# Improved Energy Management through Doppler Radar Smart Occupancy Sensing

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Manuscript submitted January 10, 2023; revised May 8, 2023; accepted June 10, 2023; published July 3, 2023.
doi: 10.12720/sgce.12.3.39-51

**Abstract**: This paper discusses the complex problem of measuring occupancy to better manage large buildings and their energy consumption profiles and explores ways that occupancy has been measured in the past. The paper then explores a novel way of measuring occupancy using a Doppler radar based occupancy sensor, TruePODS, to detect human presence, and the greater implications that this technology provides. As a proof of concept, six TruePODS modules were deployed in a single building on a university's campus over a period of six months. This paper details this case study and the methods used to empirically collect occupancy data for energy management. This paper concludes with exploring why Doppler technology could provide the answer to creating a high-resolution smart occupancy sensor that would be necessary to meet local and global energy efficiency goals.

**Key words:** Smart buildings, energy management, doppler radar

## 1. Introduction

The building sector is the largest consumer of electricity in the United States, and there are potential improvements in occupancy detection that can drastically increase the energy efficiency of buildings. The focus of the paper is to explore energy saving strategies and insights obtained from the design and implementation of a network of high-resolution, Doppler radar based occupancy sensors that were used to collect data in a single building case study on the University of Hawai'i (UH) at Manoa's campus. This paper begins by discussing the concepts of building occupancy resolution and accuracy and reviewing traditional occupancy detection methods. The Doppler radar occupancy sensors used in this study show marked improvements from existing occupancy estimation technologies, namely their ability to operate in real-time and to have high spatial resolution. Then, this paper outlines the pilot deployment of the system across three independent office spaces within the same building over a six-month period and analyzes opportunities for energy savings within the space. Additionally, this paper evaluates potential areas for further development with the data generated from this study and opportunities for increased capabilities of the high-resolution Doppler radar occupancy sensor network.

## 2. Energy Efficiency in Buildings

A thorough understanding of occupants and their indoor environment is a key component towards achieving new levels of energy efficiency of buildings. Recent studies have shown that the building sector accounts for 41% of primary energy usage, and 74% electricity usage within the U.S. In addition, electricity demand in the buildings sector has more than doubled since 1980 [1]. Other studies estimate that the building sector accounts for 39% of energy-related $CO_2$ emissions [2]. From these estimates, studies show that about half of the energy used in residential and commercial buildings is consumed by heating, ventilation and air-conditioning (HVAC), and the other half by lighting and appliances [3]. With a nearly 50% projected increase in global energy use by 2035, most of it from fossil fuels, efficient energy usage within buildings is becoming increasingly important [4].

To achieve substantial building energy efficiency, knowledge about the factors determining energy use must be gained. Oftentimes, there is a significant discrepancy between designed and real energy use in buildings. These discrepancies are poorly understood but are believed to do more with the role of human behaviour, and changes in human behaviour over time, than building design. The large variation in energy consumption for similar or identical buildings within similar locations can be explained by differences in human behavior [5]. Due to their substantial share of energy usage, there are many research areas that have suggested ways to analyze human behavior and capture unrealized energy savings within buildings. Primarily, occupancy information is a crucial component in detecting wasteful behaviors and implementing effective energy management plans. [6] High resolution temporal and spatial occupancy data coupled with adaptive building services form the basis for a successful energy management plan and offer considerable potential for energy reduction [7], [8], [9], [10]. Energy reduction occurs by analyzing robust indoor occupancy data and using it to facilitate efficient heating, ventilation, and air conditioning (HVAC) control, lighting adjustments, and other building services to achieve both occupancy comfort and energy efficiency [11]. Reports from U.S. Department of Energy [11] and the American Council for an Energy-Efficient Economy [12] have come to the conclusion that commercial buildings alone may reduce their energy consumption by 20% to 30% through an implementation of a small number of energy efficiency strategies and continuous commissioning practices [13].

## 3. Background

Traditionally, a building's occupancy is defined as whether the building has people in it or not. This definition of occupancy is inadequate and does not enable the comparison of more sophisticated occupancy sensing methods. Instead, a more modern definition of occupancy should include three independent components that all contribute to resolution. An occupancy measurement's resolution is dependent on spatial awareness, time responsiveness, and the degree of accuracy to count individual occupants as represented by Fig. 1 [14].

