eSim 2018
«BUILDING SIMULATION TO SUPPORT BUILDING SUSTAINABILITY»
IBPSA Canada
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Summertime window use behaviour in air-conditioned condominiums

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Abstract: *This paper presents a case study conducted to better understand occupants' window use behaviour in air-conditioned condominium units. Window state and temperature data loggers were deployed in twelve condominium units in Ottawa, Canada. Occupants participated in interviews addressing their comfort, and they reported their window use in provided log sheets. The window use patterns were analyzed with concurrent indoor temperature and local weather data. Multivariate logistic regression models were developed by using a forward stepwise regressor selection approach. The results indicate that the window opening and closing actions were executed infrequently, and on average the windows remained open during 18% of the monitoring period. Outdoor temperature appears to be the best of the studied predictors to explain the occupants' window use behaviour. Occupants' self-reported window opening and closing actions were shown to be unreliable.*

Keywords: *Occupant behaviour; Window use behaviour; Condominiums*

INTRODUCTION

Statistics Canada projects that the greenhouse gas (GHG) emissions from households will experience a 12% increase between 2005 to 2020 ("Canada's Emissions Trends," 2013), with most of this increase attributed to heating, ventilation, and air conditioning (HVAC) use ("Households and the Environment: Energy Use," 2011). Simultaneously, new multi-unit residential building (MURB) constructions in Canada increased by 51% from 2009-2013, while this value for single-detached housing was only 2% (Ge, 2002). Despite the trend towards a larger number of MURBs, most residential research is still conducted on detached houses.

Attempting to understand occupant behaviour in MURBs poses a new challenge as residences are more likely to feature large windows that are associated with solar gains and thermal bridging, which changes the way that occupants experience their environment (Ge, 2002; Straube, 2008). While window technologies have improved in efficiency over the past decade, the demand for larger window sizes has offset this benefit (Straube, 2008). Because MURB units often feature high window-to-wall ratios (WWRs), they demand more energy than traditional housing in order to maintain a comfortable climate.

Previous research shows that identically built homes can vary in energy consumption by a factor of two or more due to occupant behaviour (R. K. Andersen, 2012; Socolow, 1978). This supports the argument that choices made by residents have a significant impact on a unit's energy use (Bennet, O'Brien, & Gunay, 2014; Fabi, Andersen, Corgnati, & Olesen, 2012; Schweiker, Haldi, Shukuya, & Robinson, 2012). Therefore, it is essential to understand and account for occupant behaviour when designing a MURB.

It is especially important to accurately simulate the window and thermostat adjustments made by occupants, as they have been shown to produce large variations between the expected and actual energy use. A previous study performed in Japanese dwellings found that occupant behaviour, specifically window usage, was responsible for the vast majority (87%) of the total air-exchange rate (Iwashita & Akasaka, 1997). Additionally, a study conducted in Eastern Ontario found that heating and cooling accounted for 60% of a household's total energy consumption, and that occupant behaviour was responsible for a 47% variation in cooling energy usage (Bennet et al., 2014). These findings suggest that both occupant behaviour and window usage provide valuable data that can be used to predict energy consumption. While accurately predicting energy use is not necessarily essential in design, inaccurate predictions may mislead designers towards suboptimal designs (e.g., windows that have large opening areas under the assumption that occupants will not open windows in winter).

Behaviour is a complex matter heavily influenced by contextual factors. Many researchers argue that the current occupant behaviour models used in building simulation do not accurately reflect occupant behaviour patterns (R. V. Andersen, Toftum, Andersen, & Olesen, 2009; Gunay, O'Brien, & Beausoleil-Morrison, 2013). Behavioural drivers can be classified into various categories: physical (temperature, humidity, wind speed), contextual (insulation, window orientation, type of thermostat), psychological (financial concerns, environmental concerns, lifestyle), physiological (age, gender, clothing level) and social (which household member programs the thermostat or opens/closes windows) (Fabi et al., 2012). The types of adjustments an occupant can make have also

ISBN 978-2-921145-88-6

been separated into physiological (sweating, shivering), individual (adjustment of clothing/bedding level, drinking hot/cold beverages), environmental (use of HVAC, opening/closing windows and doors) and spatial (movement from one room to another, relocation of activities) (Polinder et al., 2013; Schweiker, 2010). The classification of behaviour drivers vs. adjustments allows researchers to predict when, why and how an occupant may choose to change their home environment. Using this approach, Fabi et al. and other researchers suggest that the least significant variables related to window opening behaviour are wind speed, rainfall, income and thermal sensation. Other studies found that indoor and outdoor air temperatures (Gauthier, 2016; Schweiker et al., 2012) and thermal sensation (R. V. Andersen et al., 2009) could not predict this adaptive behaviour in residential buildings.

