of preconditioning time and future occupancy patterns as a function of occupancy, indoor temperature, and weather data to make control decisions in residential buildings.

However, occupancy patterns, particularly in residential buildings, can be highly unpredictable, varying significantly from person to person, and across households and building types. In a prior study (Chu et al., 2021a), more than 50 different variables were identified that may impact the ability of an occupancy sensor system to detect occupants. While occupancy detection methods have been the focus of increasing interest in recent years, there are opportunities to improve the accuracy of existing technologies. Sensor systems can incorrectly provide occupancy information under various scenarios and edge cases. For example, for occupancy detection sensors, most typically used in residential buildings, this can be either a false positive reading (i.e., the sensor system indicates there is an occupant(s) when there is not), or false negative (i.e., the sensor system cannot detect an occupant when there is one or more present). However, the methodology used to evaluate reliability of performance, and the metrics used to report this are not uniform across the literature. Without an established standard method to evaluate the performance of these sensor systems, it is not possible to objectively evaluate and compare the performance of multiple sensor systems. To address this challenge, therefore, the focus of this research is on the development of a universal evaluation methodology to test the reliability of occupancy sensor systems in residential buildings. As a case study, the developed testing methodology was implemented to evaluate a novel occupancy detection sensor system in a controlled laboratory environment.

This research is organized as follows. Section 2 presents the proposed standard methodology to test the reliability of occupancy sensor systems, while Section 3 describes the novel occupancy detection sensor system developed and evaluated. The case study results of applying the developed reliability evaluation methodology to the occupancy detection sensor system are detailed in Section 4. Conclusions and discussion are provided in Section 5.

3.3 Evaluation Methodology for Sensor System Reliability

The proposed methodology for testing the reliability of occupancy sensor systems in residential buildings includes both "typical" testing and "failure" testing. For typical scenarios, the occupancy sensor system is tested with real occupants following occupancy schedules and activity profiles that represent typical conditions in a controlled residential environment, to determine the frequency of failures. The purpose of typical testing is to evaluate the accuracy and reliability of each occupancy sensor system under real occupancy scenarios over time. For the "failure" testing, the performance of the occupancy sensor systems is determined by testing the impact of a range of variables to determine if they are influential or not, using the one variable at a time (OVAT) testing method (Hasan et al., 2016). When a single variable is considered, all other variables are fixed at standard level, while the variable being evaluated is varied across a range of values to assess how it impacts performance. The purpose of this component of testing is to identify which variable(s) may cause sensing failures, and thus influence the performance of the occupancy sensor system.

3.3.1 Typical testing

Occupancy schedules under typical scenarios were first created, utilizing American Time Use Survey (ATUS) data (BLS 2020) as it collects activity data for people in the United States, including periods they spend at home, in residential buildings. The activity data of participants from the ATUS was then mapped to the presence or absence of occupants in residential buildings. This data was also classified based on occupant characteristics including their age group, whether it is weekday or weekend, and types of households. Three most common types of occupancy profiles, including “Day absence”, “Stay at home”, and “Night absence” profiles, were obtained from our prior study (Mitra et al., 2021), which represents approximately 88% of people in the United States. Based on these most common types of residential occupancy profiles, each was selected for use in representing typical occupancy profiles of residential buildings to evaluate the reliability of occupancy sensors systems in this research.

The occupancy schedules from the ATUS-derived data were then used to compare to the raw data in the ATUS database, from which participant’s activity data was selected that most closely matched occupancy profiles. The criteria used for matching was calculated as the participant’s activity data that had the least difference in occupancy fraction as compared to the three previously identified typical individual profiles. The detailed activity information for the selected occupant IDs was then extracted from ATUS dataset, which forms “Sche 1”, “Sche 2” and “Sche 3”.

These typical profiles are individual schedules obtained among all types of households based on ATUS data. For the evaluation of the performance of occupancy sensor systems in homes, typical occupancy schedules in households need to be then developed. Based on RECS data (2020), 1-member households and 2-member households account for around 64% of the total amount of households. Therefore, these two types of households were chosen in this work. For 1-member households, the three typical profiles were directly selected. For 2-member households, the three personal schedules were combined to form 2-person household schedules. Among these three typical profiles, the portion of household members following Sche 2 “Night absence” is relatively small, compared to the others (Mitra et al., 2021). Thus, for 2-person households, only “Sche 1” and “Sche 3” were used. “Sche 4” includes two people following “day absence”; and “Sche 5” includes one person following “day absence” and the other following “stay-at-home”. The combined schedule when two people follow “Stay-at-home” was not used in this research since it has less varied occupancy scenarios for use in evaluating sensor reliability. The five typical household profiles are summarized in Table 14.

Table 14 Five typical household types and associated occupancy profiles

Item	Household Type	Occupancy Profile
Sch1	1-person household	"Day absence"
Sch2	1-person household	"Night absence"
Sch3	1-person household	"Stay-at-home"
Sch4	2-person household	"Day absence" for both household members
Sch5	2-person household	"Day absence" for one person; "Stay-at-home" for the other

The detailed activity profiles for these five typical occupancy scenarios were then created for use in evaluating occupancy sensor systems under a range of typical conditions. As an example, Table 14 shows a sample of Sch1 over a 24-hour period, in the column “24-hour duration”, which represents the ATUS-defined schedule across this period. ATUS collects occupancy data from 4 am of one day to 4 am of the following day (e.g., Table 15) with a time interval of 5-minute. These occupancy profiles are shown in Figure 10. All typical occupancy schedules and activity data used are also included as supplemental data, in the Appendix A.

Table 15 1-person household with day work profile

Start time	End time	24-hr duration (min)	Intermediate duration (min)	Test duration (min)	ATUS activity details	Location	Motion level
4:00	6:00	120	10	10	Sleeping	Bedroom	None
6:00	6:30	30	30	10	Washing, dressing and grooming oneself	Bathroom	Minor
6:30	6:50	20	20	10	Eating and drinking	Dining room	Minor
6:50	18:20	690	10	10	Go to work	Not in home	None
18:20	19:20	60	60	20	Eating and drinking	Dining room	Minor & Major
19:20	22:30	190	190	15	Television and movies	Living room	Minor
22:30	4:00	330	10	10	Sleeping	Bedroom	None

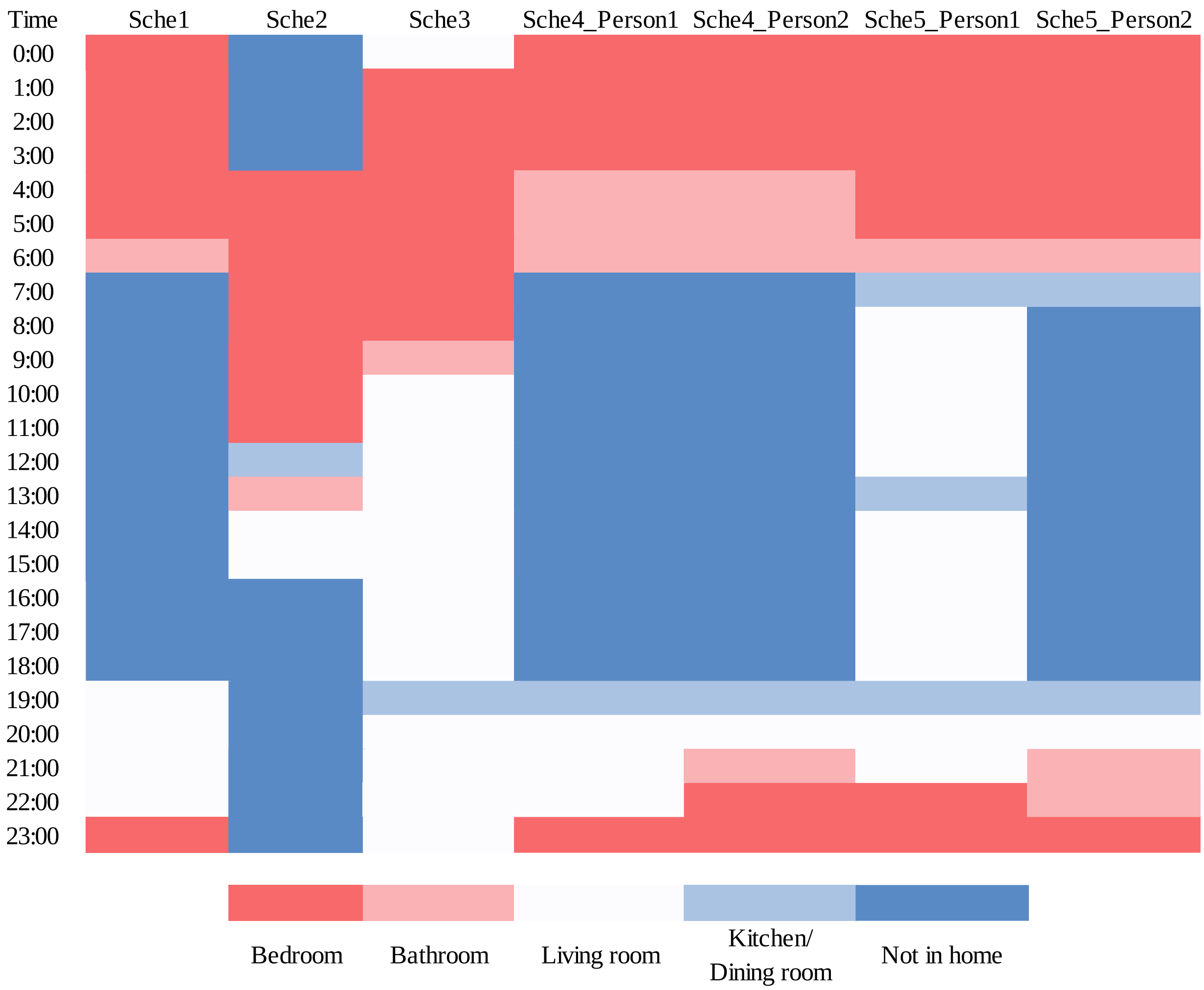


Figure 10 Occupancy profile and location data

Motion level was defined by the National Electrical Manufacturers Association (NEMA) WD 7 Occupancy Motion Sensors Standard (NEMA 2016), including four categories based on the activity level, which are major, minor, fine, and no motion. An example of major motion is people walking; an example of minor motion is people extending their arms; an example of fine motion is people sitting and typing; an example of no motion is people sleeping. Each activity was also assigned a specific location or a set of locations in the laboratory space for occupants, who follow these typical profiles.

Given that there are a number of activities that occur over long durations of many hours (e.g., “no one at home”, these activities may be shortened to optimize laboratory testing time and utilization. These testing durations proposed are included in the column “test duration”, shown in Table 15. The “Test duration” is a shorter version of *sleeping* and *not at home* activity times, since there are rarely variations in occupancy and activities occurring during these periods. The longer time periods were reduced to 10 to 20 minutes. Preliminary testing results suggested that a 10- to 20-minute duration was able to capture the behavior of a sensor system sufficiently to mimic a longer period of time. This shorter duration also enables a more time-efficient testing method which is beneficial given this test method requires human subjects to complete. There are limitations of the use of the “test” duration for extrapolating to the 24-hour duration. Further studies can be implemented in future to investigate this further.

The sensor performance is evaluated at 1-min intervals, which means that the ground truth and sensor output data is also collected and compared every 1 minute. This is based on results attained from the expert survey developed in a prior study (Chu et al., 2021a). The last question in this survey asked the time frequency of evaluation of the performance of occupancy sensor systems in residential buildings. A 1-minute frequency was the most commonly recommended. As such, for a 10-minute activity, this will result in ten classification results (occupied/unoccupied) from the sensor system, for use as input in calculating the resulting performance metrics. In order to translate the “test” duration test results into a reliability metric representative of a 24-hour period, the performance of the sensor system across the shortened activity periods must be extrapolated to the initial “24-hour duration” period. To do so, test results were scaled up from actual “Test duration” period to “24-hour duration” period by assuming the results from the “test” duration are proportional to the time for the activity across the “24-hour duration”.

3.3.2 Failure testing

A recent study (Chu et al., 2021a) conducted a comprehensive literature review on influential variables impacting the performance of occupancy sensor systems. This research compiled a list of these variables, amounting to approximately 50 variables in total. An expert survey was then used to determine what a diversity of stakeholders suggest as the “most important” variables. The resulting most important variables suggested for residential buildings included 10 variables, more specifically, *size and shape of the test area, level of motion of occupant(s), presence of pets, lighting level, spatial location of occupant(s), number of occupants, presence of large objects, presence of non-overhead interior lighting sources, number of doors,* and *use of robots (e.g., robot vacuum).* The proposed standard set of variables to be tested are the same across any occupancy sensor system that may be tested following this method.

The *size and shape of the test area* variable means different interior configuration and layouts of a controlled test space. This would also influence how many sensors are needed, and where the sensors are installed for a particular sensor system. For *level of motion of occupants*, four different motion levels are defined including major, minor, fine and no motion (Chu et al. 2021a). These motion levels are based on the National Electrical Manufacturers Association (NEMA) WD 7 Occupancy Motion Sensors Standard (NEMA 2016). Some sensor systems may have failures when occupants are not moving, such as PIR motion sensors (Kilic et al., 2013). *Lighting level* indicates a binary variable, which represents lights being on or off, since lighting levels are not typically dimmable in a residential building. Some types of sensors are sensitive to lighting levels and/or certain kinds of light (Yang et al., 2018). *Pets*, *large objects*, *interior lighting sources*, and *robots* are considered, since they could be mistaken for a person by certain types of occupancy sensor systems. For *number of doors*, there may be potential failures caused by variations in this variable if sensor systems miss detecting people entering or leaving when there are multiple entry/exit doors. This is particularly the case for door-based occupancy sensor systems, which rely on detection of occupants in these locations to determine occupancy. This set of variables is proposed as a standard set of variables to evaluate all occupancy sensor systems considered.

Apart from the above-mentioned most important variables, additional variables may also be included in the evaluation methods. These may be added based on known failures or sensitivities of certain sensors or combination of sensor types, or as suggested by the manufacturer of the sensor system who wishes to evaluate the occupancy sensor system under these conditions. Apart from the above-mentioned most important variables, additional variables may also be included in the evaluation methods. These may be added based on known failures or sensitivities of certain sensors or combination of sensor types, or as suggested by the manufacturer of the sensor system who wishes to evaluate the occupancy sensor system under these conditions. Based on how each variable might influence the sensor performance, different levels of variables are determined. For example, for the variable "motion level", there are four levels (major, minor, fine and none), indicating that the occupancy sensor system will be tested under these four different motion levels to determine which level will fail the sensor system. For each variable level, at least three trials, under identical conditions, are conducted for each scenario to make sure the testing results are more robust.

For the OVAT method, as mentioned above, a standard value must be determined for each of the variables not being tested in a particular scenario. The target for this standard set of values would be the environmental conditions that are most commonly occurring in a residential environment. In this case *lights are on*, with no *pets*, *large objects*, or *robots*. For *spatial location* *of occupants*, this was in the center of the largest main room, which was the living room area. For testing of *large objects*, *non-overhead interior lighting sources*, *robot*, and *pets*, this also occurred in center. All variables were tested under both the presence of occupants (i.e., the laboratory test home was occupied), and without occupants (i.e., when the space was unoccupied). For each variable, at least three trials, under identical conditions, were conducted for each scenario.

3.3.3 Ground truth

Ground truth provides the information that is known to be real or true by direct observation or measurement. In this paper, it refers to the real occupancy information (i.e., whether or not the test space was occupied) compared to the sensor prediction. The ground truth data must be provided to enable the comparison to the sensor output to evaluate the sensor performance. For typical testing, ground truth data was pre-defined/known based on the developed typical occupancy schedules and activity profiles. For failure testing, ground truth data was manually recorded. This data was used to compare with the sensor output to determine sensor performance. The ground truth data was recorded at the same frequency as the sensor data.

3.3.4 Laboratory Setup

In order to ensure repeatability of test results, as well as to best mimic conditions experienced by occupancy sensors in residential buildings, standard laboratory conditions are proposed and used. Variables that are untested should be within acceptable limits to reduce potential sensor failures due to these untested variables. These are as follows:

1) Exterior windows are covered with an opaque cover to eliminate exterior lighting sources. Insulated foam boards could be used to cover windows.
2) Light sources are LED.

3) Lighting levels are approximately 300 lux at the work plane in the center of the test space(s) following DiLaura et al. (2011).

4) Uniform lighting levels are present throughout the test space. The lighting level is tested initially in each room. As needed supplemental overhead lighting is used to make lighting levels uniform across different spaces.

5) Indoor temperature is 21 +/- 2 C. Indoor temperature is controlled by setting the temperature setpoint using smart thermostat in residential buildings.

6) Relative humidity must be less than 80% +/- 5%, with a targeted value of 30-60%. As suggested by Ramos et al. (2015) the sensing ability may decrease with higher humidity for IR sensors. Based on the ASHRAE Equipment and Systems Handbook (2020), 30% to 60% relative humidity is ideal for human occupancy.

7) Electronics that emit potential interference in a similar frequency band (e.g., microwaves) as the tested sensor system(s) are turned off during testing to avoid electromagnetic interference.

3.3.5 Performance metrics

Performance metrics for reliability evaluation of occupancy sensor systems have been discussed in detail in a recent study (Chu et al. 2021b). Among 80 peer-reviewed research articles, accuracy is the most widely used metric, which is the ratio of correct predictions over total number of testing scenarios. Some recent papers have used a confusion matrix to discuss failures. This method separates the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) that occur during testing. Such a method enables a stronger understanding of the types of errors that occur. However, in many cases for prior studies, only an overall accuracy value or error estimation was provided rather than analyzing these four terms in detail. Therefore, in this proposed standard methodology, a confusion matrix, and associated metrics, including precision, recall, F1-score, and accuracy were used to evaluate the "typical" testing results of the occupancy sensor systems. Precision is the percentage of true positive out of all the predicted positives as shown in Equation (1), while recall represents the ratio of true positives to all actual positives as shown in Equation (2). An F1-score is the harmonic mean of precision and recall Equation (3), which combines both false positives and false negatives, and gives precision and recall the same weight (Deng et al. 2016).

