Nudging window use behaviour through algorithmic setpoint adjustments

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Abstract

Mixed-mode buildings combine natural ventilation and mechanical ventilation. The use of mixed-mode ventilation can enhance occupant comfort and reduce energy consumption of buildings. While mixed-mode buildings are common in Canada, inappropriate usage of operable windows by occupants can result in unnecessary energy use. Therefore, regulating occupants' window use may be necessary to ensure energy efficiency. Previous research demonstrates that the implementation of behaviour-nudging algorithms has the potential to optimize window use. Building performance simulations (BPS) conducted in the past show that implementing occupant-centric control (OCC) algorithms can yield energy reductions. In this paper, field tests have been conducted in a living-lab facility in Ottawa, Ontario with 24 offices to verify simulations results. OCC algorithms applied temporary temperature setpoint overrides in the summer and winter to nudge occupants to close windows when natural ventilation was not suitable. Analyzing the results, the algorithms successfully nudged occupants to close windows when natural ventilation was not ideal and reduced the heating energy by approximately 16.7%.

Introduction

Occupants spend approximately 90% (Klepeis *et al.*, 2001) of their time indoors, prompting significant efforts to ensure their comfort in buildings. Mechanical ventilation systems have traditionally been employed to ensure occupant comfort within buildings by regulating indoor air quality and thermal comfort. Despite its benefits, it often results in high energy consumption and occupant discomfort.

As outlined by O'Brien and Gunay (2014), perceived control over the thermal environment has a strong impact on the productivity and comfort of occupants. However, occupants who lack control over their environment will develop their own remedies to discomfort which may lead to unpredictable and excessive energy usage. Recently, buildings have been adopting highly automated building systems that are aimed at improving energy efficiency and improve occupant comfort. This often results in reduced occupant satisfaction due to the loss of perceived control.

In response to these challenges, mixed-mode ventilation was introduced as an alternative approach to mechanical ventilation. Mixed-mode ventilation is the combination of mechanical and natural ventilation; it is also known as hybrid ventilation (Liu, Gunay and Ouf, 2021).

Despite the potential energy savings from using mixed-mode buildings, occupant behaviour is often ignored. However, occupants are not passive objects, and influence the environment around them (Gunay, O'Brien and Beausoleil-Morrison, 2016). As a result, neglecting occupant behaviour may result in increased energy use.

Operable windows can provide natural ventilation, reducing the need for mechanical ventilation and energy consumption in certain conditions. However, effectively incorporating operable windows with mechanical ventilation successfully, remains to be a challenge. A potential solution to incorporating operable windows in buildings is installing fully automated windows. However, installing fully automated windows in buildings is costly and may remove occupants' sense of control (Ackerly and Brager, 2013). Therefore, a method to systematically encourage occupants to voluntarily operate their windows when appropriate may be suitable.

Literature Review

As specified by Parkinson, De Dear and Brager (2020), occupants should be able to control their thermal environment, especially in hybrid buildings, where occupants can potentially benefit from natural ventilation.

A potential solution investigated by Ackerly and Brager (2013) is the use of signaling systems to inform occupants of when to open or close their windows. They conducted a study investigating why and how 'open window' signals are designed and implemented as well as the effects they have on occupant behaviour. From the study, approximately 30% of the participants were influenced by the window signal. Even though they did not monitor window use behaviour or measure the energy-saving potential of window signals, they were able to conclude that occupants are typically less likely to act unless they are uncomfortable. Another study conducted by Gunay, O'Brien and Beausoleil-Morrison (2016) found that operable windows in buildings can

increase space heating load by approximately 15%. Additionally, a study conducted in Brazil by De Vecchi et al. (2017) found that some occupants continued to rely on air conditioning rather than open their windows, even when natural ventilation would have been suitable.

A simulation-based study conducted in Ottawa by Liu, Gunay and Ouf (2021) investigated window use behaviour in two office buildings. It noted that windows stayed open the longest during the summer seasons. It also highlighted that windows were typically not opened during the shoulder seasons when natural ventilation would be ideal. Liu, Gunay and Ouf (2021) observed that some occupants tended to leave their windows open for long periods, even when natural ventilation was not favorable. It was also seen that when indoor temperatures were between 24˚C and 27˚C, occupants were less likely to open their windows and were more likely to use their thermostats to control their indoor temperature.