The factors that affect behaviour are not well understood and most residential window behaviour models come from studies conducted in Europe (R. K. Andersen, 2012; R. V. Andersen et al., 2009; Schweiker et al., 2012). While these models can be used to guide predictions, the trends in behaviour and occupancy in Canadian condominiums do not necessarily reflect those seen elsewhere, specifically in mixed-mode MURBs (where cooling is either achieved using natural ventilation or HVAC, depending on outdoor conditions) (Brager, Alspach, & Nall, 2011). This paper presents a case study conducted to better understand the window use behaviour in air-conditioned condominium units.

The window sensors used in this study produce a binary measurement; either the window is open or closed. This is similar to other studies conducted on occupant window adjustment behaviour (R. V. Andersen, 2009; Fabi, Andersen, Corgnati, & Olesen, 2013). Other researchers have chosen to elaborate, using window contact sensors that can describe various positions (Erhorn, 1988). In this study, participants were asked to use log sheets to record their window use. The method of participant self-reporting, or journaling has been shown to be problematic due to poor participation and forgetfulness (Hayman, Wilkes, & Jackson, 2012). Steps were taken in this study with the hope to engage occupants and combat these common issues.

The objectives of this paper are to better understand the factors that drive occupants' window use behaviour and to explore the viability of a data-driven window use behaviour model form for mixed-mode MURBs. To this end, upon the sensor and survey data gathered from 12 units in a MURB over a summer in Ottawa, Canada, a statistical analysis was conducted on occupants' window use behaviour. The model proposed in this paper uses data that accounts for physical drivers and environmental adjustments and attempts to establish a link between the circumstances (drivers) and actions. Additional data collected from in-depth surveys aid in qualitatively assessing contextual, psychological, and physiological drivers and individual and spatial adaptions.

METHODOLOGY

This field study was performed in Ottawa, Canada in a high-rise residential building. The data was collected during in-home visits to 12 different units between the hot and humid months of June and August. Over the course of the study, the weather station at Carleton University (less than 2 km away) measured an average temperature in Ottawa of 22°C, reaching a maximum of 36°C and a minimum of 9°C. The average relative humidity was 53%, with a maximum value of 96% and a minimum value of 13%. The units studied were situated in a MURB constructed in 2014. The layout of every floor is identical, featuring 1-2 façades (depending if it is a corner unit), with high WWRs (50%+), punched windows and access to a balcony.

To study MURB occupants' window use, twelve units had temperature and window state loggers installed (example floor plan of a room with a data collection equipment can be seen in Figure 1). These devices collected binary window state data (open or closed) and indoor air temperature.

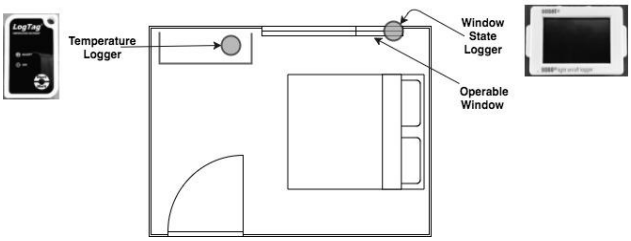

Figure 1: Generic bedroom temperature/window logger layout.

The condominium installed the same energy saving features (efficient appliances, LED lighting, water saving faucets, shower heads and toilets) into all units. There are twelve floors in total; the first three floors contained shared space (i.e. gym, lounge, outdoor patio, bar, storage) and the remaining 9 housed occupants. Table 1 presents the participants' unit storey, window orientation and the location of the window state sensor.

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Table 1: Participants' unit height, orientation and sensor location.

Unit	Unit Storey	Unit windows orientation	Location of Window State Sensor
1	5	E	Bedroom
2	6	E	Living Room
3	6	NE	Bedroom
4	11	NE	Bedroom
5	10	E	Living Room
6	10	E	Living Room
7	5	N	Bedroom
8	5	SE	Living Room
9	12	S	Living Room
10	9	S	Living Room
11	11	S	Living Room
12	8	S	Living Room

All units studied are connected to a central air conditioning system and occupants are in control of their programmable thermostats. The units are sub-metered, and residents are responsible for paying for their own utilities. This has been found to motivate some occupants to be more energy conscious in previous studies (Gunay, O'Brien, Beausoleil-Morrison, & Perna, 2014). Some participants indicated that they had struggled over previous months with the noisiness of their HVAC system and had since chosen to rely primarily on window adjustment to control their thermal environment, even after the noise problem was remedied.