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) \tag{1}$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) \tag{2}$$

$$\text{F1-score} = 2 * (\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall}) \tag{3}$$

While "failure" testing aims to test the influence of each individual variable on the sensor performance, confusion matrix (TP, TN, FP, FN) is chosen as a standard metrics so that results can be evaluated for each testing scenario. By comparing the sensor output with ground truth (actual occupancy information), a confusion matrix will be provided. TP represents that the sensor output is the same as the ground truth, which is "Occupied"; TN means that the sensor output is "Unoccupied" which is same as the ground truth; FP is that the sensor output is "Occupied" but the space is actually "Unoccupied"; FN means that the sensor output is "Unoccupied" but the space is actually "Occupied". After testing one variable, for all scenarios, if the prediction result is either TP or TN, it means that the sensor output is correct compared to the ground truth, indicating the variable is not influential since it does not appear to cause the sensor system to fail. Otherwise, if either FP or FN was observed, that means this variable is influential since it may cause the sensor system to fail at certain conditions.

3.4 Experimental Results: Case Study

3.4.1 Sensor System Description

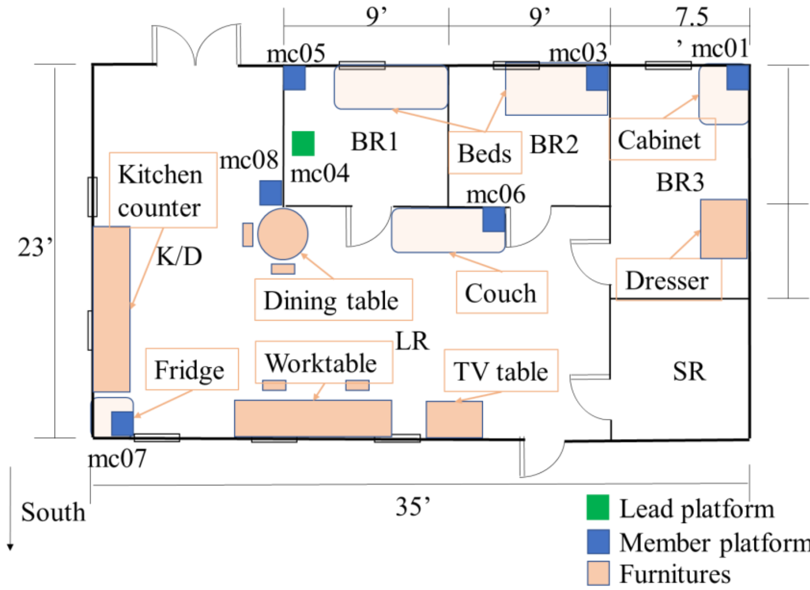
The tested sensor system is the MicroCam platform, which is a battery-powered, stand-alone sensor system designed to detect occupancy in residential homes. It contains a local processing unit, a camera, a microphone, a motion sensor, and a Near-IR Band (NIR) Light Emitting Diode (LED). Multiple MicroCam platforms operate concurrently and communicate wirelessly with each other to detect presence of people. This provides more coverage for the detection task that the system is designed for. Advanced algorithms are employed to translate data streams into actionable adjustments to home heating and cooling. The algorithms are implemented and executed locally on the sensor unit making the solution stand-alone, not relying on external computation units or cloud computing.

MicroCam platforms are designed to operate under daylight conditions as well as low-light/no-light conditions, and to detect people even when they are static. This system is also designed to differentiate different sources of motion, i.e., motions of pets, robot vacuums, etc. from people. After local data processing, the MicroCam platforms send only a binary occupancy result to the “lead platform”, which is then connected to the HVAC system of a home to adjust setpoints based on occupancy.

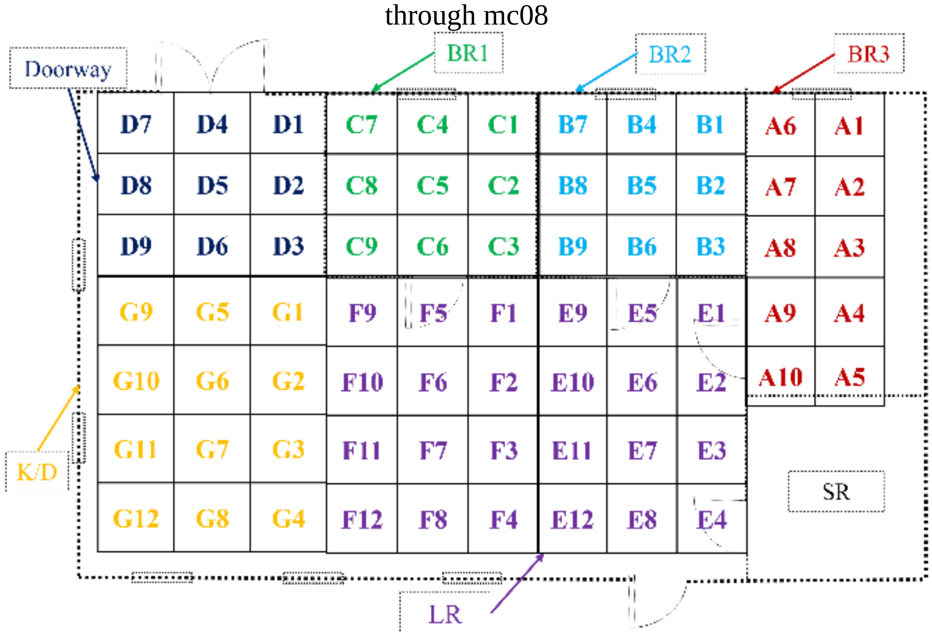
3.4.2 Test bed

For testing and evaluation of occupancy sensor systems, controlled laboratory tests were conducted using a residential building laboratory. The residential building laboratory facility, located in East Lansing, MI, includes two identical single-story wood-framed residential buildings, one of which was used in this study. This laboratory space includes eight double-glazed windows and two exterior doors. The interior includes white-colored drywall, grey floors and white ceilings, with interior walls consisting of wood studs with drywall on either side. The interior of the laboratory test space is reconfigurable, including movable interior walls to allow for testing by using different interior layouts. In this study, two configurations were chosen, including a two-bedroom and three-bedroom layout. The three-bedroom layout is shown in Figure 11 (a). To create a 2-bedroom layout, the interior wall between bedroom 1 (BR1) and bedroom 2 (BR2) was removed. Overhead LED lighting was installed and evenly distributed on the ceiling. The interior of the test space is furnished to represent a typical residential home configuration. This included a living room, kitchen, dining room, bedroom/bathroom, and storage room.

Seven occupancy sensor platforms, including one lead platform (mc04) and six member platforms (mc01, mc03, mc05, mc06, mc07, mc08), were installed on the wall and ceiling per developer's instructions. Each platform is an independent occupancy sensor component with multiple sensing technologies. Each platform utilizes sensor fusion technology to integrate motion sensors, microphones, and image sensors to detect occupancy. This configuration, as shown in Figure 11 (a), was used to provide sufficient coverage of the entire testing space. The lead platform (mc04) was connected via Wi-Fi and located in BR1. The member platforms communicated with the lead platform using Bluetooth. Platforms mc06 and mc08 were installed such that they faced the entry/exit area for each of the two exterior doors. The platforms mc01, mc03, and mc05 were used to cover each of the three bedrooms, and mc07 was used for the living room, kitchen and dining area.



(a) Interior layout showing the three-bedroom configuration and deployment of sensors platforms mc01 through mc08



(b) 1 m x 1 m grid of locations within the laboratory for use in directing occupants where to be throughout testing

(*Note: BR – Bedroom; K/D – Kitchen/Dining; LR – Living room; SR – Storage room*)

Figure 11 Residential laboratory used for testing of occupancy sensor systems

During testing it was important, for consistency, to ensure that the occupants move about the test space in a consistent manner. Therefore, the interior space was divided into seven different blocks, labeled from A to G, where each letter represents a different location. This included A through C for the three bedrooms, D for the doorway, G for the kitchen and dining area, and E and F are for the living room space. Within each quadrant, a 1 m x 1 m grid was created and labeled on the floor (Figure 11 (b)) The storage room (SR) shown is where all equipment was located, therefore it was not used as a location where occupants could go during testing. People were assigned to different locations, following the occupancy schedule and activity profiles. For example, occupants were moving in quadrant G when they are cooking and eating in the kitchen and dining area. When people were reading, watching TV, and playing video games, they sat on the couch in the living room (Blocks E and F). Bedroom 3 (Block A) is considered to be a bedroom with a bathroom. Bedroom 1 (Block C) and Bedroom 2 (Block B) were also used for sleeping.

3.4.3 Data collection

The testing was conducted across a period of several months, from April to July 2021. A web scraper was used to extract occupancy output from the sensor output interface using Home Assistant (2021), an open-source smart home platform. The sensor output collected was a binary classification of “Occupied” or “Unoccupied”. Ground truth data was manually recorded during failure testing and predefined for typical testing based on the developed typical occupancy schedules and activity profiles.

3.5 Results

3.5.1 Typical testing results

Typical testing was implemented following the five typical occupancy schedules and activity profiles, as detailed in Table 15 and in the Appendix. Table 16 shows an example of the typical testing results with the *1-person household with day absence profile,* following the “test duration” testing period. The remaining typical test results are included in Tables 27-30 in the Appendix B. The sensor performance was evaluated at 1-min intervals for these activity durations. The “error time” represents the total time that sensor failures occur for the “test duration”. For example, for the “eating and drinking” activity, the error time is eight minutes out of the 10-minute test duration, which means that there were eight detection errors out of the ten times of detection, or 80% of the time. Following the methods proposed in the methodology section, these errors were extrapolated to the 24-hour duration. From these tables, most failures occurred when occupants were using the computer, or sitting (either on the couch for reading or for eating and drinking). For these cases, the positioning of the sensor platforms greatly affects the performance. For instance, when people are using the computer, they are sitting and their back is towards the camera, causing an occlusion by the chair and thus misdetection. Similarly, as seen in Figure 11 a, the relative positioning of the couch and mc06 is the main reason for misdetection of people sitting on the couch.

Table 16 Typical testing results with "1-person household with day absence profile" using "Test Duration"

ATUS-Based Activity detail	Ground truth	Test Duration (min)	Error Time (min, %)	Intermediate duration (min)	Error Time[1] (min)	24-hour duration (min)	Error Time[1] (min)
Sleeping	Occupied	10	0 (0%)	10	0	120	0
Teeth brushing; Shower; Getting dress		10	0 (0%)	30	0	30	0
Eating and drinking		10	8 (80%)	20	16	20	16
No one in home	Unoccupied	10	6 (60%)	10	6	690	414
Cook food; Bring food to dinner table; Eating and watching TV; Remove dishes, clean kitchen and table	Occupied	20	2 (10%)	60	6	60	6
Watching TV		15	0 (0%)	190	0	190	0
Sleeping		10	10 (100%)	10	10	330	330

[1] *Calculated by extrapolation based on error time for "test duration"; see methodology section*

Performance metrics were then used to evaluate the reliability of the occupancy sensor system over time, including a confusion matrix (TP, TN, FP, and FN), Precision, Recall, F1-score, and accuracy. These metrics were calculated for the "test duration", for the five typical occupancy schedules and activity profiles (Table 15), then extrapolated to the "24-hour duration". The last column, "Summary", represents the overall performance evaluation results combining all five sets of testing results.

From Table 17, for the "test duration", for 1-person households there are more TPs and FNs with Sch3 compared to that of Sch1 and Sch2. This is because Sch3 is the 1-person with a stay-at-home profile where the test duration is longer, thus a greater number of data points is collected, compared to the other two schedules. Since there are more TPs than FNs for Sch3, the highest accuracy was attained for Sch3 in the 1-person household category. For the 2-person household, even though the total number of data points collected is higher for Sch5, there were more FNs compared to that of Sch4, therefore, Sch4 resulted in higher accuracy.

When the data is scaled to the "24-hour duration", the TPs, TNs, FPs and FNs were proportionally increasing according to the time duration when they occurred. As a result, as some schedules have different activities that were scaled, the confusion matrix TPs, TNs, FPs, and FNs are adjusted differently. Following this extrapolation, the overall accuracy with Sch1 and Sch3 decreased by 22% and 20%, respectively, from the "Test duration" to "24-hour duration", since the FP increased slightly more compared to the others. For Sch2, both TPs and FPs largely increased, but FPs increased a bit more compared to TPs, and FN slightly increased, thus the accuracy with Sch2 decreased by 20%. For Sch4, the TPs and FNs increased a similar amount, with TNs substantially increasing, thus the accuracy has a slight increase of 4%. For Sch5, since the increase in TPs and TNs are similar to that of FPs and FNs, the accuracy is similar, with a slight decrease of 1.6%.

There are some scenarios where Precision is 1, which means there are no FPs. Low Precision also appears in Sche1 and Sche2, which are less than 0.5, indicating that there are more FPs in these scenarios. However, there is no one value for Recall, which indicates there are always FNs in all scenarios, and FNs are consistent across all scenarios. On average, the Precision and Recall are 0.75 and 0.70, respectively, which means that there are a similar number of FPs and FNs across the dataset. The overall accuracy of the typical testing is also calculated. For the "Test duration" this was 76.4%, and 62.4% for the "24-hour duration".

Table 17 Performance evaluation metric calculation for typical testing results analysis

		1-person household					2-person household				Overall
		Sche1	Sche2	Sche3-Day11	Sche3-Day21	Total	Sche4	Sche5-Day11	Sche5-Day21	Total	
Test Duration	TP	55	46	69	65	235	115	125	102	342	577
	TN	4	0	3	0	7	25	0	0	25	32
	FP	6	15	0	0	21	0	0	0	0	21
	FN	20	14	18	15	67	17	45	38	100	167
	Precision	0.90	0.75	1.00	1.00	0.92	1.00	1.00	1.00	1.00	0.96
	Recall	0.73	0.77	0.79	0.81	0.78	0.87	0.74	0.73	0.77	0.78
	F1-score	0.81	0.76	0.88	0.90	0.84	0.93	0.85	0.84	0.87	0.86
	Accuracy	69.4%	61.3%	80.0%	81.3%	73.3%	89.2%	73.5%	72.9%	78.6%	76.4%
24-hr Duration (scaled)	TP	398	594	1004		1996	656	875		1531	3527
	TN	276	0	3		279	685	0		685	964
	FP	414	750	0		1164	0	0		0	1164
	FN	352	96	433		881	99	565		664	1545
	Precision	0.49	0.44	1.00		0.63	1.00	1.00		1.00	0.75
	Recall	0.53	0.86	0.70		0.69	0.87	0.61		0.70	0.70
	F1-score	0.51	0.58	0.82		0.66	0.93	0.76		0.82	0.72
	Accuracy	46.8%	41.2%	69.9%		52.7%	93.1%	60.8%		77.0%	62.4%

Note: [1] 'Day1' and 'Day2' appear when testing was completed across two days to represent one typical schedule.

3.5.2 Failure testing results

Twelve individual variables were tested, including the standard set of variables (1-10) from the stakeholder survey (Chu et al. 2021) and two additional variables that were identified to be potentially influential to the tested sensor system (11-12). These included the presence of an extra door in the entry/exit area and having the TV on. For (11), this variable was tested because of the known sensitivity of the sensor system to other doors near an entry/exit door. For (12), this was chosen to be tested because when the TV was on, its sounds and pictures could potentially be interpreted by the sensor system as being occupants. All tested variables and their range of values tested are listed in Table 18. Additional trials were added to certain variables when inconsistent results occurred within the first three trials, to collect further data on performance.

Table 18 Tested variables and associated testing levels

Variables	**Levels**							
Motion level	None		Fine		Minor		Major	
Number of occupants	1				2			
Spatial location of occupants	D7	G1	G7	F5	E10	E4	A6	C1
Interior lighting level	Off				On			
Presence of large metal objects	Non-presence				Presence			
Presence of interior lighting sources	Non-presence				Presence			
Number of exterior doors	1				2			
Presence of (vacuum) robot	Non-presence				Presence			
Presence of pets	Non-presence				Presence			
Test area configuration	Two-bedroom				Three-bedroom			

During failure testing, each scenario was tested for five minutes continuously. Across this period, data was collected every minute. Based on whether there were state changes across this 5-

min period, the resulting value was determined to be a TP, TN, FP or FN. A five-minute period was also used in between tests to allow for the sensor system to respond to changed conditions. In addition, to prevent data loss, simple occupied/unoccupied scenarios were also used as a check to make sure the sensor system was operational before each test. The results of failure testing are reported herein in two parts, including those variables found to be influential and those found not to be influential.

3.5.2.1 Non-influential individual variables

Individual non-influential variables included *number of occupants, presence of large objects, presence of large interior light sources,* and *number of doors,* as shown in Table 19. In other words, in all scenarios tested, both with and without occupants present in the laboratory test space, all resulting data collected was either TPs or TNs, as shown in the last three columns. The last three columns describe the sensor output, ground truth, and confusion matrix.

For *number of occupants*, scenarios with 1 and 2 occupants were evaluated, however this variable was not found to be impactful. The *presence of large objects* (2m metal ladder) and the *presence of interior light sources* (floor lamp) were not found to impact sensor reliability. For *number of doors,* for 1 door, occupants entered and exited from the same door. For the 2-door scenario, occupants entered from one of the two exterior doors, and then exited from the other. No impact was found for this variable.

Table 19 Testing scenarios and results of non-influential individual variables

Test variable	Occupancy	Lighting level	Presence of large object objects	Interior lighting sources	Use of robots	Presence of pets	Motion level	Location	Number of occupants	Number of doors	Sensor Output	Ground truth	Prediction result
Number of occupants	Presence	On	No	No	No	No	Major	Center	1	1	1	1	TP
									1		1	1	TP
									1		1	1	TP
									2		1	1	TP
									2		1	1	TP
									2		1	1	TP
Presence of large objects	Non-presence	On	Yes	No	No	No	-	-	0	1	0	0	TN
			Yes								0	0	TN
			Yes								0	0	TN
			No								0	0	TN
			No								0	0	TN
			No								0	0	TN
	Presence	On	Yes	No	No	No	Major	Center	2	1	1	1	TP
			Yes								1	1	TP
			Yes								1	1	TP
			No								1	1	TP
			No								1	1	TP
			No								1	1	TP
Presence of interior light sources	Non-presence	On	No	Yes	No	No	-	-	0	1	0	0	TN
				Yes							0	0	TN
				Yes							0	0	TN
	Presence	On	No	Yes	No	No	Major	Center	2	1	1	1	TP
				Yes							1	1	TP
				Yes							1	1	TP
umber of doors	Non-presence	On	No	No	No	No	-	-	0	1	0	0	TN
										1	0	0	TN
										1	0	0	TN
										2	0	0	TN
										2	0	0	TN
										2	0	0	TN
	Presence	On	On	No	No	No	Major	Center	2	1	1	1	TP
										1	1	1	TP
										1	1	1	TP
										2	1	1	TP
										2	1	1	TP
										2	1	1	TP

3.5.2.2 Influential individual variables

Lighting level was tested only under non-presence scenarios, as shown in Table 20. This was because with the presence of occupants, other variables are introduced such as *motion level*, *location*, and *number of occupants*. Seven trials were conducted with *lights on*, where FPs occurred twice. This was found to occur when, prior to testing, occupants exited the door, making the space unoccupied, however the sensor system missed detecting this event thus the output remained occupied. In other words, this does not mean that the sensor system detects occupants when the space is not occupied, but rather when there is an issue with the entry/exit event. With *lights off*, four of the five trials resulted in FPs. This may be because of light reflection, off some objects present in the test space, or an issue with the entry/exit event not being detected.