Based on the previous studies outlined, occupants need influence to prompt actions. Just-in-time adaptive intervention (JITAI) is a method used in public health to provide people with necessary information when needed (Miller *et al.*, 2022). This would allow people to make informed decisions related to their health when needed. With technological advancements, it has become easier and more cost-effective to collect data from occupants (Miller *et al.*, 2022). Miller et al. (2022) tested the potential of JITAI and its ability to influence human behaviour by collecting real-time data in a city-scale context. The collected data was beneficial in understanding the occupant's sentiments and responses based on the surrounding environment. Based on their findings, Miller et al. (2022) suggested that the application of JITAI may be beneficial across many fields. For instance, JITAI interventions could be applied to buildings with mixed-mode ventilation to influence occupants to open and close windows.

The use of heating, ventilation, and air conditioning (HVAC) terminal devices to nudge occupants to close or open windows using building performance simulations (BPS) was studied by Liu, Gunay and Ouf (2022). The simulation indicated that the percentage of open windows when window operations are regulated decreased in the heating season and increased in the cooling season. Additionally, it was demonstrated that regulated window operations can reduce building energy use by approximately 3-16%.

However, it is necessary to note that this study utilized BPS and stochastic occupant behaviour models. As a result, the response of an actual occupant remains unclear. Additionally, while BPS is valuable in providing preliminary data, field tests are necessary to gather data that more accurately represents occupant behavior. Occupant-centric control (OCC) is a control system that utilizes information about occupants to regulate building controls and operation (Park, Ouf, Gunay, Peng, O'Brien, Kjærgaard, *et al.*, 2019; Nagy *et al.*, 2023). OCC can be classified into two categories: occupancy-based controls and occupancy-behaviour controls. Occupancy-based controls focus on occupants' presence, and occupancy-behaviour controls focus on occupants' preferences. In the literature review conducted by Park, Ouf, Gunay, Peng, O'Brien, Kjærgaarde, et al. (2019) it was found that more studies focus on occupancy-based controls than occupancy-behaviour controls. Of the few occupancy-behaviour studies conducted, most of these studies considered a study duration of fewer than three months and tested the algorithm in fewer than 10 zones.

Study Objectives

Much of the research conducted in the past highlighted how occupants typically do not use windows appropriately, often resulting in excessive energy use. Occupants tend to neglect the use of natural ventilation, even when natural ventilation is ideal. Studies conducted in the past contain limitations that require further investigation. Very few field studies have been implemented in cold climates to study how behavior nudging algorithms can be utilized to encourage occupants to open and close windows.

Furthermore, a literature review conducted by Nagy et al. (2023) suggests that improving occupant window use based on occupant preferences can improve energy efficiency, indoor environmental quality (IEQ), and occupant comfort without compromising occupants' perceived control over their indoor environment. To verify the effectiveness of implementing OCC algorithms in a living-lab facility in impacting occupant behaviour and energy consumption, and to address limitations from previous studies, this study aims to:

(1) Investigate how implementing OCC algorithms in an office building will nudge occupant behaviour and;

(2) Quantify the impact of behaviour-nudging OCC algorithms on building energy use.

By analyzing occupant responses to OCC interventions and quantifying energy consumption, this paper seeks to provide insight into the potential benefit of utilizing OCC algorithms in building automation systems (BAS).

Method

Office Selection

To analyze occupant responses to OCC interventions, field tests were conducted in a living-lab facility located in Ottawa, Ontario, as represented in Figure 1. The climate of Ottawa is designated as ASHRAE Zone 6 and has heating degree days of 4500 (Canadian Commission on Building and Fire Codes and Canada. Natural Resources Canada, 2020).

