Development of an Occupant-centric Control Algorithm for Mixed-Mode Ventilation Buildings to Regulate Window Operations

by

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Abstract

Mixed-mode ventilation is a design feature to improve building energy efficiency and indoor air quality by combining natural ventilation and mechanical ventilation. Mixed-mode ventilation commercial buildings are often equipped with variable air volume (VAV) terminal device and air handling unit (AHU) as the mechanical ventilation system and operable windows to deliver natural ventilation. However, in practice, mixed-mode ventilation buildings do not always achieve better performance than mechanically ventilated buildings, largely due to inappropriate window operations. Therefore, the sequences of operation for terminal devices serving zones with operable windows should be designed in recognition of these risks, which in turn should be informed by research investigating occupants' window and thermostat use behaviour. This research examines window and thermostat use data collected from two mixed-mode ventilation buildings in Ottawa, Canada. Discrete-time Markov logistic regression models and decision tree models were established to predict the likelihood of thermostat keypress and window opening/closing instances and identify the indoor conditions that trigger these actions. Based on this analysis, a set of control algorithms are developed to improve terminal device sequencing in mixed-mode ventilation buildings in cold climates such that the comfort and energy savings potential of operable windows can be fully realized. The control algorithm applies a thermostat setpoint setback to encourage occupants to open windows when conditions are advantageous for saving energy, and discourage occupants from opening windows when energy penalties may be caused. The control algorithms are tested by using building performance simulation (BPS), and 3-16% of energy reductions could be achieved when control sequences encouraged occupants to undertake energy-efficient window use behaviours compared to an

identical buildings with unregulated window operations. It is also found that the unregulated window operations could increase the heating load up to 21% and cooling load by 22% relative to identical buildings with fixed windows in a cold climate. These findings suggest that control algorithms should be designed properly in mixed-mode ventilation buildings to realize its full energy-saving potential and avoid adverse energy impacts caused by unregulated window operations.

Preface

This integrated thesis consists of two journal papers, either published or under review. Should readers wish to refer to materials from this thesis, the current thesis is required to be cited. The articles included in this thesis are as follow:

- **Article 1** : W. Liu, H. B. Gunay, M. M. Ouf. Modelling window and thermostat use behaviour to inform sequences of operation in mixed-mode ventilation buildings. *Science and Technology for the Built Environment*, vol. 27 (2021), no. 9, pp. 1204–1220.
- **Article 2** : W. Liu, H. B. Gunay, M. M. Ouf. Regulating window operations using HVAC terminal devices' control sequences: A simulation-based investigation. *Journal of Building Performance Simulation* [Under review].

The articles have been altered slightly to help the flow of this dissertation. Reference is made to figures from other chapters to avoid redundancy.

Use of copyrighted material from the published articles is acknowledged as per the corresponding publisher's permission guidelines with respect to the authors' rights.

In the aforementioned articles, Weihao Liu was the principal contributor to the data analysis and preparation of written material and figures presented in the articles, under the supervision of Dr. H. Burak Gunay and Dr. Mohamed M. Ouf.

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Chapter 1. Introduction

1.1 Background

Natural ventilation, mechanical ventilation, and mixed-mode ventilation represent the three types of ventilation systems in buildings, as shown in Figure 1.1. Prior to the 1950s, natural ventilation was the primary approach for cooling and maintaining indoor air quality, while only 2% of North American buildings were equipped with air conditioning units [1]. Natural ventilation is a mode of ventilation leveraging wind and thermal buoyancy to drive outdoor air through building envelope openings [2]. The outdoor air driven into buildings can significantly alleviate odours and improve indoor thermal comfort. Natural ventilation is often designed as single-sided or cross-flow [3]. The single-sided natural ventilation system has one or more openings at only one façade of a closed room or building [3], whereas the cross-flow (or cross) natural ventilation has two or more openings that are on two or more facades [4]. Both single-sided and cross natural ventilation can be delivered through manually operable windows or automated windows. However, the applicability of natural ventilation is limited due to its dependence on the local climate and outdoor air quality [5]. For example, a building in a desert climate or a cold climate can only obtain effective cooling by using natural ventilation for less than half of the year, whereas buildings in a subtropical climate can utilize natural ventilation and maintain thermal comfort throughout the year [6].

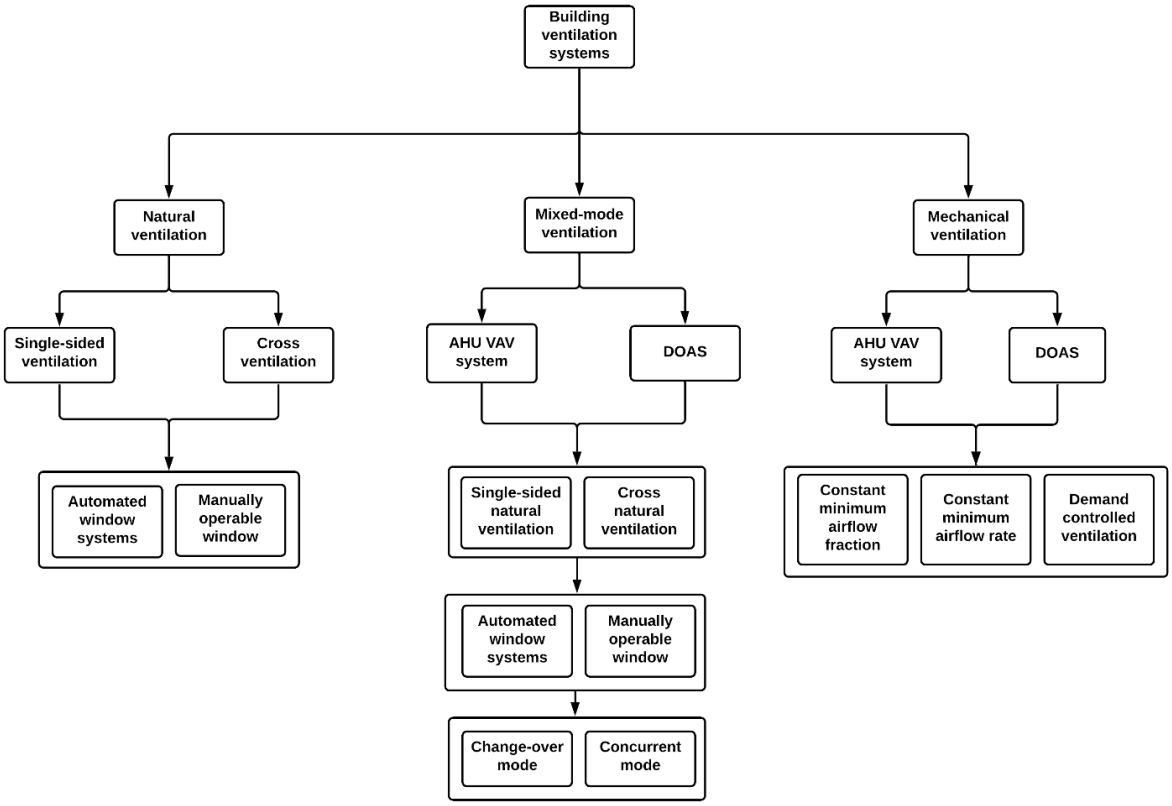

Figure 1.1: The natural ventilation, mechanical ventilation, and mixed-mode ventilation systems with their common configurations and control approaches.

Hence, mechanical ventilation has gained popularity in the past four decades. It is a mode of ventilation that relies on mechanical systems to provide outdoor air. Using mechanical systems to deliver the outdoor air also enables the opportunity to condition and filter the air before supplying it to the room, which can be done by the systems of air handling unit (AHU) and variable air volume (VAV) terminal device [7]. Research has found that thermal comfort in mechanically ventilated buildings was significantly improved relative to naturally ventilated buildings [8]. However, indoor air quality issues (e.g. “sick building syndrome”) began arising in the mechanically ventilated buildings in the 1970s [9]. The cause of “sick building syndrome” was found to be the reduction of outdoor air supply (7 L/s reduced to less than 2.5 L/s per occupant [9]) as conditioning the outdoor air and delivering it can

consume a large amount of energy, especially when outdoor air is much colder or warmer than the supply air temperature. Consequently, local building codes and guidelines have been constantly updated to ensure a sufficient amount of outdoor air is provided [10]. The HVAC systems have set the constant minimum airflow fractions or constant minimum airflow rates to ensure the minimum amount of outdoor air supplied is still complying with the standards. In addition, the approach of demand controlled ventilation (DCV) [11] and the dedicated outdoor air system (DOAS) [12] were developed to conserve energy. DCV did so by delivering outdoor air based on temporal and spatial indoor air contaminant concentration. while, the DOAS configuration achieved this by separating heating/cooling and ventilation, which ultimately eliminates the need for over-ventilation in spaces with high cooling demand.

Nevertheless, energy consumption in the building sector in North America has increased drastically with the wide use of mechanical ventilation in commercial buildings. The electricity consumption in the building sector attributed about 25% of U.S. total electricity consumption in the 1950s and grew to 40% in the early 1970s [13]. By 2014, the share has increased to 76% of total electricity consumption [13]. As a result, natural ventilation has experienced a recent resurgence of interest, mainly for its energy-saving potential [14]. Incorporating natural ventilation into mechanically ventilated buildings can accommodate the energy-saving benefits from natural ventilation while maintaining thermal comfort throughout the year by mechanical ventilation systems. Therefore, mixed-mode ventilation as a design feature is introduced to combine mechanical and natural ventilation to reduce energy consumption without compromising indoor thermal comfort and air quality [15]. Mixed-mode ventilation systems can deliver natural ventilation through manually operable windows

or automated windows, while the configurations of the window openings can be designed as single-sided or cross [16]. Mixed-mode ventilation systems can also operate in different modes, such as concurrent and change-over modes, to satisfy various demands from certain zones in a building [17]. The concurrent mode refers to the ventilation mode in which mechanical and natural ventilation are provided in the same space simultaneously. In contrast, the change-over mode allows the systems to alternate between mechanical ventilation and natural ventilation for a thermal zone or even for the entire building [18]. Extensive research has shown that mixed-mode ventilation buildings have considerable energy-saving advantages over mechanical ventilation buildings [19[20]21] while receiving higher satisfaction rates from occupants regarding thermal comfort and indoor air quality [17].

Even though a mixed-mode ventilation system improves the building energy efficiency and indoor thermal comfort, some barriers are discovered that could limit the mixed-mode ventilation from reaching its full energy-saving potential. First, mixed-mode ventilation design remains case-specific, and there are no prescriptive guidelines for individual buildings to achieve optimal performance. ASHRAE Guideline 36 only provides recommendations to take advantage of operable windows by applying heating and cooling setbacks when windows are opened [22]. However, the setback values (e.g., increase the cooling setpoint to 49℃ and decrease the heating setpoint to 4℃) were not informed by any research. In addition, consensus cannot be reached about which mode should be primarily employed in a specific building, especially when numerous contextual factors are taken into account during the design phase, such as local climate and building characteristics (e.g., building orientation, window to wall ratio, etc.) as well as occupant preferences [23]. Consequently, the actual

performance of mixed-mode ventilation relies heavily on the designer's knowledge and empirical judgment. Second, the energy-saving potential of mixed-mode ventilation is largely dependent on the effectiveness of utilizing natural ventilation [19]. As discussed previously, the efficacy of natural ventilation is limited by the local climate, which can lead to the same issue for mixed-mode ventilation. For example, employing mixed-mode ventilation in a desert climate or a cold climate can be less favourable than in a subtropical climate because the period of time that natural ventilation can be used is much shorter. Furthermore, the effectiveness of utilizing natural ventilation can also depend on the willingness and appropriateness of using windows from the occupants. It is observed that window operations are mostly unregulated in mixed-mode ventilation buildings [24], meaning that the window use behaviour from occupants is unguided and solely dependent on their habits and preferences. This can result in inappropriate window opening actions where the windows are open when the outdoor temperature is too cold or too warm that can negatively impact the building energy efficiency. The study by Gunay, O'Brien, and Beausoleil-Morrison [25] shows that inappropriate window openings during winter can increase the heating loads by 15% in a cold climate.

To leverage natural ventilation when advantageous, and regulate window operations to avoid inappropriate window openings, recent research effort has attempted to explore automated window systems [26, 27]. In these systems, the window state is controlled by an actuator so that the window state can be alternated automatically between open and close, or the opening angle is adjusted linearly. The window actuators can be controlled through a building automation system (BAS) without requiring involvement from occupants. This approach, despite being promising, requires not only the cost of additional sensors and actuators but also

resources of data processing and computing so that BAS can effectively control the window state when conditions are advantageous. Further, an automated window system can reduce occupants' perceived control over their indoor environment, which may lead to less indoor comfort [28]. Thus, the barrier of implementing automated window systems and operating them in an effective manner is high. A practical, economical approach to regulate window operations is still needed.

1.2 Research objectives and questions

Sequences of operation of terminal devices in mixed-mode ventilation buildings are often designed the same way as their mechanically ventilated counterparts, meaning that the energy and comfort impact of operable windows being used by occupants is ignored. This approach not only wastes the opportunity to effectively leverage natural ventilation when conditions are advantageous but also results in energy penalties by inappropriate window openings. For example, it was observed that windows were left open since the beginning of the COVID-19 pandemic in seven private offices (out of thirty-six offices in total that are equipped with window contact sensors to monitor window states) in two academic buildings where this research is conducted, respectively. When windows are open during the winter in a cold climate, the indoor temperature decreases drastically, and the HVAC systems controlled by current sequences are unable to address this issue. HVAC systems can only provide additional heating to increase and then maintain the indoor temperature, which can waste a substantial amount of energy. Moreover, when the windows are left open during off-hours of the HVAC system, the AHU must wake up to provide heating to the rooms with open windows in order to prevent potential freezing and damages. Given that AHU is a

system-level control device that serves multiple thermal zones in a building, this inappropriate window opening can cause greater energy waste. Therefore, improving the sequences of operation in mixed-mode ventilation buildings and regulating window operations is a crucial research topic. To date, all the existing research attempts to regulate window operations relying on automated window systems, yet manually operable windows remain unregulated, especially with no changes in the control sequences in these buildings.

The goal of this research is to develop new sequences of operations to regulate manual window operations in mixed-mode ventilation buildings in a cold climate. The development of the control sequences is undertaken in two academic buildings in Ottawa, Canada. These two buildings utilize a mixed-mode ventilation strategy by having AHU and VAV devices as the mechanical ventilation equipment and manually operable windows to deliver natural ventilation. The existing control sequences of the buildings do not take the operable windows into account, and occupants have full controllability over their operable windows. Hence, the window operations remain unregulated, and the occupants' interactions with their thermostats and windows provide invaluable information for the optimization of current control sequences. Thus, the objectives of this research are to (1) model the window and thermostat use behaviour based on the data acquired from twenty private offices in these two buildings, which covers a one-year period from August 2018 to August 2019, (2) develop control algorithms based on the insights gained from the modelling results; (3) examine the effectiveness of the control algorithms by using building performance simulation (BPS). The scope of the research is limited to improve the sequences of operations on the zone-level with AHU and VAV devices and manually operable windows. The major inquires of this

integrated thesis are broken down by chapter, and the research questions are presented for each chapter:

- Modelling window and thermostat use behaviour to inform the control sequences (Chapter 2)
    - How often do the occupants use the window and thermostat in a mixed-mode ventilation building in a cold climate?
    - What are the model formalisms suitable to gain insight of occupant behaviour patterns?
    - What are the common behaviour patterns?
    - How can the occupant behaviour patterns be used to improve the control sequences, and conversely, how do the control sequence influence occupants' behaviours to promote energy-efficient actions?
- A simulation-based investigation for the proposed control sequences (Chapter 3)
    - How can we determine when it is advantageous to initiate the control sequences to encourage occupants to use natural ventilation or stop using it?
    - What level of energy savings can be achieved by the control sequences?
    - How does the control sequence perform compared to other control scenarios, such as using an automated window system and having an inoperable window?
    - What are the constraints of the control sequences that should be considered?
    - How can the study improve current standards and guidelines in terms of the performance of mixed-mode ventilation systems?

1.3 Document structure

The remainder of this integrated thesis consists of two main body chapters on (1) modelling window and thermostat use behaviour to inform the control sequences, (2) a simulation-based investigation for the proposed control sequences. Each chapter is outlined briefly below:

Chapter 2: This chapter presents the analysis of the window and thermostat use data gathered from 20 private offices in two academic buildings. The formalisms used to analyze the window and thermostat use data are discrete-time Markov logistic regression models and decision tree models. The results of occupant behaviour models and the accuracy of models are discussed in detail. Then, the insights gathered from occupant behaviour models are synthesized to develop recommendations for improving control sequences of terminal devices. The proposed control sequences aim to encourage occupants to open the windows when conditions are advantageous and encourage occupants to close the windows when energy penalties may be caused.

Chapter 3: This chapter presents the energy performance of the control sequences developed in Chapter 2, which is tested by the building performance simulation (BPS) tool EnergyPlus. The base thermal zone model is built to mimic the private office in the case study building, and the discrete-time Markov logistic regression models developed in Chapter 2 are implemented into BPS to represent the occupants' window and thermostat use behaviours. The energy performance of using control sequences to regulate window operations is compared with three window use scenarios: manual window operation without adjusting the zone control based on window position and outdoor/indoor climatic conditions (i.e.,

unregulated window operations); automated window operations, and fixed (non-operable) window scenario.

Chapter 4: This chapter summarizes the findings and conclusions from each chapter, while the limitations of the research in each chapter are discussed. The contributions of the research from each chapter are highlighted, and the recommendations for future work are also provided.

Chapter 2

This chapter has been published as:

Modelling window and thermostat use behaviour to inform sequences of operation in mixed-mode ventilation buildings.

W. Liu, H. B. Gunay, M. M. Ouf, *Science and Technology for the Built Environment*, vol. 27 (2021), no. 9, pp. 1204–1220.

2. Modelling window and thermostat use behaviour to inform the control sequences

2.1 Introduction

Prior to the 1950s, only 2% of North American buildings were equipped with mechanical ventilation [1]. Natural ventilation was the primary approach for cooling and maintaining indoor air quality. With the widespread use of mechanical ventilation in commercial buildings in North America, thermal comfort was improved compared to naturally ventilated buildings [8]. However, mechanically ventilated buildings had much higher energy consumption, largely due to over-ventilation in low occupancy sections of a building. Further, indoor air quality issues (e.g., “sick building syndrome” in the 1970s) began arising more frequently, particularly where occupants formed large and dense clusters within parts of buildings [29]. Consequently, local building codes and guidelines have been constantly updated to ensure acceptable indoor air quality. Aiming to achieve the higher goal of balancing indoor comfort and energy consumptions, mixed-mode ventilation has gained much popularity in the past years. Mixed-mode ventilation, also known as a hybrid ventilation system, combines mechanical and natural ventilation [14]. It was described by

Wouters et al. [16] as a system that can manually or automatically shift between mechanical and natural ventilation to reduce energy consumption and improve comfort. It was found that 17% to 47% of heating, ventilation, and air-conditioning (HVAC) related energy savings can be achieved through mixed-mode ventilation [19]. In terms of indoor thermal comfort and air quality, mixed-mode ventilation buildings also tend to receive higher occupant satisfaction compared to mechanically ventilated buildings [15, 21, 30].

Despite all the benefits, there are a few barriers that restrict mixed-mode ventilation to be a fully advantageous feature. Mixed-mode ventilation design still remains case-specific, and there are no prescriptive guidelines for individual buildings to achieve optimal performance. In fact, mixed-mode ventilation buildings can be operated quite differently with various modes such as zoned, concurrent and change-over [17, 18, 23]. Currently, consensus cannot be reached about which mode should be primarily employed in a specific building, especially when numerous contextual factors are taken into account during the design phase, such as local climate and building characteristics (e.g., building orientation, window to wall ratio, etc.) as well as occupant preferences. In addition, existing guidelines and research show conflicting views about mixed-mode ventilation buildings. For instance, ASHRAE Standard 55 classifies mixed-mode ventilation buildings as mechanically ventilated buildings and restricts the use of adaptive comfort models to only natural ventilation buildings [31]. On the other hand, European standards expand the application of adaptive comfort models in mixed-mode ventilation buildings operating in natural ventilation mode [32]. National Building Code of India incorporates two adaptive comfort models to evaluate comfort in naturally ventilated buildings and mixed-mode buildings separately [33]. Further, Deuble and de Dear

[34] proposed that mixed-mode ventilation buildings with the change-over mode can be considered as naturally ventilated buildings.

Moreover, studies have identified a considerable energy and comfort performance gap between the design and actual operation of mixed-mode ventilation buildings, largely due to uncertainty caused by occupant behaviours [18, 35- 37]. For example, De Vecchi et al. [24] revealed that even when conditions were advantageous to utilize natural ventilation to save energy, occupants typically tended to adjust their indoor thermal conditions through thermostats. Further, unregulated window opening can exacerbate the variations in energy performance. For instance, Gunay, O'Brien, and Beausoleil-Morrison [25] demonstrated that manually operated windows, characterized by stochastic occupant behaviour models, can increase space heating loads by up to 15% in a cold climate. In contrast, installing motorized windows and automating the window opening on schedules can achieve energy savings by 10-65% compared to fixed windows in a cold climate [38].

Despite the energy-saving potential of the automated window, manually operated windows are more popularized due to the lower cost and mostly remain unregulated. Ackerly and Brager [39] have explored an approach of regulating the window openings through a window signalling system, which can advise occupants about when to open and close windows based on environmental conditions. However, some occupants tended to ignore the signalling systems or found it interruptive, which suggests more research is needed to identify different approaches to improve occupant engagement, where a better understanding of occupant behaviour is essential.

