Analysis of energy and cost savings potential of occupancy detection for commercial building operations - case study

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Abstract

Since fixed building operating schedules often do not correspond to the actual occupancy profile, many occupancy sensing technologies inform operations. While many technologies exist to enable "smart" operations in buildings, occupancy detection is not yet implemented on a wide scale. There is very limited information on the overall cost associated with the implementation of occupancy detection in buildings. The objective of this paper is to develop a methodology to quantify the cost, energy, and GHG emission savings for optimizing building management using occupancy data. The methodology will be tested in a case study where a medium-sized office building is analyzed. Appropriate sensor technologies were selected to implement improved space utilization, demand control ventilation (DCV), occupancy-based temperature setback, lighting, and plug load control applications. Next, overall building performance and management were simulated with different occupancy scenarios using MATLAB and EnergyPlus to identify any energy or cost-saving opportunities. Results showed that the initial cost of the energy efficiency measures can be recovered in less than one year if camera-based sensors or Wi-Fi data is used for occupancy detection. The paper discusses the challenges faced in selecting occupancy sensors and provides recommendations for improvement in the framework used for selecting occupancy sensing technology.

Introduction

New and existing buildings are required to achieve high energy performance to reduce greenhouse gas (GHG) emissions without compromising occupants' comfort and health. Occupancy detection technology can provide the required data needed to manage low-energy buildings that are adaptive to different levels of occupancy. Over the years, studies related to occupancy and its impact on building energy consumption have gained momentum. However, progress in embedding intelligence in buildings has been rather slow due to common challenges including (1) the fragmented nature of the buildings market, (2) the customized nature of incorporating intelligence into building equipment, (3) the diversity of systems configurations, and (4) lack of model transferability (Anand et al., 2022; Hong et al., 2020; Lawrence Berkeley National Laboratory (LBNL), 2017). Hong et al. (2020) reviewed the applications of big data and machine learning across all major stages of the building life cycle; from design to operation, control and retrofit. The U.S. Department of Energy developed strategies for selecting innovative technology solutions for managing and optimizing operations of building systems (LBNL, 2017). Kumar and Mani (2017) conducted a life cycle assessment (LCA) of adopting occupancy sensors in office buildings to study the effectiveness of occupancy sensors in reducing net energy consumption over their life span. Neida et al. (2001) analysed the energy and cost savings potential of occupancy sensors for commercial building lighting systems. Sanders & Chinnis (2011) evaluated the energy impact and cost difference in multiple lighting control strategies. Saqib and Azhar (2020) conducted a case study using Life Cycle Cost Analysis (LCCA) to find out best practices for reducing energy consumption in buildings. Addition of occupancy sensors for lighting in hallways and less traffic areas saved up to 2.23% electricity consumption annually.

Occupancy data can aid with many building controls, operations, and management decisions such as HVAC, lighting, and office equipment control, space management, emergency evacuation, cleaning, disease control, and security (Das et al., 2019). Note that "office equipment" here refers to the electrical load for office appliances and other miscellaneous electronic loads that are not related to the lighting or HVAC systems. Each application has different data requirements for resolution and accuracy levels and each detection technology has different capabilities to meet these data requirements.

The purpose of this study is to introduce a methodology for analysing the energy and cost savings potential of occupancy sensing technologies for buildings. A framework was developed by Azimi and O'Brien (2022) as a screening tool for building managers to select and match various occupancy sensing technologies to the appropriate set of building applications. This framework is used in the case study to obtain recommendations on technologies needed for the building applications selected.

Methodology

Figure 1 shows the overall methodology proposed for implementing occupancy sensing technology. First occupancy sensing technology is selected using the framework introduced by Azimi & O'Brien (2022). Recommended technologies should correspond to the selected applications which can be then consulted with experts/vendors to get an estimate for the number of units required for installation and the cost estimate for the technologies. The energy cost savings can be estimated by simulating different building operation modes in EnergyPlus. Additionally, the amount of rentable space can be estimated considering different occupancy levels. Lastly, through cost analysis, the potential benefit of occupancy detection can be proven. If the desired payback period is not achieved by the selected occupancy sensing technology, building applications can be reviewed and another set of occupancy sensing technology can be selected.