Figure 1: Living-lab facility used in the analysis

Within this building, 24 private offices were selected for the field implementation of the OCC algorithm to monitor occupant window use behaviour and energy consumption. As these offices are located in a living-building facility, they have unique sensor instrumentation and monitoring capabilities, not commonly found in actual buildings. Each office is equipped with zone-level thermal energy submeters that monitor each variable air volume (VAV) reheat coil and perimeter heating device, as well as thermal energy meters that monitor AHU heating coils. The offices also contain operable windows, each equipped with window contact sensors integrated with the BAS and occupancy sensors. As a result, these rooms were selected due to their capabilities, which allow for the measurement and verification of algorithmic interventions. Figure 2 outlines the floor layout of the offices included in the study.

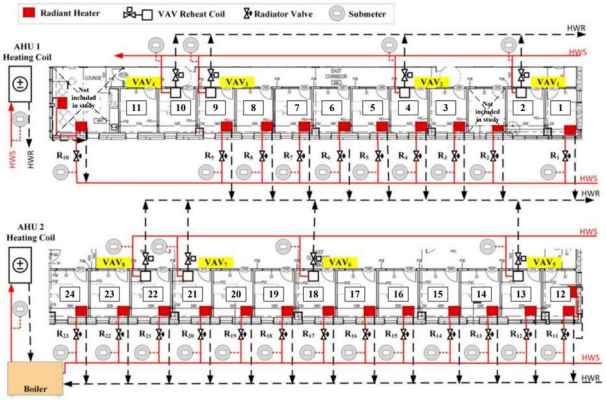

Figure 2: Floor layout of offices included in the study (Zaeri Esfahani et al.*, 2023)*

Each private office selected for the study accommodates a single occupant. The intervention was implemented by the facilities management team (FMP) without notifying the occupants to minimize potential bias. Working in collaboration with FMP, data were collected to understand the impact the intervention had on both occupants and energy consumption.

Figure 3 outlines the phases of the study that were implemented. The study was completed by collecting historical data (also known as pre-intervention data) and post-intervention data. The pre-intervention data, spanning January 2019 to April 2022, serve as a baseline for comparison with the post-intervention results.

The intervention was implemented in May 2023, and aimed to nudge occupants to close their windows when natural ventilation is not ideal, based on outdoor temperature. Data collection for the post-intervention phase began in June 2023. These data were used to determine the benefit of the intervention by comparing it to the pre-intervention baseline.

Overall, the methodology involves analyzing the window opening fraction, representing how long the window remained open, and the energy consumption before and after the intervention.

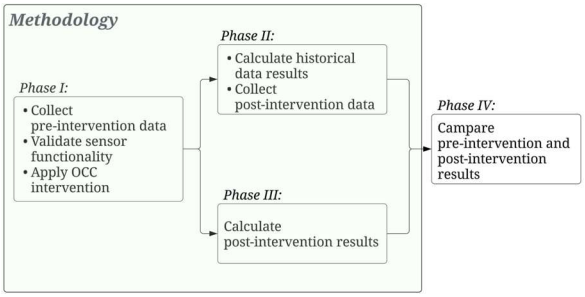

Figure 3: Phases of the study

The energy consumption analysis was conducted following Option B of the IPMVP for baseline modelling (Efficiency Valuation Organization, 2018), considering the energy use of the 24 offices included in the study. Table 1 lists the sensors utilized to conduct the energy consumption analysis.

Table 1: Sensors used in the study along with the manufacturer-provided instrumentation error (Bursill, 2020)

Measured Quantity	Instrumentation error
Radiant heater flow rate	±5% full scale (30 l/h)
Radiant heater inlet/outlet temperature	±0.2°C
Reheat coil flow rate	±5% full scale (30 l/h)
Reheat coil inlet/outlet temperature	±0.2°C
Return air temperature	±0.2°C
VAV airflow	±1% full scale (5 Pa)
VAV supply air temperature	±0.2°C

To ensure that the window sensor was working correctly, a site visit was conducted during the early stages of the study. Each window included in the study was opened and closed to validate that the sensor was recording the window action. Rooms where the sensor appeared to be faulty were exempt from the study. Furthermore, rooms that were different from the usual office setup, such as breakrooms, were not considered, ensuring consistency was maintained throughout the study.