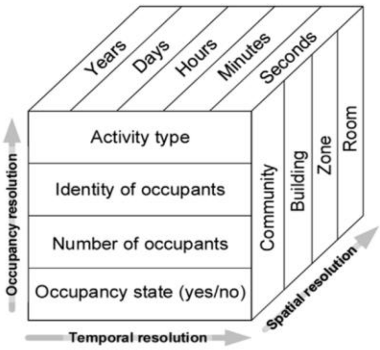


Fig. 1. Occupancy resolution [14].

This definition allows a more complete framework to highlight strengths and weaknesses of varying occupancy sensing technologies. For instance, an array of high-resolution occupancy sensors would be able to not only know if a space is occupied or unoccupied, but this array would be able to count occupants, identify the occupants, and even tell some information about the occupants' activities. Additionally, it could be able to tell exactly what room the occupants are in or, at an even higher resolution, what part of the room they are in, and the array would detect occupancy changes in real time without latency.

## 4. Occupancy Sensing Techniques

### 4.1. Passive infrared sensors

Passive Infrared (PIR) sensors are frequently employed successfully in basic energy reduction technologies. These traditional occupancy sensors output a binary value which indicates whether the area it is monitoring has at least one occupant or no occupants [14]. Although these occupancy sensors have provided some energy savings, studies have shown that these savings vary from 10% to 45% depending upon the room in which they are employed [15]. These sensors are particularly effective for controlling lighting in low traffic, infrequently occupied, and closed spaces such as storage spaces, but they are not effective for open layouts such as in libraries, cafeterias, or offices [16]. Additionally, these sensors are limited by line of sight, and the activation threshold in which they sense movement causes frequent false positives and false negatives. False positives occur when the sensor signals that there is occupancy, when in fact there is not. This equates to wasteful energy practices, mainly an empty but illuminated room. False negatives often happen due to sedentary occupant behaviors which do not meet the PIR sensor's threshold and often leave occupants in the dark [4]. The inability of PIR sensors to count occupants, give insights into occupants' behaviors and identities, or to log high-resolution spatial and temporal data makes them inadequate in providing data to make substantial energy management decisions.

### 4.2. Ultrasonic sensors

Ultrasonic sensors have also been successfully deployed to estimate occupancy. These sensors send inaudible acoustic signals within the range of 25 kHz to 40 kHz, and they have the advantage that they are not limited by line of sight. These sensors can detect motion even in large areas containing obstacles or in unusually shaped and furnished rooms such as bathrooms and office spaces [4]. Although these sensors solve some of the problems that PIR sensors have, they are more expensive than PIR sensors, and they have a higher false positive rate [4]. Additionally, they do not provide high resolution time or spatial data and only estimate a binary occupancy value like that of a PIR sensor.

### 4.3. $CO_2$ sensors

Other studies have shown that indoor $CO_2$ concentration is indicative of occupancy by proxy, as humans are the main source of $CO_2$ production. However, existing approaches suffer from the delay of detection because of the relatively long time (10 minutes to 15 minutes) it takes for $CO_2$ to build up to the level of concentration indicative of actual occupancy [17]. Occupancy estimation through $CO_2$ sensing has other shortcomings. Primarily, individual humans exhibit differing $CO_2$ emission rates which makes it an inaccurate proxy when determining the exact number of occupants. Additionally, human behaviors, such as opening and closing doors and windows, change the ventilation rate of a given area and cause an introduction of additional noise to $CO_2$ measurements [10]. This noise is difficult to filter, further affecting the accuracy of sensing. Even though studies have been successful in estimating building occupancy by taking $CO_2$ readings at the air-handling units supply and returns [18], $CO_2$ occupancy estimates lack precise spatial information as $CO_2$ emission is a transient process, and $CO_2$ concentrations diffuse and redistribute due to air currents and ventilation. The lag in $CO_2$ build up only adds to the loss of spatial resolution in this data [19].