In this chapter, the authors explore the feasibility of improving current control sequences to engage terminal HVAC devices to regulate window use behaviours with the concept of

occupant-centric control (OCC). Occupant-centric control is the mode of indoor climate control whereby occupancy and occupant comfort information is used in the sequence of operation of HVAC systems [40, 41], which represents a formal framework for the control of terminal devices in mixed-mode ventilation buildings. To the best of our knowledge, no previous study has explored the proposed approach, and it requires an understanding of window and thermostat use behaviours in mixed-mode buildings, which can be gathered by occupant behaviour modelling. Thus, the following sub-sections present a brief review of previous work on occupant behaviour modelling and implementations of OCC in actual buildings.

2.1.1 Previous work on thermostat and window use behaviour modelling

Occupants tend to be more satisfied by having the ability to control their indoor environment compared to users exposed to environments of which they have no control [17, 42]. They undertake adaptive actions (e.g., adjust setpoints, open and close windows) to mitigate discomfort, which enables learning occupant's comfort preferences by observing adaptive behaviour patterns. Many studies have developed various modelling formalisms such as Bernoulli, discrete-time Markov, discrete-event Markov, and survival models. Their strengths and weaknesses were demonstrated by a review [43], which suggest that the Markov models (i.e., discrete-time and discrete-event models) had the best predictive outcomes for occupants' adaptive behaviours (e.g., window opening actions and thermostat override actions), whereas the survival models are best suited to predict non-adaptive behaviours (e.g., light switch off actions). Moreover, occupant behaviour models often yield different accuracies even though environmental conditions are identical. For example, Rijal et al. [44], Haldi and Robinson [45] and Yun and Steemers [46] have developed models

characterizing window use, which were integrated into building performance simulation by Gunay, O'Brien, and Beausoleil-Morrison [25]. The simulations were conducted in a generic building model, and the results of comparisons demonstrated that predictions of these models varied considerably. In contrast to fixed windows, Haldi and Robinson's model predicted that the space heating load increases by ~6% and cooling load decreases by ~15%, whereas Yun and Steemers' model predicted that heating load increases by ~15% while cooling load decreases by ~40%.

2.1.2 Previous work on OCCs

The previous studies exhibit the challenge of accurately predicting occupants' thermostat and window use behaviour, and they also revealed that occupants undertake adaptive actions (i.e., override setpoints, open and close windows) to mitigate discomfort, which enables learning occupant's comfort preferences by observing adaptive behaviour patterns. As modelling approaches for adaptive behaviours become more robust, the concept of OCC gained popularity [40, 47]. Occupant behaviour models can be developed to learn occupant preferences from collected data to adjust indoor climate control and achieve energy savings. For example, Gunay et al. [48] developed a discrete-time Markov logistic regression model for thermostat use. They used this model to recursively learn occupants' preferences and to adapt the temperature setpoints in eight private offices. Learned temperature preferences were about 19 to 21°C in the heating season and 24 to 25°C in the cooling season. Compared to original default setpoints, a 2-3°C setpoint setback could be applied to save energy without causing thermal discomfort.

In lieu of passively observing adaptive behaviour to model occupant preferences (e.g., learning from thermostat use behaviour), occupant models can be developed upon actively

solicited comfort information. Actively soliciting occupant feedback can expedite the preference data collection process – which is particularly useful for types of adaptive actions that occupants infrequently undertake. For example, Jayathissa et al. [49] developed a smartwatch application to obtain user feedback about thermal comfort. The experiment gathered over 1000 data points in a month and characterized occupants' thermal preferences based on the surrounding environment. Similarly, Pritoni et al. [50] developed a web application to collect occupant feedback on thermal comfort, and the findings were used in temperature control in an academic building. Over 10,000 feedback votes were received and fed into the building automation systems (BASs), and adjustment of control sequences was made. The changes made to the BAS were estimated to reduce the energy use by 20 to 30%.

To the best of our knowledge, only a few papers demonstrated the potential of OCC in regulated window opening in mixed-mode ventilation buildings, and all of them focused on automated windows. In a simulation-based investigation, Zhao et al. [27] integrated OCC with model predictive control (MPC) algorithms in a mixed-mode ventilation building. Occupant preferences for temperature setpoints were retrieved from a web-based database in which occupant thermal feedback was stored. Meanwhile, the HVAC systems were optimized by MPC, and window operations were automated by a control logic that considers outdoor temperature and rain as the indicator of whether or not windows should be opened. The simulation results demonstrate that this integration can effectively reduce energy consumption by 37% compared to the mixed-mode ventilation strategy. Note that in this study, mixed-mode ventilation was used with automated windows, and the occupants' thermal preferences were learned from feedback within a one-week period during the shoulder season. More studies in longer timespans are needed to explore the viability of the

integrated approach of the OCC method and mixed-mode ventilation with manually operable windows since the aforementioned studies indicated that manually operable windows might adversely affect the energy performance.

To date, no research and guidelines have provided solutions to eliminate the energy impact posed by inappropriate window opening in mixed-mode buildings with manually operable windows. ASHRAE Guideline 36 recognizes the energy-saving potential of operable windows by recommending heating and cooling setpoint setback (e.g., increase the cooling setpoint to 49℃ and decrease the heating setpoint to 4℃) when operable windows are opened [22]. Putting aside the validity of setpoint setback values (as these rather arbitrary threshold values are not informed by occupant behaviour research), no recommendations are made to maximize the window openings when environmental conditions are advantageous or avoid inappropriate window openings when energy penalties can be caused.

2.1.3 Motivation and objectives

Sequences of operation of terminal devices in mixed-mode ventilation buildings are often designed the same way as their mechanically ventilated counterparts – ignoring the energy and comfort impact of occupants' window use behaviour. The energy penalties of inappropriately controlled variable air volume (VAV) terminal units can thus be particularly concerning in extremely cold or hot climates. To this end, thermostat and window use data archived within modern BASs represent an untapped opportunity to gain insights into occupant preferences. Specifically, an analysis of thermostat and window use data with concurrent indoor environmental quality data can yield personalized adaptive behaviour models which predict the thermal conditions that minimize the need for these adaptive actions. Furthermore, the acquired information provides an opportunity to optimize the

existing control schemes in mixed-mode ventilation buildings based on an occupant-centric approach.

To fulfill the energy-saving potential in mixed-mode ventilation building, the objectives of this chapter are to: (1) build adaptive behaviour models based on thermostat and window use data as well as indoor environmental quality data, (2) develop preliminary recommendations for the adjustment of control schemes for mixed-mode buildings based on developed models. Our emphasis is particularly on passively regulating window use behaviours in cold climates.

2.2 Methodology

An overview of the proposed method to develop sequences of operations for terminal devices in mixed-mode ventilation buildings is shown in Figure 2.1. First, the proposed method entails collecting environmental measurements such as indoor and outdoor temperature, relative humidity (RH), CO_2 concentration, as well as occupant behaviour data such as occupancy, thermostat keypress instances, and window opening and closing instances from BASs. Prior to the data collection, point-by-point inspection with reference temperature, RH, and CO_2 loggers, the accuracy of these sensors was examined. Offices with dysfunctional sensors or sensors with large bias (e.g., bias caused by sensor drift that exceeds acceptable range) were excluded from the study. The functionality of the motion detectors and window contact sensors was verified as well. Further, the functionality of VAV terminals is also critical for the proposed control sequence. In the case study, the authors inspected the functionality of VAV terminals serving these offices by changing their damper and reheat coil states and monitoring the discharge air temperature and flow rates by using an airflow capture hood. Then, a preliminary data analysis was conducted to gain insights into the

occupants' window and thermostat use patterns. Next, occupant models were developed to characterize behaviour patterns and infer thermal preferences. Specifically, two different model formalisms were employed: discrete-time Markov logistic regression models and decision tree models. Lastly, findings were synthesized to provide preliminary recommendations for control sequences for VAV terminal zones in mixed-mode ventilation buildings in cold climates.

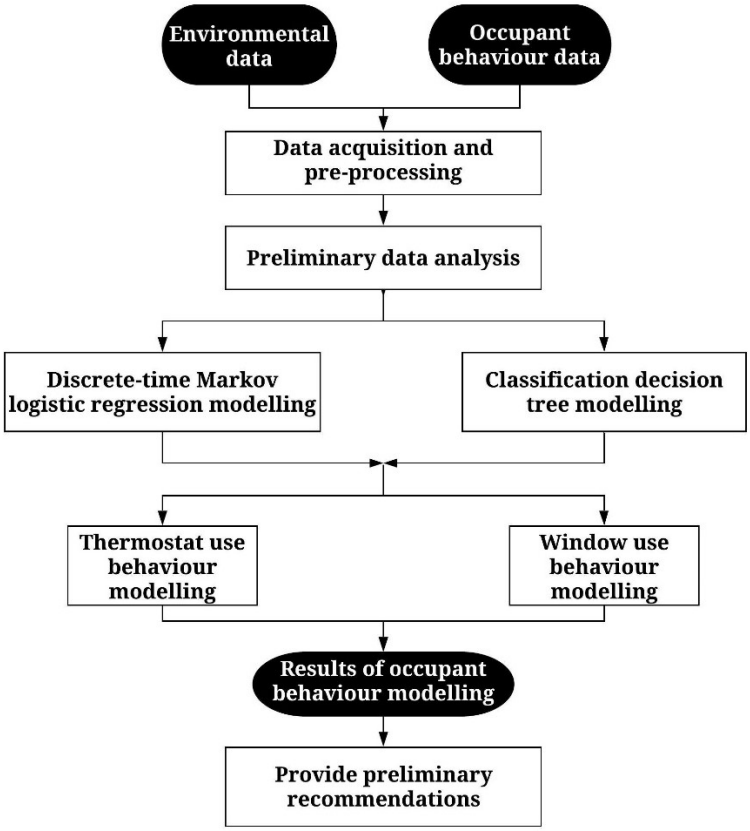

Figure 2.1: Overview of the proposed framework.

2.2.1 Overview of the buildings and data

To demonstrate the method, a case study was conducted in two mixed-mode ventilation academic buildings in Ottawa, Canada, as shown in Figure 2.2. Constructed in the 2010s, these buildings are comprised of lecture halls, conference rooms, private and shared offices,

and computer laboratories. The external wall glazing ratio is around 30% for rooms with one of four walls being external and around 80% for the corner rooms. Notably, building 1 has a three-floor high atrium at its centre, providing an open space for occupants. The local climate is designated as Zone 6 based on the National Energy Code of Canada for Buildings [51] with heating degree days of about 4500. Figure 2.3 presents the variations of outdoor temperature and indoor RH in the covered year. It shows the outdoor temperature was mostly below -5°C and indoor RH was below 30% in the winter. Given the cold outdoor temperatures during winter, natural ventilation is mostly viable to provide cooling in the summer and shoulder seasons. The buildings are served by the same central heating plant as the primary heating source, while each building has a chiller to provide cooling. The central heating plant typically provides heating between October and May, and cooling is available for the rest of the year. Buildings are equipped with air handling units (AHU) at the rooftops, and the AHU schedule in building 1 was set to operate between 7:00 am and 9:00 pm during the heating season and 7:00 am to 6:00 pm during the cooling season, while the AHU in building 2 operates 24h year-round. Each thermal zone in the case study buildings was equipped with a VAV unit, which is shared by one to four adjacent offices.

Figure 2.2: The photos of selected buildings: Building 1 (Left), Building 2 (Right).

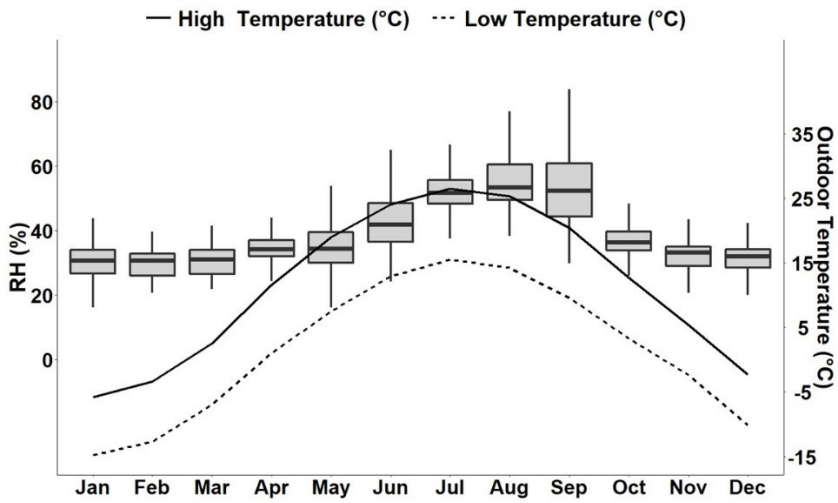

Figure 2.3: Variations in indoor RH and outdoor temperature in the covered year. The box whisker plots demonstrate the indoor RH, while the line chart illustrates the outdoor temperature.

As schematically illustrated in Figure 2.4, each private office has an independently controlled hydronic heating panel to supply additional heating. A commercial thermostat, which is integrated into the BAS, is also included in every office, which contains a CO_2 sensor, an RH sensor, and a passive-infrared motion detector. The specifications of the built-in sensors are listed in Table 2.1. In building 2, offices are equipped with an additional passive-infrared motion detector mounted on the ceilings. Selected offices in both buildings are equipped with manually operable windows and window contact sensors. The operable windows are 1 m wide by 0.6 m high awning windows. The window contact sensors report binary window status (i.e., 1 as opened, 0 as closed). Besides the window state data, thermostat keypress actions and room occupancy data are collected and stored in the BAS along with temperature, RH, and CO_2 measurements.

Table 2.1: Characteristics of sensors.

Thermostat sensors	Range/Accuracy
Temperature sensor range	$0 - 70℃$
Temperature sensor accuracy	$\pm 0.2℃$
Relative humidity sensor range	$20\% - 80\%$

Relative humidity sensor accuracy	$\pm 3\%$
Indoor co_2 sensor range	$0 - 2000$ ppm
Indoor CO_2 sensor accuracy	± 50 ppm $+ 2\%$ of reading
Occupancy sensor range	5 m

During the heating season, the default temperature setpoints are set as 22°C, while the default setpoints are 23.5°C for the cooling season. Occupants are allowed to change the temperature setpoint up to ±2°C temporarily for the rest of the day; and to avoid excessive cooling and heating provided, the adjustments are reverted to the default setting at midnight. Given that each VAV unit is shared by adjacent offices in a thermal zone and occupants can have different setpoint settings, VAV reheat coils are controlled to meet the heating requirements of the room with the highest indoor temperature among the sharing rooms during the heating season, while VAV dampers are controlled to meet the average of the room temperature during the cooling season. Even though hydronic heating panels and operable windows are equipped in the perimeter offices, the setpoint change requests are not always achieved due to the availability and granularity of terminal devices. Furthermore, the existing control sequences do not take the operable windows into account, and occupants have full controllability over their operable windows. Hence, the window use remains unregulated in the case study buildings, and the occupants' interactions with their thermostats and windows provide invaluable information for the optimization of current control sequences.

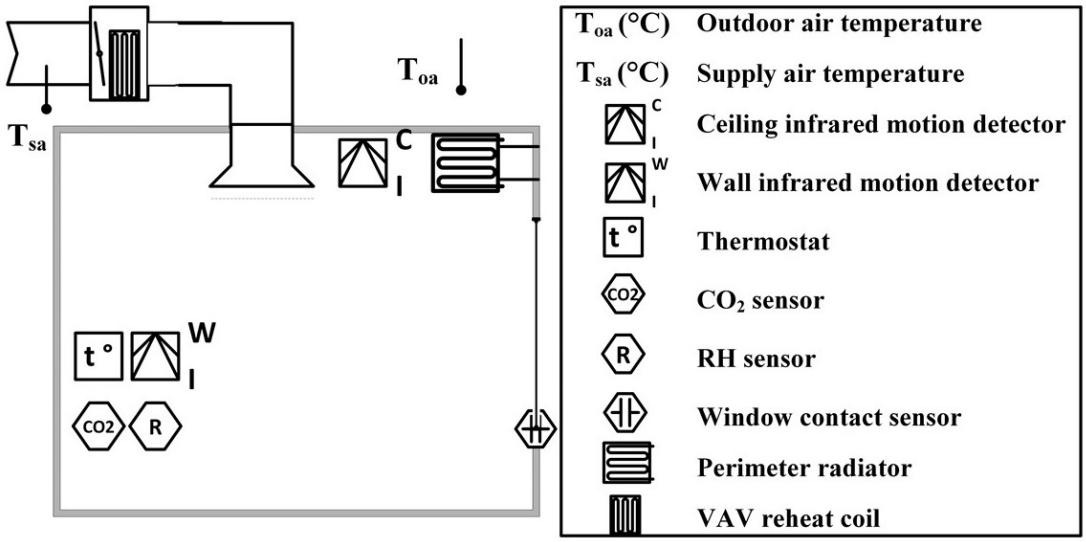

Figure 2.4: A typical configuration of office room sensors and actuators. Note that the CO2 concentration sensor, wall infrared motion detector and RH sensor are integrated with the thermostat, and the ceiling infrared motion detectors are only installed in building 2.

Prior to the case study, the integrity and accuracy of sensors and archived data were examined as previously described. Seven private offices in building 1 and 13 private offices in building 2 were selected. Of the 20 offices studied in both buildings, 14 offices were occupied by full-time professors, and the rest were occupied by university administrators. The acquired data covered a one-year period from August 2018 to August 2019 at 15-min timesteps. An overview of the characteristics of the dataset, the occupants, and the rooms of this study is provided in Table 2.2. As shown in Table 2.2, the occupancy profiles and occupant interactions with thermostats and windows differed noticeably among 20 occupants. The occupied hours for individual occupants were in the range of 673 h to 2993 h within the covered timespan. Moreover, the number of thermostat keypress instances varied from only 3 times to 126 times, while window opening instances varied from 2 times to 55 times.

Table 2.2: List of rooms from which the data were collected.

Building	Room	Occupant gender	Window orientation	Profession	Occupied duration (h)	Thermostat keypress instances	Window opening instances	Window open duration (h)
Building 1	1	Male	South	Professor	673	118	15	173
	2	Female	East	Professor	807	18	9	530
	3	Female	East	Administrator	2080	24	55	114
	4	Female	East	Professor	800	4	7	934
	5	Male	West	Professor	1700	3	5	245
	6	Male	West	Professor	436	8	3	50
	7	Female	East	Administrator	1346	4	11	269
Building 2	8	Male	West	Professor	2993	126	6	12
	9	Male	West	Administrator	865	20	8	1471
	10	Female	West	Administrator	1428	6	31	337
	11	Male	West	Administrator	1620	14	10	485
	12	Male	West	Professor	1652	50	16	37
	13	Female	West	Professor	1373	73	46	639
	14	Male	West	Professor	630	7	14	65
	15	Female	West	Administrator	3390	33	8	863
	16	Female	West	Professor	1168	34	2	192
	17	Male	West	Professor	1126	23	10	513
	18	Female	West	Professor	1102	31	30	76
	19	Female	West	Professor	2921	55	30	53
	20	Male	West	Professor	3387	16	9	2505

2.2.2 Preliminary data analysis

A preliminary analysis of window and thermostat use data was performed to gain some understandings of occupant behaviours in the case study buildings. Aggregated raw data were examined to extract information about how occupants interacting with thermostats and windows. For example, monthly average numbers of thermostat override instances and monthly window opening durations were summarized for all selected offices.

2.2.3 Discrete-time Markov logistic regression model

For each occupant, univariate and multivariate discrete-time Markov logistic regression window and thermostat use models were developed by using the built-in logistic regression function *glm* in the programming environment R [52]. The indoor environmental measurements of occupied periods (i.e., indoor and outdoor temperatures, indoor RH, and

CO_2 concentration level) were extracted first, and then used as predictors to calculate the predicted probability of observing actions in the next timestep (i.e., within the next 15 minutes). The significance of each predictor was assessed through a forward stepwise predictor selection approach. Note that this model form has been widely used in the occupant modelling literature [53], therefore the fundamentals are not repeated in the present study. The model parameters were estimated by using the maximum likelihood estimation method as implemented in the built-in descriptive statistic algorithm [52] in R. Further, we aggregated all the models to investigate the overall behaviour of occupants. The inter-occupant diversity was discovered based on the distribution of regression parameters and the correlations between each parameter. Some occupants that showed no correlations between adaptive actions and predictors were investigated as well.

The model accuracy and appropriateness were quantified by looking at the *p*-value and standard error of the parameter coefficients and the Akaike Information Criterion (AIC). The *p*-value and the standard error of the parameters provide the relevance of each parameter coefficient to characterize the modelled behaviour, whereas AIC quantifies changes in a model's overall ability to represent the behaviour at different model complexities. AIC is a function of two variables: the maximum value of the likelihood function and a penalty factor for the number of estimated parameters – intended to discourage overfitting. Note that we used AIC instead of cross-validation in model development because the window and thermostat use behaviour were infrequent (see Table 2.1) – thus, partitioning the dataset into validation and training sets was not possible.

2.2.4 Decision tree model

For the aggregated data, decision tree models for window and thermostat use behaviour were developed by using the Recursive Partitioning and Regression Trees [54] package, established by Therneau and Atkinson [55] in the programming environment R. The models aimed to classify environmental conditions on instances in which adaptive actions took place from the other occupied instances. Hence, indoor and outdoor temperature, RH and CO_2 concentration were considered as the predictors. In the hierarchical structure of the developed decision tree models, nodes represent environmental conditions that trigger occupants to take actions, while the leaves represent the adaptive actions made by the occupants. These models were developed by using around 90,000 instances (31,497 h of total occupied period × 4 timesteps/h × 0.7), which accounts for 70% of the total dataset as a training subset. As the number of data points in which adaptive actions took place is significantly lower than those with no adaptive actions, the class imbalance was addressed by under-sampling from the normal operation class.