Considering that the study encompassed private offices, each occupant could personalize their office as they pleased. Therefore, not all occupants have the same level of access to their windows, as depicted in Figure 4. In some offices, the placement of plants or other obstructions can add

obstacles to the occupants' desire to close their windows even when the use of natural ventilation is not ideal.

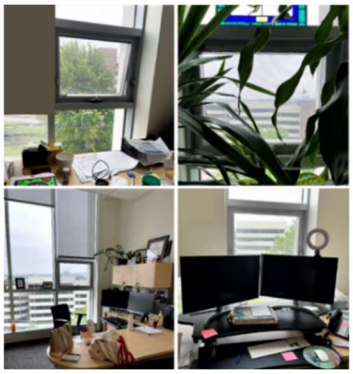

Figure 4: Private offices included in the study

Algorithm Intervention

The initial step of conducting the field studies was to implement the OCC algorithm that will nudge occupants to close their windows when natural ventilation is not ideal, as depicted in Figure 5. Since the building's cooling setpoint is 23.5 ˚C, if the window was open when the outdoor temperature was greater than 24 ˚C, a cooling setpoint of 27 ˚C was applied to nudge the occupant to close the window. Similarly, if the window was open when the outdoor temperature was less than 0 ˚C, a heating setpoint of 18 ˚C was applied to nudge the occupant to close the window. Although the occupants have not been informed of the intervention, they would still be able to observe the active setpoint and room temperature displayed on the thermostat.

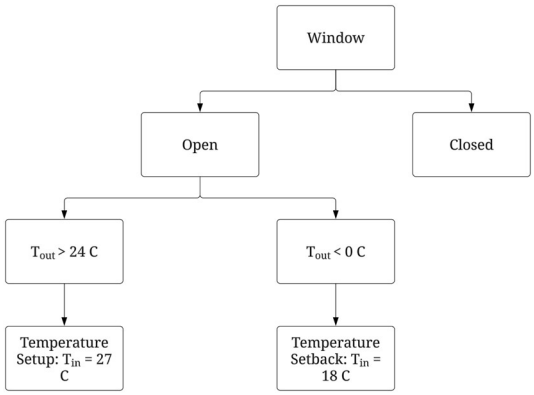

Figure 5: Algorithm implemented in the field study

Data Collection

The algorithm was implemented on May 22nd, 2023 and most of the data collection began on June 14th, 2023. Due to few issues in the data collection process, the collection of data related to energy consumption did not begin until November 22nd, 2023. As a result, the energy consumption analysis is only conducted for the heating season. As more data are collected, an energy consumption analysis to estimate the energy savings resulting from the use of OCC algorithms in both the cooling and heating seasons is planned.

To address the research questions of this paper, the analysis involved the comparison of the pre-intervention and post-intervention data. The pre-intervention and post-intervention data collected included window position data, energy use data, and outdoor temperature data.

To ensure comparability of the pre-intervention and post-intervention data, the occupancy during each period of analysis was examined. It was revealed that the occupancy between the two comparison periods was similar indicating that they can be compared to validate the effectiveness of the intervention.

These data sets were then used to determine how window use behaviour was impacted due to the implementation of the OCC algorithm. This analysis was completed by calculating the window opening fraction, representing how long the window remained open, and frequency of interaction with the window using both pre-intervention and post-intervention data. Furthermore, a univariate change point model was developed to determine the energy consumption before and after the intervention. This model was used to quantify the energy savings that resulted from the OCC intervention.

To ensure the change point model was providing accurate results, the outliers were removed from the analysis. The outliers were removed using the *isoutlier* function in MATLAB. The outliers were removed using the Grubbs' test for outliers. This method assumes that the data are normally distributed and removes outliers iteratively. The Grubbs' test static is calculated based on the sample's mean and standard deviation, where the threshold is set as 0.05 in MATLAB. If the test static exceeds the specified threshold, then the data point is considered an outlier and removed from the data set (National Institute of Standards and Technology, no date). Figure 6 depicts the impact of removing outliers from the pre-intervention data. Analyzing the pre-intervention data, a few unreasonably high points, accounting for 0.33% of the data, were removed. The post-intervention data seemed to not contain any outliers, and therefore no points were removed.