Participants were recruited using posters approved by the Carleton University Research Ethics Board and the participating condominium board. Two in-home visits were conducted in each unit. The participants completed a survey, which featured 20 written and 40 discussion questions, which took about 20-30 minutes. The questions (written, discussion) were distributed between eight categories: condominium preferences (3 written, 9 discussion), energy use (4,10), thermal comfort (2,2) green features (2,2), sleep (2,4), sensory (view, acoustics, auditory) (5,6), privacy (2,3) and adaptions (0,4). The survey format was similar to another exploratory study conducted in Canadian MURBs, aimed to address occupant comfort and adaptions (Bennet & O'Brien, 2017).

During the first round of home visits, window state and temperature loggers were installed, surveys were conducted, and log sheets were distributed. This occurred between the 14th and 28th of June. The second round of visits involved the retrieval of data log sheets, temperature and window state loggers and collection of additional anecdotes, which were meant to provide insight into any changes occupants had experienced since the first visit. The second visits occurred between August 11th and 25th. Survey data was used to explain and expand upon behaviour and substantiates the need for a better occupant behaviour model that accounts for occupant's preferences and other contextual data.

Window state and temperature were recorded in all units for approximately two months. A UX90-001 HOBO® State Data Logger was installed to record changes in the state of the window that occupants indicated they used the most frequently. Temperature was recorded every 15 minutes using a TRIX-8 LogTag®. The temperature logger was placed away from exterior walls and floor, and instead on top of furniture, to reduce inconsistencies due to thermal bridging. It was hidden behind objects (i.e. picture frames) and in areas that would provide shade, in order to reduce direct sunlight exposure.

To better understand how/why occupants chose to operate their windows, all participants were instructed to record their window adjustment behaviour on the provided log sheet. The log sheet had sections indicating the date, time, window and reason for adjustment (behaviour driver) as shown in Table 2. The log sheet was placed near the window in order to encourage occupants to record their use, however, some occupants chose to move their sheet later in the study which may have affected the accuracy of their self-reporting. The location of window state sensors was unaltered throughout the study. The log sheet data was compared against that collected from the window state sensors and was later used to reveal discrepancies in occupants' log sheets.

Table 2: Example log sheet.

Date	Time	Window	Reason
July 20	10:30 am	Bedroom	Opened for fresh air
July 20	11:00am-11:30am	Bedroom	Opened for fresh air
July 20	12:15 pm	Bedroom	Opened to check outdoor temp

The analyses of the window state data were conducted through a multi-variate logistic regression approach by using several indoor and outdoor environmental variables. These indoor and outdoor regressors were the outdoor air temperature (T_{out}), indoor air temperature (T_{in}), relative humidity (RH), binary rain status (B_{rain}), wind speed (S_{wd}) and the unit's storey (N_{storey}). By using a forward stepwise attribute selection approach and a metric for model quality, Akaike Information Criterion (AIC), these variables were ranked. Two different model formalisms were explored: Bernoulli and discrete-time Markov. The Bernoulli model form predicts the state of the window (e.g., open or closed), while a discrete-time Markov model form predicts the

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likelihood of observing a window opening or closing action in the next time step. Further information about logistic regression model development and forward stepwise attribute selection approach can be found elsewhere (Wagner, O'Brien, & Dong, 2018).

RESULTS

Self reported and surveyed occupant drivers / adaptions

As mentioned in the introduction, earlier studies have found mixed results regarding which contextual factors drive occupant adaptions. In this paper, the only adaptions investigated quantitatively are window opening and closing behaviour. The surveying of occupant behaviour collects qualitative data that can later be used to explain the quantitative measurements. The use of surveys and sensors was selected because neither can sufficiently measure everything that is expected to affect window use behaviour.

Results from the survey show that occupants open windows for a number of reasons including the dispersal of cooking smells, regardless of outdoor temperature. Occupants also opened windows to make thermal changes to their environment and to let in fresh air. They reported closing windows to mitigate outdoor noise, as the building was situated in a high-traffic area. Occupants also closed windows to increase their privacy and to reduce temperature. Discussions with occupants yielded interesting anecdotes. Some complained about condensation and reported being motivated to adjust their windows/blinds during the winter to reduce this problem.

Window usage

The data showed that windows were in a closed position an average of 82% of the time. Results indicate that living room windows spend more time closed (95% of the time) than bedroom windows (57% of the time), which is consistent with other studies (Dubrul, 1988). The same results were found anecdotally when surveying residents. This could be due to occupants preferring to sleep with their windows open to let in fresh air, as is suggested by the log sheets and survey results. Table 4 shows the fraction of time each window spent open over the course of the study, as well as the average event per day. The high frequency of closed windows is likely due to regular HVAC usage; earlier studies have shown that sub-metered units are more likely to keep their windows closed to conserve energy (Gunay et al., 2014), which may explain the behaviour seen here. Living room windows had a higher average (1.32 events/day) of events per day than bedroom windows (0.29 events/day). This may be related to the amount of time residents spend occupying the different rooms in their home. It could be hypothesized that occupants spend more active time in their common spaces (i.e. living room) and therefore more frequently adjust their windows, and spend more time sleeping in their bedrooms with their windows open, contributing to the lack of events per day and greater time with windows open.