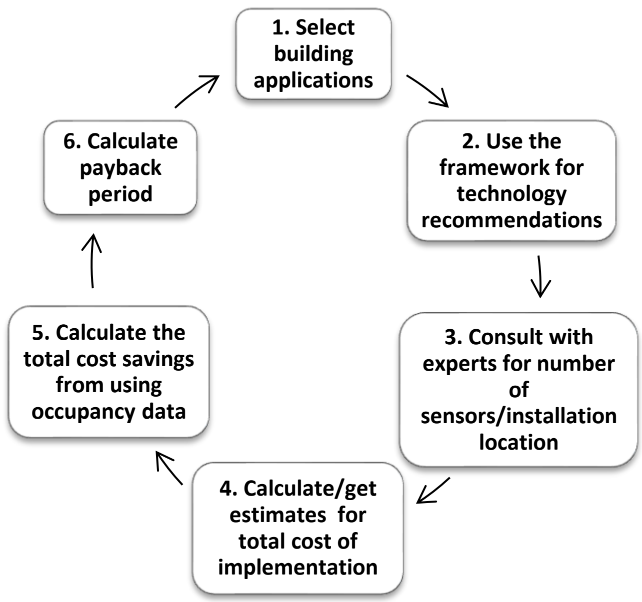

Figure 1: An overview of the proposed methodology for selecting and evaluating the impact of occupancy sensing technology

Case Study

The building selected is a medium-size office building located in Ottawa that consists of six levels, where level one is below-ground. Figure 2 shows the building geometry modelled in SketchUp and Table 1 shows the summary of the base model parameters. The base model is a modified version of the calibrated model by Hobson et al. (2021)

The following building applications are selected for this study: space allocation, demand control ventilation (DCV), occupancy-based temperature setback, lighting, and office equipment control. Using the web-based tool, appropriate technologies/technology combinations are chosen. Next, overall building energy performance is simulated with three occupancy scenarios (0% occupancy (vacant/empty building), 50% occupancy (half occupied), and 100% occupancy (fully occupied)) using MATLAB and EnergyPlus. Note that occupancy was a calibration parameter and the calibrated value for 100% occupancy level is 31.3 m^2/people. Lastly, the implementation cost of occupancy detection technology is calculated and compared with overall savings in building operation. Note that for simulating the base case, power density values for lighting and equipment were kept constant and operated based on the schedule mentioned in Table 1.

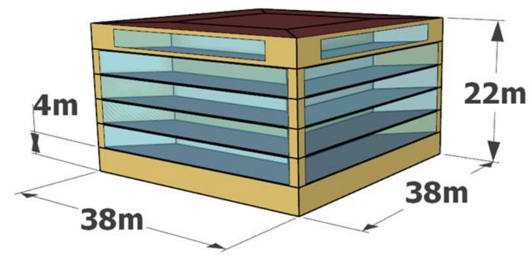

Figure 2: A medium-size office building modelled in SketchUp

Table 1: Base model description

Base model	
Number of floors	6
Total floor area	1429 m² per floor * 6 = 8573 m²
Walls	R-value = 2.24 m^2-K/W
Window to Wall Ratio (WWR)	Level 2,3,4,5 (85% WWR) Level 6 (50% WWR)
Double glazed window	U-value = 3.08 W/m^2-K, SHGC= 0.31
Infiltration	0.27 L/s-m^2
HVAC	AHU 1 serves perimeter zones across all floors AHU 2 serves core zones across all floors.
	VAV terminals with reheat coils for every zone
	Heating setpoint = 22.5 °C Cooling setpoint = 23.5 °C
Occupancy schedule	6 am to 7 pm on weekdays
Lighting and office equipment schedule	6 am to 7 pm on weekdays, with 51% and 55% of lights and office equipment remaining on after-hours respectively
Light power density	15.66 W/m^2
Office equipment power density	15.66 W/m^2

Building applications

Space allocation

Real estate is the second-highest cost for businesses, second to labour costs (Gordon Brown, 2008). In this case study, we compare real-time occupancy data with occupancy levels that are assumed for this medium-size office building to compare how space utilization and energy consumption change under different occupancy levels. The maximum measured occupancy of this building is approximately 223 people or 38 m^2/person (see Figure 3). Occupancy levels in Figure 3 are measured from Wi-Fi data. The calibrated model shows that the building is operated with the assumption that people density is closer to 31.3 m^2/person. In this case study, the impact of different occupancy levels on demand for space is studied.