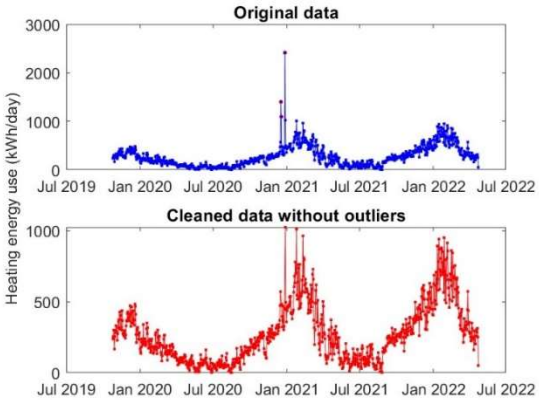

Figure 6: Pre-intervention heating energy use before and after outliers were removed

Additionally, to ensure consistency in the energy consumption analysis, the pre-intervention period considered was equivalent to the post-intervention period. As a result, the pre-intervention period considers the timeframe from November to April. Afterward, the model was used to compare predicted and measured energy use.

Results

Window Opening Fractions

As the window position data is binary, with 0 and 1 indicating a closed and open window, respectively, a logistic linear regression model was created. This model was used to determine the relationship between the window opening fraction and the outdoor temperature. As shown in Figure 7, the window opening fraction fluctuates from year to year, with the most significant variation between 2019 and 2020-2022. Nevertheless, it is evident that before the intervention was implemented, a considerable number of windows were open when natural ventilation was not ideal. Before the intervention was implemented, approximately 25-35% of the windows were open when the temperature was below 0 ˚C. When the temperature was above 25 ˚C, approximately 25-45% of the windows were open. After the algorithm was implemented, when the temperature was below 0 ˚C, the window opening fraction was reduced to near 0%. When the outdoor temperature was above 25 ˚C, the window opening fraction was reduced to approximately 5%. The logistic regression equations are listed in Table 2 where t is the outdoor temperature and y is the window opening fraction.

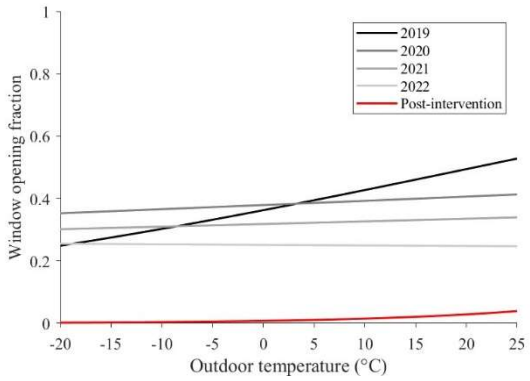

Figure 7: Logistic regression models presenting the relationship between the window opening fraction and the outdoor temperature

Table 2: Logistic linear regression equations

Year	Equation
2019	y = 1/{1+exp(-[-0.5633 + 0.0270×t])}
2020	y = 1/{1+exp(-[-0.4928 + 0.0057×t])}
2021	y = 1/{1+exp(-[-0.7613 + 0.0039×t])}
2022	y = 1/{1+exp(-[-1.0903 - 0.0010×t])}
Post-intervention	y = 1/{1+exp(-[-4.8299 + 0.0653×t])}

Window Opening Duration

Further analysis was conducted to represent the percentages of windows open based on the outdoor temperature. These percentages represent the number of hours where the specific conditions were met, relative to the total number of hours observed during the analysis period. The pre-intervention analysis period considers the timeframe from October 2019 to April 2022. The post-intervention analysis considers the timeframe from June 2023 to April 2024.

During the cooling season, when the outdoor temperature is above 24 ˚C, some windows remained open for an average of 43% of the time before the intervention was implemented, as seen in Figure 8. After the intervention was implemented, the duration during which windows were left open when natural ventilation was not ideal decreased to an average of 2.9%.

There are a few occupants who appear to have their windows open for longer periods after the intervention compared to before, such as the occupants in rooms 8, 10, 13, 20, and 23. However, the majority of the occupants were nudged to close their windows when the outdoor temperature was above 24 ˚C.