When developing decision tree models, the confusion matrix was calculated to assess model accuracy. The importance factor, which measures the reduction in entropy due to decision tree splitting [56], was then used to determine the significance of each environmental parameter. Moreover, the criteria for terminating the decision tree splitting were also critical, and redundant leaf nodes should be pruned to avoid over-specific or over-fitted results [57]. The complexity parameter *cp* and the relative error were introduced as the termination and pruning criteria, which can be calculated by functions in RPART package [54]. The complexity parameter is a metric based on the R^2 of the model. If any split does not increase

the overall R^2 of the model by the value of cp, then the split should be terminated. The relative error equals to 1- R^2.

2.3 Results and discussion

After a preliminary data analysis, discrete-time Markov logistic regression models and decision tree models were developed, and the results were used to infer occupant thermostat and window use behaviour patterns. Then, the findings were synthesized to provide preliminary recommendations for control sequences for VAV terminal zones in the studied mixed-mode ventilation buildings.

2.3.1 General observations from preliminary data analysis

Figure 2.5 presents the results of preliminary data analysis about thermostat and window use behaviours. Figure 2.5(a) shows the fraction of time during which windows remained open each month. In June and July, windows were open for the longest periods (around 10-15% of the time) when chillers were operational to deliver cooling to these zones. In contrast, windows remained open for much shorter periods (around 5%) in the shoulder months (i.e., April, May, September, and October), even though occupancy was significantly higher in these months than in June and July. Hence, the current control sequence should be improved to increase the utilization of natural ventilation in the shoulder seasons to leverage relatively moderate outdoor climatic conditions. In Figure 2.5(b), the monthly average number of thermostat overrides is shown. It was found that each occupant tends to increase the thermostat setpoint around three times per month on average in January, May, and October, while the average number of increase actions was below two times for the rest of the year. It also shows that occupants decreased setpoints more frequently in April and May. According

to the typical dates of change-over from heating to cooling (i.e., May and October), these results suggest thermal discomfort in shoulder months when heating or cooling mode just started.

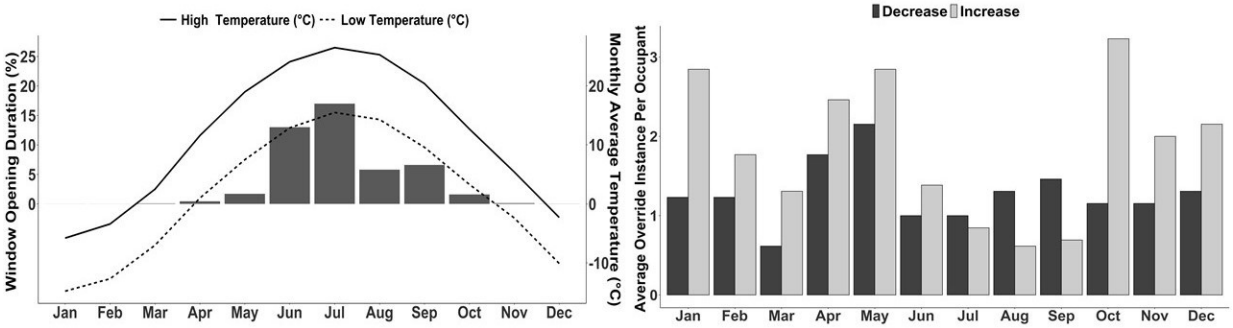

Figure 2.5: The results of preliminary data analysis about thermostat and window use behaviours that consists of: (a) bar chart of the fraction of time that the windows remain open each month, and the line charts showing the monthly average outdoor temperature; (b) monthly breakdown of the average number of thermostat override instances.

2.3.2 Discrete-time Markov logistic regression

2.3.2.1 Multivariate discrete-time Markov logistic regression

The multivariate discrete-time Markov logistic regression models not only show that environmental variables have different impacts on occupant's adaptive actions but also each adaptive action was not equally predictable by selected environmental variables. Figure 2.6(a) illustrates the number of occupants that each environmental variable has significant correlations (p-value < 0.05) with at least one adaptive action. It shows that indoor temperature was the most significant predictor that affected occupants' adaptive behaviours in surveyed buildings. Figure 2.6(b) shows the number of occupants that each adaptive action has significant correlations (p-value < 0.05) with at least one environmental variable. Surprisingly, window closing actions had significant correlations with at least one variable for only 6 occupants, which indicates that window closing actions may be affected more by

factors different from the environmental variables considered in the present study. Section 2.3.2.5 will present the investigation of occupants whose window closing actions had no significant correlation with any predictors.

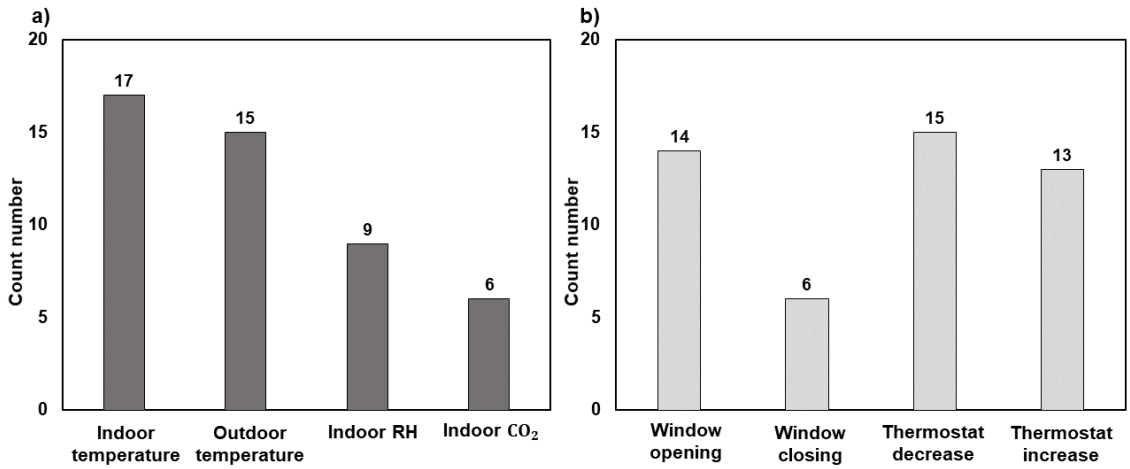

Figure 2.6: The number of occupants were found that: (a) each environmental variable has significant correlation (p-value < 0.05) with at least one adaptive action; (b)each adaptive action has significant correlation (p-value < 0.05) with at least one environmental variable.

2.3.2.2 Window opening and closing actions

After discovering that indoor temperature was the most significant predictor for most occupants, the rest of the analysis with the logistic regression models was conducted as a univariate analysis with the indoor temperature only. Figure 2.6 provides the aggregated results of the predicted probability of window opening and closing actions based on indoor temperature. The average values of parameter estimates (i.e., the average a and b in the following form: $p = 1/(1 + e^{-(b+aT_{in})})$ from occupants whose actions had significant correlations with indoor temperature are provided in Table 2.3. The probability profiles based on average parameter estimates are illustrated as the red dashed lines in Figure 2.7. The results reveal that most occupants opened and closed their windows less frequently when the indoor temperature was at around 23°C (i.e., red dashed lines). Occupants also opened or

closed their windows around three times more frequently when indoor temperature rose above 26°C or dropped below 20°C than they were at around 23°C, respectively. Note that the predicted probability for a few occupants differed noticeably from one another, which demonstrates significant inter-occupant diversity. The predicted probabilities for several occupants were not changing while the indoor temperature was increasing (i.e., the straight lines and some lines overlapped with the x-axis), which reflected the weak correlations between indoor temperature and window use behaviour.

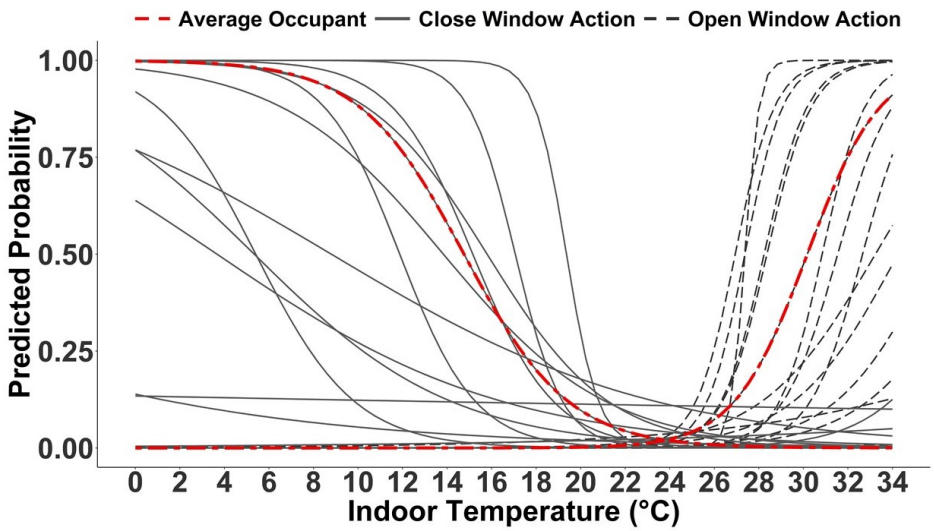

Figure 2.7: Discrete-time Markov logistic regression model results for window opening and closing actions. The red lines illustrate the average predicted probability of window use behaviour from the occupants whose actions were significantly correlated with indoor temperature.

Table 2.3: The average parameter estimates for the window use behaviour models from the occupants whose actions were significantly correlated with indoor temperature. (Highlighted in red lines in Figure 2.7).

	Parameter estimates	
Adaptive actions	a	b
Window opening action	0.61	-18.35
Window closing action	-0.43	6.28

The probability of window state change in the next 15-min is defined as $p = 1/(1 + e^{-(b+aT_{in})})$

2.3.2.3 Thermostat override actions

Figure 2.8 presents the predicted probability of thermostat overrides taking place in the next 15 minutes based on indoor temperature. The average parameter estimates of logistic regression models from occupants whose actions had significant correlations with indoor temperature are provided in Table 2.4. The probability profiles based on average parameter estimates are illustrated as the red dashed lines in Figure 2.8. It demonstrates that when indoor temperature reached 16°C and 28°C, the probability of increasing setpoints and decreasing setpoints rose drastically, meaning that occupants were more inclined to undertake actions at these conditions. It also shows that when indoor temperature was in the range of 22°C to 24°C, occupants had the least tendency to override the thermostat setpoints. The straight lines indicate the weak correlations between indoor temperature and thermostat override actions for some occupants.

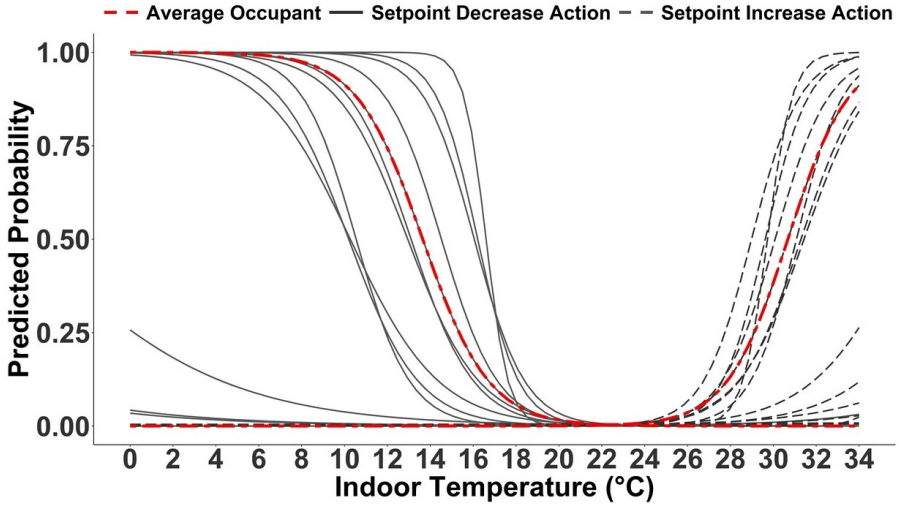

Figure 2.8: Discrete-time Markov logistic regression model results for thermostat override actions. The red lines illustrate the average predicted probability of thermostat override actions from the occupants whose actions were significantly correlated with indoor temperature.

Table 2.4: The average parameter estimates for the thermostat override action models from the occupants whose actions were significantly correlated with indoor temperature. (Highlighted in red lines in Figure 2.8).

	Parameter estimates	
Adaptive actions	a	b
Setpoint decrease action	0.70	-21.55
Setpoint increase action	-0.65	8.84

The probability of thermostat setpoint change in the next 15-min is defined as $p = 1/(1 + e^{-(b+aT_{in})})$

2.3.2.4 Inter-occupant diversity

The inter-occupant diversity investigation was presented in Figure 2.9 and 2.10. Figure 2.9 reports the properties of the parameter estimates of all occupant behaviour models successfully developed in selected offices. It exhibits that the standard deviations of parameters were considerably large, which indicates that each adaptive behaviour could vary tremendously between occupants even encountered with the same indoor temperature conditions. Figure 2.9(a) and 2.9(c) illustrate the standard deviation of parameter estimates of the window opening model and setpoint decrease models were the highest among other adaptive behaviour models. Figure 2.10 presents the correlations between the eight parameter estimates of all behaviour models from the offices where models could be successfully established. The variables a and b represent the parameter estimates of logistic regression models, while *Increase*, *Decrease, Open,* and *Close* indicate the associated behaviours. It illustrates that the parameter estimates of each behaviour were highly dependent on each other, while the parameters of each behaviour were not correlated with the parameters of other behaviour. It suggests that the likelihood of each adaptive behaviour was independent and was not affected by other actions. Thus, each adaptive behaviour was modelled separately, while the results of the discrete-time Markov logistic regression model were not used to make predictions due to substantial inter-occupant diversity. Nevertheless, these results provided valuable information about indoor temperature at which occupants were more inclined to take adaptive actions.

Some factors such as gender of occupants, clothing habits, occupancy and window orientations could exacerbate the inter-occupant diversity in occupant behaviours. In other words, these factors have a great impact on underlying variables such as metabolic rate, clothing insulation level and internal heat gains of offices, which were found critical to occupant behaviours by many studies. However, due to insufficient sample size, these factors were not analyzed in the present study.

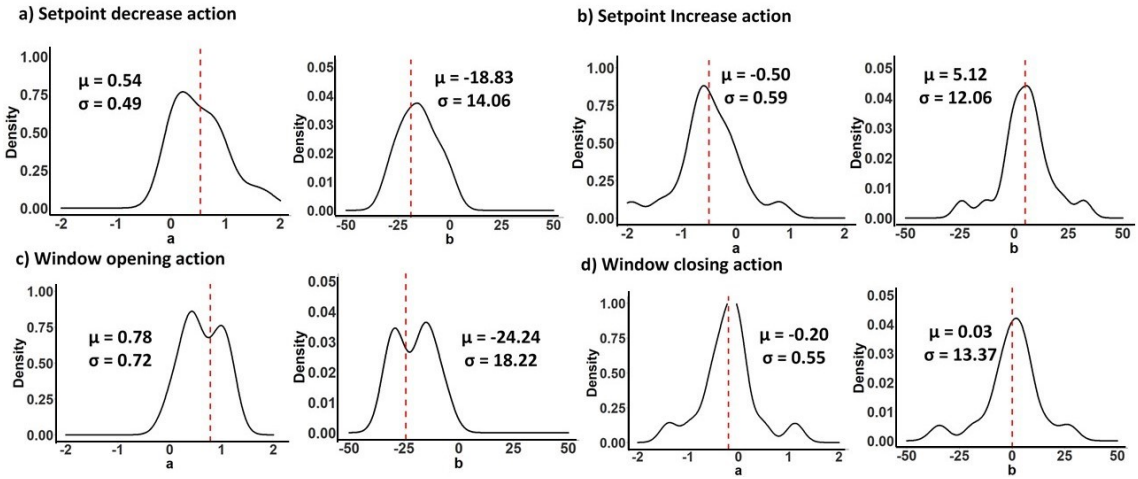

Figure 2.9: The density plots presenting properties of regression parameters of four types of occupant behaviour models among selected private offices in which models were successfully established. The standard deviations and means were also highlighted.

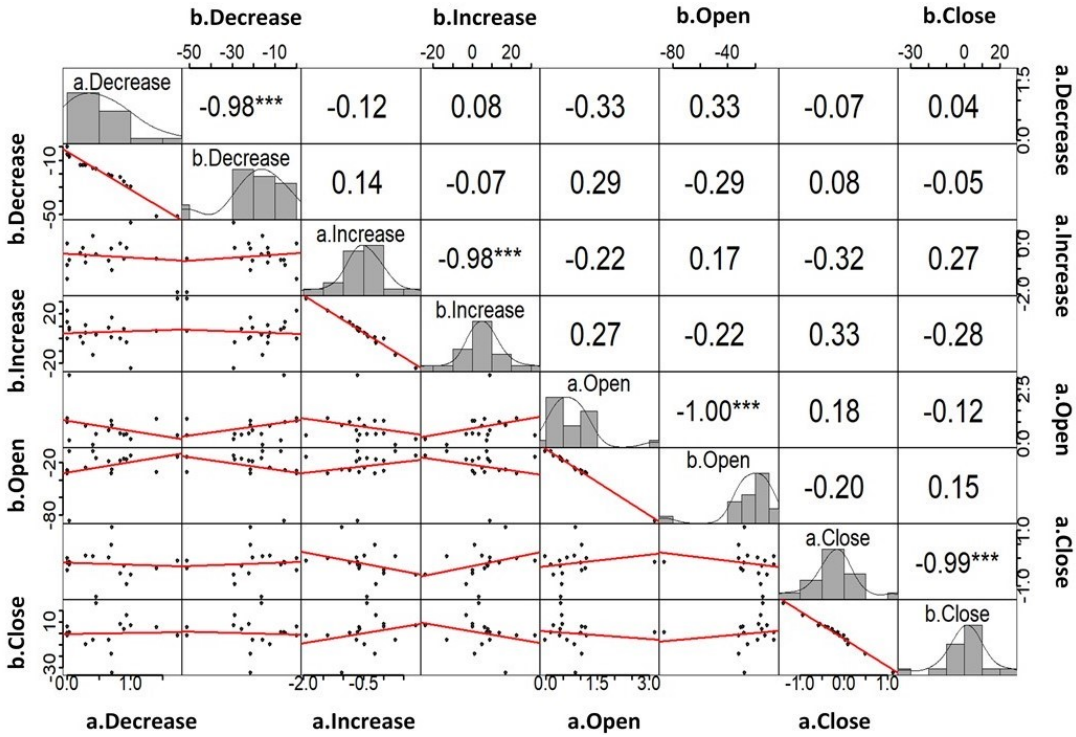

*Figure 2.10: The scatter matrix plots demonstrate the correlations between the 8 regression parameters of discrete-time Markov logistic regression models. Note that the significance of correlations was determined by Pearson correlation coefficients, and the "***" indicates a statistically significant correlation between two parameters of each behaviour.*

2.3.2.5 Investigation of occupants with insignificant correlations between window closing actions and indoor temperature

As noted previously, there were only 6 occupants whose window closing actions were significantly correlated with the indoor temperature. To better understand the window closing action patterns of the rest of occupants, their occupant behaviour data were investigated concurrently with the conditions at which adaptive actions took place. As a result, two typical window use behaviour patterns were discovered, shown in Figure 2.11 and 2.12. Figure 2.11 shows a repeated behaviour pattern in which occupants tended to close the window shortly after every window opening action (within 15 minutes). As this behaviour was repeated throughout the covered time span, we interpreted it as a habit rather than an action triggered

by thermal discomfort. It also suggests that window opening action and opening duration should be encouraged when outdoor conditions are deemed advantageous for energy saving since the outdoor temperature remained moderately below indoor temperature during the timespan shown in Figure 2.11. Another typical pattern was found in which occupants tended to leave the windows open for a long period of time and close them at arrival when noticing the window state. For example, it was discovered that the occupant kept the window open for over five days and closed it at arrival on the sixth day, as shown in Figure 2.12. Furthermore, this occupant also decreased the setpoint to adjust the indoor temperature while the window was opened, and the outdoor temperature was above 27°C, which indicates that unregulated window operations can lead to significant energy waste. A previous study by Haldi and Robinson [45] found a similar pattern and introduced an occupant behaviour model with additional sub-models to predict the probability of window closing actions at arrival. This may explain the reason why logistic regression models failed to find correlations between window closing actions and indoor temperature in fourteen of the investigated offices.

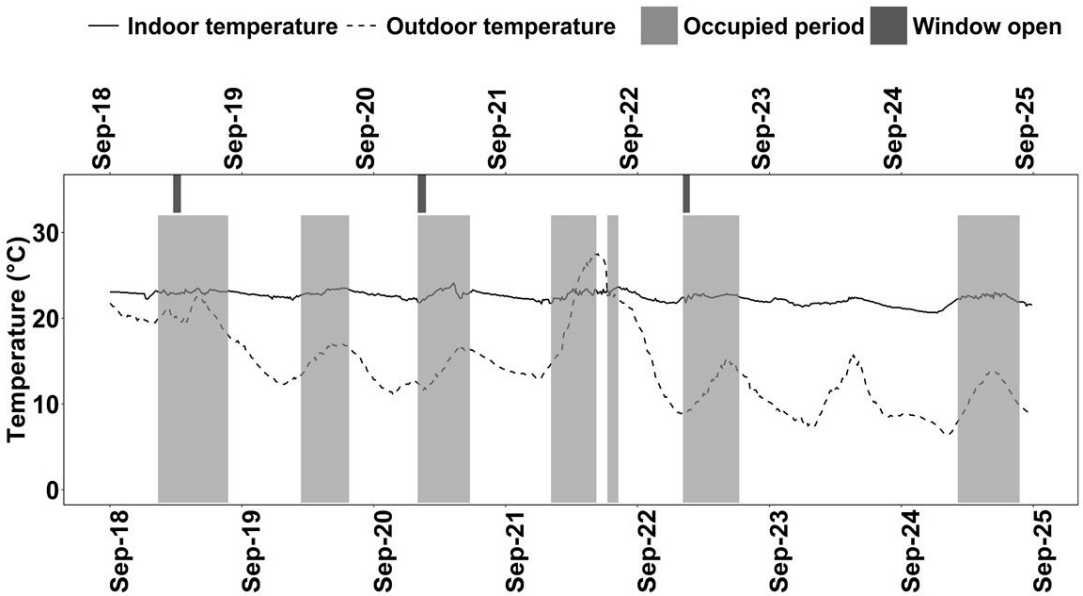

Figure 2.11:Seven-day time-series plot showing the indoor temperature and window operations from September 18th to September 25th in one room where window closing actions were not correlated with indoor temperature.