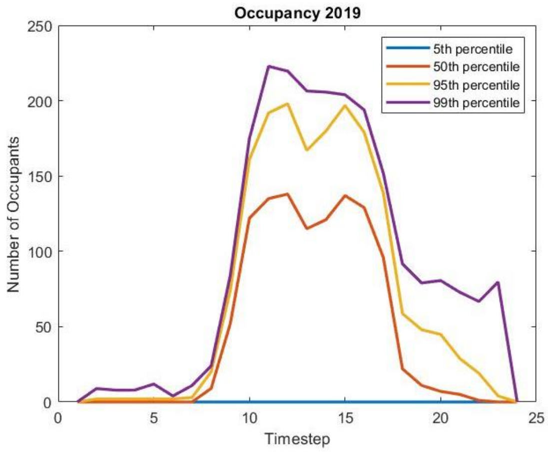

Figure 3: Measured occupancy for the building being studied

Demand Controlled Ventilation (DCV)

In HVAC systems with variable drive air handling units, ventilation rates can be adjusted to the level of occupancy (Shih and Rowe, 2015). In this case study, we look at the impact of occupancy on energy consumption and quantify savings in energy and GHG emissions. Energy usage can be reduced by adjusting the opening rate of the air damper or air conditioner based on occupancy count information. Demand controlled ventilation (DCV) is simulated in EnergyPlus where outdoor ventilation air is delivered to occupied zones based on CO_2 levels, which vary based on occupancy levels.

Temperature setback

While the AHUs operate based on a schedule, the air system for this model is set up such that if one or more zones become too hot or too cold, AHUs will turn on. Thus, to reduce heating consumption for the building, the heating temperature setpoint is scheduled to change based on occupancy arrival/departure times. During occupied times, the temperature setpoint for heating is 22.5℃. When zones are unoccupied temperature setpoint for heating is set to 17℃.

Lighting

To promote energy savings in buildings, the occupancy-based lighting control strategy is used. Occupancy-based lighting control refers to controlling luminous intensity based on the presence of occupants in a given space (de Bakker et al., 2017). To simulate occupancy-based control, lighting for above-ground levels is adjusted based on the occupancy schedule in EnergyPlus. 5% of underground level lights are kept on after-hours for safety purposes.

Equipment

A significant portion of office equipment energy use occurs when occupants are not present (Gunay et al., 2016). One way to lower office equipment energy use is to activate electrical receptacles when occupants are present and deactivate receptacles when the space is vacant (O'Brien et al., 2017). In this study, we simulate the impact of occupancy by activating office equipment based on the occupancy schedule in EnergyPlus (office equipment in above-ground levels turns off when the zones are unoccupied). Equipment loads for the underground level are kept on (not adjusted based on occupancy) to represent additional loads like fridges and network equipment.

Recommended occupancy sensing technologies

The web-based tool introduced by Azimi and O'Brien (2022), recommends sensors/technologies based on the most demanding data requirement from the selected applications, thus each recommended technology should be able to provide adequate occupancy data for all the selected applications. See Table 2 for the recommended technologies.

Table 2: Recommended sensor types from the website

Sensor type	Occupancy resolution	Spatial resolution
Time of flight (TOF)/ Binocular/ Structured light (SL)/Thermal camera	Count	Workstation
Optical camera	Identity	Workstation
Wi-Fi	Tracking	Workstation

Expert recommendations/cost estimate

The number of sensors is determined based on the applications' data requirements. Based on the applications selected, we need an occupancy count at the workstation level (see Table 3).

Table 3: Application data requirement according to Azimi and O'Brien (2022)

Application	Occupancy resolution	Spatial resolution	Accuracy
Space utilization	Count	Floor	Medium
DCV	Count	Floor	Low
Temperature setback	Presence	Floor	Low
Lighting	Presence	Room	High
Equipment	Presence	Workstation	High

The total cost of implementing occupancy sensors includes the hardware, installation, and recalibration/maintenance costs. The installation costs include labour costs for installing sensors and supporting infrastructure if it does not already exist. In an email (A. Saydi, personal communication, February 22, 2022) it was suggested that the major cost for implementing occupancy sensors is associated with the delivery of the project (site visits, cabling, proposing locations, and installation). During an interview conducted on February 25, 2022, J. Lampert mentioned that overall implementation cost will decrease as the number of units requested increases across multiple buildings.

After consulting vendors for camera-based occupancy sensors in an email (M. Steg, personal communication, February 23, 2022), thermal cameras were eliminated from the selection as they require technicians to install and maintain, thus not recommended for widespread implementation as it's not cost-effective.