### 4.4. Other technologies

Other innovative methodologies exploit existing sources of implicit occupancy information that are already collected but not necessarily used for building control decisions. Examples of these methodologies may be data created from elevator usage, detection of mobile devices at Wi-Fi access points, computer network traffic, or entry and exit events that are required in secure access areas [19]. These methodologies do have the advantage that the sensors are already present, and therefore there is little infrastructural investment required. Additionally, they are typically powered and capable of communication and can be incorporated into building control systems. Other research areas have used dedicated sensors like chair sensors [20], image processing occupancy sensors [21], relative humidity and temperature sensors [22], IT infrastructure including computer networking, phone calls, computer usage and access badges [23], and various other sensor arrays [24]. Unfortunately, none of these technologies are sufficient for high-resolution decision making.

## 5. Doppler Radar Occupancy Sensing

Doppler radar is a specialized radar that transmits an electromagnetic signal and deduces information from the modulated signal that reaches the receiver. Most commonly, this modulated signal can be processed to ascertain velocity of an object, as used by law enforcement officers in traffic patrolling duties. This modulated signal is commonly used to determine location, displacement, or acceleration. Given this phenomenon, it is possible to use a Doppler radar frequency shift to measure human movement in, out, and within buildings. Some may argue that it is difficult to extract meaningful information from Doppler radar signals, and although these sensors are more complex than a conventional PIR or ultrasonic sensor, it is in this complexity that these sensors showcase their ability to outperform methods previously mentioned in this report. In terms of temporal data, Doppler radar sensors can give accurate, real-time resolution like most other conventional approaches. In terms of occupancy resolution, studies have shown that this sensing methodology can count individuals [25], [26], classify their behaviors, and even identify individuals based on cardio-respiration patterns that are unique to each individual [27]. The following section will further elaborate on the Doppler radar occupancy sensor used in this case study.

## 6. Doppler Radar Sensor Design

The True Presence Occupancy Detection Sensor (TruePODS™) modules, developed by Adnoviv, Inc., were used in this study [28, 29]. These sensors employ Doppler radar cardiopulmonary sensing technology to detect true human presence. These innovative sensors detect occupancy based on a Doppler radar frequency shift that senses a motion-modulated signal during movements as small as chest deflection during normal respiration. In simple terms, this device transmits a low-power microwave radio source, radiated at power levels lower than typical cell phones or WiFi routers, and they receive the signal back and sense any modulation patterns that correspond to occupancy. Fig. 2 shows the TruePODS block diagram and photograph. TruePODS system includes a wireless interface with a data user platform, with an option to log the data on an SD card, offering opportunities for the development of long-term decision models or independent studies by building managers. An RF signal is generated on the programmable microcontroller and split into two signals for transmitting and downconversion. The transmit portion of the signal is fed to the antenna through a power amplifier and another RF power splitter, and the downconversion portion of the signal is fed to the RF mixer's local oscillator input port. The signal is transmitted by the antenna, and the reflected signal is received by the same antenna. The RF power splitter directs the received signal to the mixer's RF input port. The output from the mixer is a baseband signal proportional to the motion of the objects off which the RF signal reflected. This baseband signal is amplified and filtered before being returned to the microcontroller to be digitized and processed. If the objects in the room are entirely stationary, there is no time-varying phase shift between the transmitted and received signal. However, if there is movement within the room, the returned signal will have a unique modulation signature that can be demodulated to ascertain information. Through signal processing, body movement is detected, and a corresponding occupancy event is logged via a time reference.

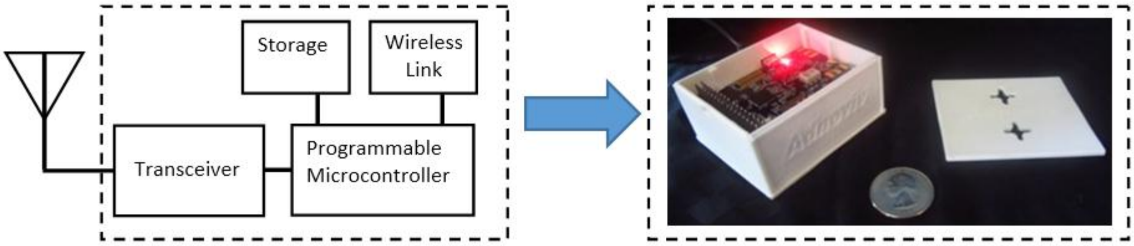


Fig. 2. Block diagram and photograph of TruePODS doppler radar occupancy sensor.