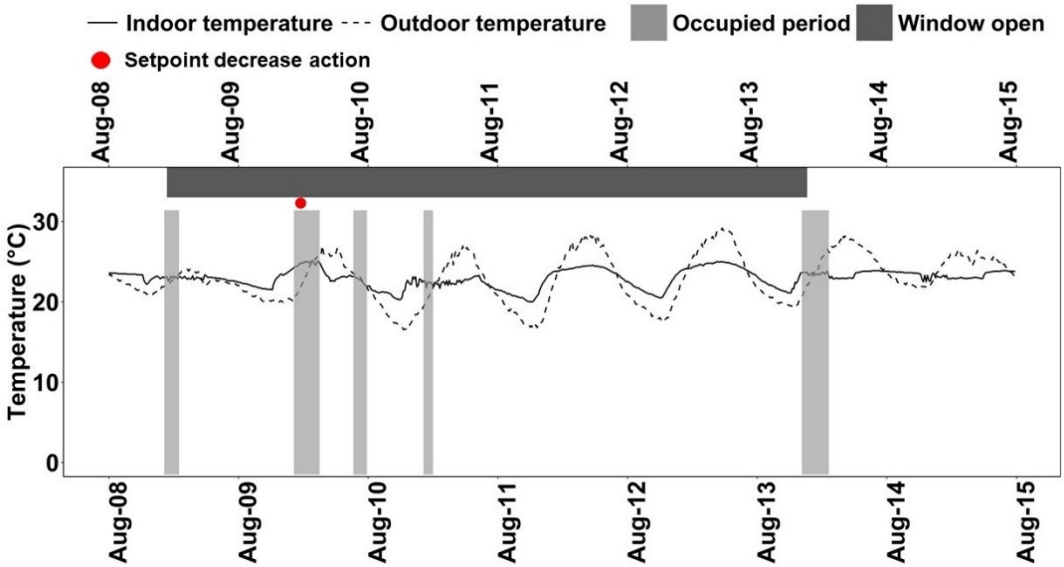

Figure 2.12:Seven-day time-series plot showing the indoor temperature, window operations and thermostat use from August 8th to August 15th in one room where window closing actions were not correlated with indoor temperature.

2.3.3 Classification Decision Trees

In this section, the results of decision tree models present the environmental conditions that triggered the window opening actions, and thermostat decrease and increase actions. However, it was found that the decision tree model failed to extract useful information for window closing actions. A possible explanation for this is that only 6 occupants' window closing actions were found significantly correlated with environmental variables (see Figure 2.6), and the actions of the rest of occupants were influenced more by their habits than indoor and outdoor environmental conditions. Furthermore, the decision tree models were pruned to avoid over-specific results so that the generated results can represent the behaviour patterns from most occupants. When having most window closing actions not associated with environmental conditions, the decision tree models can thus fail to deliver useful results.

2.3.3.1 Window opening actions

In Figure 2.13, the decision tree model suggests that the indoor and outdoor temperature and indoor RH are the most significant predictors for window opening actions. The actions took place if the indoor temperature was below 24°C while indoor RH was above 30%, and outdoor temperature was above 3°C. Alternatively, if the indoor temperature was above 27°C while the indoor RH was above 25% and outdoor temperature was above 3°C, window opening actions also took place. Both observations demonstrate occupants were unlikely to open the windows during winter (outdoor temperature < 3°C), which is expected in a cold climate. It is worth mentioning that occupants were less likely to open the windows when indoor temperature was between 24°C and 27°C. It could be interpreted that occupants were more inclined to use the thermostat to adjust indoor temperature if perceived discomfort occurred in this temperature range.

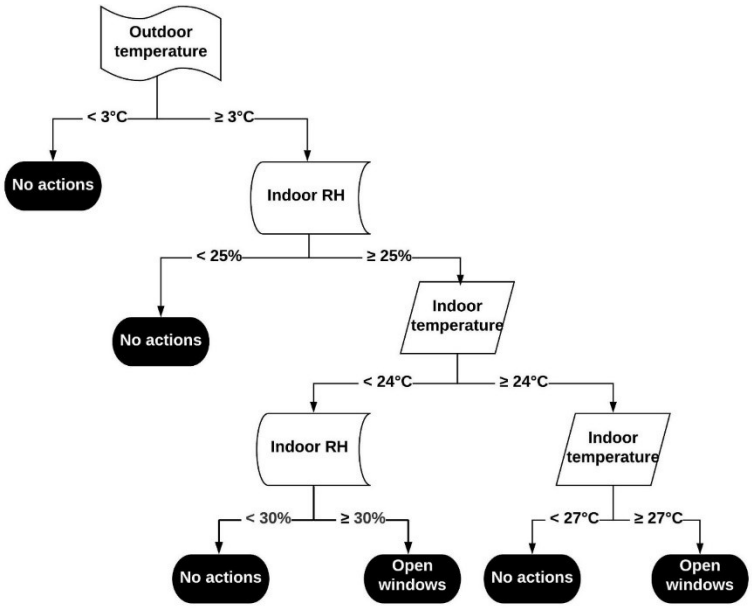

Figure 2.13: Classification decision tree diagram to show triggering conditions for opening window actions.

In Table 2.5, the confusion matrix provides the accuracy of the tree model classifying the window opening conditions. It shows that 319 records of validation sets were correctly classified, which indicates 73% of classification accuracy. During the training process, the redundant leave nodes were pruned, and the most significant information was preserved while the classification accuracy was still maintained. Hence, only the indoor and outdoor temperatures and indoor RH are shown in the diagram, even though CO_2 concentration level was considered during the training process, but they were not found significant. In contrast to two previous studies [58, 59] conducted in natural ventilation buildings, window opening actions were found less dependent on CO_2 concentration in mixed-mode ventilation buildings. The possible reason is that mixed-mode ventilation buildings rely less on window opening actions to improve indoor air quality than in natural ventilation buildings, given that CO_2 concentration is a proxy of indoor air quality.

Table 2.5: Classification decision tree confusion matrix of window opening action.

Classification Decision Tree Confusion Matrix		
	Classified as	
Actual	Null	Open Window
Null	129	90
Open Window	29	190

2.3.3.2 Thermostat override actions

Figure 2.14 and Figure 2.15 present the decision tree models developed based on the training sets to identify factors driving thermostat decrease and increase actions, respectively. Figure 2.14 shows that occupants decreased the setpoints if the indoor temperature was above 22°C while indoor RH was above 50% or if outdoor temperature was below 14°C while indoor RH

was below 50% and indoor temperature was above 22°C. Recall that when indoor RH was above 50%, it was mostly during the cooling season, whereas when indoor RH was below 40%, it was mostly during the heating season (see Figure 2.3). In other words, the classification results indicate that setpoint decrease events tend to take place when indoor temperature was above 22°C during both the heating and cooling seasons.

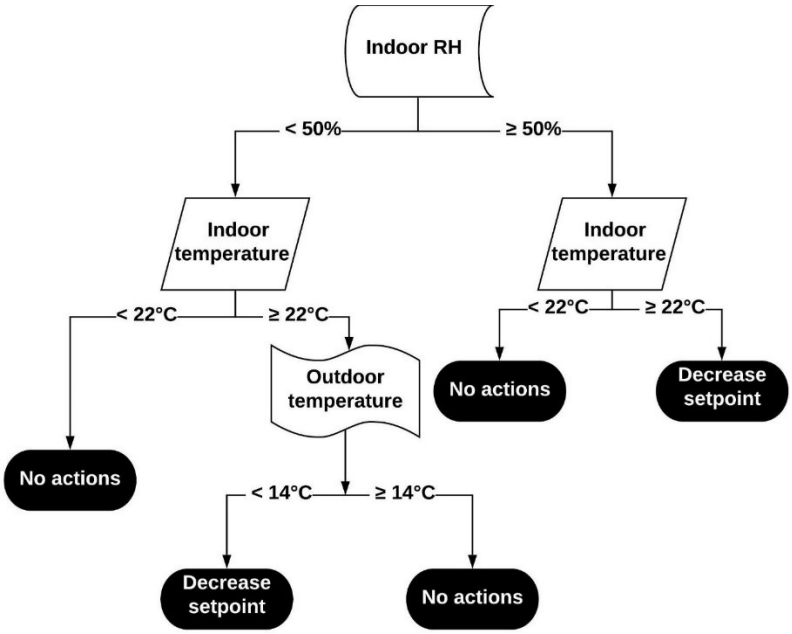

Figure 2.14: Classification decision tree diagram to show triggering conditions for setpoint decrease actions.

Figure 2.15 illustrates that setpoint increase actions occurred if the indoor temperature was below 22°C while the indoor RH was below 30%. Recall that when indoor RH was below 40%, it was mostly during the heating season (see Figure 2.3). Hence, the classified results can be inferred that when the indoor temperature was below 22°C during the heating season, the setpoint increase action tended to take place.

Notably, it was found that 22°C was the indoor temperature threshold of classifying setpoint increase and decrease actions in the decision tree models (i.e., setpoint increase action occurred when indoor temperature was below 22°C while setpoint decrease action occurred

when above 22°C). However, 22°C should not be considered as the comfortable indoor temperature for all occupants and used as a threshold to distinguish discomfort when indoor temperature is above or below it. The modelling results were not employed to make predictions of occupant's adaptive actions at certain environmental conditions. Instead, the results provide valuable visualization of occupants' tendencies of undertaking adaptive actions within a range of indoor and outdoor temperatures and indoor RH. In light of these results, the proposed control sequences aim to create an indoor environment that increases or decreases occupants' tendencies to take certain actions when needed, which will be elaborated in the later section.

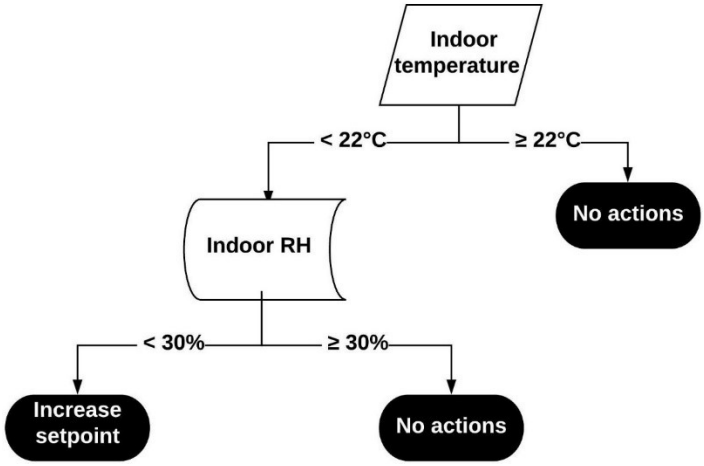

Figure 2.15: Classification decision tree diagram to show triggering conditions for setpoint increase actions.

After developing decision tree models based on training sets, confusion matrices were then calculated from validation sets. Table 2.6 and Table 2.7 presents the confusion matrix of the decision tree model for setpoint decrease actions and setpoint increase actions based on the undersampled datasets due to the imbalance of null actions relative to behaviour action instances. Table 2.6 indicates that 325 records were correctly classified among 389 total records of the validation set, which shows 84% of accuracy. Table 2.7 shows that 428 data

points were classified correctly among 596 total records of the validation set, and the classification accuracy was 72%.

Table 2.6: Classification decision tree confusion matrix of setpoint decrease action model.

Classification Decision Tree Confusion Matrix		
	Classified as	
Actual	Null	Decrease Setpoint
Null	151	45
Decrease Setpoint	19	174

Table 2.7: Classification decision tree confusion matrix of setpoint increase action model.

Classification Decision Tree Confusion Matrix		
	Classified as	
Actual	Null	Increase Setpoint
Null	207	93
Increase Setpoint	75	221

2.3.4 Preliminary recommendations for sequencing of terminal devices

Preliminary recommendations were developed, as shown in Figure 2.16, which aim to maximize the use of operable windows when conditions are favourable to reduce HVAC energy use and to minimize window opening actions when conditions are not. These conditions can be defined based on indoor and/or outdoor temperatures, or they can be designed to match the economizer or the economizer with cooling modes. When indoor and outdoor temperatures both meet favourable conditions, occupants should be encouraged to open their windows or to keep their windows open. When conditions are not advantageous, occupants should be discouraged from opening their windows or encouraged to close them if they were already open. Here, we discuss the mechanisms to encourage/discourage such behaviour in light of the occupant modelling exercise presented in the previous sections. It is

worth noting that the discussions in this section are based on the assumption that window state information is available – e.g., either via window contact sensors or algorithmically through virtual sensors.

Recall that occupants have the least tendencies of opening windows when indoor temperature in the range of 22-23°C, and the tendencies rise to three times higher when the indoor temperature reaches 26°C (see Figure 2.7). Also, occupants are more inclined to use thermostats to adjust indoor temperature rather than opening the windows if perceived discomfort occurs when indoor temperature in a range of 24-27°C (see Figure 2.13). With this in mind, to encourage more occupants to open their windows when it is advantageous to do so to reduce energy use, control sequences can apply a 3°C setback on thermostat setpoints without offering controllability to change the setpoint as opposed to allowing overrides up to 2°C in original control sequences (i.e., assuming a 22°C default heating setpoint and a 23.5°C default cooling setpoint, apply the setback to decrease heating setpoint to 19°C or increase the cooling setpoint to 26.5°C). If the windows are already open when natural ventilation can provide sufficient cooling, a 3°C of setback can be applied to cooling setpoints to save energy and encourage occupants to keep the window state. To discourage occupants from opening windows when the conditions are disadvantageous, the controllability of thermostats can be increased. Recall that the original control sequence only allows occupants to override setpoints up to 2°C, and all the adjustments were reset to default at midnight. Hence, increased controllability of thermostats can be given to occupants to cater to various needs to reduce the likelihood of opening windows. If windows are already open, a 3°C of setback can be applied to the thermostat setpoints while the controllability of thermostat is restrained. Given that setpoint increase actions tend to take place when indoor

temperature was below 22°C (see Figure 2.15), occupants would be more inclined to close windows as the only way to address temporary discomfort. Full controllability can be given again when the windows are closed as well as the setpoints will be reset to the default.

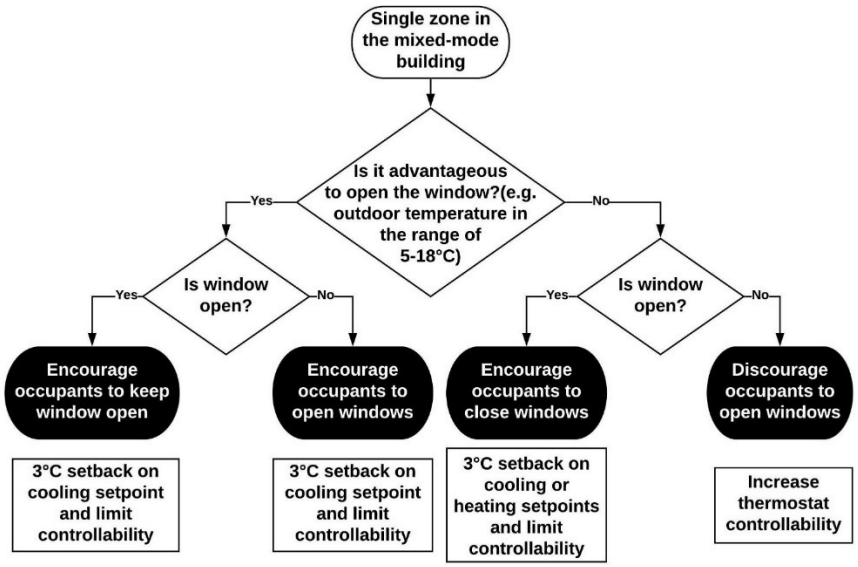

Figure 2.16: The flow chart presents the proposed building control sequence based on recommendations. The textbox below demonstrates the ways of passively encouraging and discouraging occupants from opening or closing windows.

2.3.5 Limitations and future work

The present study focused on analyzing indoor environmental conditions that triggered occupants' adaptive actions on windows and thermostats. Future work is still needed to determine the viable ranges of outdoor temperature, which can be used as thresholds in the proposed control sequences. The authors recommend investigating the outdoor temperature range with respect to local climatic conditions and the building characteristics (e.g., building orientations, window to wall ratio). For example, the viable outdoor temperature range proposed by Zhao et al. [27] in which natural ventilation was advantageous to be utilized, was between 15°C and 25°C in Pittsburgh, USA. But it may not be plausible for the mixed-

mode ventilation buildings in Ottawa, Canada, concerning the different local climates and building characteristics. Moreover, occupants' perceived comfort can also be affected by humidity when using natural ventilation. Outdoor air cannot be dehumidified when entering the zone through natural ventilation, which imposes a critical constraint when determining the optimal conditions for the window opening. Therefore, building energy simulations are required to determine the range of outdoor temperature and relative humidity in which using natural ventilation can maximize energy savings and thermal comfort in local climates. By integrating the developed occupant behaviour models for window and thermostat use into these simulations, the performance of the proposed control sequences would be better represented. Such analysis can also account for inter-occupant diversity by randomly sampling occupant behaviour models' parameters from the distributions established in this study (See Figure 2.9).

The authors acknowledge that the proposed control sequences can be improved in two aspects. First, additional factors should be incorporated into occupant behaviour modelling approaches such as different occupancy profiles, clothing behaviour of occupants (e.g., dress code), and cultural differences (e.g., habits of drinking cold and hot beverages). These factors are impactful on occupants' perceived comfort or behavioural patterns, which can increase the inter-occupant diversity, as shown in section 2.3.2.4. Second, constraints for window opening and closing actions should be addressed in the control sequences. For example, the outdoor conditions such as wind speed, precipitation, outdoor air quality and noise, and interior constraints such as the accessibility of building components (e.g., the ease of use of thermostats, the distance of windows from occupants) can impose negative effects on occupants' tendency of undertaking adaptive actions.

The applicability of proposed control schemes remains limited to private offices at the zone level. Since the case study was conducted in two academic buildings on a university campus, and all selected offices were private offices, future work is required to investigate the applicability of these findings to open-plan offices in commercial buildings. In fact, the review by Park et al. [47] indicated that only a few studies were conducted in open-plan offices, and most of them were associated with lighting systems. This research gap remains in occupant-centric window operation controls in mixed-mode commercial buildings.

The authors recommend discovering the applicability of proposed control strategies in open-plan offices with automated operable windows. If the outdoor temperature is in a favourable range, the BAS can modify thermostat setpoints and actuate windows automatically rather than nudging occupants to do so. Automated operable windows can also mitigate the negative energy impacts if occupants forget to close windows. For instance, it was found that occupants left the window open for five days in some cases, as shown in Figure 2.12, which decreased room temperature significantly during the night and may have increased heating requirements. Although automated operable windows can address these issues, they could also have a negative impact on thermal comfort in private offices, given that they reduce occupants‘ perceived control over their indoor environment [60]. Nonetheless, automated operable windows can be instrumental in open-plan offices. Studies revealed that occupants in open-plan offices typically have less control over indoor environmental conditions relative to private offices [61], which can lead to infrequent window use and inefficient utilization of natural ventilation. Therefore, automated operable windows can maximize natural ventilation without requiring occupants to open and close windows.

2.4 Closing remarks

This chapter proposed a method to derive sequences of operations for VAV terminal zones in mixed-mode ventilation buildings. The methods are established from the perspective of occupant-centric controls, aiming to reduce the uncertainty in the performance of mixed-mode ventilation buildings due to occupant behaviour while maximizing energy efficiency and occupant comfort. The proposed solutions incorporate the findings from occupant behaviour modelling (e.g., discrete-time Markov logistic regression models and classification tree models) to identify indoor environmental conditions that can influence window and thermostat use behaviour to improve energy efficiency.

To validate the proposed approach, data from two mixed-mode ventilation buildings in a cold climate was collected to develop sequences of operations for their VAV terminals. When indoor and outdoor temperatures are deemed favourable for natural ventilation, occupants can be encouraged to open windows by giving them less controllability of thermostat setpoints and by applying a setback, which is determined based on the analyzed data collected from these buildings. On the other hand, when outdoor conditions are not advantageous, occupants can be discouraged from opening the windows by giving more controllability over thermostat settings.

Finally, the environmental conditions which indicate if natural ventilation is advantageous to maximize energy savings need to be further investigated by a simulation-based study in the next chapter. The energy-saving potential can also be examined by building energy simulations. Given that the recommendations for control sequences are still preliminary, the

authors recommend that other potential predictors for window opening and closing actions, such as wind speed and weather factors, should also be included in future studies.