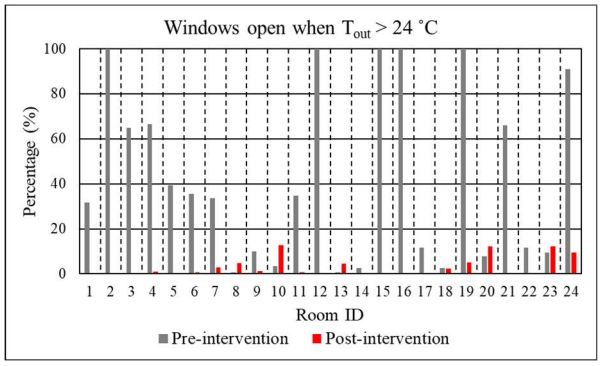

Figure 8: Windows open during the cooling season

A similar analysis was performed for the heating season when the outdoor temperature is below 0 ˚C. As can be seen in Figure 9, some occupants leave their windows open for an average of 31% of the time. When the intervention is implemented, the duration to which a window is left open is reduced significantly, and the average of windows open is 0.3%.

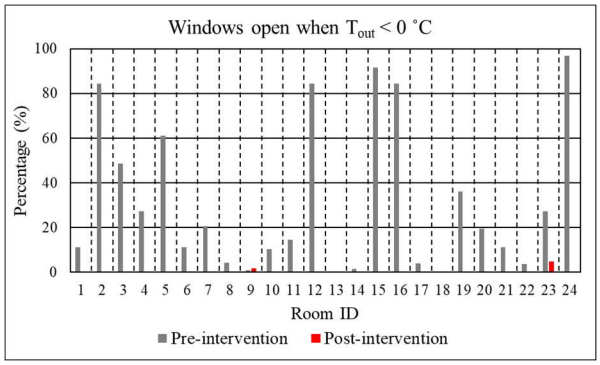

Figure 9: Windows open during the heating season

When analyzing how the intervention influenced occupant behaviour when the outdoor temperature was between 0 ˚C and 24 ˚C, it was seen that applying an algorithm that only nudges occupants to close windows may have unintended consequences, as seen in Figure 10. Before the intervention was implemented, some windows were open for an average of 35% of the time when natural ventilation was ideal. However, after the intervention was implemented, the duration of which windows were open when natural ventilation was ideal reduced to an average of 2.4%.

Notably, as seen in Figure 10, the occupants in rooms nine and 23 may not be reflective of the typical behaviour observed among occupants in private offices. These occupants are the only individuals who opened the window for a longer duration post-intervention compared to pre-intervention.

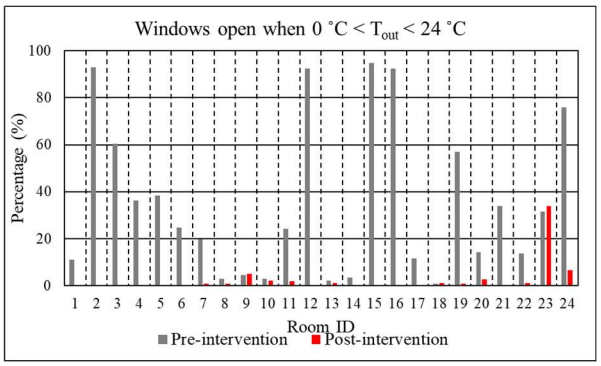

Figure 10: Window open when natural ventilation is ideal

Window Opening Frequency

Additionally, the frequency of occupants' interactions with the windows in their offices was also examined, as represented in Figure 11. It is apparent that the occupant interactions with the window remains relatively consistent before and after the intervention was implemented. This suggests that the implemented intervention was successful in reducing the duration of which the window is left open when natural ventilation is not ideal without significantly impacting the occupants' interaction with it, allowing occupants to continue to have perceived control over their window use.