Although advised to record all window opening and closing actions, many occupants only recorded their opening actions. If a recorded opening did not have a corresponding closing action (i.e. Window open 10:30am-?) then the opening was assumed to only exist for an instant. An example of how log sheet data was represented during analysis can be seen in Table 3.

Table 3: Example log sheet analysis (see Table 2 for log sheet data source). Data from Table 2 shown as 'Log Sheet Data'. Associated actions (opening or closing instances) shown in 'Window Actions'

Date	Time	Log sheet data	Window Actions
July 20	10:15		
July 20	10:30	open	opening
July 20	10:45		
July 20	11:00	open	opening
July 20	11:15	open	
July 20	11:30	open	
July 20	11:45	closed	closing
July 20	12:00	closed	
July 20	12:15	open	opening
July 20	12:30		

An example of the method of categorizing window instances, using data from log sheets and window sensors, can be seen in Table 5. The same method was used to categorize both window opening and closing data. The data was divided between four categories: true actions, false actions, omitted actions, and null.

Table 4: Percentage of time each window was in an open position. Dark blue (>50%), medium blue (5%-50%) and light blue (<5%) categorize the percentage of time windows spent open. Rooms are either bedroom (BR) or living room (LR).

Unit number	7	3	2	1	4	9	6	10	12	8	11	5
Time window in open position (%)	98	49	23	12	13	8	4	4	1	0.7	0.5	0.4
Room	BR	BR	LR	BR	BR	LR	LR	LR	LR	LR	LR	LR
Average events per day	0.26	0.07	2.5	0.06	0.16	1	2.2	2	1.4	0.9	0.2	0.4

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To be categorized as a true action, both the sensor and log sheet must have identical states (i.e. sensor: opening, log sheet: opening) within an allowance of 30 minutes. This tolerance was chosen because it accounts for a realistic amount of error between the entry in the log sheet and record of the window sensor. It should be noted that too much tolerance reduces the value of the data as it becomes harder to draw connections between predictors (i.e. temperature rise) and actions. False actions describe instances at which log sheet data reports an action where the sensor does not (i.e. Sensor: null, log sheet: closing). This instance is likely to occur due to occupants' tardiness; if an occupant waits more than 30 minutes to record the opening/closing, that entry is categorized as a false action. Omitted actions describe cases where the sensor has recorded a window opening/closing and the log sheet has not (i.e. Sensor: opening, log sheet: null). If an occupant forgets to record their opening or closing adjustments (within 30 minutes), those results will be categorized as omitted actions. The null category represents all the instances which are null data (sensor: null, log sheet: null). The meaning of null data changes depending which data is being analyzed. Figure 2 and 3 depict the fraction of opening and closing results. Figure 2 displays window opening data, thus, in this case, null data represents all instances which are non-opening. Figure 3 shows fractions of closing data, so in this case, null data describes all non-closing instances.

Table 5: Categorizing method for measured vs. recorded window adjustment dat. Examples for opening (above) and closing (below).

	Recorded OPENING	**Recorded** NULL
Measured OPENING	'True Openings'	'Omitted Openings'
Measured NULL	'False Openings'	'Null'
	Recorded CLOSING	**Recorded** NULL
Measured CLOSING	'True Closings'	'Omitted Closings
Measured NULL	'False Closings	'Null'

Null measurements (the measurements at time-steps without an opening or closing action) represent the majority of the data (~99.5% in both categories). This is expected, as these results are in line with previous studies (Bennet et al., 2014) which found that occupants infrequently interact with their windows. The null data was not included in Figure and 3 as it did not offer useful window operation information. The tendency of occupants to mis-report their actions is a likely contributor to omitted actions, making it the most common type of opening (77% in Figure 2, 94% in Figure 3). True actions represent a small fraction of results (19% in Figure 2, 4% in Figure 3), suggesting that occupants have a tendency to inaccurately report their own window use behaviour. The fraction of false actions (4% in Figure 2, 2% in Figure 3) speaks more perhaps to occupant accuracy (or lack thereof) than the true events. Most false action instances can be attributed to occupant tardiness or forgetfulness, as many occupants would report their actions outside of the 30-min window.