Chapter 3

This chapter has been submitted for publication as:

Regulating window operations using HVAC terminal devices' control sequences: A simulation-based investigation. W. Liu, H. B. Gunay, M. M. Ouf. *Journal of Building Performance Simulation*

3. A simulation-based investigation for the proposed control sequences

3.1 Introduction

People spend over 90% of their time in buildings, and a large fraction of energy consumption in buildings is dedicated to maintaining their thermal comfort and indoor air quality [62]. It is reported that nearly 60% of the total energy consumption of buildings in Canada can be attributed to space heating and cooling [63]. Mixed-mode ventilation is a design feature introduced to reduce energy consumption without compromising indoor air quality [15]. It is a system that can manually or automatically shift between mechanical and natural ventilation [16]. It can also operate in different modes, such as concurrent and change-over modes, to satisfy various demands from certain zones in a building [17]. The concurrent mode refers to the ventilation mode in which mechanical and natural ventilation are provided in the same space simultaneously. In contrast, the change-over mode allows the systems to alternate completely between mechanical ventilation and natural ventilation for a thermal zone or even

for the entire building. Extensive research has shown that mixed-mode ventilation buildings have considerable energy-saving advantages over mechanical ventilation buildings [18-20] while receiving higher satisfaction rates from occupants regarding thermal comfort and indoor air quality [21, 30]. As a result, mixed-mode ventilation has gained popularity over the past decade.

Similar to natural ventilation (i.e., mode of ventilation leveraging wind and thermal buoyancy to drive outdoor air through building envelope openings [2]) and mechanical ventilation (i.e., mode of ventilation relying on fans to provide outdoor air [64]), the actual energy and comfort performance of mixed-mode ventilation buildings can vary significantly depending on individual building's characteristics, such as glazing surface area and building orientation [65, 66]. However, unlike natural and mechanical ventilation, there are no prescriptive guidelines for mixed-mode ventilation to follow to achieve optimal performance. For instance, the design parameters such as window size, shape and positions that can largely influence the building performance are found to lack guidance from building codes and standards. Meanwhile, existing simulation models were found inaccurate in predicting the effectiveness of natural ventilation by underestimating the airflow rate through operable windows [67], which can cause an over-ventilated design. Currently, ASHRAE Guideline 36 only provides recommendations to take advantage of operable windows by applying heating and cooling setpoint setbacks when windows are opened [22]. However, the setback values (e.g., increase the cooling setpoint to 49°C and decrease the heating setpoint to 4°C) were not informed by occupant behaviour research. The guideline does not indicate when the windows should be opened or a setback logic to encourage window openings should be used. As a result, the design and operation of the mixed-mode ventilation remain case-specific, and it is

challenging to tailor ventilation strategies to specific buildings without guidance and accurate simulation tools.

Moreover, the energy-saving potential is largely dependent on the utilization of natural ventilation to provide cooling in mixed-mode ventilation buildings, where the local climate plays a significant role. For example, Chen, Tong and Malkawi [6] have investigated natural ventilation potential for over 1000 cities by looking at the amount of time that natural ventilation is applicable to save energy. They found subtropical and Mediterranean climates were the most favourable climates for natural ventilation, with over 6000 h per year suitable to save energy. Regions with desert climate and cold climate had only 3000 h, whereas the climate in southeast Asian regions had no energy-saving potential by using natural ventilation. Furthermore, the local air quality [68] and ambient noise [69] can also restrict the utilization of natural ventilation. Tong et al. [68] have discovered the impact of ambient air pollution on reducing the energy-saving potential by using natural ventilation. The study incorporated building energy simulations with local climate data and air quality data from 35 cities in China. The simulation results showed that the total annual energy reductions could reach 155 GWh in these cities using natural ventilation to decrease the cooling demand from mechanical ventilation. However, the amount of energy savings can drop by 43 GWh considering local air pollution in these 35 cities. A study by Song et al. [69] revealed that ambient noise could cause reluctance of opening windows and less natural ventilation utilization. The study estimated that the loss of energy savings resulting from loss of natural ventilation potential due to noise pollution in London, UK, was found to be 8.1 kWh/m^2. These studies suggested that the control sequences should be designed to realize the full energy-saving potential from natural ventilation where the climatic and ambient conditions

are favourable, while on the contrary, mixed-mode ventilation should be used sparingly when conditions can cause adverse effects.

Another constraint that restricts mixed-mode ventilation from realizing its potential can be imposed by the uncertainties of occupant behaviour, i.e., window use behaviour. For example, De Vecchi et al. [24] discovered that even when conditions were advantageous to utilize natural ventilation, some occupants typically tended to adjust their indoor thermal conditions through thermostats due to fewer fluctuations of indoor temperature if the environment is conditioned by the mechanical ventilation system. Several studies [30, 46, 70] have also observed another window use pattern in which the occupants tended to open windows due to discomfort without reverting to the original state until the next instance of discomfort occurred. Both behavioural patterns suggested that window opening and closing actions should be regulated for higher energy performance.

3.1.1 Previous research on regulating window operations

Currently, there are two types of approaches to regulate occupants' window use behaviour: (1) using fully automated window systems [26, 27, 71-75] or (2) using occupant feedback systems that advise occupants about when to open and close windows [39, 76]. Automated window systems can be controlled through a building automation system (BAS) to adjust the window states without requiring involvement from occupants. Prevalent studies mostly employed automated window systems to deliver natural ventilation by using rule-based control logic with fixed conditions [26, 27, 71-75]. For example, Tanner, Henze, and Pless [26] proposed a control sequence for automating window states based on wind speed, outdoor temperature and RH. When wind speed was lower than 8 m/s, outdoor RH lower than 50%, and outdoor temperature between 18°C and 23°C, the BAS opened windows and

closed VAV dampers. The effectiveness of the proposed control sequence was tested using BPS, and occupants' window use behaviour was characterized by the model developed by Haldi and Robinson [77]. The simulation results illustrated that HVAC-related energy consumption could be reduced by 3-15%. Zhao et al. [27] developed a control logic to automate the window state based on indoor and outdoor temperature, zone setpoint, wind speed, and outdoor enthalpy. When outdoor temperature is between 15°C and 25°C, wind speed lower than 10 m/s, indoor temperature higher than zone setpoint, and outdoor air enthalpy between 20000 and 30000 J/kg, the BAS shut down the AHU and open windows. The simulation results show that the energy use can be reduced by 37% compared to a scenario in which the window state is not automated.

In contrast to automatic window systems, occupant feedback systems target manually operable windows, which require occupants to adjust the window position. The effectiveness of occupant feedback systems could be influenced by factors such as the types of occupant feedback systems (e.g., light indicators or thermostat feedback interface) and locations of the system. However, the influence imposed by these factors remains unknown due to limited research, and the energy-saving potential is largely dependent on how well the system can engage the occupants to undertake actions in the long run. A simulation-based study by Chen et al. [76] illustrated the difference in energy-saving potentials when the occupant feedback systems engaged the occupants differently. Because the engagement of occupants was hard to quantify, the study assumed three scenarios in which the occupants had 80%, 50%, and 20% probability of undertaking actions when they were notified by the feedback system. Then, these scenarios were converted into stochastic models and tested with BPS. The results showed that the occupant feedback systems achieved 60% of energy savings (compared to

the fixed-window baseline model) under temperate climatic conditions regardless of occupant response probabilities. In more extreme climates (e.g., cold or hot climates), the occupant feedback system with 80% of response probability can only achieve 5% of energy savings, whereas the occupant feedback system with 50% and 20% of response probability had energy penalties. Meanwhile, the automated window systems can achieve 80% of energy savings in a temperate climate and 10-20% of energy savings in more extreme climates. It suggested that the occupant feedback system can improve energy efficiency only when it can effectively engage the occupants. Ackerly and Brager [39] conducted a field study to investigate the actual response probability from occupants. They implemented an occupant feedback system with light indicators (i.e., green as open the windows, and red as close the windows) into actual buildings, and the occupants were informed about these systems through in-person explanations or e-mails. The survey results showed that only 30% of occupants were following the signals and operated the windows accordingly. The rest of the occupants tended to ignore the signals or found it interruptive, which suggested that more research is needed to improve the engagement of occupants.

To better engage occupants and guide them to use the windows appropriately, Chapter 2 of this dissertation [78] explored an approach by employing HVAC terminal devices to nudge occupants to undertake window opening and closing actions. Specifically, Chapter 2 proposed applying setbacks to increase the likelihood of opening and closing windows according to the indoor and outdoor temperature. For instance, if windows are opened during the heating season, thermostat setpoints are decreased to nudge occupants to close the windows with the intent to avoid energy waste. Thermostat setpoints were increased to encourage occupants to open the windows during the cooling season if outdoor conditions

were favourable. This approach was established based on occupants' window and thermostat use behaviour in private offices in a cold climate. Nonetheless, the outdoor environmental conditions that determine whether it is viable to open windows and use natural ventilation remained undiscovered in this study, and the energy-saving potentials were not investigated either.

As mentioned above, the conditions that determine when windows should be opened are not always clear. Early research suggested that windows should be opened when the outdoor temperature was in the range of 20-26℃ [79], while Tanner, Henze, and Pless [26] proposed a range of 18-23°C, and Zhao et al [27] proposed a range of 15-25°C. However, it is found that the fixed range of outdoor temperature is not ideal because the optimal outdoor conditions for using natural ventilation were highly dependent on seasons [29]. As a result, the outdoor temperature thresholds should be frequently examined and adjusted. Recent studies started to use different approaches to find the optimal conditions that maximize energy and comfort performance. For example, a study by Chen, Tong and Malkawi [6] proposed to calculate the thresholds by incorporating the adaptive comfort model and the monthly average outdoor temperature. Chen et al. [80] introduced an approach using reinforcement learning (RL) to make window control decisions at each timestep by constantly evaluating the environmental conditions. The simulation results showed that 13-23% of HVAC-related energy consumption could be reduced compared to using natural ventilation based on fixed thresholds of outdoor temperature. Despite the advantages, the barrier of implementing this approach in actual buildings is high since it requires resources for data processing and computing. More research is needed to explore approaches that

improve the effectiveness of natural ventilation and can be easily implemented in existing buildings.

3.1.2 Motivation and objectives

The reviewed studies showed that automated window systems should be the best option to maximize energy savings. However, the high initial and maintenance cost and the complexity of designing control sequences are major constraints to the widespread use of automatic window systems. In contrast, manually operable windows provide controllability of the indoor environment to occupants, which can improve perceived comfort [28]. Due to their lower cost and ease of use, manually operable windows are more widely installed in existing buildings but remain unregulated, which may increase energy consumption.

A few studies attempted to regulate the window operations in mixed-mode ventilation buildings but mainly relied on automated window systems. To the best of our knowledge, only the method proposed in Chapter 2 of this dissertation [78] aimed to improve the control sequences for HVAC terminal devices to regulate window operations with manually operable windows. The approach proposed to encourage/discourage manual window opening/closing actions through temperature setbacks based on analyzing the occupant behaviour data, but the energy-saving potentials and the conditions deciding when to apply the setbacks remained undiscovered. In this chapter, we examined the effectiveness of the proposed approach by (1) investigating the practical thresholds for encouraging or discouraging natural ventilation using the proposed control sequences and (2) quantifying the energy-saving potential of control sequences through BPS using stochastic occupant behaviour models for window and thermostat use. Results were compared with three window use scenarios: manual window operation without adjusting the zone control based on window position and

outdoor/indoor climatic conditions (i.e., unregulated window operations); automated window operations, and fixed (non-operable) window scenario. This analysis can assist building designers with developing the sequence of operation for terminal zones to take the energy impact of operable windows into account. This research focuses on investigating the effectiveness of the control sequences [78] for private offices in the VAV terminal zone with manually operable windows in a cold climate. The results are to inform the policymakers to improve the current guidelines (e.g., ASHRAE Guideline 36) to realize the potential of mixed-mode ventilation in a cold climate.

3.2 Methodology

To examine the proposed control sequence, simulations were performed by using the BPS tool, EnergyPlus [81]. The weather file used to perform the simulations was from the database of Canadian Weather Year for Energy Calculation (CWEC) for Ottawa, Canada [82]. The climate was designated as Zone 6 based on the National Energy Code of Canada for Buildings [83] with heating degree days of about 4500. Then, a thermal zone model was developed to mimic a typical private office in the previously surveyed building from Chapter 2 [78]. The energy performance of proposed control sequences implemented into the thermal zone was investigated by examining the energy use intensity (EUI), heating and cooling loads, and fan energy use in four orientations: south, east, north, and west. The unmet hour [84] was defined as the duration of occupied time when the indoor temperature was outside the range of 21.5-24℃. The unmet hour data were also collected to inspect how well the indoor temperature could be maintained. Occupant behaviour models developed from Chapter 2 [78] were incorporated into BPS to represent the window and thermostat use

patterns. The occupancy schedules and the plug load and light load schedules were collected from 20 private offices in two academic buildings and implemented into BPS. The following subsections present the implementation of the BPS model, the occupant behaviour models, and the control sequences in detail.

3.2.1 The characteristics of the base thermal zone model

3.2.1.1 The envelope characteristics

Figure 3.1 illustrates the base thermal zone model developed with characteristics of private office provided by Liu, Gunay, and Ouf [78], as listed in Table 3.1. The zone model is implemented in EnergyPlus v.9.3 [81]. The area of the thermal zone is 16 m^2 with a 41.7% of window-to-wall ratio. The surveyed private offices from the previous study [79] are equipped with single-sided awning operable windows. The operable window is measured as 2.5 m-by-2 m with 0.1 m^2 of effective opening area. The effective opening angle is 30 degrees. The U-factor of the glazing is set as 2 W/m^2-K [84], and the solar heat gain coefficient is 0.5 [84]. As it represents a private office located at an intermediate level within a multi-floor building, only the boundary condition of the wall with operable windows is set as outdoor. The floor, ceiling, and three interior walls are set as adiabatic. The thermal transmittance of walls is set as 0.22 W/m^2-K [84]. The infiltration rate into the office is fixed at 0.2 L/s-m^2 normalized by the exterior surface area for commercial buildings [85]. The natural ventilation airflow rate is modelled as a function of wind speed in EnergyPlus [86], and can be calculated by equations as follow:

$$Q_w = C_w A_{opening} V \quad (3.1)$$

$$C_w = 0.55 - \frac{|EffectiveAngle - WindDirection|}{180} \cdot 0.25 \quad (3.2)$$

where the Q_w is the airflow rate driven by wind in m^3/s while C_w is the opening effectiveness (dimensionless), and $A_{opening}$ is the window opening area (m^2). V represents the local wind speed in m/s. It is worth noting that the airflow rate driven by the stack effect is neglected because the zone only has a single floor.

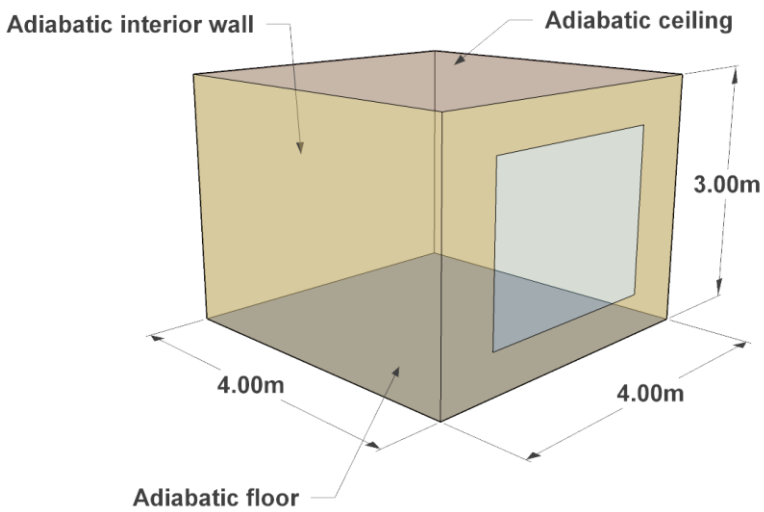

Figure 3.1: Geometry of zone model.

Table 3.1: Zone model envelope characteristics.

Parameter	Value	Unit
Office type	Private office	-
Zone area	16	m^2
Ceiling height	3	m
Window-to-wall ratio	41.7	%
Glazing area	5	m^2
Window type	Operable awning window	-
Opening area of the window	0.1	m^2
Effective opening angle	30	degree

3.2.1.2 HVAC systems

The HVAC system serving the thermal zone consists of an air handling unit (AHU) and a variable air volume (VAV) unit. An electric baseboard heater with a 900 W capacity is available during winter to provide supplementary heating. The system is modelled as a

packaged VAV system in EnergyPlus. When the zone requires either cooling or heating, the VAV damper position exceeds the minimum position (i.e., 0.2). When the zone requires heating, the reheat coil in VAV is activated, while the baseboard heater is operated as well. An economizer is also incorporated into the HVAC system, and it is controlled based on the differential dry bulb temperature. The minimum outdoor airflow rate is 8.6 L/s, and the maximum outdoor air temperature threshold for economizer operations is 21°C [84], while no minimum temperature limit is set because the economizer is allowed to operate during winter to mitigate high indoor temperature caused by solar heat gains. The HVAC system is available between 7:00 am and 9:00 pm during the heating season and 7:00 am to 6:00 pm during the cooling seasons. The switch-over dates are set to be May 1st and October 1st. During the heating season, the default temperature setpoint is 22°C, while the default setpoint is 23.5°C for the cooling season. When the air handling unit (AHU) is off, the temperature setpoint is set as 18℃ during the heating season, while the temperature setpoint is set as 27℃ for the cooling season. The night cycle control feature in EnergyPlus is set to operate the HVAC systems to prevent the indoor temperature from exceeding the range of 18-27℃ during the off hours.

3.2.2 Representation of occupancy and occupant behaviour in EnergyPlus

3.2.2.1 Occupancy

The occupancy, plug load and lighting load data were obtained from 20 private offices in the surveyed building from August 2018 to August 2019. In each office, a passive infrared motion detector was installed, collecting binary occupancy data (i.e., one as occupied, zero as unoccupied) every 15 minutes. Among 20 private offices, occupancy data from three offices are selected to represent three common occupancy profiles in academic buildings. The first

occupancy profile (hereafter will be represented as Occupant 1) shows an occupant who uses the office from 8 am to 5 pm but regularly leaving for academic activities. Occupant 1 rarely occupies the office during the summer, and the total occupied hours consist of 865 h throughout the covered timespan. The second occupancy profile (i.e., Occupant 2) shows an occupant who uses the office from 8 am to 5 pm throughout the year, and the office is only vacant in May and December, which consists of 1652 h occupied hours in total. The third profile (i.e., Occupant 3) represents a heavy occupancy pattern in which the office is occupied from 8 am to 7 pm with sporadic departures. The total occupied hours are 2920 h in the covered year, and the office is only vacant for one week in December. Similarly, loads of plug-in equipment and lighting were collected every 15 minutes from these three offices, and the average loads of plug-in equipment and lighting during occupied and unoccupied hours were calculated, as shown in Table 3.2. It is worthing noting that the lighting system can automatically dim down the lights when zone is unoccupied. As a result, the light loads of all offices are detected as 2 W during unoccupied hours. Then, the occupancy, the load of plug-in equipment and lighting load are converted into schedule objects in EnergyPlus separately. Other variables that were unable to be obtained from surveyed buildings are assumed as default values. For instance, the clothing insulation levels of the simulated occupant are set as 0.5 clo during the cooling season and 1.0 clo during the heating season. The occupant has a constant standard activity level of 1.1 during occupied hours in compliance with ASHRAE Standard 55 clo/met assumptions [31].

Table 3.2: The total occupied hours from three occupancy profiles and the average loads of plug-in equipment and lighting during occupied and unoccupied.

	Total occupied hours	Plug-in equipment load		Light load	
		Unoccupied	Occupied	Unoccupied	Occupied
Occupant 1	865 h	75 W	150 W	2 W	20 W

Occupant 2	1652 h	40 W	105 W	2 W	13 W
Occupant 3	2920 h	93 W	180 W	2 W	15 W

3.2.2.2 Occupant behaviour representation

The occupant behaviour models of window and thermostat use actions developed from Chapter 2 [78] are converted into the simulation as the EnergyPlus runtime language (ERL) scripts implemented into the Energy Management System (EMS) environment. At the beginning of runtime, the parameter estimates of both models, as highlighted in Tables 3.3 and 3.4, are input into the simulation. Given different individuals have different behavioural tendencies to undertake adaptive actions (e.g., open and close windows, override thermostat setpoints), the parameter estimates of occupant models are assumed as normally distributed stochastic quantities so that different parameter estimates can be sampled at the beginning of each simulation to create a unique behavioural tendency. This approach can represent the inter-occupant diversity similar to the approach proposed by Haldi [87], even though it was found to have tendencies of exaggerating the diversity [88]. The probabilities of undertaking actions in the next timestep are computed during the simulation via a logistic function as follows:

$$p = 1/(1 + e^{-(b+aT_{in})}) \quad (3.3)$$

where a and b are the parameter estimates shown in Table 3.3 and 3.4, and p is the estimated probability of adaptive action. Notably, the occupant behaviour models were established on the concept of discrete-time Markov logistic regression models in Chapter 2 [78], which indicates that the estimated probability is dependent on the size of timestep. Thus, the timestep should be identical to the timesteps in the previous study to obtain meaningful results (15 minutes).

Table 3.3: Parameter estimates of discrete-time Markov logistic regression model for window use behaviour.

	Parameter estimates	
Adaptive actions	a_1	b_1
Window opening action	0.61±0.38	-18.35±8.83
Window closing action	-0.43±0.40	6.28±8.27

Each parameter estimate is presented in the form of mean ± standard deviation.

Table 3.4: Parameter estimates of discrete-time Markov logistic regression model for thermostat override behaviour.

	Parameter estimates	
Adaptive actions	a_2	b_2
Setpoint decrease action	0.70±0.15	-21.55±3.97
Setpoint increase action	-0.65±0.18	8.84±2.78

Each parameter estimate is presented in the form of mean ± standard deviation.