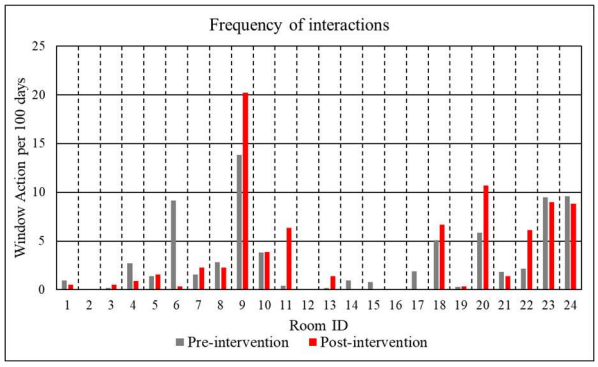

Figure 11: Frequency of occupant interactions with window

Energy Consumption

A baseline energy function was created referencing the ASHRAE Guideline 14 three-parameter univariate change point model (ASHRAE, 2014), as seen in Figure 12. The change point model correlates energy consumption with outdoor temperature, specifically focusing on heating energy use.

Overall, the analysis reveals that before the intervention was implemented, more energy was typically required to heat all the offices as compared to after the intervention was implemented.

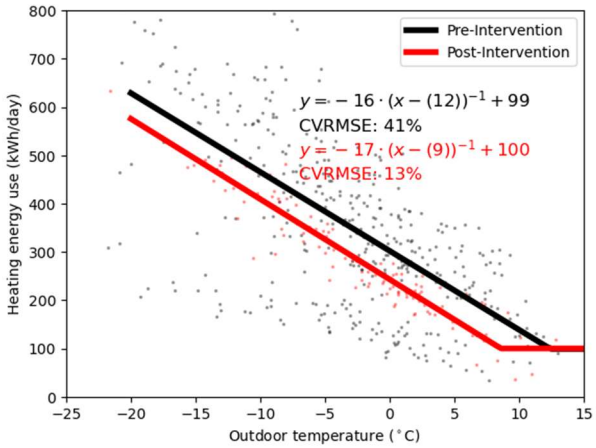

Figure 12: Univariate change point model

The Coefficient of Variation of the Root-Mean-Square Error (CV[RMSE]) and the Normalized Mean Bias Error (NMBE) represent how well a mathematical model describes the variability in measured data (ASHRAE, 2014).

To meet the ASHRAE Guideline 14 targets, the CV(RMSE) metric needs to be less than 10% for monthly energy use data and less than 30% for hourly energy use data. Similarly, the NMBE needs to be less than 5% for monthly energy use data and less than 10% for hourly energy use data.

As can be seen in Figure 12, the CVRMSE values are 41% and 13% for pre-intervention and post-intervention energy use, respectively. Additionally, the NMBE was calculated and found to be 0% for both pre-intervention and post-intervention energy use.

Although the CV(RMSE) of the pre-intervention model exceeds the ASHRAE Guideline 14 targets, it is important to consider that the living-lab facility is an internal load building. In internal load buildings, internal sources of heat may also significantly influence the heating energy consumption. As a result, a high CV(RMSE) indicates that only considering the outdoor temperature as the regressor may not adequately capture the influence the internal loads have on energy use. However, when the pre-intervention change point model is compared to the post-intervention change point model, it still demonstrates a reduction in energy use due to the implemented OCC algorithms. This

suggests that the algorithm has had a positive impact on energy efficiency.

To further estimate energy savings, Figure 13 was created which, using the trained model and the weather data from the post-intervention period, presents the energy predictions for the post-intervention period as the red line. This represents the energy use that would have been required to heat the offices if the OCC algorithms had not been implemented. The black line in the figure represents the actual energy used after the intervention was implemented.

Overall, it is apparent that the intervention has mostly reduced the energy consumption required to heat the offices in the analysis. By comparing the predicted and measured energy use, the model indicates that the intervention has led to a 16.7% reduction in energy use.