During an interview conducted on February 16, 2022, A. Saydi stated that for occupancy count, camera-based sensors are typically installed at access points to monitor the flow of traffic on each floor. For more granular analytics such as monitoring occupancy at the workstation level, motion sensors (e.g., PIR, ultrasonic, microwave, and break beam) or electro-mechanical sensors (e.g., door sensor, piezoelectric sensors) are recommended as they are more cost-effective.

In an email with A. Saydi, the following locations were suggested for the installation of camera-based sensors: near elevators, exits leading to staircases, meeting rooms, and lobby entrances. Sensors above each access point to different levels will provide data on movement and visits to each floor. Monitoring occupancy levels at floor level can help to identify unoccupied or underutilized spaces for rent. Sensors installed at lobby entrances can count how many people are entering the building and what times are the busiest. This can help security teams to understand when to staff doors or have greeters. With the recommended installation locations, approximately 48 camera-based sensor units are required, and the cost of implementing the technology is listed in Table 4.

Wi-Fi data is another option for occupancy detection. In an email (S. Storey, personal communication, February 22, 2022) it was stated that Wi-Fi data can be collected at each control zone which may vary depending on the application. For instance, for HVAC control purposes, each area served by a VAV box can be considered a control zone. For this building, we consider 30 zones for Wi-Fi data collection.

Typically, buildings have Wi-Fi, thus no hardware/infrastructure cost is associated with counting occupancy using Wi-Fi data. Additionally, there are no recalibration and maintenance costs since the data is simply collected from the existing IT infrastructure. However, there is an additional license required to access Wi-Fi location service data, typically charged by the number of Wi-Fi Wireless Access Points (WAP). The cost of Wi-Fi data for occupancy detection purposes is listed in Table 4.

Table 4: Occupancy detection technology implementation cost

Sensor type	Initial investment (includes hardware and one-time installation cost)	Monthly cost (includes calibration/ maintenance cost)
Camera-based sensor	\$100,000-150,000	\$1200-\$2000
Wi-Fi data	\$40,000	N/A

Energy and Cost Savings

According to data collected from Ottawa commercial brokerages, the net annual rental cost for a medium-sized office building (6-10 levels) is around \$3,700,000 (Mullin and Satmari, 2021). If the space demand is less than what is assumed (real occupancy density is closer to 38 instead of 31), it is estimated that around 1,596 m^2 of space can be made available, resulting in \$687,043 savings in rental costs. For this case study, there is no information provided on different types of space and how the space is currently utilized and it is assumed that space utilization is strictly impacted by the number of people across every floor.

Table 5: Rental cost vs. occupancy detection implementation cost

Maximum simulated occupancy	31.3 (m^2/person)
Maximum predicted real occupancy	38 (m^2/person)
Monthly lease cost (Mullin and Satmari, 2021)	430.56 (CAD \$/m^2/year)
Total floor area	8573 m^2
Annual rental cost for the whole building	3,691,208 (CAD\$/year)
Potential rentable space	(38-31.3 m^2/person) * 223 person= 1596 m^2
Rent cost savings	687,043 (CAD \$/year)

Occupancy-based lighting, office equipment (or plug load) control, temperature setback, and DCV individually can improve overall energy performance (see Figure 4). The most energy reduction occurs when all the occupancy-based control measures are combined. The impact is more significant when the building is empty, with up to 75% reduction in electricity and 45% reduction in cooling energy consumption. Occupancy-based lighting and office equipment control reduce internal heat gains, resulting in higher demand for heating as shown in Figure 4 (up to 20% and 21% increase in heating consumption for occupancy-based lighting and office equipment control respectively). However, DCV saves up to 6% when the building is empty and occupancy-based temperature setpoint saves up to 14.4% when the building is fully occupied for heating consumption. The heating coils for this building are gas-powered and the cooling and baseboards are electric. When all the technologies are combined, there is still a reduction in heating coil energy usage as electric baseboards compensate for a portion of heating demand (see Figure 4 and Figure 5). As shown in Figure 5, there is a 47,464,300 gCO_{2eq} reduction in GHG emissions for electricity when the building is empty and a 4,702,200 $kgCO_2$ reduction in GHG emissions for natural gas when the building is fully occupied. GHG emissions are calculated by multiplying total electricity consumption by the annual Average Emission Factor (AEF) for Ontario, which is 31 g CO_{2eq}/kWh (The Atmospheric Fund, 2021), and for natural gas CO_2 emissions factor is 63.29 (kg CO_2/GJ) in Ontario (Government of Ontario, (2016)).