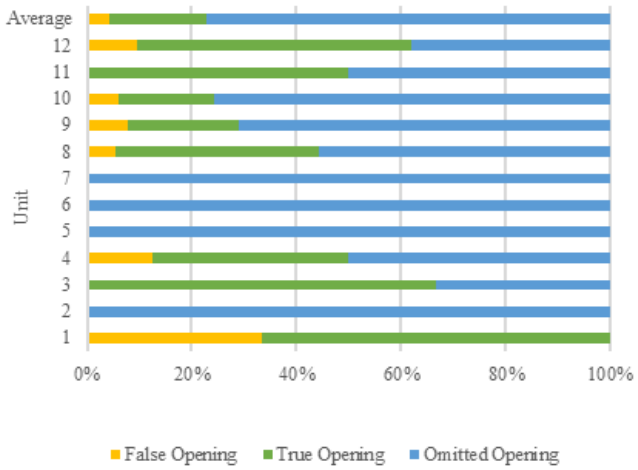

Figure 2: Relative fractions of true openings, omitted openings and false openings for June-August.

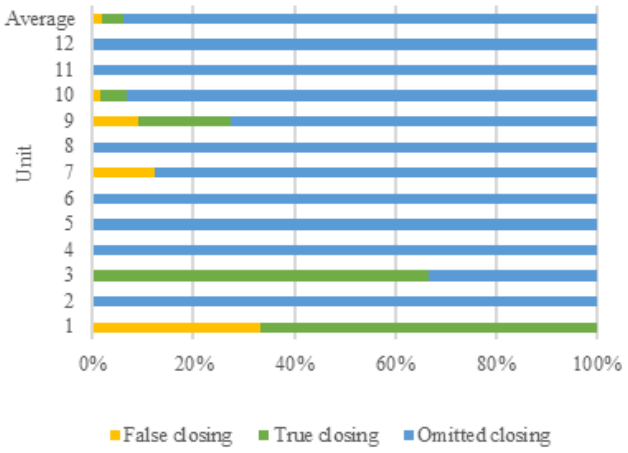

Figure 3: Relative fractions of true closings, omitted closings and false closings for June-August.

The frequency of log sheet entries dropped 57% between June and August, although window use increased 102%, suggesting that occupants lost motivation to record their behaviour. For a better understanding of window use

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patterns over the course of the study, Figure 4 illustrates the window state trends observed in June, July and August.

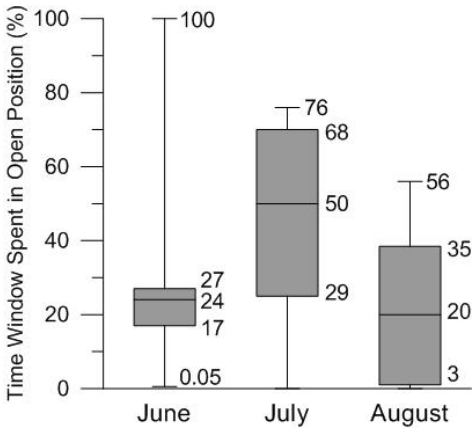

Figure 4: Distribution of time windows spent open over the 3 months of study.

To investigate which drivers have the greatest impact on window opening or closing behaviours, the outdoor air temperature (T_{out}), relative humidity (RH_{in}), wind speed (S_{wd}), binary rain measurement (B_{rain}) and indoor air temperature (T_{in}) were compared under different circumstances (see Figure 5). The driver with the most impact on window state was the outdoor air temperature, followed by relative humidity. Wind speed, rain and indoor air temperature did not show significant correlations with window operation. The upper and lower whiskers seen in Figure 5 enclose 90% of the data. It should be noted that rain is a binary measurement and data is only situated in the upper whisker because the majority of measurements are zero (0 = no rain).

A logistic regression analysis was performed on the data by using a forward stepwise regression approach. The quality of each model generated was assessed by looking at the AIC metric which provides a relative measure of information lost when a model is generated from data. In Figures 6 to 8, variables are plotted against outdoor air temperature to create three models used to predict window use actions and window states.

Figure 6 presents the fraction of windows open as a function of the outdoor temperature. The AIC plots indicate that the selected regressors with decreasing ranking in forward stepwise selection are as follows: T_{out}, S_{wd}, B_{rain}, T_{in} and N_{storey}. The number of storeys may be a significant regressors because the storey height encapsulates information about the distance from a busy street and stack pressure distribution (Proskiw & Phillips, 2008). Four different variables including rain, wind speed, indoor and outdoor air temperature were considered and modelled using the following equation:

$$p(open) = \frac{1}{1+e^{-(x_o+T_{out}x_1+S_{wd}x_2+B_{rain}x_3+T_{in}x_4+N_{storey}x_5)}}.$$