## 7. Case Study

### 7.1. Building specifications

The building in which the sensors were placed is Sakamaki Hall, a building that is centrally located on the University of Hawai'i at Manoa's campus. It is a four-floor building with two atria that provide natural lighting and space between four distinct zones on each floor as depicted in Figure 3. The building is primarily comprised of faculty offices on the second, third, and fourth floors, with sixteen classrooms located on the first floor. These offices and classrooms are primarily used by the Departments of Philosophy, History, Psychology, and Religion. Two elevators are located between the atria, and stairs flank the north and south ends of the building. Sakamaki Hall is centrally cooled. However, this cooling system is also connected to other surrounding buildings.

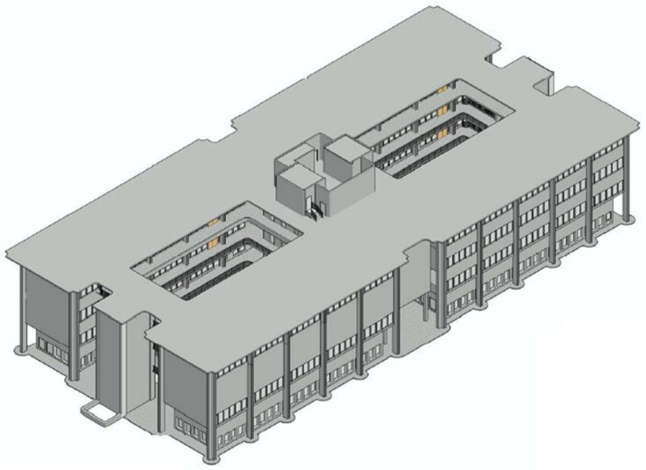

Fig. 3. Sakamaki hall

### 7.2. Sensor locations

All the sensors used in this study were placed on the fourth floor of Sakamaki Hall. Six sensors were positioned in entryways of three separate zones as annotated in Figure 4. It is important to note that there is no way to enter or exit these zones without passing these sensors. Sensors are labeled according to their location, with the first two letters representing cardinal directions, and the third letter corresponding to whether the sensor is near (N) or far (F) from the elevators. For example, SWF is on the southern end of the building, western side, and far from the elevators. The TruePODS modules were placed in electrical outlet cover boxes and plugged in to existing standard 120V AC power outlets. Figure 5 shows this protective enclosure and the sensor within.