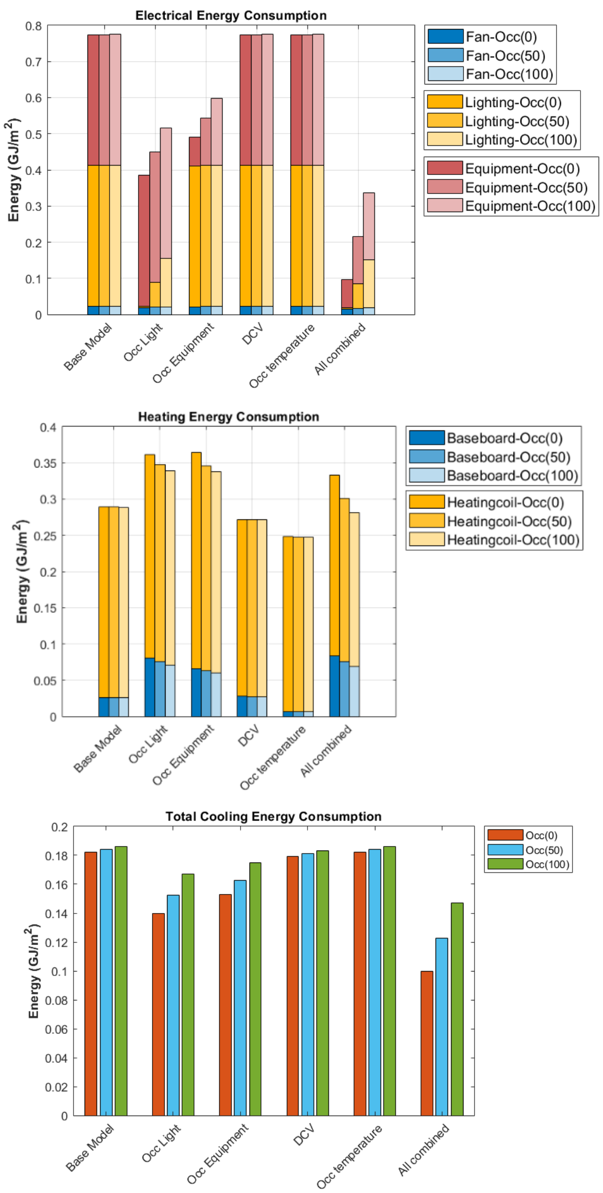

Figure 4: Impact of occupancy-based lighting, equipment control, DCV, occupancy-based temperature setback, and all occupancy-based control measures combined for electricity, heating, and cooling energy consumption