For motion level, Table 20 presents the testing scenarios and results. Before each test, the occupant exited the space to ensure the sensor system started in an unoccupied state, then the occupant entered the space and maintained the design motion level across each trial period. The results indicate there were no failures for “Major”, “Minor” and “Fine” motion levels, and only one failure for the “None” motion level. For location of occupants, eight locations were used. These locations (Figure 11 b) included in the center of spaces (E10), corners (E4, D7, G1), locations near sensor platforms (G7), and in locations that are anticipated to be challenging for the sensor system to detect people correctly (F5, A6). Results (Table 21) show that the only failure occurred at E10. This may be because of its proximity to the door, causing the sensor system to register that the occupant is leaving the space when they did not.

Table 20 Testing scenarios and results of "Lighting level" and "Motion level" variables

Test variable	Occupancy	Lighting level	Presence of large metal objects	Interior lighting sources	Use of robot	Presence of pets	Motion level	Location	Number of occupants	Number of doors	Output	Ground truth	Prediction result
Lighting level	Non-presence	On	No	No	No	No	-	-	0	1	0	0	TN
		On									0	0	TN
		On									1	0	FP
		On									0	0	TN
		On									0	0	TN
		On									0	0	TN
		On									1	0	FP
		Off									1	0	FP
		Off									1	0	FP
		Off									0	0	TN
		Off									1	0	FP
		Off									1	0	FP
Motion level of occupants	Presence	On	No	No	No	No	Major	Center	1	1	1	1	TP
							Major				1	1	TP
							Major				1	1	TP
							Minor				1	1	TP
							Minor				1	1	TP
							Minor				1	1	TP
							Fine				1	1	TP
							Fine				1	1	TP
							Fine				1	1	TP
							None				0	1	FN
							None				1	1	TP
							None				1	1	TP

Table 21 Testing scenarios and results of "Location of occupants", "Use of robots", and "presence of pets" variables

Test variable	Occupancy	Lighting level	Presence of large metal objects	Presence of interior lighting sources	Use of robots	Presence of pets	Motion level	Location	Number of occupants	Number of doors	Output	Ground truth	Prediction result
Location of occupants	Presence	On	No	No	No	No	Major	D7	1	1	1	1	TP
								G1			1	1	TP
								G7			1	1	TP
								F5			1	1	TP
								E10			0	1	FN
								E4			1	1	TP
								A6			1	1	TP
								C1			1	1	TP
Use of robot	Non-presence	On	No	No	Yes	No	NA	NA	0	1	1	0	FP
											1	0	FP
											1	0	FP
	Presence	On	No	No	Yes	No	Major	Center	1	1	1	1	TP
											1	1	TP
											1	1	TP
Presence of pets	Non-presence	On	No	No	No	Yes	NA	NA	0	1	1	0	FP
											1	0	FP
											1	0	FP
	Presence	On	No	No	No	Yes	Minor	Center	2	1	1	1	TP
											1	1	TP
											1	1	TP

For *use of robots,* a robot vacuum was used. For *non-presence scenarios*, the occupants were in the space initially and turned on the robot, then left the space, keeping robot running for at least five minutes without the presences of occupants. Results show consistent FPs when the space was unoccupied. No failures occurred for *presence* scenarios. For *presence of pets,* two rabbits were used, which were placed in an enclosure in the center of the test space and allowed to move freely within this space during testing. Similar to *use of robots*, there were consistent FPs during *non-presence* scenarios. This was an unexpected result. After discussions with the developer, supplementary tests were conducted for these scenarios, wherein the system started in an unoccupied state, meaning there were robot vacuum or pets but no occupants in the space. From this supplemental testing, it was determined that when the initial state is unoccupied, the presence of robot vacuum or pets did not cause FPs, indicating that the FPs in the prior tests were not due to robot vacuum or pets being detected as people, but rather due to exit events of the people (who were initially in the space) not being properly registered, which is caused by the continuous motion in the entry/exit area. Testing was also completed a second time for when the sensor system began in an occupied state (i.e., the robot vacuum or pets as well as occupants), then the occupants left the space, while the robot vacuum or pets remained. The results from this testing was consistent with the first set of testing results reported in Table 21. The supplemental results are included in Appendix C.

As discussed, several additional variables were also tested beyond those considered to be the "most important." These include the *presence of another door in the entry/exit area*, and having the *TV on,* the results of which are shown in Table 22. Figure 11 shows that the "entry/exit" platform mc06 can "see" both the exterior door and the interior bedroom door. This scenario was tested with an occupant entering and exiting the BR3 door. Results indicated FNs during this scenario, indicating the sensor system interpreted this as the occupant exiting the space when they did not or the person in BR3 was in a blind region. For the *TV on* scenario, the results indicate consistent FPs occurring when the TV was left on in an unoccupied space. This is likely because the sensor system incorrectly interpreted the TVs picture and/or sounds as being an occupant. This is another scenario, for which supplementary testing was performed. Results suggested that this kind of error can be avoided.

Table 22 Testing scenarios and results of additional variables, including "Presence of another door in Entry/Exit area", and "TV On"

Test variable	Occupancy	Lighting level	Presence of large metal objects	Interior lighting sources	Use of robots	Presence of pets	Motion level	Location	Number of occupants	Number of doors	Output	Ground truth	Prediction result
Another door in E/E area	Presence	On	No	No	No	No	Major	Center	1	1	0	1	FN
											0	1	FN
											1	1	TP
											0	1	FN
											1	1	TP
											1	1	TP
											0	1	FN
TV on	Non-presence	On	No	No	No	No	NA	NA	0	1	1	0	FP
											1	0	FP
											1	0	FP
	Presence	On	No	No	No	No	Major	Center	2	1	1	1	TP
											1	1	TP
											1	1	TP

3.6 Conclusions

This research proposes a standard evaluation methodology to test the reliability of occupancy sensor systems in residential buildings. The proposed methodology includes both "Typical testing" and "Failure testing". Typical testing is used to evaluate the reliability of each occupancy sensor system under scenarios that mimic real occupancy scenarios. Failure testing follows one variable at a time (OVAT) methods to test the most important variables based on a stakeholder survey, to determine if these variables impact sensor system reliability. The developed methodology was then implemented for a novel occupancy detection sensor system to test the sensor system's reliability. The following overall conclusions can be made for this study:

(1) Cluster analysis methods were used to analyze American Time Use Survey-derived data, resulting in three main types of occupancy profiles for residential buildings, specifically "Day absence", "Stay at home", and "Night absence" profiles. These representative residential occupancy profiles for individuals were then used, in combination, to create five 1-person and 2-person household, representative, 24-hour occupancy and activity scenarios, using activity data from the ATUS database that most closely match these occupancy profiles.

(2) The resulting five activity schedules were followed by real occupants in a controlled, residential laboratory environment to evaluate occupancy sensor system performance. Occupancy sensor systems were tested using a shortened "test duration" for all activities, which allowed for all unique activities to occur, but shortening longer duration activities to reduce the need to test continuously for 24 hours. The results were extrapolated to "24-hour duration" results, with the 24-hour results representing the predicted reliability of the sensor system over a typical 1-day period in a residential building. Results show that on

average, the Precision and Recall are 0.75 and 0.70, respectively, which means that there are similar number of FPs and FNs across the whole dataset. The overall accuracy of the tested novel system ranged from 62.4% to 76.4%.

(3) For failure testing, individual variable testing provided insights as to the impact of a range of levels of individual variables on sensor system performance. Variables were identified for testing based on a both stakeholder feedback, as well as based on known possible sensitivities of the sensor system being evaluated. This resulted in the testing of a total of 12 individual variables. For the tested sensor system, the “Number of occupants”, “Presence of large objects”, “Presence of interior light sources”, and “Number of doors” are not influential, while “Lighting level”, “Location of occupants”, “Another door in the entry/exit area”, and “TV on” variables were determined to impact sensor system performance.

(4) Supplementary tests showed that the performance of the evaluated system is affected most by the positioning of the platforms monitoring the entry/exit doors. Individual sensor evaluations showed that the system can differentiate between the sources of motion, i.e. can differentiate between people and robot vacuums and pets.

The proposed methodology for evaluating the reliability of occupancy sensor systems presents an opportunity for use as a standardized method to evaluate residential occupancy sensor systems that currently does not exist. The focus on typical scenarios enables the reporting of metrics representing the reliability of the sensor system under typical U.S. household scenarios. This could be used as a comparative measure of performance across sensor systems. The focus on failure testing enables a focus on the potential weaknesses in the sensor system reliability, as well as targets for further testing and development.

APPENDICES

APPENDIX A: Typical occupancy schedules and activity profiles

Table 23 Sche2: 1-person household with night absence profile

Start time	End time	24-hr duration (min)	Test duration (min)	ATUS activity details	Specific location	Motion level
4:00	12:00	480	10	Sleeping	Bedroom	None
12:00	13:00	60	15	Eating and drinking	Dining room	Minor & Major
13:00	13:10	10	10	Laundry	Bathroom	Major
13:10	13:40	30	10	Washing, dressing and grooming oneself	Bathroom	Minor
13:40	15:30	110	15	Computer use for leisure	Living room	Minor
15:30	4:00	750	15	Go to work	Not in home	None

Table 24 Sche3: 1-person household with stay home profile

Start time	End time	24-hr duration (min)	Test duration (min)	ATUS activity details	Specific location	Motion level
4:00	9:00	300	10	Sleeping	Bedroom	None
9:00	9:20	20	10	Washing, dressing and grooming oneself	Bathroom	Minor
9:20	9:23	3	3	HH & personal mail & messages (except e-mail)	Not in home	Major
9:23	9:28	5	5	Food and drink preparation	Kitchen	Major
9:28	9:29	1	1	Eating and drinking	Dining room	Minor
9:29	11:00	91	10	Reading for personal interest	Living room	Minor
11:00	12:00	60	16	Television and movies (not religious)	Living room	Minor
12:00	12:10	10	10	Financial management	Living room	Minor
12:10	14:30	140	10	Reading for personal interest	Living room	Minor
14:30	17:00	150	15	Television and movies (not religious)	Living room	Minor
17:00	17:30	30	10	Reading for personal interest	Living room	Minor
17:30	18:30	60	15	Television and movies (not religious)	Living room	Minor
18:30	19:00	30	10	Food and drink preparation	Kitchen	Major
19:00	19:15	15	10	Eating and drinking	Dining room	Minor
19:15	23:30	255	15	Television and movies (not religious)	Living room	Minor
23:30	0:30	60	10	Reading for personal interest	Living room	Minor
0:30	4:00	210	10	Sleeping	Bedroom	None

Table 25 Sche4: 2-person household where both with day absence profile

Start time	End time	24-hr duration (min)	Test duration (min)	ATUS activity details	Specific location	Motion level
4:00	6:00	120	10	Both are sleeping	Bedroom	None
6:00	6:30	30	10	Both washing, dressing and grooming oneself	Bathroom	Minor
6:30	6:40	10	10	1 food preparation other Eating and drinking	Kitchen/Dining room	Major
6:40	6:50	10	10	Both Eating and drinking	Dining room	Minor
6:50	6:55	5	5	1 left for job, other Eating and drinking	Not in home/Dining room	None/Minor
6:55	18:20	685	25	Both left for work	Not in home	/
18:20	18:30	10	5	1 is not in home, other one is Eating and Drinking	Not in home/Dining room	None/Minor
18:30	18:45	15	5	1 is food preparation other Eating and drinking	Kitchen/Dining room	Major
18:45	19:15	30	20	Both Eating and drinking	Dining room	Minor
19:15	19:20	5	5	1 Eating and drinking and other computer use for leisure	Dining room/Living room	Minor
19:20	21:00	100	20	1 Television and Movies and other computer use for leisure	Living room	Minor
21:00	21:30	30	10	1 watching Television and movies and other washing, dressing and grooming oneself	Living room/Bathroom	Minor/Major
21:30	21:32	2	2	1 watching Television and movies and other Health related selfcare	Living room/Bedroom	Minor/Major
21:32	22:30	388	20	1 watching Television and movies and other Sleeping	Living room/Bedroom	Minor/None
22:30	4:00	270	10	Both Sleeping	Bedroom	None

Table 26 Sche5: 2-person household where one with day absence profile and the other with stay home profile

Start time	End time	24-hr duration (min)	Test duration (min)	ATUS activity details	Specific location	Motion level
4:00	6:00	120	10	Both are Sleeping	Bedroom	None
6:00	6:20	20	10	Both are Washing, dressing and grooming oneself	Bathroom	Major
6:20	6:40	20	10	1 interior cleaning and other Washing, dressing and grooming oneself	Whole space/Bathroom	Major
6:40	7:00	20	10	1 Eating and drinking and other Washing, dressing and grooming oneself	Dining room/Bathroom	Major
7:00	7:10	10	10	Both are Eating and drinking	Dining room	Minor
7:10	7:15	10	10	1 interior cleaning and other Eating and drinking	Whole space/Dining room	Major/Minor
7:15	7:20	5	5	1 interior cleaning and other left for job	Whole space/Not in home	Major/None
7:20	7:45	25	10	1 in home and doing kitchen and food clean up	Kitchen/Not in home	Major/None
7:45	7:50	5	5	1 in home and doing interior cleaning	Whole space/Not in home	Major/None
7:50	8:10	20	10	1 in home and doing Care for animals and pets (not veterinary care)	Living room/Not in home	Minor/None
8:10	8:30	20	10	1 in home and doing Computer use for leisure (exc. Games)	Living room/Not in home	Minor/None
8:30	9:30	60	15	1 in home and doing television and movies (not religious)	Living room/Not in home	Minor/None
9:30	10:30	60	10	1 in home and doing Reading for personal interest	Living room/Not in home	Minor/None
10:30	10:45	15	5	1 in home and doing Telephone calls	Living room/Not in home	Minor/None
10:45	11:45	60	10	1 in home and doing Playing games	Living room/Not in home	Minor/None
11:45	12:45	60	15	1 in home and doing television and movies (not religious)	Living room/Not in home	Minor/None
12:45	12:55	10	10	1 in home and doing Food and drink preparation	Kitchen/Not in home	Major/None
12:55	13:25	30	10	1 in home and doing Eating and drinking	Dining room/Not in home	Minor/None
13:25	15:25	120	20	1 in home and doing television and movies (not religious)	Living room/Not in home	Minor/None
15:25	15:55	30	10	1 in home and doing Sleeping	Bedroom/Not in home	None
15:55	16:55	60	15	1 in home and doing television and movies (not religious)	Living room/Not in home	Minor/None
16:55	18:25	90	15	1 in home and doing Playing games	Living room/Not in home	Minor/None
18:25	18:30	10	10	1 in home and doing Food and drink preparation	Kitchen/Not in home	Major/None
18:30	18:35	5	5	1 is doing Food and drink preparation and other Eating and drinking	Kitchen/Dining room	Major/Minor
18:35	19:05	30	10	Both are Eating and drinking	Dining room	Minor
19:05	19:30	25	10	1 is Eating and drinking and other Kitchen and food clean-up	Kitchen/Dining room	Major/Minor
19:30	19:35	5	5	1 is Television and movies and other Kitchen and food clean-up	Living room/Kitchen	Minor/Major
19:35	20:00	25	15	Both watching television and movies (not religious)	Living room	Minor
20:00	21:00	60	10	1 watching television and movies and other socializing and communicating with others	Living room	Minor
21:00	21:30	30	10	1 watching television and movies and other Washing, dressing and grooming oneself	Living room/Bathroom	Minor/Major
21:30	22:00	390	10	1 Computer use for leisure (exc. Games) and other watching television and movies	Living room	Minor
22:00	22:20	20	20	1 sleeping and other Washing, dressing and grooming oneself	Bedroom/Bathroom	None/Major
22:20	4:00	280	10	Both Sleeping	Bedroom	None

APPENDIX B: Typical testing results with associated typical occupancy schedules and activity profiles

Table 27 Typical testing results with "1-person household with night absence profile"

ATUS-Based Activity detail	Ground truth	Test duration (min)	Error time (min)	Intermediate duration (min)	Error Time	24-hr duration (min)	Error Time
Sleeping	Occupied	10	0	10	0	480	0
Heat food; Bring food to dinner table; Eating and watching tv, using phone; Remove plates and cleaning kitchen and table		15	0	60	0	60	0
Collecting dresses from bedroom and put them in washer for laundry		10	1	10	1	10	1
Shower; Dressing & grooming		10	0	30	0	30	0
Computer use for leisure (exc. Games)		15	13	130	113	110	95
Left for job	Unoccupied	15	0	15	0	750	0

Table 28 Typical testing results with "1 person with stay home profile"

ATUS-Based Activity detail	Ground truth	Test duration (min)	Error time (min)	Intermediate duration (min)	Error Time	24-hr duration (min)	Error Time
Sleeping	Occupied	10	0	10	0	300	0
Mouthwash; Shower and others; Dressing		10	0	20	0	20	0
Outside house: HH & personal mail & messages (except e-mail)	Unoccupied	3	0	3	0	3	0
Food and drink preparation	Occupied	5	0	5	0	5	0
Eating and drinking		1	0	1	0	1	0
Reading for personal interest		10	9	91	82	91	82
Television and movies (not religious)		16	0	60	0	60	0
Financial management		10	0	10	0	10	0
Reading for personal interest		10	9	140	126	140	126
Television and movies (not religious)		15	0	150	0	150	0
Reading for personal interest	Occupied	10	5	30	15	30	15
Television and movies (not religious)		15	0	60	0	60	0
Bring stuff from refrigerator and preprocess; Using range, cook food; Bring all cooked food to table		10	0	30	0	30	0
Eating and drinking		10	0	15	0	15	0
Television and movies (not religious)		15	0	255	0	255	0
Reading for personal interest		10	0	60	0	60	0
Sleeping		10	10	30	30	210	210