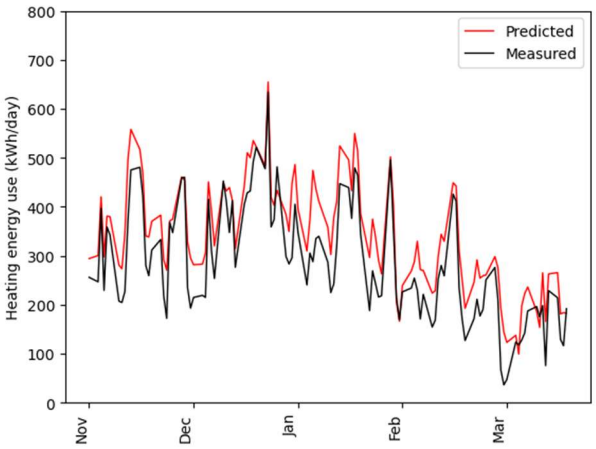

Figure 13: Heating Energy Use

Discussion

Based on the findings, it is evident that the OCC algorithm has influenced the occupants' behaviour and impacted the energy consumption required to heat the offices.

As outlined by Ackerly and Brager (2013), occupants were less likely to change their window position unless they are uncomfortable. As the algorithm implemented in the study introduced heating and cooling setpoints, causing slight occupant discomfort, the implementation of the OCC algorithm successfully nudged occupants to close their windows when the outdoor temperature was not ideal for natural ventilation. Before the algorithm was implemented, many windows remained open, even when natural ventilation was not ideal. This led to an increase in the energy consumption required to heat the building during the heating season. Similarly, during the cooling season, it is likely that excessive energy was consumed to cool the building as many windows were left open when the outdoor temperature was above 24 ˚C. After the algorithm was implemented, the window opening fraction was reduced significantly.

The reduction in window opening fraction is apparent in the change point model and the heating energy use model. It was observed that reducing the window opening fraction when natural ventilation was not ideal reduced the energy consumed to heat the offices by approximately 16.7%. This aligns with the simulations conducted by Liu, Gunay and Ouf (2022), which suggests that regulating window use can reduce energy consumption by approximately 3-16%.

Although no data were collected to estimate energy consumption during the cooling season, it was clear that the intervention nudged occupants to close their windows when natural ventilation was not ideal when the outdoor temperature was too high. As a result, it is reasonable to assume that the energy consumed to cool the offices was reduced.

An unintended consequence of applying an intervention that nudges occupants to close windows was observed in this analysis. When occupants were nudged to close their windows, they tended to keep them closed even when natural ventilation was ideal. Therefore, there is a need to improve the intervention to nudge occupants to open windows when natural ventilation is ideal, which would result in greater energy savings.

In the next phase of this research, a survey will be conducted to understand what influences occupants to open or close their windows. Additionally, the algorithms will be further developed to notify the occupants of the optimal window position. This will allow for the algorithm to include an intervention that nudges occupants to open windows. Using the thermostat that is available in the rooms, as seen in Figure 14, the algorithm will change the colours of the thermostat to notify the occupant if the window should be closed or opened. The data collected from this intervention will be compared to the intervention that was explored in this paper to determine the effects of notifying the occupants of the intervention as compared to not notifying them of the intervention.

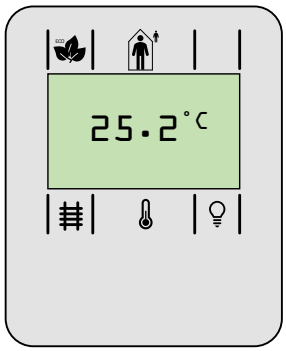

Figure 14: A BACnet-compatible thermostat with a multi-colour backlit LCD screen

Conclusion

As occupants spend a significant amount of their time indoors, it is important to ensure buildings are designed so that they are comfortable while also minimizing energy consumption. While numerous measures have been implemented to ensure occupant comfort while minimizing

energy use, neglecting occupant behaviour may actually result in increased energy use. This study demonstrated that unregulated window use can contribute to higher energy consumption, as seen from the findings of the pre-intervention data.

When window use is regulated, through the use of OCC algorithms, occupants are influenced to use their windows more appropriately. The data presented in this paper showcases the benefit of OCC algorithms in reducing energy use. Due to the implemented intervention, the energy use in the living building facility was reduced by 16.7%.

To further explore the potential of OCC algorithms, ongoing research will explore the benefit of notifying the occupant of the implementation. Exploring this scope will help provide more information on occupant behaviour and if notifying the occupant will result in more energy savings as compared to the intervention discussed in this paper.

Acknowledgments

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