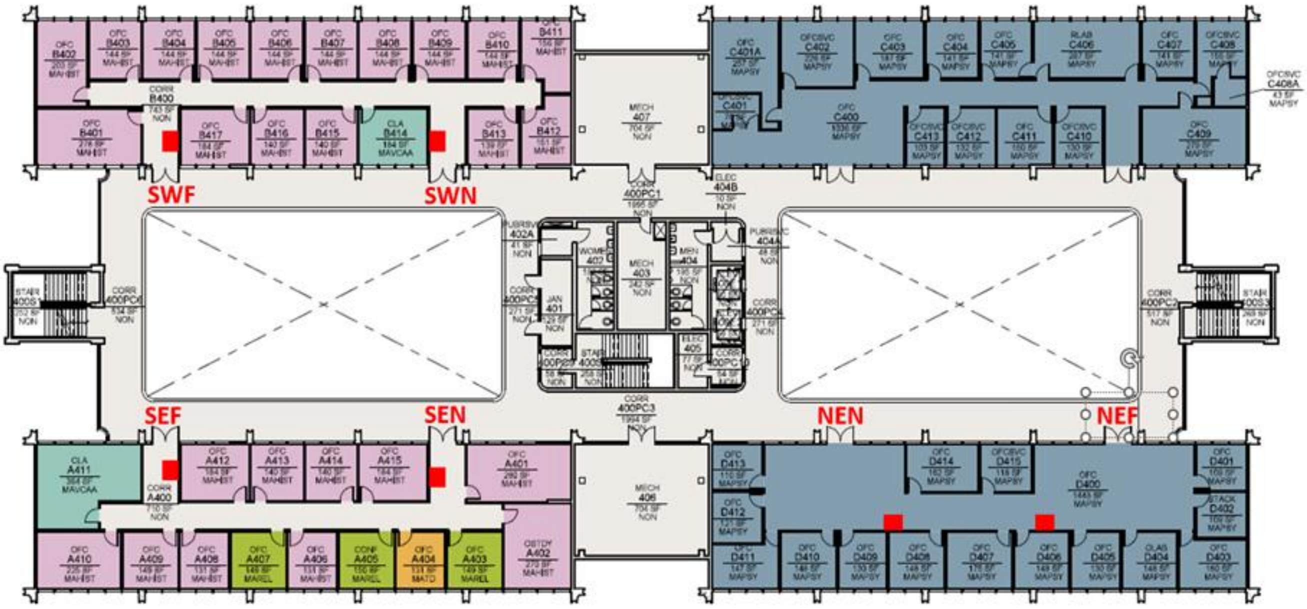


Fig. 4. Fourth floor of Sakamaki Hall with six sensor locations annotated

### 7.3. Data collection and processing

Data was analyzed using MATLAB to determine occupancy intervals. The events recorded demonstrate when one person enters or exits the building zone. These events do not distinguish between entering and exiting. Therefore, in analyzing the data, it is assumed that the first event of the day is an entrance event, and the last event of the day is an exit event. This is a reasonable assumption given the building type and the fact that this building is locked every evening and accessible to only individuals with keys. With this assumption, all occupancy measurements are conservative, and occupancy is defined as the period between the first person entering the building and the last person leaving. This conservatively assumes that the building is occupied at all times between the first and last event of the day. Temporally, occupancy events are high-resolution, and they are recorded to the accuracy of a second. Occupancy is then measured as a percentage representing the percentage of a day that the building is occupied. Building power draw data includes entire power draw of Sakamaki Hall and of HVAC alone in kilovolt-amperes (kVA), in 15 minute intervals. To create congruency between power draw data and occupancy data, occupancy events in this study are rounded to the nearest fifteen-minute interval.

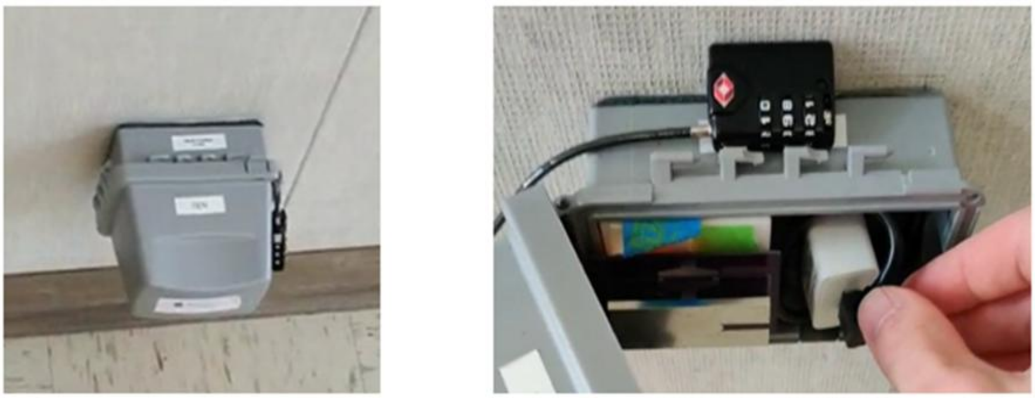

Fig. 5. TruePODS plugged in to AC outlet. Protective enclosure (left), and microSD card access (right).