Table 29 Typical testing results with “2-person where both with day absence profile”

ATUS-Based activity detail	Ground truth	Test duration (min)	Error time (min)	Intermediate duration (min)	Error Time	24-hr duration (min)	Error Time
Sleeping	Occupied	10	2	10	2	120	24
Mouth wash; Taking shower; Dressing; Grooming.		10	0	30	0	30	0
Food preparation		10	0	10	0	10	0
Eating and drinking		15	0	15	0	15	0
Left for work	Unoccupied	25	0	25	0	685	0
Having snacks while waiting for other person	Occupied	5	0	10	0	10	0
Heating and bringing food to table		5	0	15	0	15	0
Eating, discussing and using phone		20	0	30	0	30	0
Eating and drinking		5	0	5	0	5	0
Television and Movies		20	15	100	75	100	75
Taking shower; Getting dressed for sleep		10	0	30	0	30	0
Health related self-care		2	0	2	0	2	0
Sleeping		20	0	73	0	388	0

Note: Only one of the two activity profiles is provided in the “Activity detail” column

Table 30 Typical testing results with “2-person where 1 with day work profile and other one with stay home profile”

ATUS-Based activity detail	Ground truth	Test duration (min)	Error time (min)	Intermediate duration (min)	Error Time	24-hr duration (min)	Error Time
Sleeping	Occupied	10	0	10	0	120	0
Mouthwash; Shower; Dressing.		10	0	20	0	20	0
Arrange bedroom		10	0	20	0	20	0
Making food for breakfast; Bring food to table, start eating		10	1	20	2	20	2
Eating and drinking		10	0	10	0	10	0
Interior cleaning		10	0	10	0	10	0
Kitchen and food clean up		10	0	25	0	25	0
Interior cleaning		5	0	5	0	5	0
Clean plates for pet and bring food for them; Playing with pets		10	7	20	14	20	14
Computer use for leisure (exc. Games)		10	10	20	20	20	20
Television and movies (not religious)		15	15	60	60	60	60
Reading for personal interest		10	0	60	0	60	0
Telephone calls		5	0	15	0	15	0
Playing games		10	0	60	0	60	0
Television and movies (not religious)		15	0	60	0	60	0
Food and drink preparation		10	2	10	2	10	2
Eating and drinking		10	10	30	30	30	30
Television and movies (not religious)		20	9	120	54	120	54
Sleeping		10	0	30	0	30	0
Television and movies (not religious)		15	0	60	0	60	0
Playing games		15	0	90	0	90	0
Food and drink preparation		10	5	10	5	10	5
Eating together and discussing, use mobile		10	0	30	0	30	0
Bring used plates from table to kitchen, start cleaning the kitchen		10	3	25	8	25	8
Kitchen and food clean-up		5	1	5	1	5	1
Watching television and movies (not religious)		15	11	25	18	25	18
Socializing and communicating with others		10	0	60	0	60	0
Taking shower; Dressing for sleep		10	0	30	0	30	0
Sleeping		10	9	65	59	390	351

Note: Only one of the two activity profiles is provided in the “Activity detail” column

APPENDIX C: Supplemental variable testing results

Table 31 Supplemental testing results for individual variable -- “Presence of robot” with the initial Occupied/Unoccupied state of the test space

<table>
<tr><th>Test variable</th><th>Occupancy</th><th>Initial State</th><th>Lighting level</th><th>Presence of large metal objects</th><th>Interior lighting sources</th><th>Use of robots</th><th>Presence of pets</th><th>Motion level</th><th>Location</th><th># of occupants</th><th># of doors</th><th>Output</th><th>Ground truth</th><th>Prediction result</th></tr>
<tr><td rowspan="6">Presence of robot</td><td rowspan="6">Non-presence</td><td rowspan="3">Occupied</td><td rowspan="6">On</td><td rowspan="6">No</td><td rowspan="6">No</td><td rowspan="6">Yes</td><td rowspan="6">No</td><td rowspan="6">NA</td><td rowspan="6">NA</td><td rowspan="6">0</td><td rowspan="6">1</td><td>1</td><td>0</td><td>FP</td></tr>
<tr><td>1</td><td>0</td><td>FP</td></tr>
<tr><td>1</td><td>0</td><td>FP</td></tr>
<tr><td rowspan="3">Unoccupied</td><td>0</td><td>0</td><td>TN</td></tr>
<tr><td>0</td><td>0</td><td>TN</td></tr>
<tr><td>0</td><td>0</td><td>TN</td></tr>
</table>

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CHAPTER 4 – TYPICAL ACADEMIC BUILDING ENERGY MODEL DEVELOPMENT AND ENERGY SAVING EVALUATION OF OCCUPANT-BASED CONTROL

4.1 Abstract

Studies on occupant-based controls have been increasing over the past decade because of the significant energy saving potentials they can offer in buildings. Many of these studies focus on office buildings. However, there are very few studies that focus on academic buildings, which represent a significant number of buildings in the U.S., and a substantial amount of energy consumption. The space use, occupant types, and energy-use patterns in academic buildings at universities and colleges can vary substantially from other prototypical building types. The objective of this paper is thus to develop typical academic building models and then use these models to evaluate the energy savings potential of implementing occupant-based control (OBC) in the developed models using EnergyPlus. The U.S. DOE reference office building model was modified and rezoned to add new space types to represent the typical characteristics and space use compositions of academic buildings based on the space type and functional use data collected from 293 academic buildings across five diverse U.S. universities/college. Four types of typical academic building models were then determine based on clustering analysis, including "*Office-dominated*", "*Laboratory-dominated*", "*Study room-dominated*", and "*Mixed-use*" academic building models. The occupancy schedules were then updated to include stochastic occupancy schedules representing academic building use. Next, the baseline and proposed models were built, of which a fixed setpoint schedule and minimum outdoor air flowrate were used for the baseline model. The proposed model uses OBC, resetting the temperature schedule and minimum outdoor air flow schedule based on occupancy, following the recommendations of ASHRAE 90.1, and 62.1. Results show that there is significant energy saving potential for academic buildings with the

implementation of OBC, including an HVAC energy savings of 35% to 51% under "Occupancy presence" scenarios, and a further energy saving increase (3-9%) from "Occupancy presence" scenarios to "Occupancy counting" scenarios. The results of this work also provide typical academic building models with integrated occupancy schedules which can be used to evaluate other energy saving measures, and aid building designers and operators in making informed decisions in applying appropriate control strategies to optimize building energy systems, as well as predict energy use and demand.

Keywords: Typical Academic Building Models; Occupant-based Control; Energy Saving Evaluation

4.2 Introduction

Building energy consumption accounts for approximately 40% of the total primary energy consumption in the U.S. (Robinson et al., 2017). In commercial buildings, heating and cooling energy consumption takes up the largest portion, which is more than 30% of this energy use, among all different energy end uses (U.S. EIA 2021). Therefore, in an effort to reduce energy use overall, it is important to develop energy saving approaches to help reduce heating and cooling energy use in commercial buildings.

In modern commercial buildings in the U.S., mechanical ventilation that brings in outdoor air is required by energy codes to maintain acceptable levels of indoor air quality. Based on the Commercial Building Energy Consumption Survey (U.S. EIA 2021), energy consumption associated with ventilation accounts for approximately 50% of total HVAC energy use in commercial buildings in U.S. Per ASHRAE Standard 62.1-2019 (2019), the minimum required outdoor airflow is dependent on the number of occupants in commercial buildings as well as the size of the space being ventilated. With the emergence of various occupancy sensor systems to better predict real-time presence/non-presence and/or number of occupants in commercial buildings, there are significant opportunities to save energy by applying occupancy-based controls. In addition, consideration of occupancy sensing technologies has also been included in ASHRAE Guideline 36 - High Performance Sequences of Operation for HVAC Systems (ASHRAE, 2018). Given these recent developments in state-of-the art controls, there is a need to evaluate the level of energy savings that can be achieved using such controls.

Commercial building reference models (Deru et al., 2011) have been created to represent the most common types of commercial buildings and their energy use patterns. Existing studies mainly focus on evaluating the energy saving potential from OBC for typical office buildings using energy simulation tools. However, these prototypical building models use simplified perimeter and core zoning methods that are not conducive to accurately modeling room based OBC. Various studies have been conducted to improve typical office building models. For example, Im et al. (2019) updated the small and medium office prototype models to include multiple new space types, which enables the updated models to be more flexible in applying OBC by space types. Pang et al. (2021) also proposed a detailed zoning plans for medium and large office reference building models and implemented OBC, of which the potential energy savings was determined to be up to 45%.

Buildings used for educational purposes are among the subgroups of commercial buildings in the U.S. that consume a large amount of HVAC energy (U.S. EIA, 2021). Academic buildings at colleges and universities are included among these. These can vary substantially in their space use, occupancy patterns, and resulting energy use. However, despite their substantial energy use, there are no established prototypical building models for academic building types, nor any that can be used to evaluate energy savings potential from occupancy sensors. Given the intermittency in which many spaces in academic buildings are used, this suggests substantial potential for energy savings from occupancy-based control. Therefore, the objective of this research is the development of typical academic building energy models that can be used to evaluate the potential energy savings of occupant-based controls.

In an initial study by the authors (Chu et al., 2020) two simplified typical academic building models were developed using five conditioned zones (4 perimeter and 1 core zone) on each of the three stories of the building. The occupancy schedules used for each zone were based on typical characteristics and space use compositions of academic buildings from (Mitra et al., 2019). However, using this simplified version of occupancy modeling and zoning, the energy savings from the use of occupancy-based control likely is underestimated. This is because each zone modeled includes multiple space types, thus if one of the spaces within a particular zone becomes unoccupied, while the others in the same zone are still be occupied, the entire zone is still considered occupied. As such, an improved method to model each space type is to consider each space as a single zone, such that each space may be controlled separately based on the occupancy in that zone. To achieve this, this research first proposes a data-driven method, based on academic building data, to determine the typical space distribution in academic buildings. This research then develops zoning for each floor by assigning a variety of space types and their areas, where each space type is considered as a thermal zone. Sketchup OpenStudio plug-in was used to build the geometry of the typical academic building models, and EnergyPlus was used to complete the building energy simulation.

The remainder of this research is organized as follows. Section 2 introduces the methodology for creating academic building energy models, including developing typical space distributions, energy model geometry, occupancy schedules, and occupancy-based controls.

Section 3 presents the energy saving estimates from the assigned controls for the typical academic building models developed in this paper. Section 4 summarizes the conclusion of this paper.

4.3 Methodology

4.3.1 Typical space types and distribution in academic buildings

To create prototypical academic building models, first the typical space distributions of U.S. academic buildings was determined, based on data collected from multiple universities. The Postsecondary Education Facilities Inventory and Classification Manual (FICM) (Cyros and Korb, 2006) was used for assigning space classifications. Within FICM, there are 10 major space use categories of assignable space and 3 major space use categories of non-assignable space. In this context, “assignable” space means all spaces which are assigned to, or available for assignment to an occupant(s) or specific use, including classrooms, laboratories, offices, study areas, special use space, general use space, support rooms, health care, residential and unclassified space. “Non-assignable” space indicates the spaces cannot be assigned to specific use but are still necessary for the general operation of a building. This includes building service areas, circulation areas, and mechanical areas. The existing space type codes that colleges and universities use have the same categories and the same coding; however, they can have different subcategories of space types under each main space type category.

The Carnegie Classification of Institutions of Higher Education (CCIHE) (2018) provides the college/university size categories according to FTE-based enrollment (FTE = Full-Time Headcount plus 1/3 part-time headcount) of the college/university. Based on 2018 CCIHE data, 60% of the 4,323 institutions in the U.S. are four-year institutions. In this research, given the potentially substantial differences in how two-year and four-year institutions operate, this study is limited to only four-year institutions. In order to consider a diversity of university sizes, data was collected from all buildings at five U.S. universities and colleges, each under a different CCIHE size class. Data was obtained from these universities through their facilities management organizations and through publicly available data (THED 2020). The collected data includes detailed building and room information, including the predominant purpose and function of each building, the corresponding spaces, their sizes, and their functional use based on FICM. For the studied colleges and universities, FTE-based enrollment data was obtained from the Integrated Postsecondary Education Data System (IPEDS) (2019) under the National Center for Education Statistics. Table 32 summarizes the five universities with different sizes and associated information. The last column indicates the number of academic buildings at each college/university used for the determination of typical space distributions in this research.

Table 32 Colleges and universities, by CCIHE size category and associated characteristics, from which, building and space use data were utilized

CCIHE 2018 Class	Four-year Institutions	FTE-based Enrollment	# of Academic Buildings
Very small	Jarvis Christian College	<1000	5
Small	Sul Ross State University	1000 to 3,000	19
Medium	Lamar University	3,000 to 10,000	42
Large	Texas A & M University-College Station	> 10,000	190
	Iowa State University		37

Among the 293 selected academic buildings, the total area of classroom, laboratory, office, and study facilities makes up more than 50% of the total space area, for approximately 188 academic buildings. Therefore, in this research, we mainly focus on the academic buildings with office, classroom, laboratory, and study room being used as the main occupied spaces. Those buildings like health care facility and special uses were not considered here. Based on this assumption, we defined functional use spaces, which indicate the mostly used spaces, including offices, classrooms, laboratories, and study rooms.

In order to determine the percentage of each space type, interquartile range was used to detect outliers for special use, general use, supporting facilities, health care, residential, non-assigned spaces, and other spaces. Using this method, the interquartile range (IQR) of each data is calculated first, then the IQR is multiplied by 1.5, which is then used as a threshold above which data points are considered outliers. Next the outliers are removed, and the mean value of the new data was used as the percentage of each space, including special use (0.32%), general use (2.38%), supporting facilities (0.44%), health care (0%), residential (0%), non-assigned spaces (0%), and others (25.5%). After that, we use 100% to subtract the sum of these spaces other than functional use spaces to attain the percentage of the functional use spaces (71.36%).

According to the functional use spaces data, the majority of spaces in these buildings are either office, laboratory, or study room spaces, amounting to more than 70%. A “study-room” is defined as a room or area used by individuals to study at their convenience (FICM, Cyros and Korb, 2006). Since different occupant activities occur due to different functional use space types, this results in varied energy use and savings potential. As such, different typical academic building models are needed to represent different functional uses. First, K-mean clustering (Warne and Ganorkar, 2015) was used to segment the space distribution and composition data from the selected academic building into groups and group the data with similar distributions into one group. In this case, K=5 was used since there are four different functional use space types, and the buildings with 100% office space should be defined as an office building, which would use the existing prototypical office building models. After the clusters of building types (by space use distribution) were attained, the space distribution and composition data were manually checked within each group to confirm buildings appeared to be in the correct cluster.

The resulting five groups of buildings include 100% office, study room-dominated, office-dominated, laboratory-dominated, and mixed-use. In these categories “dominated” means that more than 70% of the total space use is associated with that space use type, while the remaining space is for other purposes. Mixed-use indicates that the distribution of functional space types is more evenly distributed compared to those “dominated” space types and no space type accounts for more than 50% of the total space use. Table 33 shows the distribution of the typical academic building types after our classification. Note that the 100% office building type was not developed further as it represents a typical office building, for which a detailed building model already exists (Deru et al 2011). From Table 33, after eliminating the 100% office building type, we can see that the laboratory-dominated academic building group takes up the largest percentage of these four typical academic building models, followed by office-dominated. Mixed-use and study room-dominated academic buildings only account for approximately 12% of the four typical academic building types.

Table 33 Typical academic building types based on K-means clustering

Building type	# of academic buildings	Percentage
100% Office	67	22.9%
Office-dominated	86	29.3%
Laboratory-dominated	114	38.9%
Mixed-use	15	5.1%
Study room-dominated	11	3.8%

For each typical academic building type from Table 33, Figure 12 shows the box plot of functional use space distribution. After removing the outliers using the same interquartile range rule as mentioned above, the mean value of each space type was determined. The distribution of the functional use spaces is shown in across the 293 buildings (Figure 12), which presents the mean percent (by area) of functional space use type in the four defined typical academic buildings. Multiplying the total percentage of the functional area use (71.36%), as calculated before, by the percentage of each functional use space type in Figure 12, we attained the space distribution across the ten assignable spaces and non-assignable space as defined in FICM (Cyros and Korb, 2006), which can be seen in Table 35. Others refers to the spaces that don’t fall into any of the categories defined in FICM (Cyros and Korb, 2006).