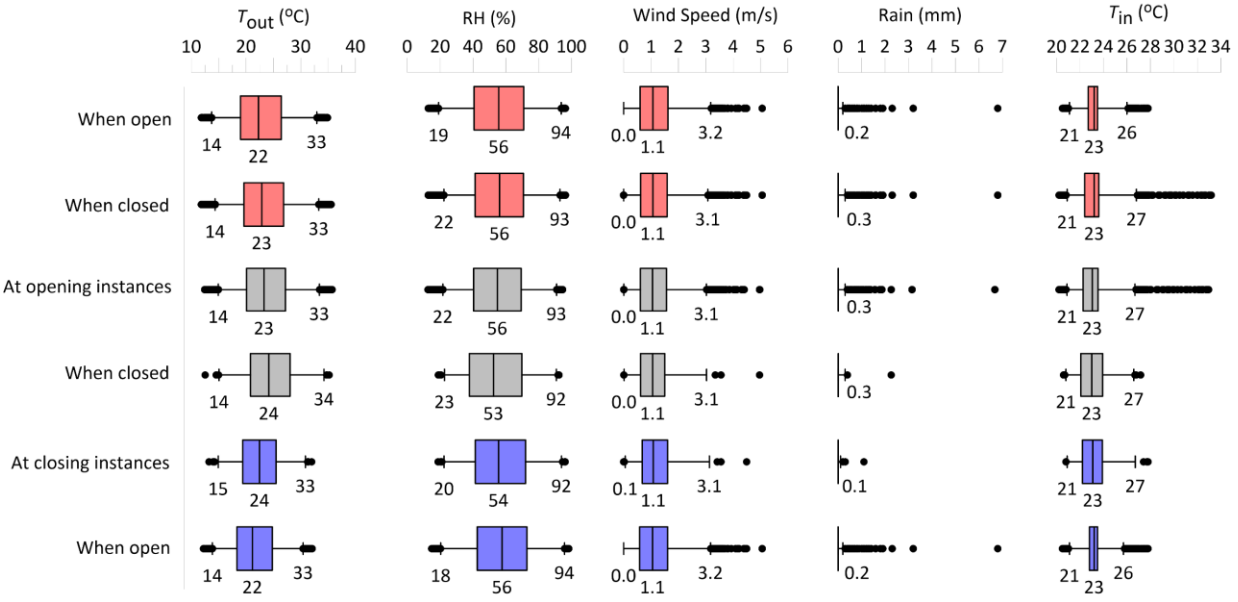

Figure 5: Box-and-whisker plot of variables vs. window states/actions. The data were separated into six categories (as labelled at right) and then the corresponding conditions are plotted for each category.

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The model predicts that as the outdoor temperature gets colder, indoor temperature gets warmer and wind speed increases, the likelihood of observing the windows open increases, albeit at diminishing rates.

Figure 7 shows model 2, which predicts the probability of a window opening action within the next 15 minutes. AIC comparison showed that outdoor temperature, unit storey and wind speed were the selected predictors for window opening, and that considering rain, indoor temperature and relative humidity would be detrimental. Three variations of storey and wind speed were explored using the following equation:

$$p(open|closed) = \frac{1}{1 + e^{-(x_o + T_{out}x_1 + N_{storey}x_2 + S_{wd}x_3)}}$$

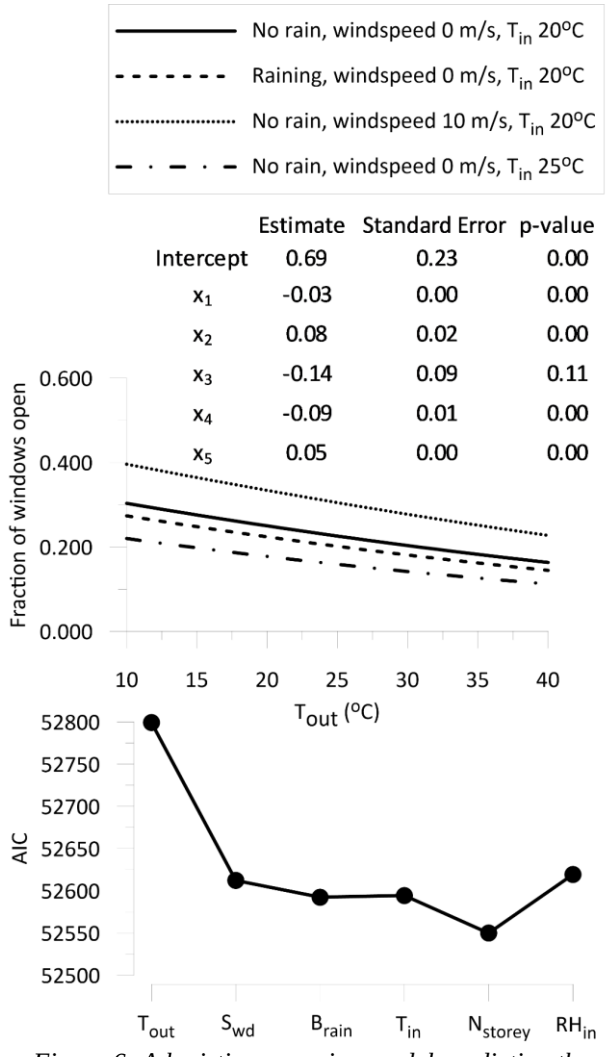

Figure 6: A logistic regression model predicting the fraction of windows open. Note that the five variables that minimize the AIC were used in the is model.