## 8. Findings

Ideally, a building's energy usage serves its occupants. It provides its occupants with thermal comfort, adequate illumination, and the energy resources necessary to perform a task. Theoretically, there is little need for energy usage when a building is unoccupied. This is especially true in the case of Sakamaki Hall, as it serves no purpose without occupants. Exceptions to this would include buildings that require consistent air temperatures, such as museums with ancient artifacts and server farms, or buildings that automate tasks such as factories or laboratories. With time-referenced occupancy events and energy data, it is possible to study trends in the data to see if Sakamaki Hall effectively matches its power draw to its occupancy. As the data shows, Sakamaki Hall's occupancy and power draw differ across varying categories. Additionally, the data reveals changing correlations between occupancy and power draw, signifying changes in building efficiency given specific parameters. Table 1 and Fig. 6 shows average building power draw and HVAC power draw from March 2020 to February 2021, and occupancy data from June to December 2020. September and October are typically the hottest months at UH Manoa campus, leading to increased HVAC power draw and overall building energy consumption. Taking this factor into account, "weatherized" power draw does not change much during the year.

Table 1. Occupancy and building power draw averages

| Month | Average % Occupancy (by time) | Average Building Power Draw (kVA) | Average HVAC Power Draw (kVA) | HVAC Power Draw (%) |
|---|---|---|---|---|
| Mar '20 | N/A | 63.5 | 13.0 | 21% |
| Apr '20 | N/A | 55.5 | 11.7 | 21% |
| May '20 | N/A | 55.7 | 11.9 | 21% |
| Jun '20 | 56% | 56.7 | 12.0 | 21% |
| Jul '20 | 43% | 60.3 | 15.6 | 26% |
| Aug '20 | 35% | 67.5 | 20.4 | 30% |
| Sep '20 | 36% | 71.9 | 24.8 | 34% |
| Oct '20 | 38% | 65.7 | 20.6 | 31% |
| Nov '20 | 38% | 62.8 | 17.6 | 28% |
| Dec '20 | 27% | 60.3 | 13.0 | 22% |
| Jan '21 | N/A | 58.5 | 12.5 | 21% |
| Feb '21 | N/A | 59.7 | 13.5 | 23% |

Plotting the average percentage of time occupied monthly, average total monthly power draw, and average HVAC power draw, it is immediately apparent that not all three are directly correlated. HVAC and total power draw follow similar trends consistent with outdoor climate, with March appearing to be an outlier. However, average occupancy seems almost entirely uncorrelated with power draw, as shown in Table 1 and Figure 6. Calculations confirm that the correlation coefficient between total power draw and HVAC power draw is almost perfect at 0.93 while the correlation coefficient between total power draw and occupancy is -0.47.

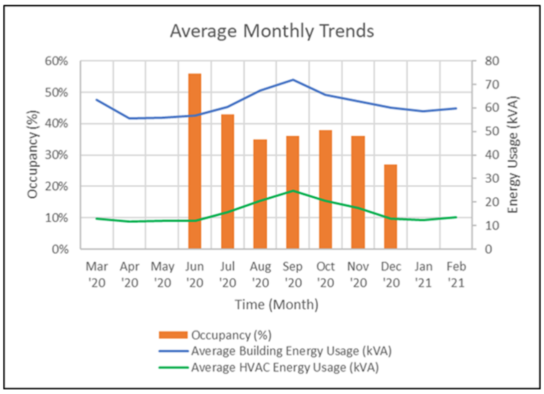


Fig. 6. Average monthly trends

In terms of energy efficiency, ideally a building's energy usage should mirror its periods of occupancy, as was previously discussed. Table 2 shows the average power draw and total power draw during periods of occupancy and vacancy. Although the average power draw in Sakamaki Hall is higher in times of occupancy, the building was unoccupied more than it is occupied. Thus as Table 2 indicates, the total power draw is higher over the combined periods of vacancy than the combined periods of occupancy.

Table 2. Occupied and unoccupied building data

| | Total Power Draw (kVA) | Average Building Power Draw (kVA) |
|---|---|---|
| Occupied | 516,087.90 | 71.5 |
| Unoccupied | 609,951.20 | 56.4 |
| % Change | 18% | -21% |

In a school building, one would expect to find a difference in the occupancy rates, and therefore power draw, on weekdays as opposed to weekends. Most of the academic instruction takes place during the week and faculty can be expected to spend the most time working between Monday and Friday as well. Table 3 shows the average occupancy and average power draw for a weekday and a weekend day. Although data shows that both average power draw and average occupancy percent decrease on the weekends, average power draw only sees a 14% reduction while average occupancy decreases by 30%. This disparity once again demonstrates that there is room for improvement to increase energy efficiency.