As the stochastic occupant behaviour models are incorporated into building energy simulations, it is found that the predicted energy use varied for each simulation run. To the best of our knowledge, there is no standard providing the criterion for the number of runs in order to obtain accurate results. Therefore, 50 runs of the simulation are performed to understand the distribution of the predicted values. Then, the necessary number of simulations is determined so that the average values of all simulation results can reasonably represent the predicted energy use. Figure 3.2 illustrates the fluctuations of average EUI in the zone models with four different orientations when the number of simulations increases. It shows that the average EUI becomes stable after 20 runs (i.e., the change in average EUI was less than 1% after 20 simulations), which suggests that 20 simulation runs should be adequate to obtain accurate predictions. It is also in line with simulation results from Gilani and O'Brien [89], in which the average energy use in 20 runs was found almost identical to the values in 100 runs.

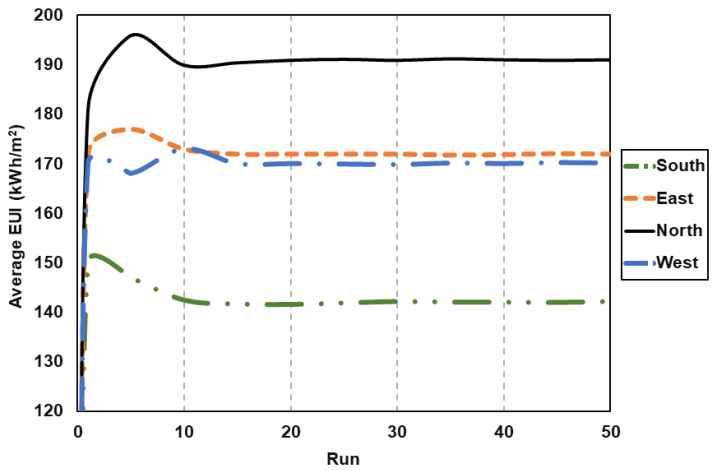

Figure 3.2: A demonstration of the fluctuations of average EUI when the number of simulations increases.

3.2.3 Control sequences

The proposed control sequences provided an approach to regulate the use of manually operable windows, which is illustrated by the pseudocode in Algorithm 1. First, the precipitation (e.g., rain and snowfall) and high wind speed (e.g., wind speed greater than 10 m/s) [45] should be regarded as constraints at which window opening should be restricted even if the outdoor temperature may be favourable. Then, we propose that the conditions determining whether windows should be opened to utilize natural ventilation can be linked directly with the thermal demands of the zone. The rationale of this approach is that the window operations based on a single fixed threshold of outdoor temperature cannot achieve the optimal performance for various buildings and different seasons, as previously reviewed. Next, the VAV damper position and reheat coil status in VAV are monitored in every timestep as indicators of the thermal demands of the zone to inform the control sequence. When the zone requires cooling (i.e., VAV damper position greater than its minimum position and reheat coil off), outdoor temperature is colder than the indoor temperature, and the maximum outdoor air temperature threshold of the economizer (i.e., 20°C) is not violated,

the conditions are deemed as advantageous, and a setback is applied within the next two hours so that a slight increase of indoor temperature can nudge occupants to open the window. If the windows are already open when conditions are advantageous, a setback is applied to fully exploit the energy-saving benefits from using natural ventilation. Otherwise, the outdoor conditions are not advantageous for opening the window. The setback is applied to nudge occupants to close windows if windows are open.

The energy performance of regulated window operation is examined along with the performance of three other window operation scenarios, namely unregulated window operation, fixed window, and automated window operation. The scenario of unregulated window operations is regarded as the baseline in which the operable windows are solely controlled by occupants (i.e., characterized by occupant behaviour models as described in the previous section) without any interventions. The regulated window operations mean that the control algorithms are implemented to regulate occupants' window use behaviour based on outdoor conditions. The fixed window scenario refers to the scenario that the window remains closed throughout the simulation. The automated window operation refers to the scenario where the control sequences directly control the automated window systems. The difference between the regulated window operation and the automated window operation is that a setback is applied to nudge occupants to open/close windows in the scenario of regulated window operations, whereas window state can be altered instantaneously in the scenario of automated window operation. Lastly, the different window operations on July 9th and July 10th are demonstrated as an example for the cooling season, while the window operations on February 4th are illustrated as an example for the heating season.

Algorithm 3.1: A pseudocode illustrates the control sequences in zone models to regulate window operations with manually operable windows.

```
Cooling setpoint = 23.5
Heating setpoint = 22

If Outdoor temperature < 20°C & Indoor temperature > Outdoor temperature & Precipitation
= none & Wind speed < 10 m/s & Reheat coil = Off & VAV damper position > minimum & current
time < 20 & current time > 6
       Setback start time = current time
End If

If Window = closed & Setback start time + 2 < current time
       Cooling setpoint = 26.5
       Heating setpoint = 19
End

If Window = open
       Cooling setpoint = 26.5
       Heating setpoint = 19
End
```

3.2.4 Implementation of control sequences and occupant models in EMS application of EnergyPlus

Figure 3.3 illustrates the implementation framework of occupant models and control sequences in the EMS application of EnergyPlus. The communication between EMS application (i.e., occupant behaviour models and control sequences) and EnergyPlus (i.e., building components and HVAC system model) is carried out through EMS sensors and actuators. As discussed earlier, the indoor temperature is the environmental variable considered in occupant behaviour models along with the occupancy schedule, which are both represented by EMS sensors. The indoor and outdoor temperatures, wind speed, precipitation status, VAV damper position, and reheat coil status are also monitored as EMS sensors to inform the control sequences, as previously discussed. The building components (i.e., window state and thermostat setpoints) manipulated by occupant behaviours and control sequences are represented as EMS actuators. These EMS actuators are linked to schedule values of thermostat setpoint and window state objects in EnergyPlus to represent occupant interactions as well as the outcome of the proposed control sequences.

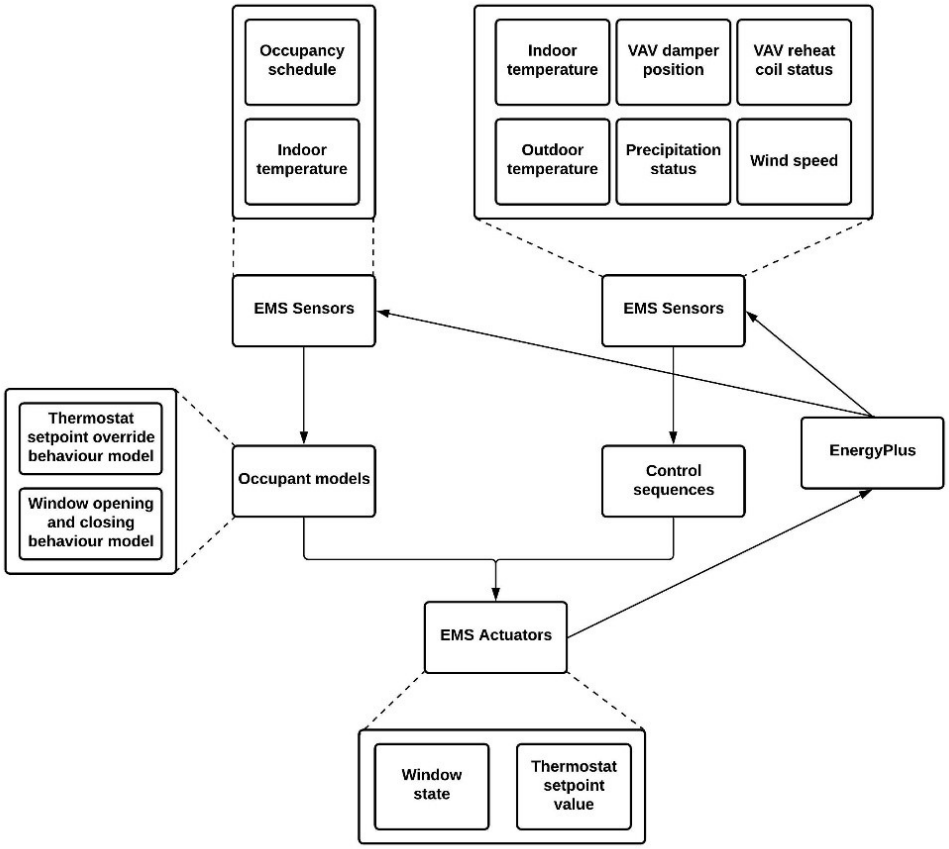

Figure 3.3: Implementation of occupant behaviour models and control sequences in the EMS application of EnergyPlus.

3.3. Results

In this section, the energy performance with different control scenarios is presented and compared. The analysis EUI, monthly window opening percentage, and airflow rate through windows are collected from the simulation results and highlighted in section 3.3.1, while the cooling load and heating load analysis is illustrated in sections 3.3.2 and 3.3.3, respectively. Then, the analysis of fan energy use is shown in section 3.3.4.

3.3.1 Comparisons of EUI and monthly window opening percentage

Through building energy simulations, the EUI results were extracted for the four window use scenarios: automated windows, fixed-window, unregulated window operation and regulated window operations. The EUI results of using three occupancy profiles were compared in the south, east, north, and west-facing offices, as shown in Figure 3.4. It illustrates that unregulated window operations resulted in the highest energy consumption with the largest fluctuations in all tested offices. The regulated window operations led to 3-16% of energy reductions depending on the occupancy and orientations, while the automated window operations resulted in the highest energy reductions by 6-17% compared to the baseline model with unregulated window operations. Another noticeable advantage of regulating window operation was that the fluctuations of EUI were considerably less than those in models with unregulated window operations, while fixed-window and automated window models had nearly zero variations in EUI. In particular, models with higher occupancy levels (e.g., Occupant 3) tended to have greater fluctuations of EUI, largely due to uncertainties caused by occupant behaviours. The fluctuations could be reduced considerably by the regulated window operations. For instance, Figure 3.4(a) shows that the EUI of the south-facing office occupied by Occupant 3 with unregulated window operation fluctuated from 138 to 164 kWh/m^2 (i.e., 36 kWh/m^2 variations), whereas the EUI for the same model with regulated window operations only had around 6 kWh/m^2 of fluctuations. While the control sequences significantly lowered EUI in models with regulated and automated window operations, the unmet hours of all the models were significantly lower than the 300 h limit from ASHRAE 90.1 [84].

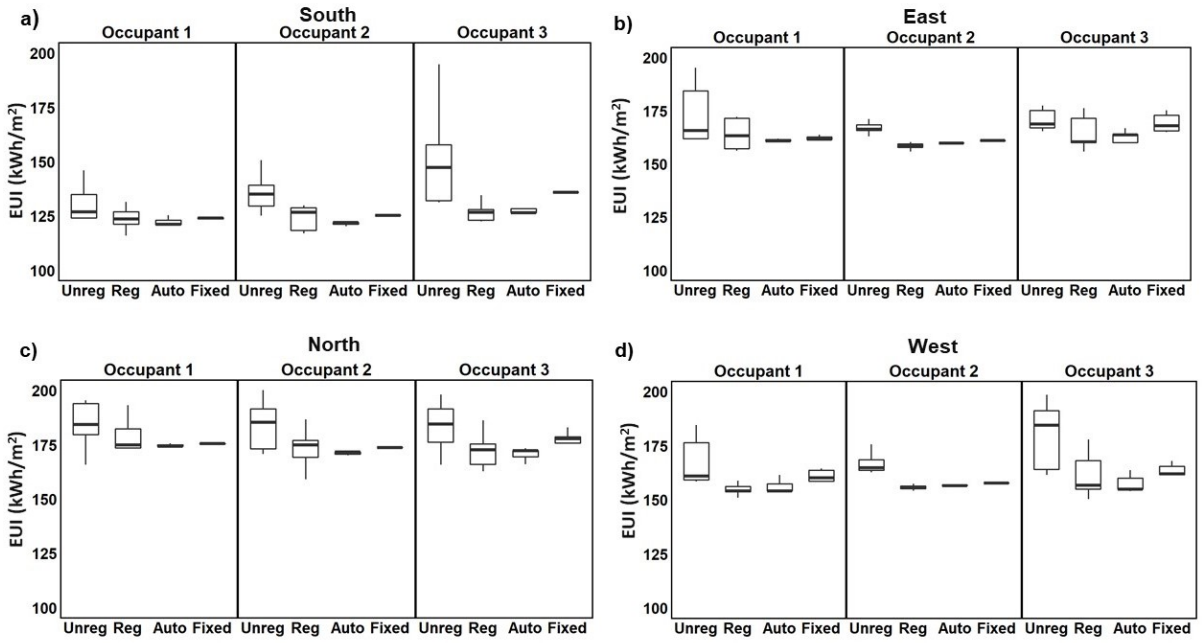

Figure 3.4: Box whisker plots of annual EUI for models with different window operations and three occupancy profiles in the south, east, north, and west orientations. "Auto" represents the automated window operations, and "Fixed" means that the window remained closed. "Reg" means regulated window operations, while "Unreg" stands for unregulated window operations.

Figure 3.5 shows the monthly average percentages of window opening duration (i.e., the total number of hours windows were open relative to 720 or 744 hours in a month) in zone models from all orientations and compared with different occupancy profiles and window operations. It highlights that all zone models with unregulated window operations had windows open for a shorter period during the cooling season compared to models with automated and regulated window operations. In particular, when the office was occupied by Occupant 1 with the lowest occupancy level, the window opening percentages were less than 10% in most of the cooling season. For regulated window operation, the window opening percentages increased to approximately 12-16%, while it further increased to 20-45% if the office was occupied by Occupant 2 and 3 with higher occupancy levels. It implies that utilization of natural ventilation was not adequate in models with unregulated window operations, and the energy-

saving potential was not realized. This finding was in line with the observation by De Vecchi et al. [24] that even when conditions were advantageous to utilize natural ventilation, occupants typically had low tendencies of opening windows.

During the heating season, windows were open for around 1-2% of the time in February and December (i.e., approximately 7 hours each month) in zone models occupied by Occupant 1 and 2 with unregulated window operations, and it rose to around 4% (i.e., approximately 30 hours each month) if occupied by Occupant 3. This period could waste a substantial amount of energy, given the low outdoor temperature. The regulated and automated window operations could eliminate this energy waste by minimizing the window opening percentages to around 0.5%. The reason for inappropriate window openings in models with unregulated window operations was examined in Section 3.3.3.

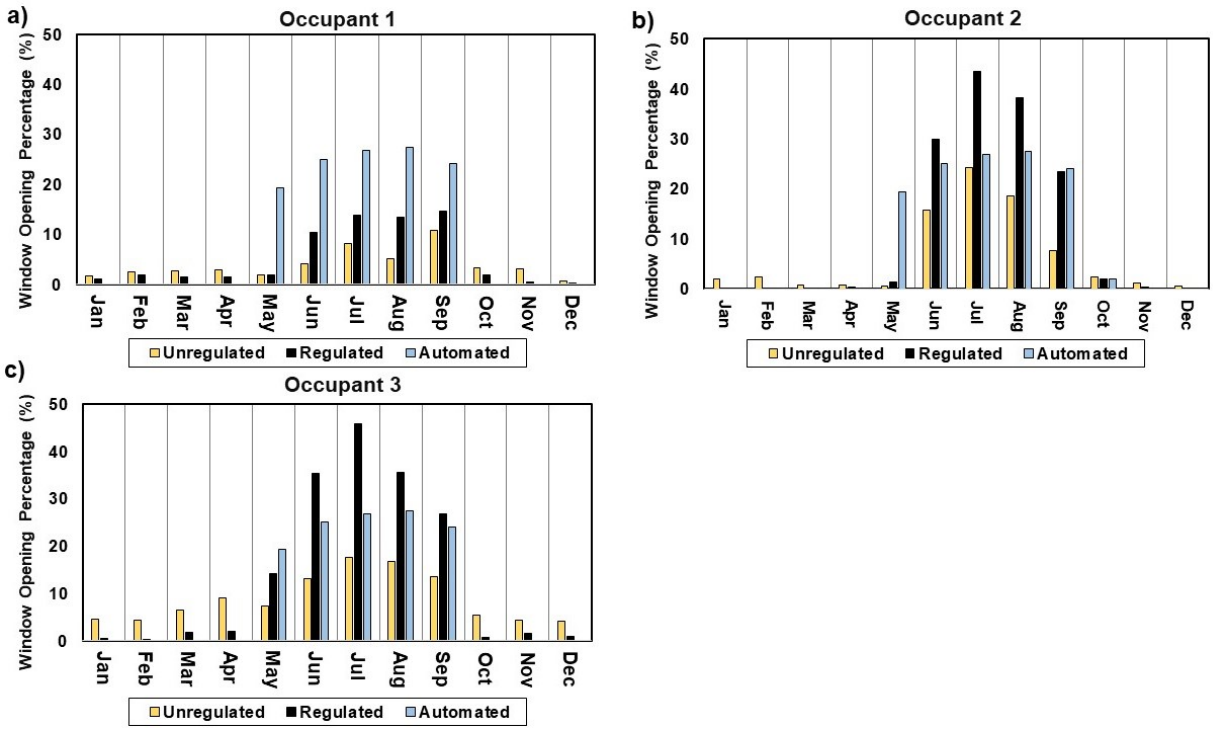

Figure 3.5: Monthly average window opening percentage in unregulated, regulated, and automated window operations scenarios with three different occupancy profiles.

Figure 3.6 illustrates the airflow rate through operable windows in zone models with regulated window operations from all orientations. It shows that the airflow rate of natural ventilation provided by the single-sided operable window in each private office was above 20 L/s throughout the year. In May and June, when natural ventilation is largely encouraged due to moderate outdoor temperature, the airflow rate of natural ventilation was above 40 L/s (i.e., around 3 air changes per hour), which can provide sufficient cooling to reduce the cooling load from HVAC system.

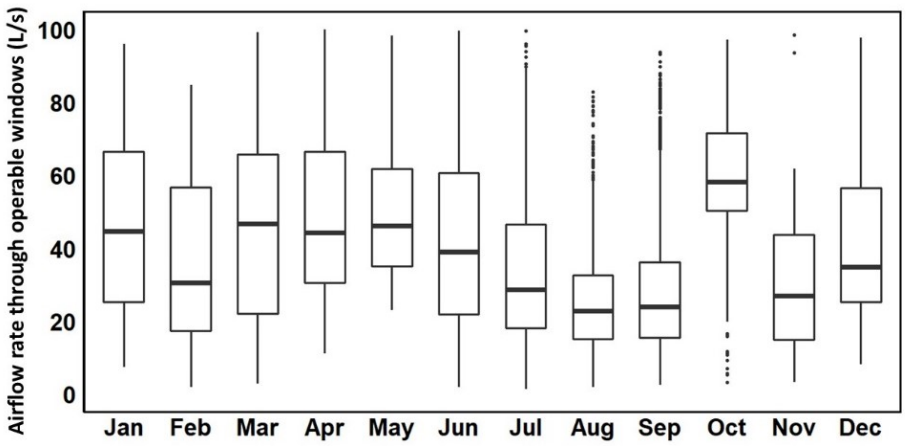

Figure 3.6: Box whisker plots of airflow rate (L/s) through operable windows when the window operations are regulated by the control algorithm.

3.3.2 Cooling load

Figure 3.7 presents the annual cooling load comparisons between window operation scenarios with three occupancy levels. It reveals that equipping operable windows does not always lead to cooling load reductions. The median of cooling load in the unregulated window operation scenario can vary from being 8% lower than the value of the fixed-window scenario (see Figure 3.7(d) Occupant 1) to being 22% higher (see Figure 3.7(c) Occupant 1). In contrast to unregulated window operations, models with regulated window

operations can realize the energy-saving potential by reducing the cooling load by 4-19%, while automated window operations decreased the cooling load by 13-38%.

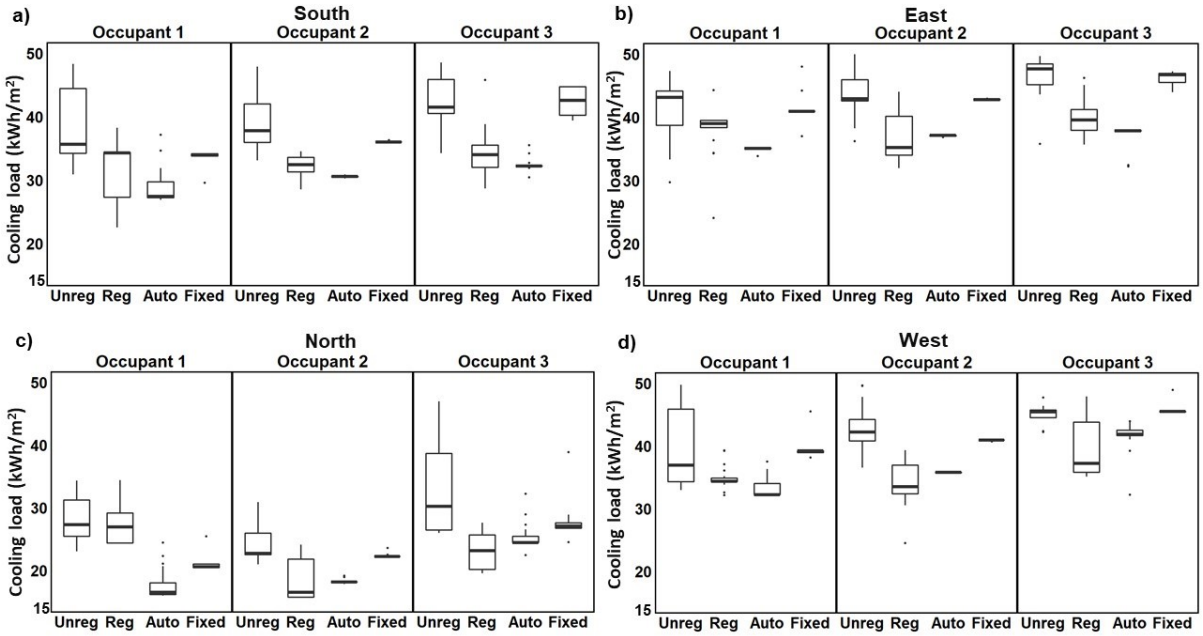

Figure 3.7: Box whisker plots of annual cooling load for models with different window operations and three occupancy levels in south, east, north, and west orientations. "Auto" represents the automated window operations, and "Fixed" means that the window remained closed. "Reg" means regulated window operations, while "Unreg" stands for unregulated window operations.