An upwards trend indicates that a window opening action (within the next 15 minutes) is more likely to occur as outdoor temperature increases, unit storey and wind speed are low.

Model 3, as shown in Figure 8, is used to predict the probability of a window closing action within the next 15 minutes and uses the equation:

$$p(closed|open) = \frac{1}{1 + e^{-(x_o + N_{storey}x_1 + T_{out}x_2 + S_{wd}x_3)}}$$

Similarly, to model 2, AIC comparison indicates that storey, outdoor temperature and wind speed will preserve information. This model found unit storey to be of greater influence than outdoor temperature, unlike that seen in model 2. Three difference variations of storey and wind speed were explored. The likelihood of a window closure (in the next 15 minutes) shows an upwards trend as outdoor temperatures increase, unit storey remains low and wind speed remains low.

DISCUSSION

Future studies should aim to incorporate different window state prediction variables, longer data collection periods and larger sample sizes in hopes to generate stronger correlations in the data. The variables used in this study (indoor/outdoor air temperature, relative humidity, wind speed, binary precipitation and unit storey) did not produce strong enough correlations for proper model validation and implementation in building performance simulation (BPS).

This study samples from the same building to eliminate a range of contextual factors between occupants such as wide variations in income, HVAC usability, window opening mechanism, WWR's, outdoor noises and room layout.

Other contextual factors such as the quality of construction, HVAC usability, stack effect and number of residents in a unit should be investigated further to clarify and identify occupant comfort issues.

The use of surveys in this research allowed qualitative data to be collected, however, it is important to note that responses are shaped by the subjective variation in occupants' norms, expectations, and experiences of comfort, which limits the data's suitability for comparative analysis (Himelein, 2015).

Many occupants indicated in both log sheets and surveys that outdoor noise was a driver for window closure. Measuring this in a home may be challenging, as many occupants may not be comfortable with the privacy intrusion that audio recording represents, however, it could yield significant results. Additionally, it may be difficult for researchers to discern between street-level noise and noises that come from within and between units. Odours were also

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identified by occupants in this study as a reason to open windows. Other researchers have found that air quality can be used to predict window adjustment (R. V. Andersen et al., 2009), thus, this should be further explored within North American buildings. Humidity and dry bulb temperature should also be investigated as drivers as they both may have a more immediate effect on occupant comfort. It is important to document both significant and insignificant influencing factors for window state changes and adaptive behaviours as this information can guide future research.

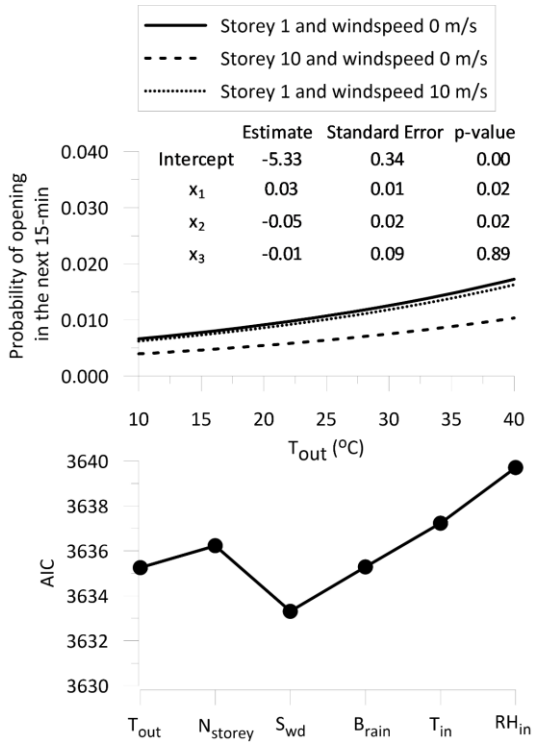

Figure 7: A logistic regression model predicting the likelihood of a window opening action in the next 15 minutes. Note that the three variables that minimize AIC were used in this model.

In order to accurately track window adjustment behaviour, it is imperative to install window state sensors. Throughout the study, the accuracy of self-reporting data was explored. It can be concluded from vast discrepancies between sensor and log sheet data that occupants are unable or unwilling to provide a reliable description of their behaviour. In order to improve the accuracy of self-reporting, the positioning of log sheets should be considered (place sheet nearby action site, provide a clock beside log sheet for better time accuracy). Additionally, different self-reporting platforms should be explored, such as one that incorporates a participants' mobile device. While self-reporting should not be relied upon as an indicator of window use, it can be used to identify window opening/closing drivers and patterns of behaviour specific to the occupant. Future research could use self-reporting to identify which occupants are interacting with the window(s), whereas sensors would not be able to differentiate in this way.