Table 3. Weekday and weekend data

| | Average Power Draw (kVA) | Average Occupancy (%) |
|---|---|---|
| Weekday | 64.1 | 43% |
| Weekend | 55.1 | 30% |
| % Change | -14% | -30% |

School buildings also experience seasonality. Although summer classes are offered, it can be assumed that most classes are offered during the traditional school year and that more students attend those classes than ones held in the summer. Therefore, it is reasonable to expect that occupancy rates, and therefore power draw, would be lower during the summer months. However, the summer months are traditionally hotter and HVAC power draw in Sakamaki Hall amounts to an average 25% of total power draw. Therefore, it is also reasonable to expect the opposite to be true, that average power draw would be higher in the summer months, regardless of occupancy. A data comparison of July, a summer month, and October, a traditional school month, shows that neither assumption is correct. Table 4 shows the average power draw and average occupancy for July and October. In this unique case, there is higher power draw in October and lower occupancy, even though more students are expected to be on campus attending classes. One possible explanation for this anomaly is that increased COVID-19 prevention measures during October deterred students and faculty from spending time on campus, but the building continued to consume energy as if classes were taking place to maintain ventilation.

Table 4. Comparison of July and October

| | Average Power Draw (kVA) | Average Occupancy (%) |
|---|---|---|
| July | 60.3 | 43% |
| October | 65.7 | 38% |
| % Change | 9% | -12% |

Other considerations should be made for events on the school calendar which disrupt the normal schedule of events. One such example is the holiday recess which typically occurs in December. In comparing data from the months of October and December shown in Table 5, the average occupancy decreased by 29% while the average power draw only decreased by 8%. This decrease in occupancy is significant even though term-end finals may bring more students than normal to campus in December and the average temperatures are noticeably lower in December than in October. Therefore, there are likely methods which could be implemented to align power draw more closely with occupancy in cases such as this.

Table 5. Comparison of October and December

| | Average Power Draw (kVA) | Average Occupancy (%) |
|---|---|---|
| October | 65.7 | 38% |
| December | 60.2 | 27% |
| % Change | -8% | -29% |

## 9. Recommendations

Although usually expensive, technological improvements to campus buildings could greatly improve the energy efficiency as it relates to occupancy. Creating an effective HVAC model from occupancy sensor data could be used to control HVAC more efficiently. For example, HVAC set points could be adjusted based on the average timing of entrance and exit events or class schedules.

There are also energy saving alternatives in which little to no investment in infrastructure needs to be made. In cases where energy is unnecessarily expended on lighting, and other building loads when there are no occupants present, behavioral change can mitigate some of these losses. The simplest recommendation is to conduct an increased campaign or educational program to build a culture of energy consciousness in faculty, staff, and students. Part of this campaign could include nudges for turning off lights and using posters or signs to prime more energy conscious behavior. Descriptive norms have been proven to be even more effective than an ordinary poster. For example, informing occupants that 85% of students remember to turn off a light is more likely to result in future occupants remembering to turn off the light. Outside agencies could improve energy efficiency on campus through incentives or regulations similar to the state's efforts to transition to 100% renewable energy by 2045 which focuses on transportation and electricity generation. In a similar light, the states could consider creating tiered goals over the next few decades to increase building efficiency and decrease energy waste as buildings account for a large percentage of energy used. The university already has established internal goals and design standards to help us achieve those goals as part of Executive Policy EP4.202 [30].