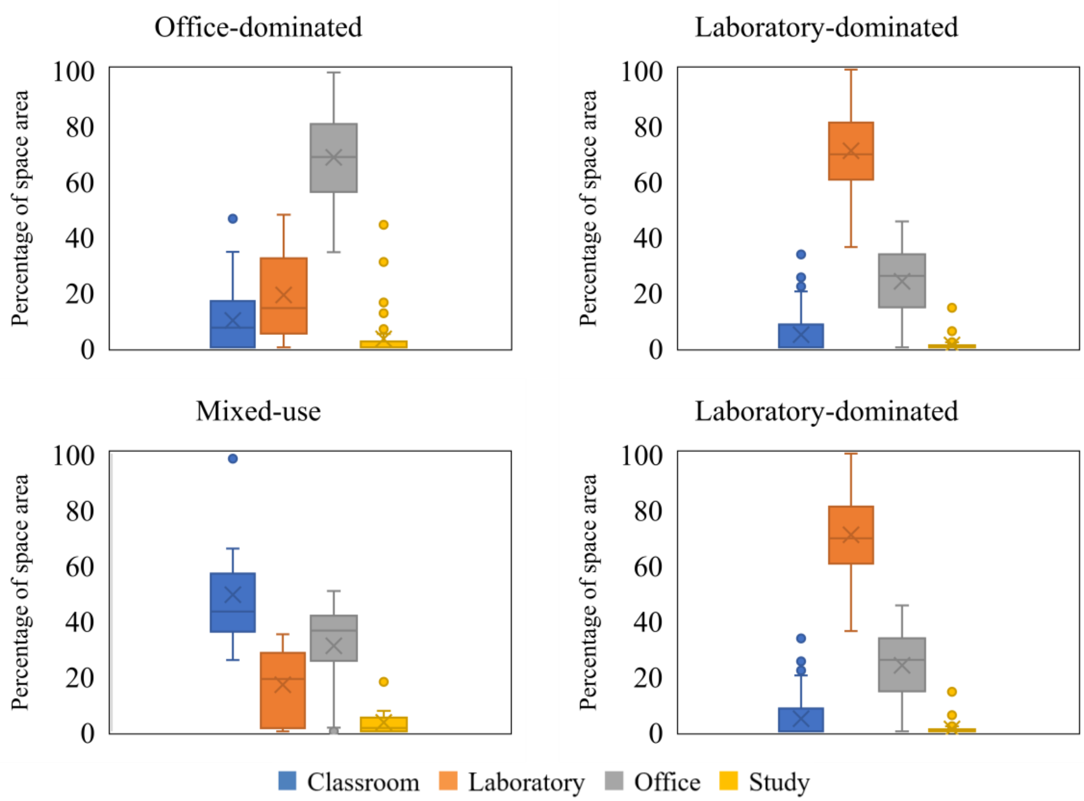


Figure 12 Functional space use in the four defined typical academic buildings, including the percent of building area used for classroom, laboratory, office, and study areas

Table 34 Mean percent (by area) of functional space use type in the four defined typical academic buildings

	Office-dominated	Laboratory-dominated	Study room-dominated	Mixed-use
Classroom	9.74%	3.38%	0.06%	42.28%
Laboratory	20.14%	73.57%	7.17%	20.64%
Office	69.39%	22.96%	19.92%	34.50%
Study room	0.73%	0.09%	72.85%	2.59%

Table 35 Mean of FICM space types as a percent (by area) of total available space in the four defined typical academic buildings

Category from FICM	Office-dominated	Laboratory-dominated	Study room-dominated	Mixed-use
Classroom	6.95%	2.41%	0.04%	30.17%
Laboratory	14.37%	52.50%	5.12%	14.73%
Office	49.52%	16.39%	14.21%	24.62%
Study room	0.52%	0.07%	51.99%	1.85%
Functional use	71.36%	71.36%	71.36%	71.36%
Special use	0.32%	0.32%	0.32%	0.32%
General use	2.38%	2.38%	2.38%	2.38%
Supporting facility	0.44%	0.44%	0.44%	0.44%
Health care	-	-	-	-
Residential	-	-	-	-
Non-assigned space	-	-	-	-
Other	25.50%	25.50%	25.50%	25.50%
Total	100%	100%	100%	100%

4.3.2 Typical academic building models

Next the building energy model was developed in which the space types and occupancy schedules are to be applied. The medium office DOE Reference Building model (Deru et al 2011), which is a three-story building with a total area of 4,982 m^2, was used as a starting point for the academic building models. This is based on the finding that the average college/university building is 4,496 m^2, which is closest to the medium size office DOE Reference Building model, based on the 2018 CBECS (Commercial Buildings Energy Consumption Survey) data. In the initial model, there are five zones on each floor, including four perimeter zones and one core zone. The gross window-wall ratio (WWR) is 33%. The HVAC system is a VAV (variable air volume) system with reheat. This model was then used to create the four academic building models, as defined above. Based on the total area of the building and percentage space distribution (Table 35), the total area of each space type was calculated (Table 36). Each space type was then further divided into sub-categories, for example, the "classroom" space type was defined to include "classrooms" and "seminar rooms" to represent the space types under that category according to their functionality, as shown in the second column of Table 36. The subcategory area fractions were attained from Im et al. (2019), which indicates the space types and area fractions for major zones of updated small and medium office models, and from Mitra et al. (2020), which explored the area distribution of different academic spaces, including staff/faculty office, conference, seminar room, graduation student office, and classrooms.

After determining the area of each space type throughout the building, the spaces must be assigned to each floor. When assigning space types to each floor, the typical unit area of a space type was first studied. For example, the area of a typical office. This was defined based on various resources, such as the Whole Building Design Guide (2021), which provides the floor area of a typical space for a variety of space types. The Time-Saver Standards for Building Types (De Chiara, 2001) was also reviewed, which also provides typical size of different space types for various building types, including educational buildings. The selected typical space type areas are summarized in the third column of Table 36.

Table 36 Space types under each category and space area distribution in each typical academic building type

Category from FICM	Space types	Selected typical unit space area (m^2)	Office-dominated (m^2)	Laboratory-dominated (m^2)	Study room-dominated (m^2)	Mixed-use (m^2)
CLASSROOM	Classrooms	72.46	346	120	2	1503
	Seminar rooms	55.74				
LABORATORIES	Research labs	117.06	716	2615	255	734
	Teaching labs	62.71				
OFFICES	Staff offices	13.94	2,467	816	708	1,227
	Faculty offices	13.94				
	Graduate student offices	27.87				
	Conference rooms[1]	44.96				
STUDY FACILITIES	Study rooms	62.71	26	3	2,590	92
SPECIAL USE	Special use	16.00	16	16	16	16
GENERAL USE	Meeting rooms[1]	70.61	119	119	119	119
	Lounge/ Recreation	18.58				
	Food facilities	11.15				
SUPPORTING FACILITIES	Active storage[2]	14.86	22	22	22	22
OTHERS	Corridor	-	1,270	1,270	1,270	1270
	Stairway	5.30				
	Restroom	13.01				

[1]*Note: A conference space is typically equipped with tables and chairs, and is used by a specific organizational unit or office area; Meeting Rooms are used for general purposes such as community or campus group meetings and not associated with a particular department*

[2]*Note: Active storage is an area for use as a part of routine operation of a business. This suggests that occupants will visit this space routinely. This is in contrast to inactive storage which may be visited less frequently.*

For each typical academic building type, a combination of different space types was assigned to each floor (50 m x 33 m) based on the total area of each space type and typical unit space area. For all three floors, perimeter zones are 5 m in width, and core zone is 35 m x 18.3 m. The corridor in between the perimeter zones and core zone has a width of 2.5 meters. The perimeter zones and core zones were further assigned with different space types to represent each typical academic building type. Dividing the total area of a certain space type on each floor by the typical unit space area, the number of each space types on that floor was then obtained. A summary of the final assignment of space types, the number of rooms for each space type and associated area on each floor for the *Office-dominated* typical academic building model is presented in Table 37 as an example. The summary for the *Laboratory-dominated, Study room-dominated,* and *Mixed-use* academic building models are listed in Table 40-42 in Appendix A.

Table 37 Space types of assignment on each floor for the *Office-dominated* typical academic building model

Category from FICM	Area of Office-dominated	Space types	1st floor		2nd floor		3rd floor	
			Number of rooms	Area (m^2)	Number of rooms	Area (m^2)	Number of rooms	Area (m^2)
CLASSROOM	346	Classroom	2	145	2	145	-	-
		Seminar	-	-	-	-	1	56
LABORATORIES	716	Research lab	1	117	1	117	3	351
		Teaching lab	2	125	-	-	-	-
OFFICES	2467	Staff office	-	-	15	209	-	-
		Faculty office	-	-	-	-	12	167
		Graduate student office	25	697	18	502	13	362
		Conference	-	-	6	270	6	270
STUDY FACILITIES	26	Study room	1	26	-	-	-	-
SPECIAL USE	16	Special use	-	-	-	-	1	16
GENERAL USE	119	Meeting room	1	71	-	-	-	-
		Lounge-Recreation	1	38	-	-	-	-
		Food facilities	-	-	-	-	-	-
SUPPORTING FACILITIES	22	Active storage	1	23	-	-	-	-
OTHERS	1270	Corridor	1	291	1	290	1	290
		Stairway	1	15	1	15	1	15
		Lobby	1	105	1	105	1	105
		Restroom	1	15	1	15	1	15

Sketchup (2019) and OpenStudio Sketchup plug-in (2020) were then used to draw the geometry of the typical academic building models. Figure 13 shows the floor plans of the *office-dominated* typical academic building model, including detailed space types, and the building geometry. The floor plans for the other three typical academic building types are summarized in Figure 20-22 in Appendix B. Figure 13(d) presents the 3-D geometry in SketchUp for the typical *office-dominated* academic building model.

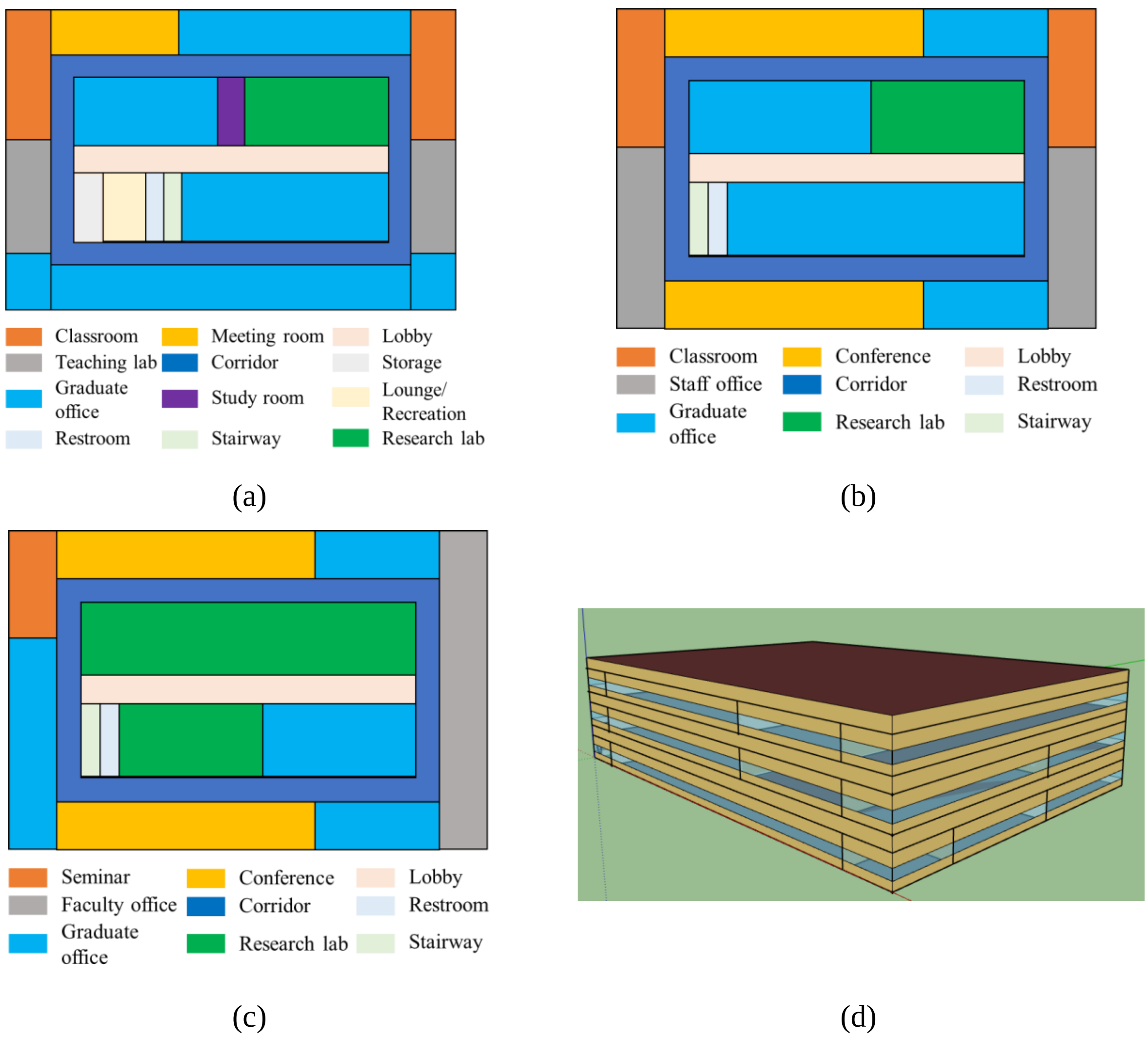


Figure 13 Floor plans and building geometry for *office-dominated* typical academic building model, including (a) 1st floor; (b) 2nd floor; (c) 3rd floor; (d) whole building geometry

The geometry was then transferred to EnergyPlus (2020), which was used as the energy simulation tool in this paper. An Energy Management System (EMS) in EnergyPlus was used to apply occupant-based control using the python package Eppy (2020).

4.3.3 Typical occupancy schedule in academic buildings

To represent the stochastic nature of occupancy in academic buildings, several methods were used to develop occupancy schedules representative of the space types in these buildings. The LBNL Occupancy Simulator (Chen et al., 2016) was developed to simulate the typical occupancy schedules in commercial buildings. Given that academic buildings have many space types similar to that of commercial buildings and are generally considered one of the subcategories of commercial buildings, this tool was used to aid in the generation of stochastic occupancy schedules. There are, however, only three space types defined in the LBNL Occupancy Simulator, including *Office*, *Meeting Room* and *Others*, yet there is a broader diversity of space types in typical academic building models. Therefore, for the remaining space types not covered, alternative methods and/or assumptions were used.

Table 38 summarizes the assumptions for all space types and associated occupancy density for each space type according to ASHRAE Standard 62.1 (2019). The *Classroom* has similar intermittent occupancy pattern to a *Meeting room* since there are 1-hour or 1.5-hour classes that occur several times a week in a classroom. However, there is no design population in the *Meeting room* defined in the LBNL Occupancy Simulator because people who may come to a meeting have already been assigned to offices or classrooms. In addition, the occupant density in classrooms is generally much higher compared to other space types, thus requiring larger amounts of outdoor air for ventilation, and therefore occupancy-based controls are likely to have a more substantial positive impact on energy use.

Therefore, the classroom space type was first treated as an *Open office*, which is the same concept of an office defined in LBNL simulator, but with a lower occupant density compared to a private office. This is to reflect the design population in the classrooms and the whole building since the LBNL simulator calculates the design population for each space through dividing the area of the space by the occupancy density of that space. This schedule was then updated to be a *Meeting room* schedule because of the similar intermittent occupancy pattern. *Seminar* was similar to the classroom, but since there is a very small portion of spaces that are seminar rooms, it was considered to be a *Meeting room*. Research lab, Graduate student office, and Study room spaces were assumed to be *Open office* with occupancy densities defined based on ASHRAE Standard 62.1. Teaching lab spaces were defining using *Meeting room*. Staff and faculty offices were assumed to be *Private office*. Conference and Meeting rooms were treated as *Meeting room*. The other spaces, including Lounge/Recreation, Food facilities, Active storage, Corridor, Lobby, Stairway, and Restroom were considered as *Other* space type.

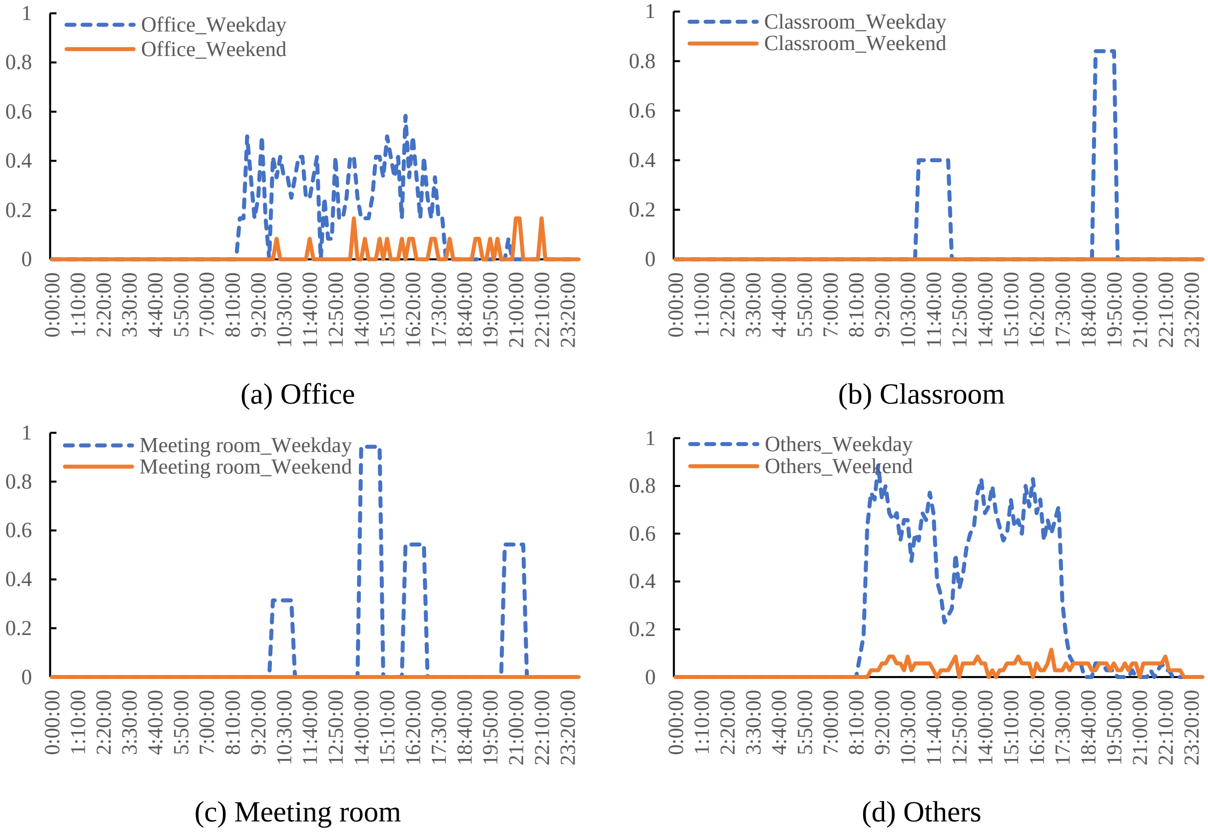
Table 38 Assumptions of space types used in LBNL Occupancy Simulator and associated occupancy density from ASHRAE Standard 62.1-2019

Space types	Assumption in LBNL Occupancy Simulator	Occupancy density[2] (m^2/person)
Classroom	Meeting room/Open office	2.86
Seminar room	Meeting room	2
Research lab	Open office	4
Teaching lab	Meeting room	4
Staff office	Private office	20
Faculty office	Private office	20
Graduate student office	Open office	13[1]
Conference	Meeting room	2
Study room	Open office	10
Meeting room	Meeting room	2
Lounge/Recreation	Other	-
Food facilities	Other	-
Active storage	Other	-
Corridor	Other	-
Lobby	Other	-
Stairway	Other	-
Restroom	Other	-

[1] *Occupancy density value is from LBNL Occupancy Simulator.*

[2] *Occupancy density values from ASHRAE Standard 62.1*

The LBNL Occupancy Simulator assumes that there are no people working on weekends, including Saturday and Sunday. However, this is not always the case in academic buildings, as students may go to campus to do work and/or study on weekends. To reflect this situation, a new occupant type was added, named “Student”. This was added into the occupant types for Office and Research lab space types, with 10% student attendance among all different occupancy types in the building. The example daily occupancy profiles of each space type, including *Classroom*, *Office*, *Meeting Room* and *Others*, for the typical academic building models on both weekdays and weekends are presented in Figure 14.