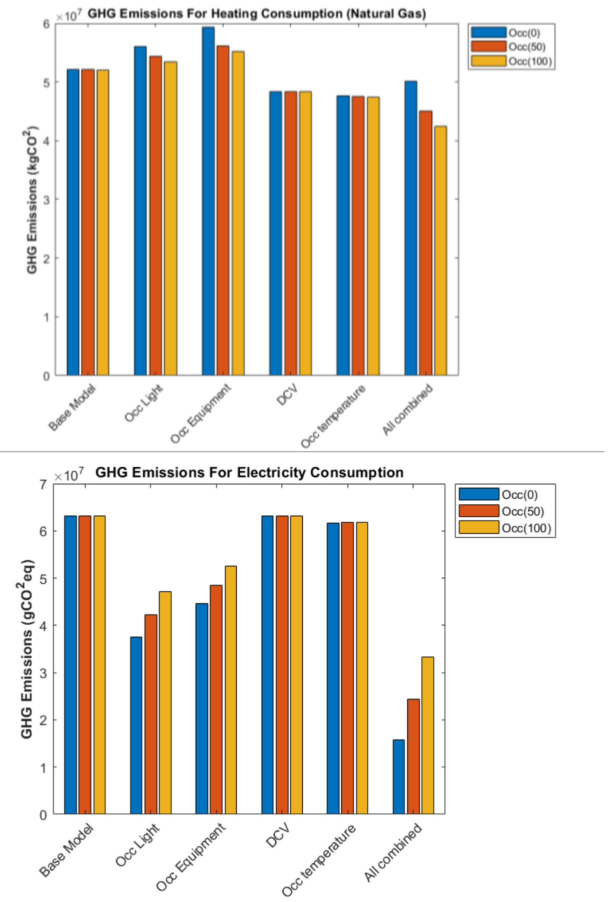

Figure 5: Annual GHG emissions from electricity and natural gas consumption

The web-based tool recommended technologies that are best suited for the applications selected, though some issues were discovered. First, the tool suggests that Wi-Fi data provides tracking information at the workstation level. S. Storey indicated in an email that although Wi-Fi data is relatively inexpensive and scalable, it is not sufficiently accurate for the workstation level of resolution (personal communication, February 22, 2022). Wi-Fi data was recommended mainly for HVAC control purposes.

The camera-based sensors were another recommendation for the applications selected in this case study. The tool suggests that camera-based sensors can collect information at the workstation level however after consulting with vendors, it was advised to install camera-based sensors at floor or room level (not recommended to install in all private offices) for the selected applications. Based on the recommended installation locations, Wi-Fi data and camera-based sensors can provide occupancy count data at floor/room level. This is sufficient data to control ventilation rate and turn HVAC equipment on/off based on occupancy and studying space utilization. Though the recommended technologies and the installation locations do not provide sufficient data to control equipment plug load or lighting for private offices/workstations. Thus, other solutions need to be considered to implement all the required applications. The recommended technologies can provide sufficient information to provide occupancy data to study space utilization and implement occupancy-based HVAC control. Figure 6 shows that when DCV and occupancy-based temperate setback are combined, there are up to 2.38% reduction in electricity and 1.80% reduction in cooling energy consumption when the building is empty, as well as 23% reduction in heating when building is fully occupied. As shown in Figure 7, from using DCV and occupancy-based temperature setback combined, there is up to 2.38% reduction in electricity cost when building is empty and 19.4% savings in natural gas cost when building is fully occupied.

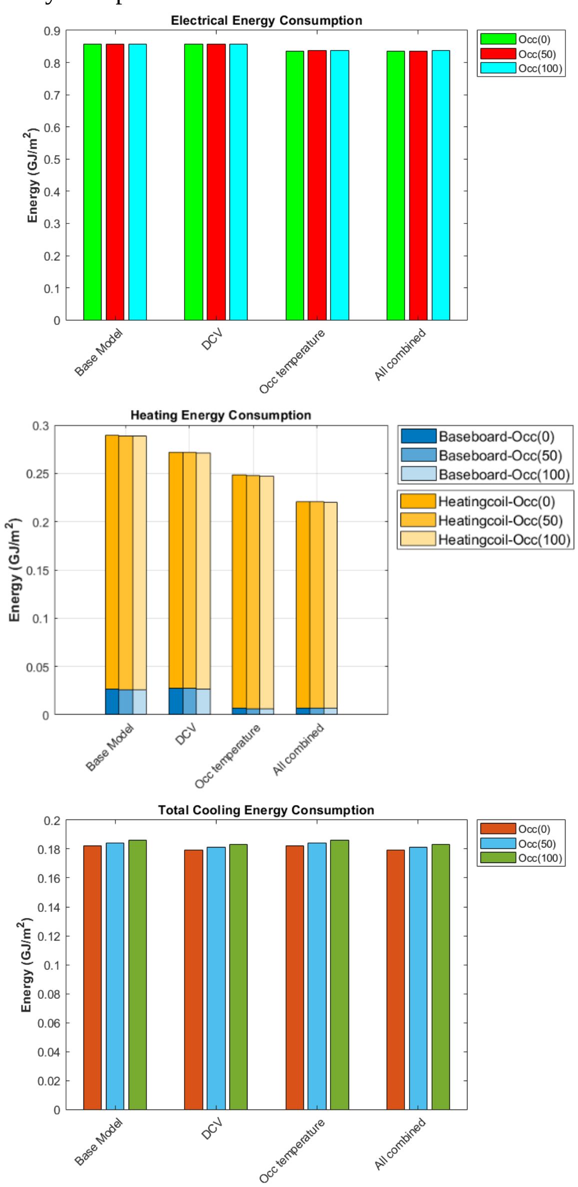

Figure 6: Electricity, heating, and cooling energy consumption for DCV, occupancy-based temperature setback, and the two combined