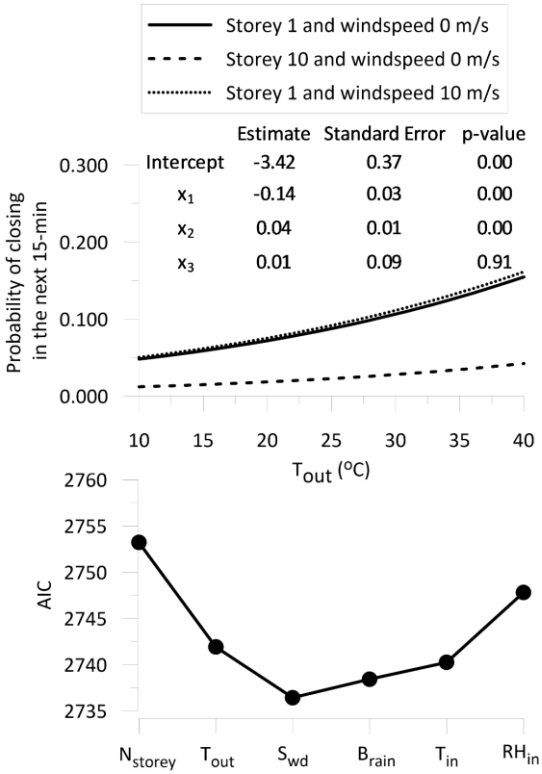

Figure 8: A logistic regression model predicting the likelihood of a window closing action in the next 15 min.

To improve quantitative data, window sensors should be placed in multiple rooms to attain a better understanding of why/when occupants are driven to adjust their home's windows. More participants as well as a longer study period could provide insight into how window adjustment drivers change with season. It should be noted that this study was performed during peak vacation time and that some occupants may have left for extended periods, which introduces the possibility of anomalous window use.

Some occupants admitted during the second meeting, when sensors were collected, that they had altered their behaviour throughout the study, as they were aware that their actions were being observed (i.e., the Hawthorne effect). In this case, occupants admitted having become more proactive with their window/blind adjustment and refraining from energy-intensive HVAC use (i.e. Leaving windows open while AC is running). However, participants indicated that after some time, they reverted to their earlier habits. This anecdote suggests that window operation drivers may

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change based on the recentness of impelling interactions. Additionally, the motivation for self-reporting, and associated log sheet accuracy, experience a similar decline in motivation as time passed. These results might suggest that studies hoping to observe regular or routine occupant behaviour should run for extended periods of time to reduce any initial Hawthorne effect. Researchers should also try to quantify the extent of Hawthorne effect by periodically re-introducing motivating interactions and observing any changes that occur.

This research was done in collaboration with the condominium board, which allowed access to additional resources such as technical information about the HVAC system, purchase agreements and clarification of other questions pertaining to the building. Future studies should pursue these kinds of partnerships, which can be especially useful when trying to validate occupants' statements.

Due to the sample size, the findings of this research can be used to describe key issues and trends in occupant behaviour, can help inform design (whether to give more operable windows, whether to disable air conditioning when windows are open, etc.) and could serve as a guide for identifying new predictor variables to be used in future studies. However, models developed in this paper are not suitable for implementation in BPS. Results showed that occupants infrequently adjust their windows, and that bedroom windows spend more time open than living room windows. Further investigation into different types of windows in a home is needed to further assess the implications of these findings.

CONCLUSIONS

This paper presented a case study conducted to better understand the summertime window use behaviour in air-conditioned condominium units.

Twelve units in a condominium building in Ottawa, Canada were instrumented with window state and temperature data loggers, and their residents were interviewed and asked to self-report their window usage in log sheets. Using sensor and survey data with concurrent local weather data, a statistical modeling exercise was carried out to reveal the factors that influence occupants' window use patterns.

The preliminary results indicate that occupants in air-conditioned condominium units tend to undertake window opening and closing actions less frequently than once every two days, on average. The windows were observed to remain open during 18% of the monitoring period. Likelihood of finding the windows open appeared to increase with a decrease in the outdoor temperature and an increase in the wind speed and indoor temperature. Future work should investigate air-conditioner state and the impact of non-thermal environmental factors such as the ambient noise and indoor air quality on the window use behaviour.

ACKNOWLEDGEMENT

This research is funded by research grants provided by the Natural Sciences and Engineering Research Council (NSERC) and the Ontario Ministry of Research, Innovation and Science which are gratefully acknowledged.

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