To demonstrate the adverse impact caused by inappropriate window openings, unregulated window operations on two summer days (i.e., July 9th and July 10th) in the south-facing model were illustrated as an example in Figure 3.8. It shows that the window was opened for over eight hours when the outdoor temperature was around 27℃ on July 10th. The indoor temperature was maintained at 23.5℃ (as the cooling setpoint was 23.5℃) due to sufficient cooling provided by the HVAC system.

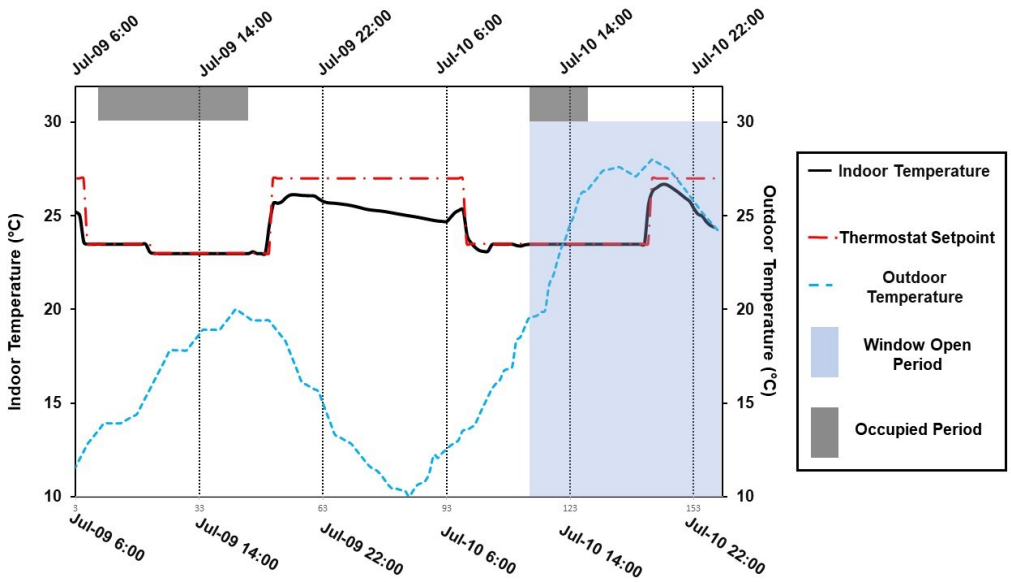

Figure 3.8: A two-day time-series plot showing the simulated indoor and outdoor temperatures, window operations and thermostat setpoints from a south-facing zone model with unregulated window operations.

For regulated and automated window operations, as respectively shown in Figure 3.9 and Figure 3.10, both window operations had windows open on July 9th when the outdoor conditions were favourable and then avoided inappropriate window openings on July 10th when the outdoor temperature was higher than the indoor temperature and thermostat setpoints. However, the difference between regulated window operations and automated window operations was demonstrated when promoting window openings when conditions were favourable. For the regulated window operation shown in Figure 3.9, the setback was applied to encourage occupants to open the window when the outdoor temperature was advantageous on July 9th. Due to the gradual increase in indoor temperature, the occupant was nudged to open the window after four hours when the indoor temperature reached 26.5°C. The window was then left open overnight after the occupant's departure and closed at the occupant's next arrival. In contrast, Figure 3.10 shows that the automated window operation instantly opened the window when outdoor conditions were deemed advantageous and closed it when HVAC systems were shut down to avoid overnight opening. Further, the

window was opened for about two hours and then closed when the outdoor temperature rose to over 20°C at noon on July 10th, which suggested that the automated window operations can control the window state with greater flexibility. This would be hardly achievable for regulated window operations because it requires the presence of occupants and immediate occupants' response.

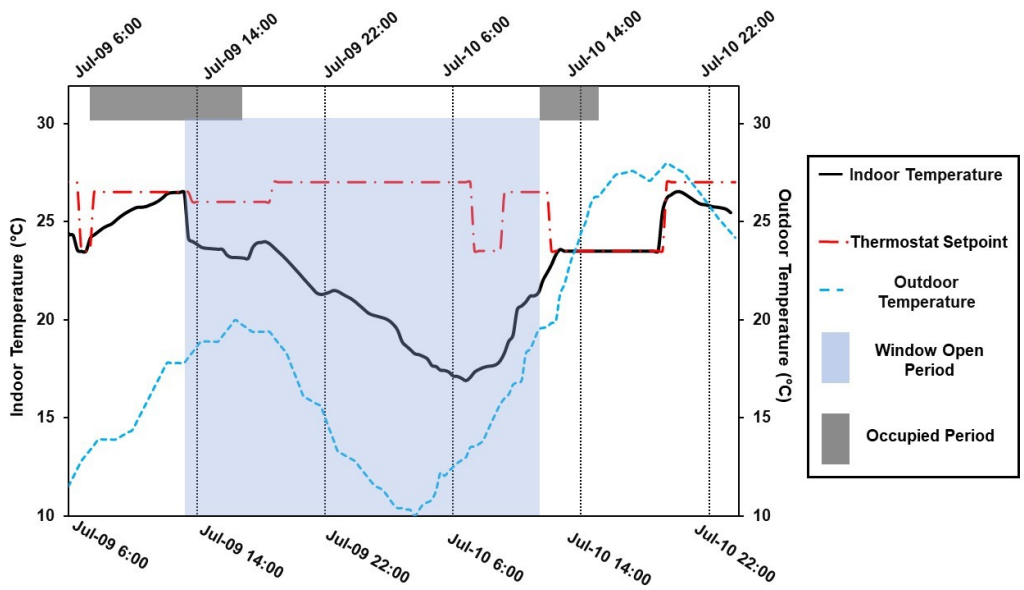

Figure 3.9: A two-day time-series plot showing the simulated indoor and outdoor temperatures, window operations and thermostat setpoints from a south-facing zone model with regulated window operations.

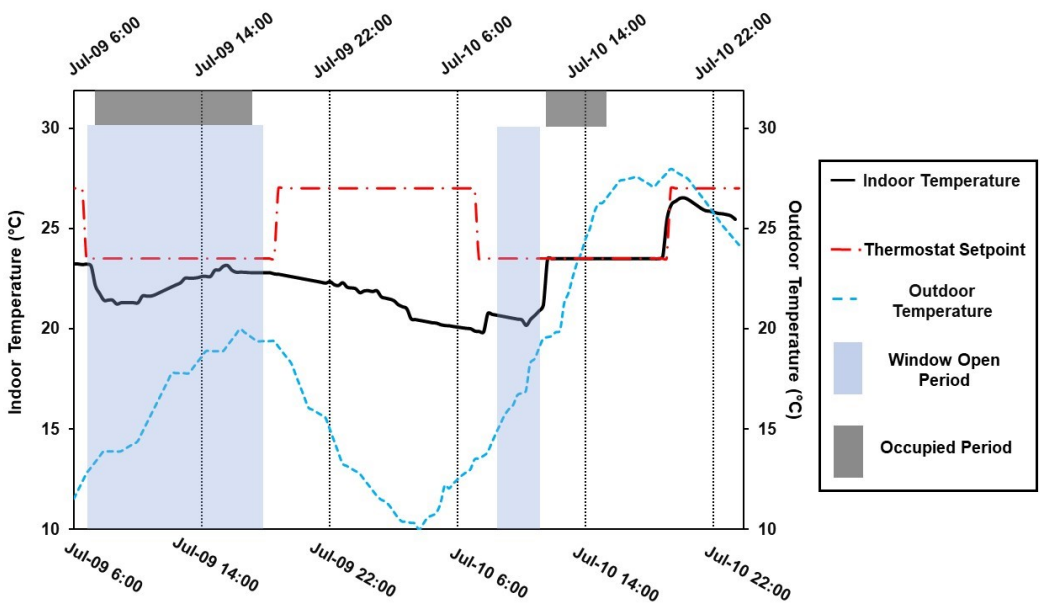

Figure 3.10: A two-day time-series plot showing the simulated indoor and outdoor temperatures, window operations and thermostat setpoints from a south-facing zone model with automated window operations.

3.3.3 Heating load

Figure 3.11 demonstrates the comparisons of annual heating load between four window operation cases with three different occupancy profiles. It indicates that the heating loads in the models with regulated window operations were 3-14% lower than the unregulated counterpart. The fluctuations of heating load can also be reduced by the regulated window operations. In Figure 3.11(b), the heating load varied the most in the east-facing model with unregulated window operations occupied by Occupant 3 from 57 to 76 kWh/m^2 (i.e., 19 kWh/m^2 variations). The spread of annual heating load data was narrowed down to around 5 kWh/m^2 by the regulated window operations. Besides, the heating load of models with fixed windows and automated window operations could be 5-21% lower than the heating load in models with unregulated window operations. This finding was similar to the simulation results from Gunay, O'Brien, and Beausoleil-Morrison [25], which indicated that unregulated window operations could increase the heating load by 6-15% in a cold climate. The reason for the increase in heating loads was due to inappropriate window opening during winter when the outdoor temperature was well below the indoor temperature.

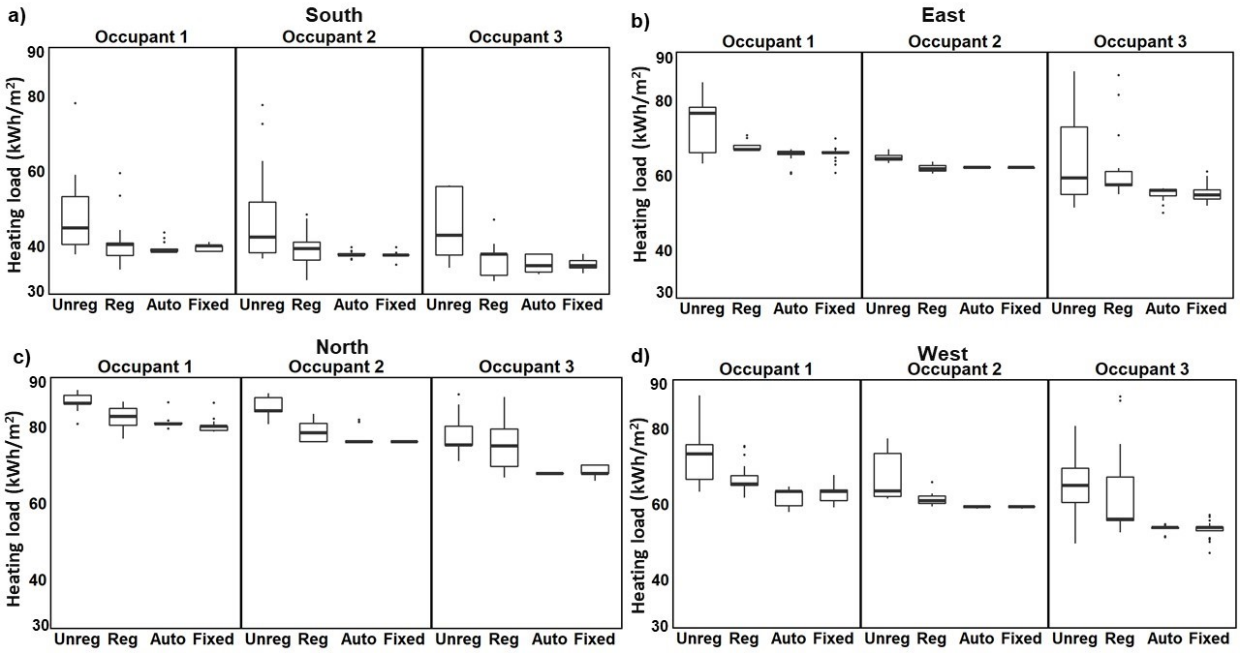

Figure 3.11: Box whisker plots of annual heating load for models with different window operations and three occupancy levels in south, east, north, and west orientations. "Auto" represents the automated window operations, and "Fixed" means that the window remained closed. "Reg" means regulated window operations, while "Unreg" stands for unregulated window operations.

Figure 3.12 presents the window operations on February 4th during the winter to demonstrate the reason for inappropriate window openings when window operations were unregulated. It illustrates that indoor temperature was raised due to solar heat gains, and the thermal discomfort triggered the occupant to open the window. Note that the indoor temperature was maintained at 22℃ during the window opening period because of sufficient heating provided by the HVAC system and baseboard heater. As a result, no immediate attention was raised by the occupant concerning the window state after occupant undertook the window opening action. The window was left open for five hours and closed at the occupant's final departure, which caused a tremendous amount of energy waste. For regulated window operation, Figure 3.13 demonstrates the effectiveness of the proposed control sequences on encouraging the

occupant to close the window. The occupant opened the window during the winter due to thermal discomfort caused by solar heat gains. When the window state was detected as open, a setback was applied to decrease the heating setpoints. After around one hour, the occupant was nudged to close the window by the decrease of indoor temperature. Even though the proposed control sequence can effectively nudge occupants to close the windows during the winter, the energy waste can still be considerable due to the response time between when the setback was applied and the closing action, which explained that why automated window operations with instantaneous window state change can achieve better energy savings.

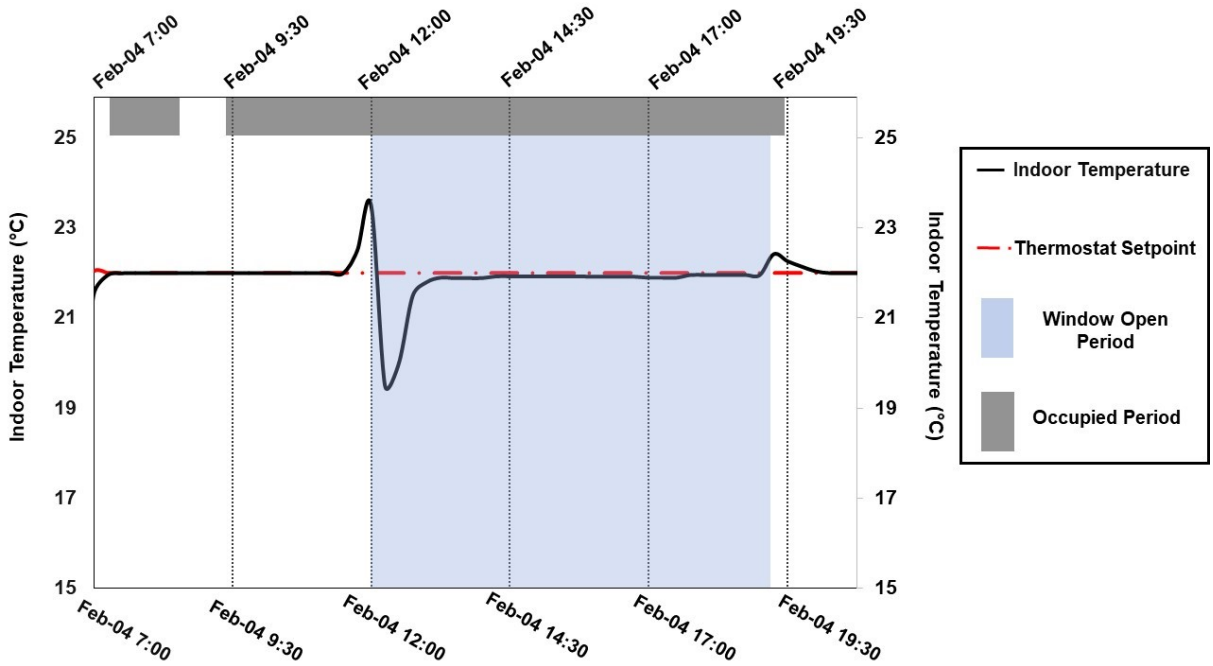

Figure 3.12: A one-day time-series plot showing the window states, indoor temperature, and thermostat setpoints in a south-facing model with unregulated window operations on February 4th. Note that the outdoor temperature was below -10℃ during the covered timespan, which was not shown in the plot.

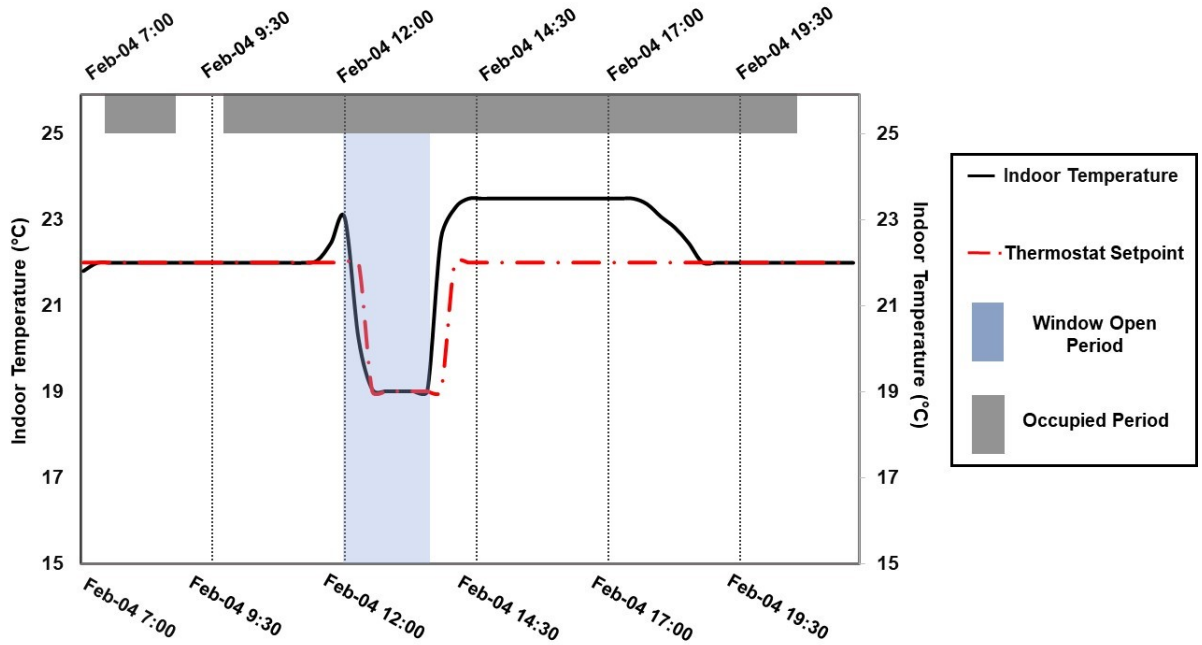

Figure 3.13: A one-day time-series plot showing the window states, indoor temperature, and thermostat setpoints in south-facing models with regulated window operations on February 4th. Note that the outdoor temperature was below -10℃ during the covered timespan, which was not shown in the plot.

3.3.4 Fan energy use

Figure 3.14 illustrates the fan energy use comparisons for all four operation scenarios in the south, east, north, and west-facing zones. As the fan energy use represented the energy demand posed by the economizer, it indicates that efficient utilization of natural ventilation can reduce its energy demand significantly. The regulated window operation could decrease fan loads by 5-39%, while automated window operation could reduce fan loads by 8-42% compared to unregulated window operation scenarios. Furthermore, the fluctuations were noticeably reduced in models with regulated and automated window operations relative to unregulated window operations.

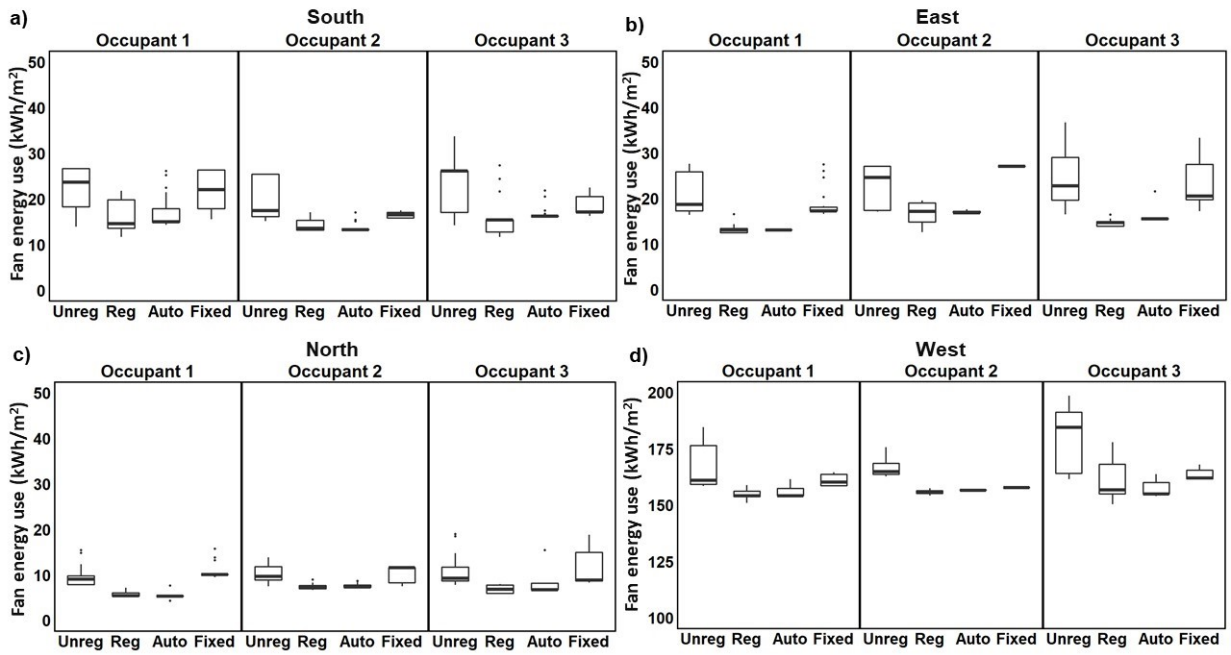

Figure 3.14: Box whisker plots of annual fan energy use for models with different window operations and three occupancy levels in south, east, north, and west orientations. "Auto" represents the automated window operations, and "Fixed" means that the window remained closed. "Reg" means regulated window operations, while "Unreg" stands for unregulated window operations.