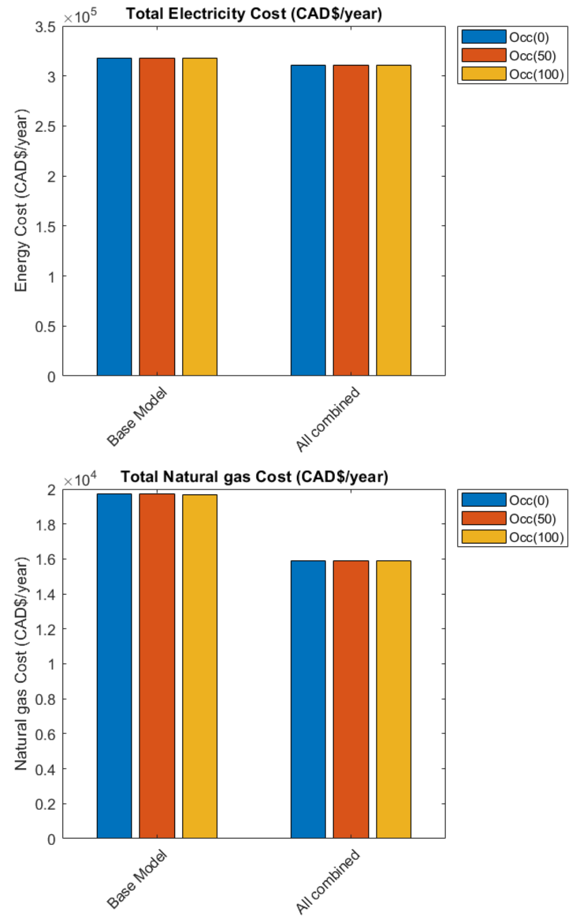

Figure 7: Annual electricity and natural gas cost for base model vs. DCV and occupancy-based temperature setback combined

Payback period (PBD)

The payback period is an indicator to define the amount of time it takes to recover an investment. Using the net present value method, the payback period of installing occupancy sensors can be calculated using equation (2) (Norouziasl et al., 2019). *C* is the total cost of the investment for implementing occupancy sensing technology. *AES* is the estimation of annual energy and rents savings in dollars from installing the sensors. *r* is the inflation rate (which is 1.9% as of 2019 according to (*Statistics Canada, 2019*). This value is considered as representative of a long-term average inflation rate in Canada. Lastly, PBP is the payback period of installing occupancy sensors as the number of years.

$$C = AES\left[\frac{(1-(1+r)^{-PBP}}{r}\right] \tag{1}$$

$$PBD = -log_{(1+r)}\left(1-\frac{C}{AES}*r\right) \tag{2}$$

Based on the rent savings (see Table 5) and energy cost savings shown in Figure 7, the discounted payback period for camera-based technology is about 0.22 year and for Wi-Fi is 0.06 year, all less than one year which is acceptable for this case study. Note that the cost of electricity and natural gas was calculated based on the utility rates stated in a report for the building being studied (*Carleton Energy Master Plan Final Report*, 2021). For electricity the blended average rate is \$0.156/kWh and for natural gas the average rate is \$0.246/m^3.

Conclusion

The study reports on the impact of occupancy-based controls on building performance and management. The benefits of occupancy sensing technology were proven by studying the potential energy and cost savings. Originally, space allocation, demand control ventilation (DCV), occupancy-based temperature setback, lighting, and office equipment control applications were selected. However, after consulting with experts it was concluded that the selected occupancy sensing technologies were sufficient to provide data for space utilization, DCV and occupancy-based temperature setback purposes. Results show that when DCV and occupancy-based temperate setback are combined, there are up to 2.38% reduction in electricity and 1.80% reduction in cooling energy consumption when the building is empty, as well as 23% reduction in heating when building is fully occupied. If the space demand is less than what is assumed (real occupancy density is closer to 38 instead of 31 m^2/person, it is estimated that around 1,596 m^2 of space can be made available, resulting in \$687,043 savings in rental costs. Based on the energy and rent savings mentioned, the discounted payback period for camera-based technology is about 0.22 year and for Wi-Fi is 0.06 year, all less than one year which is acceptable for this study.

Space utilization was only measured based on occupancy density for the case study. In the future, usable spaces such as meeting rooms, office space, etc should be monitored on each floor. This can be done through manual observations (Tagliaro et al., 2021) or occupancy sensors. Additionally, future work should focus on improving the web-based tool suggestions and providing alternative solutions for more granular levels of data collection that are cost-effective.

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