(a) Office (b) Classroom

(c) Meeting room (d) Others

Figure 14 The example daily occupancy profiles of (a) *Classroom*, (b) *Office*, (c) *Meeting room* and (d) *Others*, for typical academic building model on both weekday and weekend

4.3.4 Occupant-based control Strategies

4.3.4.1 Temperature setback

According to ASHRAE Standard 90.1 (2019), Occupied-Standby Controls are recommended to be implemented to help support reduced energy use. Following this, active heating and cooling setpoints should be setback at least 0.5 °C when a space is in occupied-standby mode (scheduled to be occupied but there are no occupants in the space). In this research a 1°C temperature setback was applied.

4.3.4.2 Ventilation setback

Occupant-based ventilation setbacks were also included. These include zone-level and system-level ventilation setbacks (Pang et al., 2020), according to the Ventilation Rate Procedure in the current version of ASHRAE Standard 62.1 (2019). For zone-level control, the breathing zone outdoor air flow rate, *Vbz*, zone outdoor air flow rate *Voz*, and zone minimum primary air flow, *Vpz-min*, are dynamically reset based on the occupancy information. For the system-level, the system minimum outdoor air intake is also dynamically reset based on real-time occupancy information. The system ventilation efficiency *Ev* is also reset based on detailed methods related to occupancy.

Table 39 summarizes the occupant-based control strategies for energy saving analysis of typical academic building models (Pang et al., 2020). It is noted that in Table 2, there are four scenarios considered: Baseline, Temperature setback, Occupancy sensing, and Occupancy counting. The "Baseline" is the model which calculates the energy consumption of an academic building without any occupant-based controls; the "Temperature setback" model includes zone-level temperature setbacks, which decrease/increase the zone setpoint temperature by 1 ℃ depending on if the system is in heating or cooling mode; the "Occupancy presence" model includes the use of occupancy detection technology such that the air handling unit (AHU) outdoor air intake is able to be adjusted based on the presence and non-presence of occupants; the "Occupancy counting" model includes occupancy counting technology enabling ventilation setbacks to be applied depending on the real time number of occupants. All occupant-related variables that require adjustment are summarized in Table 39 with detailed calculations from ASHRAE Standard 62.1.

Table 39 Occupant-based control strategies for typical academic building models (Pang et al., 2020)

Control Strategy		Attribute	Baseline	Temperature setback	Occupancy presence	Occupancy counting
Venti-lation setback	Zone level	Zone population	$Pz = P(zdesign)$	Same as baseline	Same as baseline	$Pz' = P(zactual)$
		Breathing zone outdoor air flow	Vbz=Rp∗Pz+Ra∗Az	Same as baseline	If Occupied, Same as baseline; If Unoccupied, Vbz=0	If Occupied, Vbz'=Rp∗P_z'+R_a∗A_z; If Unoccupied, V_bz=0
		Zone air Distribution effectiveness	Ez = constant: Ez = 1 for cooling, Ez = 0.8 for heating	Same as baseline	Same as baseline	Same as baseline
		Zone outdoor air flow	Voz=Vbz/Ez	Same as baseline	If Occupied, Same as baseline; If Unoccupied, Voz=0	If Occupied, V_oz'=V_bz'/E_z; If Unoccupied, V_oz=0
		Zone minimum primary air flow	V(pz-min) =Voz∗1.5	Same as baseline	If Occupied, Same as baseline; If Unoccupied, V(pz-min) =0	If Occupied, V_(pz-min)'=V_oz'∗1.5; If Unoccupied, V_(pz-min) =0
	System level	System Minimum Uncorrected outdoor air intake	$V_{ou} = \sum_{AllZones} Vbz$	Same as baseline	If the zone is Occupied, Same as baseline; If Unoccupied, Vbz=0	$V_{ou}' = \sum_{AllZones} Vbz'$
		System Ventilation efficiency	D= Ps/Pzsum Ev=0.88∗D+0.22 for D<0.6 Ev=0.75 for D≥0.6	Same as baseline	Uncorrected system outdoor air fraction: Xs=Vou'/Vps Zone outdoor air fraction: Z(d,i)=V(oz,i)/V(dz,i) Z(d,imax)=Max(Z(d,i)) Ev'=1+Xs-Z(d,imax)	X_s=V_ou''/V_ps Z_(d,i)=V_(oz,i)/V_(dz,i) Z_(d,i_max)=Max(Z_(d,i)) E_v''=1+X_s-Z_(d,i_max)
		System Minimum outdoor air intake	Vot= Vou/Ev	Same as baseline	Vot'= Vou'/Ev'	V_ot''= V_ou''/E_v''
Temperature setback		OBC Temperature setback	No	1℃	1℃	1℃

4.4 Results

4.4.1 Baseline energy consumption comparison

Chicago (ASHRAE Climate Zone 5A) was chosen as the climate zone for assessment of the energy savings potential for comparison. This is because Chicago is in a cold climate zone where heating is dominant. In this scenario, there will be more energy saving potential in winter with the use of OBC when less outdoor air in required based on a smaller number of occupants. The four typical academic building models developed have different occupancy profiles due to different composition of space types, resulting in different energy consumption. Figure 15 includes the baseline energy consumption each of the four typical academic building models. It is noted that the *Mixed-use* typical academic building model energy consumption is largest compared to the other three typical academic building models. This may be because that the classroom space type accounts for the largest portion of all spaces in the *Mixed-use* model. In addition, the maximum number of occupants is the largest; it also has the largest average real-time number of occupants in the building. This is followed by is the typical *Laboratory-dominated* academic building model which is slightly higher than that of the typical *Office-dominated* academic building model. This is likely because the portion of laboratory space type in the typical *Laboratory-dominated* model is higher than the percentage of office space type in the typical *Office-dominated* model. The occupancy density is also slightly lower in the office space types compared to that in laboratory spaace types. The *Study room-dominated* model consumes the least energy because it has the lowest portion of classroom, laboratory, and office, and the occupancy density in study area is not as high as in the classroom and laboratory spaces.

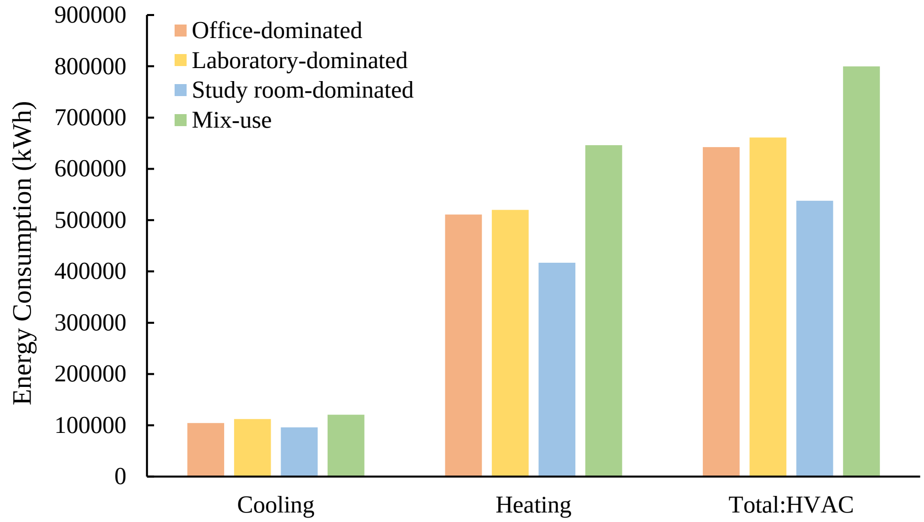


Figure 15 Baseline annual energy consumption comparison among four types of typical academic building models in ASHRAE Climate Zone 5A (Chicago)

4.4.2 Occupant-based control – Ventilation Setback

4.4.2.1 Zone-level ventilation setback

The zone minimum primary air flow Vpz_min was reset based on occupancy information under both "Occupancy presence" and "Occupancy counting" scenarios. Figure 16 shows the zone minimum primary air flow profiles in four different space types, including office, classroom, meeting room and others, in typical Office-dominated academic building model. Zones on the first floor were selected to represent these four space types, which inlude "Perimeter_bot_GA_OF_1", "Perimeter_bot_Classroom_1", "Perimeter_bot_Meeting_RM", and "FirstFloor_Corridor_1", respectively. The name of the zones are the names used in EnergyPlus. The notation after each of the zone names represents the three different scenarios, where "_B" indicates the "Baseline" scenario; "_P" indicates the "Occupancy Presence" scenario; and "_C" represents the "Occupancy Counting" scenario.

From Figure 16, it can be seen that compared to the baseline, the Vpz_min decreases to zero when the space is unoccupied under both “Occupancy Presence” and “Occupancy Counting” scenarios, while for “Occupancy Counting” scenario, the zone minimum primary air flow decreases further with a decrease in number of occupants. Among the four different space types, “Classroom” and “Meeting room” have more vacancy. As a result, the zone minimum primary air flow in these space types decreases, thus these areas have a larger potential energy savings, compared to “Office” and “Others” space types. The zone minimum primary air flow rate profiles in the other three typical academic building models are similar to Figure 16.

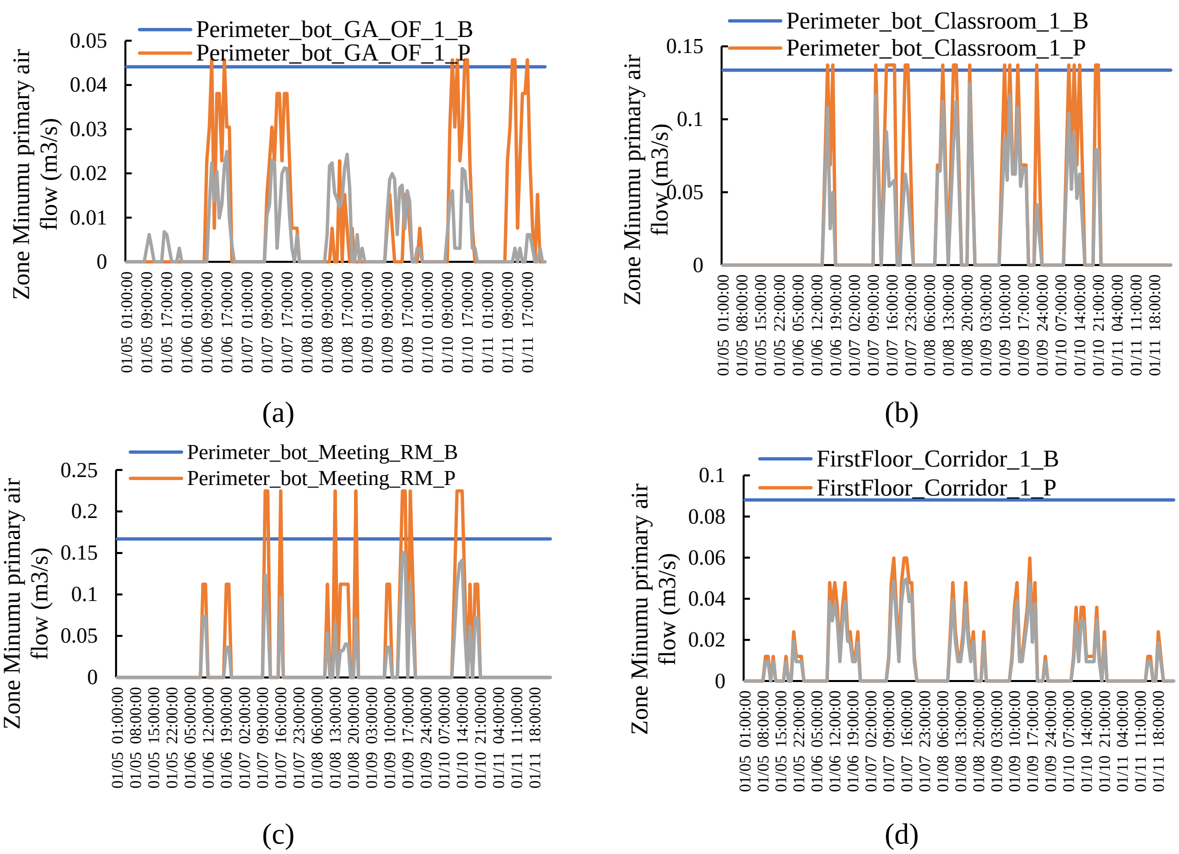


Figure 16 Zone minimum primary air flow rate (m3/s) in example spaces: (a) Office -- *Perimeter_bot_GA_OF_1*; (b) Classroom -- *Perimeter_bot_Classroom_1*; (c) Meeting room -- *Perimeter_bot_Meeting_RM*; (d) Others -- *FirstFloor_Corridor_1*. (*Note: B = Baseline; P = Occupancy presence sensing; C = Occupancy counting sensing*)

Figure 17 shows the zone outdoor air flow rate profiles in the same four example spaces, including *Perimeter_bot_GA_OF_1*, *Perimeter_bot_Classroom_1*, *Perimeter_bot_Meeting_RM*, and *FirstFloor_Corridor_1*, respectively. From this figure, the zone outdoor air flow rate decreases from the “Baseline” scenario to “Occupancy Presence” scenario. It decreases further for the “Occupancy Counting” scenario during the daytime while the space is occupied, compared to the “Occupancy Presence” scenario. Similar to the zone minimum primary air flow rate, the zone outdoor air flow rate decreases with a larger vacancy period in the “Classroom” and “Meeting room” space types compared to others. The zone outdoor air flow rate profiles in the other three typical academic building models are similar to Figure 17.

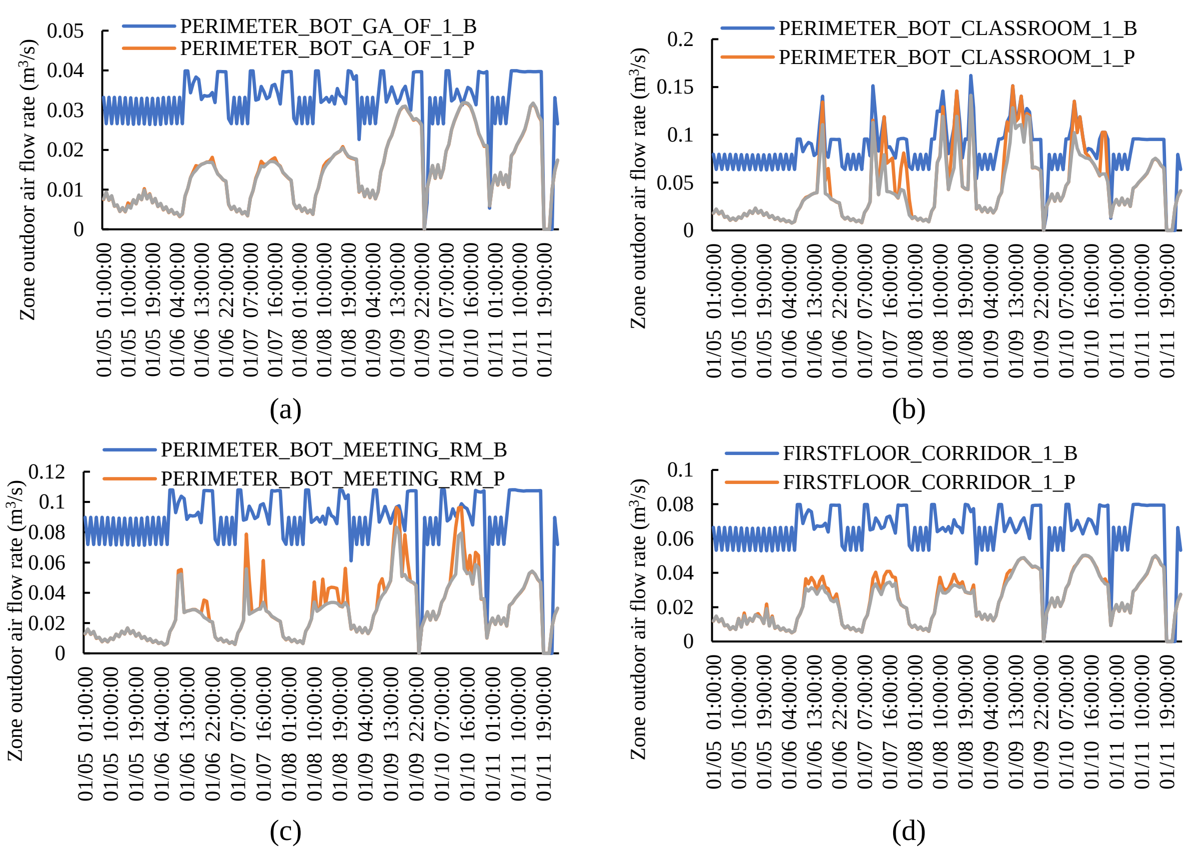


Figure 17 Zone outdoor air flow rate (m^3/s) in example spaces: (a) Office -- *Perimeter_bot_GA_OF_1*; (b) Classroom -- *Perimeter_bot_Classroom_1*; (c) Meeting room -- *Perimeter_bot_Meeting_RM*; (d) Others -- *FirstFloor_Corridor_1*

4.4.2.2 System-level ventilation setback

For the system-level ventilation setback, the system *VAV_1*, the air handler servicing the first floor, is used to illustrate the system outdoor air flow profiles under all scenarios. The systems servicing the second (*VAV_2*) and third floor (*VAV_3*) are similar to *VAV_1*. Figure 18 summarizes the outdoor air flow rate for VAV_1 under the "Baseline", "Occupancy presence" and "Occupancy Counting" scenarios in all typical academic building models. "OD" represents "*Office-dominated*"; "LD" represents "*Laboratory-dominated*"; "SD" represents "*Study room-dominated*"; "M" represents "*Mixed-use*". Figure 18 shows that the outdoor air mass flow rate substantially decreases from the "Baseline" to "Occupancy presence" scenario regardless of if the space is occupied or unoccupied. For the "Occupancy counting" scenario, the outdoor air flow rate further decreases based on the actual, real-time number of occupants in each space.