## 10. Limitations and Future Research

Advanced building studies should not only be based on the contribution of a building's energy usage to the campus's total load, but also based on realistic and feasible upgrades that can be achieved. In addition to considering buildings with higher load profiles, sensors should be deployed in buildings that have different occupancy profiles and topologies. For instance, labs, auditoriums, and the library all experience very different usage patterns and structural layouts. This would allow differing energy management strategies to be studied for spaces with differing baseloads and variability in occupancy. Confounding variables such as temperature should also be further explored to create a more robust energy management model. The addition of more variables and further research will only expand the uses of this data set. It should also be noted that this data was generated during the onset of the COVID-19 global pandemic which undoubtedly impacted occupancy rates and patterns. Therefore, it cannot be assumed that the data presented here is representative of traditional occupancy in years before the pandemic occurred, or current occupancy trends.

Since TruePODS are deployed with the aim of improving energy management, another promising advancement would be expanding the data that they provide through additional sensors. If, for instance, a light and a temperature sensor were included, wasteful behaviors would become more evident and building specific policies and management strategies could be designed to eliminate these. In this case, the sensor would provide data showing when a space was unoccupied and lights were left on, and changes in building temperature over time could assist in developing intelligent HVAC reduction measures. Other research has already proven that Doppler radar can be used to identify direction of movement [31], number of occupants [32], and even individual identity authentication [33]. This increased resolution could be implemented within the current sensor arrays to create even more accurate occupancy data and therefore implement more intelligent energy management practices.

Finally, this research could be expanded by exploring additional uses for the occupancy sensor data. For instance, more robust demand response programs could be developed at the utility level with this data. High resolution occupancy data would enable utilities to better predict which loads could be shed and when during an event that required demand response intervention. This data could enable a prioritization of various zones within a building or could inform a utility as to what loads could be throttled during unforeseen shortfalls. Alternatively, these sensors could be used for space analysis to determine if space resources are used efficiently. Such analysis could reduce the space constraints as student population continues to grow.

## 11. Conclusion

This single building case study illuminated the need for improved energy management strategies on university campuses. Although there are many different sensor technologies which could be used to analyze occupancy, Doppler radar occupancy sensors offer the most advanced methodology and have already proven successful in this setting. More widespread deployment of such occupancy sensors would allow the university to effectively tailor HVAC set point practices and other energy management strategies to specific building occupancy behaviors and trends. This sensor expansion, coupled with a continued and ongoing energy education campaign among building users and occupants, could have a profound impact on reducing energy waste.

## Conflict of Interest

This research was supported in part by the National Science Foundation (NSF) under grant IIP-1831303. Dr. Boric-Lubecke and Dr. Lubecke hold equity and serve as president and vice-president of Adnoviv, Inc, the company that is the prime awardee of the NSF STTR grant that is supporting this work. The University of Hawaii has granted a license to Adnoviv, Inc, to commercialize Doppler radar technology for occupancy sensing purposes, and owns equity in Adnoviv, Inc.

## Author Contributions

Ryan L. Neville wrote the manuscript under Dr. Olga Boric-Lubecke's guidance and aggregated the occupancy data and the power draw data. Farjana Snigdha and Khaldoon Ishmael collected occupancy data with Ryan, and assisted in the analysis of the data. Shekh MM Islam conducted the signal processing that generated accurate occupancy events. Miles Topping provided power draw data for Sakamaki Hall. Dr. Olga Boric-Lubecke, provided oversight and guidance to the research effort. Dr. Olga Boric-Lubecke, Miles Topping, and Victor Lubecke all reviewed the final manuscript.

## Acknowledgement

This paper and the research behind it would not have been possible without the exceptional support of my supervisor, Dr. Olga Boric-Lubecke. Her dedication, enthusiasm, and leadership have been nothing short of inspirational. I am deeply grateful for Farjana and Khaldoon, my faithful lab partners. With their perseverance, dedication, and friendship, onerous hours in the lab passed with ease. I am also grateful for Shekh MM Islam. Without his expertise in signals processing, none of this research could have taken place. A huge aloha and thank you to Miles Topping, the director of Energy Management at the University of Hawai'i. He not only provided power draw data from Sakamaki Hall for this study, but he also gave crucial insights for the university's cutting edge energy management strategies as well as invaluable feedback for this paper. Lastly, thank you to Dr. Victor Lubecke for your insightful comments and invaluable feedback. The generosity and expertise of all have improved this study in numerous ways and saved me from many errors. Those errors that still inevitably remain are entirely my own responsibility.

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