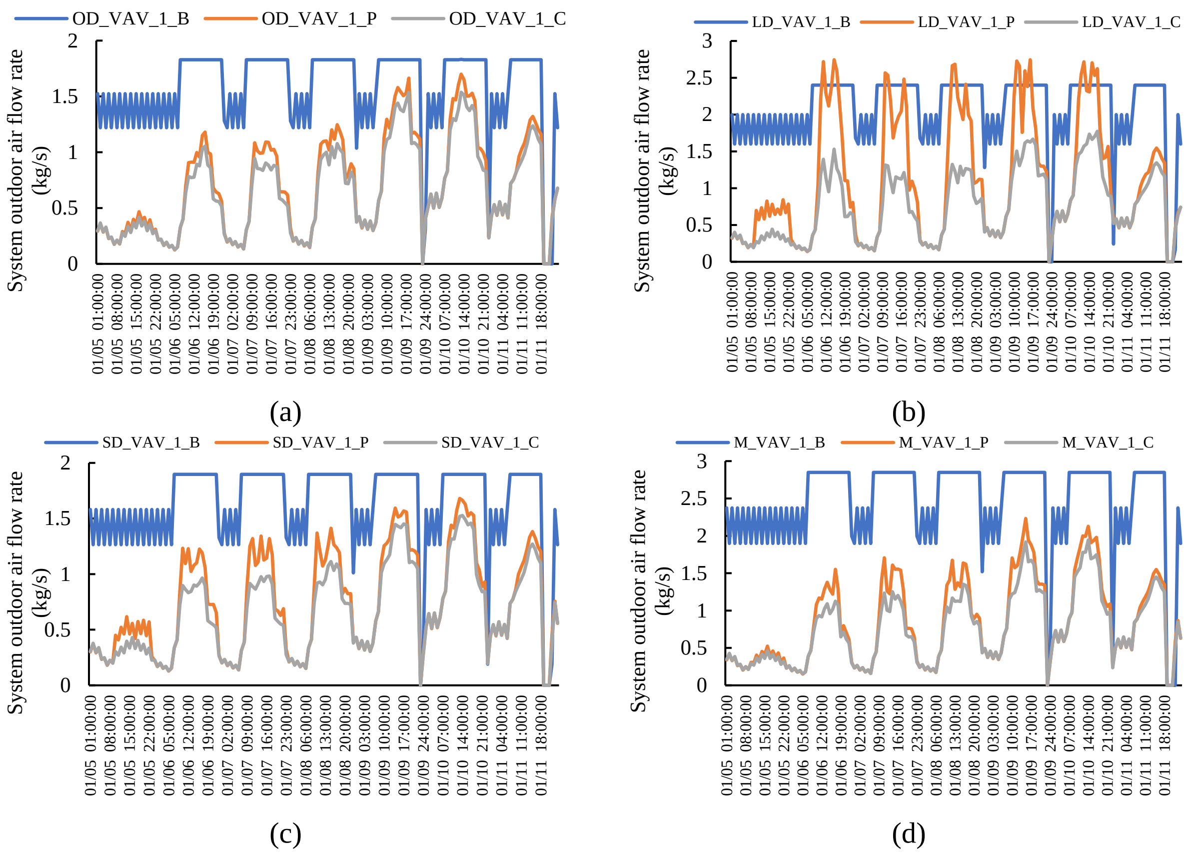


Figure 18 System outdoor air flow rate (kg/s) in example VAV_1 system of (a) Typical *Office-dominated*; (b) Typical *Laboratory-dominated*; (c) Typical *Study room-dominated*; and (d) Typical *Mixed-use* building models

4.4.3 Energy savings

The overall energy savings achieved through the use of occupant-based control using temperature and zone- and system-level ventilation setbacks for all types of typical academic buildings are shown in Figure 19. This figure shows that significant energy savings is possible by applying the proposed occupant-based control, especially occupant-related ventilation setback controls, for typical academic buildings. For ASHRAE Climate Zone 5A, the total annual HVAC energy savings ranges from 35%-52% for "Occupancy presence" scenarios across all types of typical academic buildings.

Among "Occupancy presence" scenarios, the typical *Mixed-use* academic building achieves the highest HVAC energy savings, which may be because it has the largest portion of classroom spaces, with the highest occupancy density. The larger the design population is, the larger the amount of energy savings is that can be achieved when the space is unoccupied or when there is a smaller number of occupants utilizing this pace. This is followed by the typical *Office-dominated* model, then the typical *Laboratory-dominated* model. The typical *Study room-dominated* academic building model achieves the least energy savings, but it is still a significant amount, which is around 35%.

The same ranking is also observed when comparing cooling and heating energy savings separately for the "Occupancy presence" scenarios. However, the heating energy savings is much higher compared to the cooling energy savings. This is weather dependent, and is most likely because the climate zone considered is Chicago, where heating requirements are greater due to the cold climate. When comparing "Occupancy presence" and "Occupancy counting", there is an increase in the energy savings, ranging from 3% to 10%.

Among the four typical academic building models under "Occupancy counting" scenarios, the energy savings ranking is similar to that of "Occupancy presence". The main difference is that energy savings of typical *Laboratory-dominated* academic building models are similar to that of typical *Office-dominated* academic building models. This may be because laboratory space type was assumed as *Open Office*, therefore, a similar occupancy profiles were considered for both typical *Office-dominated* and *Laboratory-dominated* academic building models. From "Occupancy presence" scenarios to "Occupancy counting" scenarios, the largest increase in energy savings was observed for the typical *Laboratory-dominated* model, which is around 9%, indicating that the typical *Laboratory-dominated* academic building models have larger variations in occupancy profiles when the space is occupied.

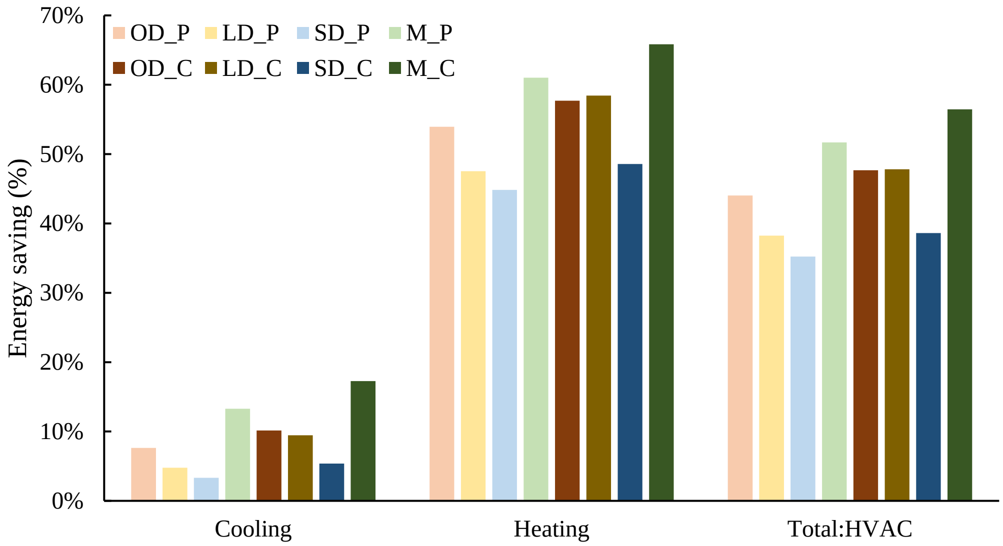


Figure 19 Energy saving achieved through Occupant-based Control for typical academic building as compared to the baseline buildings with no OBC in ASHRAE Climate Zone 5A (Note: lighter colors indicate "Occupancy presence" scenarios; darker colors indicate "Occupancy counting" scenarios; _P = occupancy presence scenarios; _C = Occupancy counting scenarios; OD=office-dominated; LD=laboratory-dominated; SD=study room-dominated; M=mixed-use)

4.5 Conclusions

Building energy consumption is highly impacted by occupants and their energy use patterns, therefore, there are significant opportunities for energy efficiency improvement by applying occupant-based controls in buildings. This research focuses on, first, defining what a typical academic building is and how it is structured, as currently there no prototypical academic building model available. It then uses this to assess the energy savings potential of the use of occupancy sensors in such buildings.

The space type and functional use data was collected from 293 academic buildings across five U.S. universities of different sizes was used to define typical space distribution and composition for use in typical academic building models. Four types of typical academic building models were then defined, which are typical *Office-dominated*, *Laboratory-dominated*, *Study room-dominated*, and *Mixed-us*e academic building models, using clustering. Next the medium size office DOE Reference building model was used as a baseline, as it is similar to that of academic buildings in size, then re-zoned to represent the typical characteristics and space use compositions of academic buildings, to develop the four typical academic building models. The occupancy schedules were initially built using LBNL Occupancy Simulator with some additional modifications. The baseline and proposed models when then built, of which a fixed setpoint schedule and minimum outdoor air flowrate were used for the baseline model. The proposed model utilizes occupant-based controls, which resets the temperature schedule and minimum outdoor air flow schedule under both "Occupancy presence" and "Occupancy counting" scenarios.

Baseline energy consumption were first compared across the four building models, indicating that the energy savings evaluation for each of the buildings should be separated since different academic building models have different energy patterns due to different mixes of space functional uses. After applying the occupant-based controls, results show that there is significant energy saving potential for the proposed typical academic building models with the implementation of occupant-based controls. Among all these four typical academic building models, the total HAVC energy savings ranges from 35% to 51% under "Occupancy presence" scenarios. An additional energy saving increase (3~9%) from "Occupancy presence" scenarios to "Occupancy counting" scenarios is also achieved. The results of this work provide typical academic building models with integrated occupancy schedules which can be used to evaluate energy saving measures, and aid building designers and operators in making informed decisions in applying appropriate control strategies to optimize building energy systems, as well as predict energy use and demand.

We also noted that the energy savings could vary depending on different variables, such as building characteristics, space distributions, and occupancy schedules, among others. Future efforts should consider a sensitivity analysis to investigate how much influence the variations of these variables could have on building energy savings.

APPENDICES

APPENDIX A: Space types of assignment for typical academic building model

Table 40 Space types assignment on each floor for the *laboratory-dominated* typical academic building model

Category from FICM	Area of Laboratory -dominated	Space types	1st floor		2nd floor		3rd floor	
			Number of rooms	Area (m^2)	Number of rooms	Area (m^2)	Number of rooms	Area (m^2)
CLASSROOM	120	Classroom	1	72	-	-	-	-
		Seminar	-	-	-	-	1	56
LABORATORIES	2615	Research lab	4	492	7	940	8	1014
		Teaching lab	2	126	-	-	-	-
OFFICES	816	Staff office	-	-	2	166	-	-
		Faculty office	-	-	-	-	1	166
		Graduate student office	4	392	-	-	-	-
		Conference	-	-	2	130	-	-
STUDY FACILITIES	26	Study room	1	23	-	-	-	-
SPECIAL USE	16	Special use	-	-	-	-	-	-
GENERAL USE	119	Meeting room	1	71	-	-	-	-
		Lounge-Recreation	1	38	-	-	-	-
		Food facilities	-	-	-	-	-	-
SUPPORTING FACILITIES	22	Active storage	1	23	-	-	-	-
OTHERS	1270	Corridor	1	291	1	290	1	290
		Stairway	1	15	1	15	1	15
		Lobby	1	105.00	1	105	1	105
		Restroom	1	15	1	15	1	15

Table 41 Space types assignment on each floor for the *study room-dominated* typical academic building model

Category from FICM	Area of Study room-dominated	Space types	1st floor		2nd floor		3rd floor	
			Number of rooms	Area (m^2)	Number of rooms	Area (m^2)	Number of rooms	Area (m^2)
CLASSROOM	2	Classroom	/	/	/	/	/	/
		Seminar	/	/	/	/	/	/
LABORATORIES	255	Research lab	1	122	/	/	/	/
		Teaching lab	2	126	/	/	/	/
OFFICES	708	Staff office	/	/	2	189	/	/
		Faculty office	/	/	/	/	1	166
		Graduate student office	4	215	/	/	/	/
		Conference	/	/	/	/	1	135
STUDY FACILITIES	2,590	Study room	5	642	9	1048	8	935
SPECIAL USE	16	Special use	/	/	/	/	/	/
GENERAL USE	119	Meeting room	1	71	/	/	/	/
		Lounge/ Recreation	1	38	/	/	/	/
		Food facilities	/	/	/	/	/	/
SUPPORTING FACILITIES	22	Active storage	1	23	/	/	/	/
OTHERS	1,270	Corridor	1	290	1	290	1	290
		Stairway	1	15	1	15	1	15
		Lobby	1	105	1	105	1	105
		Restroom	1	15	1	15	1	15

Table 42 Space types assignment on each floor for the mixed-use typical academic building model

Category from FICM	Area of Mixed-use	Space types	1st floor		2nd floor		3rd floor	
			Number of rooms	Area (m^2)	Number of rooms	Area (m^2)	Number of rooms	Area (m^2)
CLASSROOM	1,503	Classroom	4	442	5	661	4	433
		Seminar	/	/	/	/	1	56
LABORATORIES	734	Research lab	1	122	1	122	2	382
		Teaching lab	2	126	/	/	/	/
OFFICES	1,227	Staff office	/	/	4	319	/	/
		Faculty office	/	/	/	/	2	301
		Graduate student office	4	392	/	/	/	/
		Conference			1	135	/	/
STUDY FACILITIES	92	Study room	1	23	/	/	1	65
SPECIAL USE	16	Special use	/	/	/	/	/	/
GENERAL USE	119	Meeting room	1	71	/	/	/	/
		Lounge/ Recreation	1	38	/	/	/	/
		Food facilities	/	/	/	/	/	/
SUPPORTING FACILITIES	22	Active storage	1	23	/	/	/	/
OTHERS	1,270	Corridor	1	290	1	290	1	290
		Stairway	1	15	1	15	1	15
		Lobby	1	105	1	105	1	105
		Restroom	1	15	1	15	1	15

APPENDIX B: Detailed floor plans and whole building geometry for typical academic building model

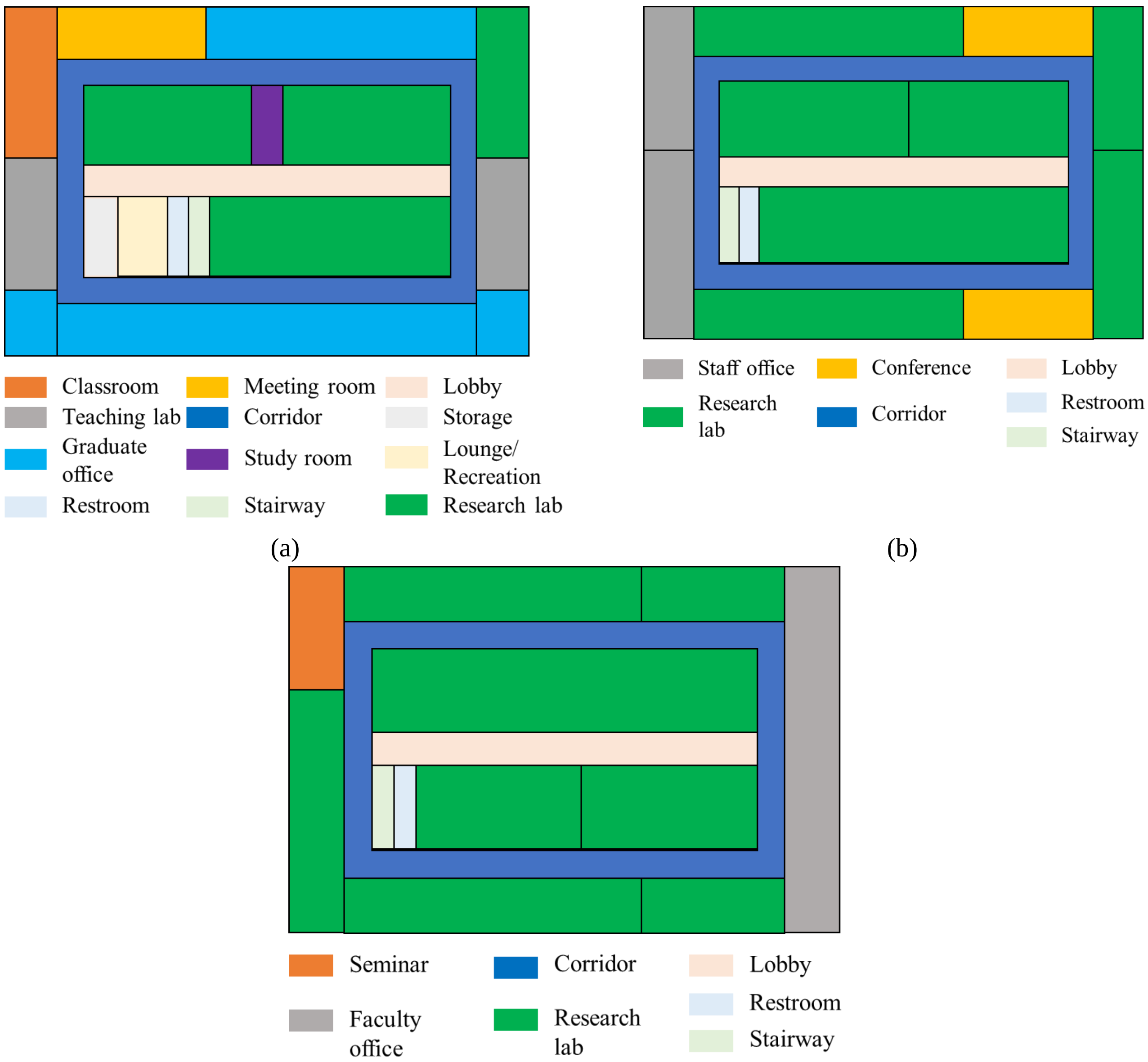


Figure 20 Detailed floor plans and whole building geometry for *laboratory-dominated* typical academic building model, including (a) 1st floor plan; (b) 2nd floor plan; (c) 3rd floor plan

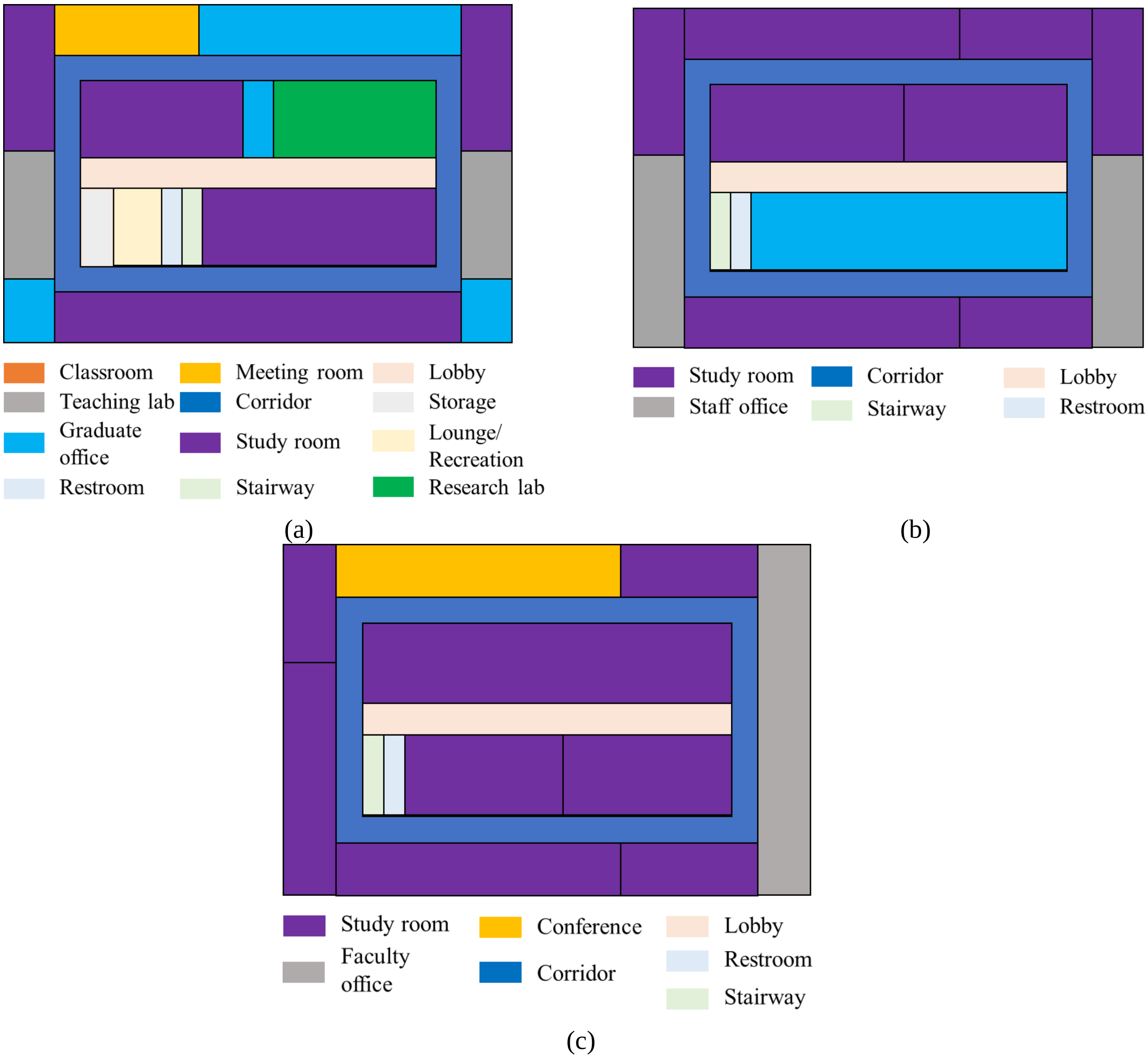


Figure 21 Detailed floor plans and whole building geometry for *study room-dominated* typical academic building model, including (a) 1st floor plan; (b) 2nd floor plan; (c) 3rd floor plan

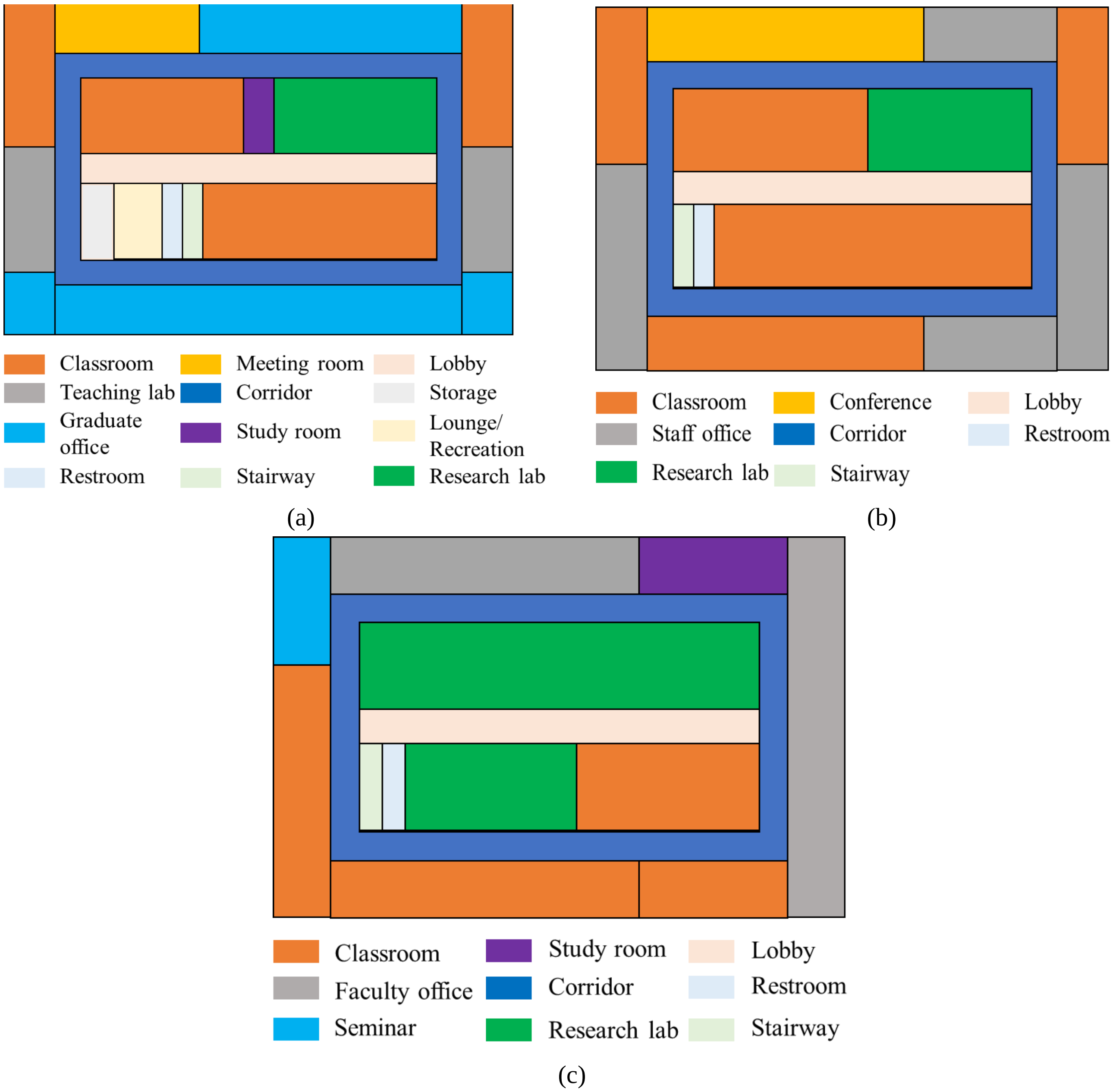


Figure 22 Detailed floor plans and whole building geometry for *mixed-use* typical academic building model, including (a) 1st floor plan; (b) 2nd floor plan; (c) 3rd floor plan

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CHAPTER 5 – CONCLUSIONS AND FUTURE WORK

The research presented in this dissertation has led to an expansion of knowledge on the influential variables that impact the reliability of occupancy sensor systems, a standard methodology to test the reliability of various occupancy sensor systems, and the development of typical academic building models and their use to assess the energy savings potential of the use of these technologies. The research findings provide a novel methodology for evaluating the performance of occupancy sensor systems and for developing and accessing technology-based energy savings potential in typical academic building models.

5.1 Conclusions and Contributions

Based on the results in this dissertation, the following conclusions can be drawn:

5.1.1 Influential variables impacting the reliability of building occupancy sensor systems

Existing occupancy sensor technologies were reviewed and summarized to attain a comprehensive list of the potential influential variables that may cause sensor failures along with stakeholder discussion. Then an expert survey was conducted across a diversity of stakeholders on the most and least important variables impacting occupancy sensor performance based on this comprehensive influential variable list. This resulted in a final list of most and least important variables for assessing energy for both residential and commercial buildings. The most important variables are summarized in Table 43. The results of this work provide insights for sensor manufacturers on what variables industry stakeholders consider to be most important when assessing the performance of occupancy sensor systems. This also provides initial results for use in considering a standard set of variables by which to test occupancy sensor systems for comparative performance evaluation. The unique contribution of this work is the comprehensive influential variable list that might influence occupancy sensor performance based on literature review, and list of the most important variable list for residential and commercial buildings attained from an expert survey.

Table 43 Most important variables for residential and commercial buildings

Building type	Most important (Tier 1)
Residential buildings	A2. Size (length/width) and shape of test area
	C5. Level of motion of occupant(s)
	D1. Presence of pets
	B1. Lighting level (regardless of source of light) (lux)
	C4. Spatial location of occupant(s)
	C1. Number of occupants (including 0)
	A9. Presence of large objects (especially metal objects) within or near a space
	B3. Presence of interior lighting sources (non-overhead)
	A4. Number of doors (entrances/exits)
	D4. Use of robots
Commercial buildings	A2. Size (length/width) and shape of test area
	C1. Number of occupants (including 0)
	B1. Lighting level (regardless of source of light) (lux)
	C4. Spatial location of occupant(s)
	A9. Presence of large objects (especially metal objects) within or near a space
	C5. Level of motion of occupant(s)
	B7. Presence of sunlight - direct
	C7. Clustering of occupants (distance between occupants)

5.1.2 A standard methodology to test the reliability of various occupancy sensor systems

A standard evaluation methodology was proposed to test the reliability of occupancy sensor systems in residential buildings, including both “Typical testing” and “Failure testing”. “Typical testing” is used to evaluate the reliability of each occupancy sensor system under scenarios that mimic real occupancy scenarios. “Failure testing” follows one variable at a time (OVAT) methods to test the most important variables based on a stakeholder survey (see previous section), to determine if these variables impact sensor system reliability.

The proposed methodology for evaluating the reliability of occupancy sensor systems presents an opportunity for use as a standardized method to evaluate the reliability of residential occupancy sensor systems that currently does not exist. The focus on typical scenarios enables the reporting of metrics representing the reliability of the sensor system under typical U.S. household scenarios. This could be used as a comparative measure of performance across sensor systems. The focus on failure testing enables the ability to assess the potential weaknesses in sensor system reliability, which can provide valuable information for sensor developers to adapt their design to avoid sensor failures from the impact of various influential variables, thus improving sensor performance beyond that which could be assessed from typical scenario testing only.

Standardized performance metrics were also proposed in this research for both the “typical” and “failure” testing, which are summarized from a state-of-art literature review. Both a detailed confusion matrix and associated metrics were provided, instead of only the use of overall accuracy for “typical” testing evaluation.

A case study was completed to verify the feasibility of the proposed methodology. The developed methodology was implemented for a novel occupancy detection sensor system to test the sensor system’s reliability. For “typical testing”, results show that on average, the Precision and Recall are 0.75 and 0.70, respectively, which means that there are similar number of false positives (FPs) and false negatives (FNs) across the dataset. The overall accuracy of the tested novel system ranged from 62.4% to 76.4%. For "failure testing", individual variable testing provided insights as to the impact of a range of levels of individual variables on sensor system performance. For the tested sensor system, the "Number of occupants", "Presence of large objects", "Presence of interior light sources", and "Number of doors" are not influential, while "Lighting level", "Location of occupants", "Another door in the entry/exit area", and "TV on" variables were determined to impact sensor system performance. Supplementary tests showed that the performance of the evaluated systems is affected most by the positioning of the platforms monitoring the entry/exit doors. Individual sensor evaluations showed that the system can differentiate between the sources of motion, i.e., can differentiate between people and robot vacuums and pets.

The unique contributions of this work include the proposed a novel methodology to evaluate the reliability of occupancy sensor systems, including both typical testing and failure testing, in residential buildings. The proposed methodology for evaluating the reliability of occupancy sensor systems presents an opportunity for its use as the basis for development of a standardized method to evaluate residential occupancy sensor systems, including existing sensor systems as well as those being developed and commercialized. Within this methodology, the focus on typical scenarios enables the reporting of metrics representing the reliability of the sensor system under typical U.S. household scenarios. This could be used as a comparative measure of performance across sensor systems. The focus on failure testing enables the ability to identify potential weaknesses in the sensor system reliability, as well as targets for further testing and development. In summary, this effort could help establish and form standards that define a standard way to evaluate occupancy sensor systems' performance to push forward the applications of various occupancy sensor technologies. With an understand of a testing metric indicating the performance of various sensors systems, this should help encourage those that may be skeptical of performance to realize their potential.

5.1.3 Typical Academic Building Energy Model Development and Energy Saving Evaluation of Occupant-based Control

A methodology was proposed to develop typical academic building models. First, the space type and functional use data collected from 293 academic buildings across five U.S. universities covering different sizes of universities was used to attain the typical space distribution and composition in typical academic building models. Four types of typical academic building models were then determined based on cluster analysis, which include typical *Office-dominated*, *Laboratory-dominated*, *Study room-dominated*, and *Mixed-use* academic building models.

Next, the medium size office DOE Reference building model was used as the basis to develop the academic building models in EnergyPlus. It was re-zoned to represent the typical characteristics and space use compositions of academic buildings, to develop the four typical academic building models. The stochastic occupancy schedules were built based initially on the LBNL Occupancy Simulator. Next the baseline and proposed models were created, of which a fixed setpoint schedule and minimum outdoor air flowrate were used for the baseline model. The proposed models utilize the occupant-based controls, which resets the temperature schedule and minimum outdoor air flow schedule under both "Occupancy presence" and "Occupancy counting" scenarios.

Baseline energy consumptions were first compared, indicating that the energy savings evaluation should be separated since different academic building models have different energy patterns due to different space functional uses. After applying the occupant-based controls, results show that there are significant energy saving potentials for the proposed typical academic building models with the implementation of occupant-based controls. Among all these four typical academic building models, the total HVAC energy savings ranges from 35% to 51% under "Occupancy presence" scenarios, compared to baseline energy consumptions, and a further energy saving increase (3 - 9%) from "Occupancy presence" scenarios to "Occupancy counting" scenarios, resulting in an overall energy savings potential for "Occupancy counting" of 38-56%.

The developed typical academic building models with integrated occupancy schedules can be used as a comparative measure of energy savings across different energy saving measures, and aid building designers and operators in making informed decisions in applying appropriate control strategies to optimize building energy systems, as well as predict energy use and demand. The unique contributions of this work include proposing a novel methodology to define the space distribution and composition for typical academic buildings and classify the typical academic buildings into four different categories, including typical office-dominated, laboratory-dominated, study-room dominated, and mixed-use academic buildings, which could be used for defining typical academic building models.

5.2 Limitations

5.2.1 Influential variables impacting the reliability of building occupancy sensor systems

There are many different influential variables and combinations of variables that can impact occupancy sensor systems, some of which may be more important in some building scenarios as compared to others. It was not attempted to rank the order of importance for different building types, such as hospitals versus schools. It is anticipated that they may be variations in these ranking among building types, as well as the frequency of occurrence of various variables.

However, this effort was an attempt to define the most and least important variables for residential and commercial building applications overall. The stakeholders that participated in the survey were also mostly based in the U.S., which may influence results.

5.2.2 A standard methodology to test the reliability of various occupancy sensor systems

When evaluating the "Typical testing" results, given that there are a number of activities that occur over long durations of many hours (e.g., "unoccupied"), shortened testing durations were proposed to optimize laboratory testing time. The longer time periods were generally reduced to 10 to 20 minutes. Preliminary testing results suggested that a 10- to 20-minute duration was able to capture the behavior of a sensor system sufficiently to mimic a longer period of time. This shorter duration also enables a more time-efficient testing method which is beneficial given this test method requires human subjects to complete. However, there are limitations of the use of the "test" duration for extrapolating to the 24-hour duration that could benefit from further testing as a part of future work.

5.2.3 Typical Academic Building Energy Model Development and Energy Saving Evaluation of Occupant-based Control

The typical space distribution and composition for typical academic building models were attained from 293 academic buildings across five U.S. universities covering different sizes of universities. Assumptions were made for the percentage of each space types based on the existing studies, however, there are not any standards or guidelines to use as a reference. In addition, the occupancy schedules were developed, in part, based on the LBNL occupancy simulator, which may also have some limitations.

5.3 Future Work

5.3.1 Sensor Reliability and Performance Improvement

After the standard methodology for reliability testing, it is also important to consider that if a reliability issue is identified for a certain type of occupancy sensor system, further efforts are needed to mitigate these to improve the sensor's reliability and performance. For example, if a sensor system is determined to be sensitive to natural daylight, it may be recommended to not install this sensor system near exterior windows, or additional changes to the sensor system may be made to reduce the sensitivity to daylight.

5.3.2 Standardized Performance metrics for reliability evaluation

Performance metrics were summarized from a state-of-art literature review. Both a detailed confusion matrix and associated metrics were provided, instead of only the use of overall accuracy for "typical" testing evaluation. However, it is noted that there is not currently a standard that suggests a certain level of performance using these metrics merits a sensor system would "pass". This could be an opportunity for future work.

5.3.3 Typical academic building models improvement

293 academic buildings across five U.S. universities covering different sizes of universities were used to attain the typical space distribution and composition in typical academic building models. In the future, more university data could be collected to evaluate and further improve the typical academic building models.

We also noted that the energy savings could vary depending on different variables, such as building characteristics, space distributions, and occupancy schedules. Future efforts would benefit from a sensitivity analysis to investigate how much influence the variations of these variables would have on building energy savings.