3.4. Discussion

In this chapter, we examined the effectiveness of a control sequence for HVAC terminal devices to regulate window operations in which engagement of occupants is a necessity. We compared the performance of this method with other window operation scenarios such as unregulated window operations (i.e., solely controlled by occupants), automated window operations and with the fixed-window scenario. The results showed that the models with unregulated window operations had the worst energy performance among all window operation scenarios. With regulated window operations, the model could achieve energy savings of 3-16% while significantly reducing the fluctuations of EUI. This finding

confirmed the effectiveness of the control sequences developed in Chapter 2 of this dissertation [78].

It is evident that the amount of energy savings achieved by the control sequences can vary based on room orientation and occupancy. For example, results showed that 3% of energy savings were obtained in the east-facing model occupied by Occupant 1, while 16% of energy savings were obtained in the south-facing model occupied by Occupant 3. Furthermore, the model with higher occupancy levels (i.e., Occupant 2 and 3) could achieve greater reductions in heating and cooling loads, and fan energy use than that in models with Occupant 1. It indicated that the effectiveness of control sequences could be maximized when the office was occupied for a longer duration. On the other hand, the advantage of using automated window systems was revealed as they did not require occupant interventions to alter the window state and decreased energy use by 6-17%. Automated window opening percentages in July were also lower than those with the regulated window operation when occupied by Occupant 2 and 3 (see Figure 3.5). The reason was that the automated window operations could alternate the window states with more flexibility and no response time from occupants, whereas the regulated window operations required the presence of occupants and an extended period of time for occupants' response (see Figure 3.9, 3.10). Even though the automated window operation showed better energy performance, this research focused on manually operable windows regulated by the control sequences as it could provide occupants with more controllability over their indoor environment, which can result in greater perceived comfort [28].

Another advantage of using the proposed control sequences to control the natural ventilation was revealed when compared to using an economizer to deliver the outdoor air. The control

sequences provide finer granularity by controlling natural ventilation on a zone level, whereas the economizer is a system-level measure. In reality, an AHU system can serve multiple thermal zones in actual buildings. The natural ventilation cannot be delivered to specific zones with higher cooling demand (e.g., south and west-facing zones) if the economizer is off on the system level. Thus, delivering natural ventilation through operable windows in a regulated manner can enable greater opportunities of reducing energy consumptions while meeting the thermal demands of the specific zone.

To better cater to the thermal demands of the zone, we proposed that the conditions determining whether windows should be opened to utilize natural ventilation were linked directly with the thermal demands of the zone. If the zone requires cooling while the outdoor temperature is cooler than the indoor temperature, natural ventilation should be used. If the zone requires heating and the window was opened, window opening should be avoided. This approach has a considerable advantage compared to the approach using a fixed threshold of outdoor temperature where natural ventilation can only be leveraged under a predetermined condition without considering the variability of thermal demands in different seasons. In comparison with the approach reviewed previously in section 3.1.1, where the conditions of determining when to use natural ventilation were calculated at every timestep by RL algorithm [80], our approach requires much fewer resources for data processing and computing so that fewer barriers could be encountered when implemented in existing buildings.

The authors recommend conducting field implementation of the proposed control sequences to verify the effectiveness in actual buildings. As the plan of field implementation was intervened by the COVID-19 pandemic, the study was substituted with a simulation-based

investigation. Although the simulation suggested promising results, a few factors that impacted the effectiveness remained undiscovered. First, the response to control sequences from actual occupants is unclear. Even though stochastic occupant behaviour models based on data from an existing building were incorporated with consideration of the inter-occupant diversity, the variability of occupant behaviours may not be fully captured. For instance, Chapter 2 [78] revealed considerable inter-occupant diversity among 20 private offices in a surveyed buildings. While some occupants adjusted thermostat setpoints and opened windows over 100 times per year, some occupants were found to make these actions less than ten times throughout the entire year due to different behavioural tendencies, clothing habits, metabolic rates and so on. As a result, the feedback responses collected from field implementation can be instrumental. Second, the limitations of building energy simulation tools can hinder us from obtaining accurate performance of implementing the control sequences. For example, Schuss et al. [67] have discovered that EnergyPlus models and current calculation formalisms may miscalculate the airflow rate through window openings, which leads to mispredictions of the efficacy of natural ventilation. It is worth noting that implementing the control sequences in actual buildings could enable greater energy-saving potentials than the energy simulation suggested. When the HVAC systems serve multiple thermal zones in actual buildings that are all equipped with operable windows, the energy penalties imposed by inappropriate window openings can be even higher compared to the single zone model simulated in the present study. In other words, the energy reductions achieved by the proposed method in actual buildings can be considerably higher if the window states are controlled accordingly. The authors also encourage experimenting with the combination approach of implementing the proposed control sequences with occupant

feedback systems in actual buildings. When the setback is applied, the occupants can be informed through the display of thermostats with the intent of increasing engagement and reducing the response time. An occupant feedback interface developed by Brackley et al. [90] showed the potential of these feedback systems for helping occupants understand the operation status of HVAC systems. It is worth mentioning that the cost of implementing control sequences into actual buildings should be considered, and the comparison with the cost of installing automatic window systems should be made as well. Putting aside the investment of installing BASs, implementing the proposed control sequences requires installing window contact sensors, whereas the automated window system requires window contact sensors as well as window actuators.

We acknowledge that there are a few limitations of the present study. First, the discrete-time Markov logistic regression models developed from the previous study [78] were incorporated into BPS to represent the occupant behaviours in the present study. Despite the formalism of models is widely used and proved to have high accuracy [43], the occupant behaviours may not be fully captured due to the limitations of the formalism, such as the tendency of overestimating the window open duration [45]. As a result, the window opening percentages (see Figure 3.5) for different window operation scenarios might be overestimated. Second, three sets of occupancy data were selected to represent different occupancy profiles in this study. They were used to examine the performance of control sequences when the number of occupied hours, departure and arrival events are different. However, this approach may not adequately represent the diversity of occupancy profiles in actual buildings, which can have an impact on the performance of control sequences. Moreover, the authors acknowledge that even though the effectiveness of control sequences was confirmed in the present study with

consideration of occupant diversity to some extent, the setback value in the control sequences proposed by Liu, Gunay, and Ouf [78] may not be valid for all occupants and all buildings. The appropriateness of the setback value should be tested if the control sequences are to be implemented in other buildings. If substantial variation is observed, the setback value should be updated by following the framework proposed by Liu, Gunay, and Ouf [78] while a set of recursive self-adaptive algorithms [91] can also be used to learn individual setback value for each thermal zone in the same building. The authors also acknowledge that the effectiveness of proposed control sequences remains limited to private offices at the zone level as the control sequences were developed based on the understandings of occupant behaviours obtained in private offices. The viability of manipulating the indoor environmental conditions to engage multiple occupants to adjust the window states in open-plan offices remains undiscovered. In fact, a previous study [44] has revealed that occupants in open-plan offices had less perceived control over indoor environmental conditions, which may result in fewer tendencies of opening and closing windows, and the automated window systems could be a better approach. Lastly, the influence of ambient noise and air quality on window operations was not considered in the present study. These factors can be critical constraints for opening windows even when the outdoor temperature is favourable [68, 69]. In addition, although different clothing insulation levels were applied for different seasons in the simulation, the variability of clothing behaviours between different occupants was not considered. It can be impactful on occupants' perceived comfort and tendencies of undertaking adaptive actions.

3.5 Closing remarks

The approach proposed in Chapter 2 recommended creating environmental conditions to encourage occupants to adjust the window states according to outdoor environmental conditions in order to avoid energy waste and better leverage the energy-saving potential from natural ventilation. This chapter examined the effectiveness of the proposed control sequences using BPS tools. We proposed that the conditions determining whether windows should be opened to utilize natural ventilation were linked directly with thermal demands of the zone instead of using a fixed threshold of outdoor temperature. The energy performance of models implemented with proposed control sequences was compared with other models with different window use scenarios, such as unregulated window operations and fixed-window, to examine the applicability of control sequences. It was found that the regulated window operations by proposed control sequences can achieve energy savings of 3-16% while considerably reducing the fluctuations due to inter-occupant differences in window and thermostat use behaviours. The regulated window operation also minimized the window opening percentage in winter and significantly increased the percentage in summer and shoulder seasons. Even though more factors should be considered to refine the control sequences, their effectiveness was verified.

The findings of this chapter could inform ASHRAE Guidelines 36 [22] to improve existing control sequences with recommendations as follow: (1) Window opening should be avoided in a cold climate during the heating season to prevent energy penalties. If the window is opened during winter, applying setbacks to decrease indoor temperature can effectively encourage occupants to close the window. (2) During the cooling season, window operations should be regulated to maximize the energy-saving potential. Otherwise, the energy savings

can be easily offset by energy waste imposed by inappropriate window openings. If the thermal zone requires cooling and the outdoor temperature is cooler than the indoor temperature, applying setbacks to increase the indoor temperature can encourage occupants to open the window. (3) The setback values (i.e., 49°C during cooling and 4°C during heating) proposed by ASHRAE Guideline 36 should be revised with field data from occupant behaviour research. Finally, the findings also provide evidence for building designers that the energy impact from occupants' window use behaviours should always be taken into account. Mixed-mode ventilation systems can realize the energy-saving potential when window operations are regulated.

Chapter 4

4. Conclusion

4.1 Summary

This research project aimed to regulate window operations in mixed-mode ventilation buildings in cold climates by improving the control algorithms of HVAC terminal devices in these buildings. A summary of the conclusions is presented, and the research questions answered in each chapter are provided in the following subsections.

4.1.1 Modelling window and thermostat use behaviour to inform the control sequences

This chapter analyzed the window and thermostat use data acquired from 20 private offices in two academic buildings in Ottawa, Canada, and established occupant behaviour models for occupants' window and thermostat use behaviour. The insights gathered from the models were used to develop recommendations to improve the control sequences so that occupants can be nudged to operate the windows in an energy-efficient way. The research questions posted in Chapter 1 were answered as follows to demonstrate the main findings of this chapter:

- *How often do the occupants use the windows and thermostats in a mixed-mode ventilation building in a cold climate?* The fraction of time during which windows remained open each month (i.e., the total number of hours windows were open relative to 720 or 744 hours in a month) was investigated in Chapter 2. It is showed that windows were open for less than 10% of the time in the shoulder months (i.e.,

April, May, September, and October), which indicates that natural ventilation was not effectively exploited to conserve energy when the outdoor conditions were advantageous during shoulder months. The monthly average number of thermostat overrides was also shown in Chapter 2. The results indicate that each occupant tends to increase the thermostat setpoint around three times per month on average in January, May, and October, while the average number of increase actions was below two times for the rest of the year. It also showed that occupants decreased setpoints more frequently in April and May. These results suggested that thermal discomfort occurred more frequently in the shoulder months.

- *What are the model formalisms suitable to gain insights into occupant behaviour patterns?* In this chapter, discrete-time Markov logistic regression models and classification decision tree models were developed for window and thermostat use behaviours. The discrete-time Markov logistic regression model has been widely used in the occupant modelling literature and found to have the best predictive outcomes for occupants' adaptive behaviours (e.g., window opening actions and thermostat override actions) [53]. Classification decision tree models are suitable to classify environmental conditions on instances in which adaptive actions took place from the other occupied instances. Classification decision tree models were instrumental for understanding occupant behaviour patterns and developing the adjustment of control sequences.
- *What are the common window and thermostat use behaviour patterns?* For window use behaviour, it was found that occupants opened and closed their windows less frequently when the indoor temperature was at around 23°C. When the indoor

temperature rose above 26°C or dropped below 20°C, occupants opened or closed their windows around three times more frequently than they were at around 23°C, respectively. For thermostat use behaviour, it was found that when the indoor temperature was in the range of 22°C to 24°C, occupants had the least tendency to override the thermostat setpoints. When indoor temperature was in a range of 24-27°C, occupants were more inclined to decrease setpoints to adjust indoor temperature instead of using windows.

- *How can occupant behaviour patterns be used to improve the control sequences, and conversely, how do the control sequences influence occupants' behaviours to promote energy-efficient actions?* Firstly, it was found that when indoor temperature rose above 26°C, occupants would be more inclined to open windows to allow the natural ventilation to cool the rooms. However, when indoor temperature was in a range of 24-27°C, occupants were more inclined to decrease setpoints to adjust indoor temperature instead of using windows. This indicated that natural ventilation was not effectively leveraged, and the control sequences should be improved to encourage occupants to primarily use windows to conserve energy. With this in mind, the new control sequences apply a 3°C setback on cooling setpoints (i.e., assuming a 23.5°C default cooling setpoint, apply a setback to increase the cooling setpoint to 26.5°C) without offering controllability to change the setpoint when conditions are advantageous to use natural ventilation. Second, it was found that occupants were more inclined to close their windows when indoor temperature dropped below 20°C. Thus, this finding was used in the new control sequences where a 3°C setback was

applied on heating setpoints (from the default 22°C to 19°C) to nudge occupants to close their windows when they were open during the heating season.

The authors acknowledge that a few factors that can impact window operations in mixed-mode buildings remain undiscovered in this chapter. Firstly, the ambient noise and poor air quality can cause reluctance of opening windows and less natural ventilation utilization [68, 69] even though the outdoor temperature may be suitable for opening the windows. Given that the data obtained from case study buildings do not include information of ambient noise and air quality, future work is needed to take these two factors into account. Second, the impact of configurations of operable windows on occupants' window use behaviour remains unknown. The types of windows and the accessibility of the windows (e.g., the distance between windows and occupants' workspace) may affect occupants' willingness to use windows. The number of existing studies that investigate these factors is still limited, which suggests that more research is needed.

4.1.2 A simulation-based investigation for the proposed control sequences

This chapter examined the effectiveness of the control sequences proposed in Chapter 2 by using the BPS tool EnergyPlus. The occupant behaviour models developed in Chapter 2 were also implemented into BPS to represent the occupant behaviours. The weather file used to conduct the simulations was from the database of Canadian Weather Year for Energy Calculation (CWEC) for Ottawa, Canada [82] to demonstrate the performance of control sequences in a cold climate. The research questions were answered to demonstrate the main findings of this chapter as follows:

- *How can we determine when it is advantageous to initiate the control sequences to encourage occupants to use natural ventilation or stop using it?* We propose that the conditions determining whether windows should be opened to utilize natural ventilation can be linked directly with the thermal demands of the zone. When a zone requires cooling (i.e., VAV damper position greater than its minimum position and reheat coil off), outdoor temperature is colder than the indoor temperature, and the high-limit outdoor air temperature threshold for economizer availability (i.e., 21℃ according to ASHRAE 90.1 for Climate Zone 6A [83]) is not violated, the conditions are deemed as advantageous, and a setback is applied within the next two hours so that a slight increase of indoor temperature can nudge occupants to open the window. If the windows are already open when conditions are advantageous, a setback is applied to fully exploit the energy-saving benefits from using natural ventilation. The rationale of this approach is that the window operations based on a single fixed threshold of outdoor temperature cannot achieve the optimal performance for various buildings and different seasons, as previously reviewed in Section 3.1.1.
- *What level of energy savings can be achieved by the control sequences?* After implementing the control sequences, the simulated results showed that the EUI could be reduced by 3-16% while the heating and cooling loads decreased by 3-14% and 4-19%, respectively. The fan energy use can also be reduced by 5-39%. Another noticeable benefit was that the control sequences could considerably reduce the risk of extremely high heating and cooling demand due to windows left open for prolonged periods.

- *How does the control sequence perform compared to other control scenarios, such as using an automated window system and having a fixed window?* When the control sequences directly control the automated window system, the EUI could be reduced by 6-17% compared to the baseline model with unregulated window operations, whereas the control sequences could decrease the EUI by 3-16% with manually operable window. The reason for the better performance from automated window systems was that the automated window operations could alternate the window states with more flexibility and without a delayed response time from occupants, whereas the manually operable windows required the presence of occupants and an extended period of time for occupants' response. In comparison to the model with a fixed window, the model with regulated window operations by the control sequences can have better energy performance, mainly due to lower cooling loads and fan energy use.
- *What are the constraints of the control sequences that should be considered?* The effectiveness of the control sequences remains limited to private offices at the zone level as the control sequences were developed based on the understandings of occupant behaviours obtained in private offices. Furthermore, the viability of using the control sequences to engage multiple occupants to adjust the window states in open-plan offices remains undiscovered.

The authors acknowledge that there are several limitations of the study conducted in this chapter. First, the limitations of building energy simulation tools can hinder us from obtaining accurate performance of implementing the control sequences. Schuss et al. [67] have discovered that EnergyPlus models and current calculation formalisms may

miscalculate the airflow rate through window openings, which leads to mispredictions of the efficacy of natural ventilation. Moreover, several variables that were unable to be obtained from the case study were assumed as default values, such as occupants' clothing insulation levels and activity levels. Even though different clothing insulation levels were applied for different seasons in the simulation, the variability of clothing behaviours between different occupants was not considered. The implementation of the control algorithms into actual buildings is needed, and the recommendations for future work are provided in section 4.3.

4.2 Research contributions

4.2.1 Modelling window and thermostat use behaviour to inform the control sequences

The analysis presented in this chapter contributes to a growing body of literature on occupant behaviour modelling and occupant-centric control. The occupant behaviour modelling particularly focused on window and thermostat use behaviour in mixed-mode ventilation buildings in a cold climate. The parameter estimates of discrete-time Markov logistic regression models for window and thermostat use behaviour were provided in the journal article "Modelling window and thermostat use behaviour to inform sequences of operation in mixed-mode ventilation buildings" in *Science and Technology for the Built Environment* to allow other researchers to test and compare. Furthermore, the study proposed a novel method of regulating window operations with manually operable windows by adjusting control sequences of HVAC terminal devices. The modelling results and proposed control sequences were presented at the 5th expert meeting of IEA-EBC Annex 79 and ASHRAE's 2021 Winter Conference in Chicago, Illinois.

4.2.2 A simulation-based investigation for the proposed control sequences

The analysis of this chapter examined the effectiveness of the control sequences proposed in Chapter 2 by using the BPS tool, EnergyPlus. The findings confirmed that the proposed control sequences could effectively regulate window operations and improve building energy efficiency. Further, the findings can inform ASHRAE Guideline 36 [22] to improve existing control sequences to better leverage natural ventilation and avoid inappropriate window openings. In addition, the study contributed to IEA-EBC Annex 79 for the topic of occupant-centric control. These findings are under review for publication in *Journal of Building Performance Simulation* as "Regulating window operations using HVAC terminal devices' control sequences: A simulation-based investigation". The control algorithms were provided alongside the journal article to allow other researchers to test in actual buildings.

4.3 Recommendations for future work

Due to the COVID-19 pandemic, the implementation of the proposed approach in existing buildings was stalled. Thus, the recommendations for future work are provided as follow:

- The author recommends conducting field implementation of the proposed control sequences to verify the effectiveness in actual buildings. In Chapter 3, the effectiveness was examined by the building simulations where the stochastic occupant behaviour models based on data from an existing building were incorporated with consideration of the inter-occupant diversity. The feedback responses collected from field implementation can still be instrumental as the occupant behaviour modelling cannot fully represent the occupant behaviours. In reality, occupants may take other adaptive actions in response to the adjusted indoor

environment from the control sequences, such as increasing and decreasing clothing insulation levels and drinking cold/hot beverages [92]. These adaptive actions were found as common measures for occupants to mitigate thermal discomfort but can hardly be represented by occupant behaviour models. In addition, ambient noise and air quality issues were not considered in this research but can cause reluctance of opening windows from occupants. The ambient noise level and air quality should be inspected prior to implementing the control algorithms into actual buildings.

- The authors also encourage experimenting the proposed control sequences with occupant feedback systems in actual buildings. To date, the approaches to regulate window operations with manually operable windows are limited in the literature. An approach is to notify the occupants to open/close windows through emails or messages [93], but the effectiveness remains unknown. Ackerly and Brager [39] explored an approach of regulating the window openings through occupant feedback systems by using light indicators to advise occupants about when to open and close windows based on environmental conditions, but the engagement of occupants has yet reached the optimal level. If the proposed control sequences with occupant feedback systems are implemented, a setback can be applied while the occupants are informed through occupant feedback systems to increase engagement and reduce the response time.
- As the sequences of operation in many mixed-mode ventilation buildings were designed the same way as the sequences in mechanically ventilated buildings, the energy-saving benefits are not effectively exploited. Even though the findings in this dissertation are limited to zone level control in a cold climate, the framework

provided in this dissertation (see Figure 2.1 in section 2.1) can be utilized to establish occupant behaviour models and improve the control sequences of mixed-mode ventilation buildings in different climates.

- The approach of regulating window operations with manually operable windows in multi-occupant spaces, particularly the spaces without seating dedicated to individuals (e.g., libraries, desk-sharing offices) could be another future topic that needs exploration. There were a limited amount of studies completed on this topic, and most of them were associated with occupant-centric control of lighting systems [47]. In fact, occupants in the aforementioned spaces typically have less control over indoor environmental conditions relative to the occupants in private offices [61], which may lead to infrequent window use that can cause inefficient utilization of natural ventilation and windows being left open for prolonged periods without intervention. As a result, using automated window systems can be a more suitable approach in multi-occupant offices. The sequence of operation should also be developed to effectively control the automated window systems. The framework highlighted in section 2.2 (see Figure 2.1) provides a tool for future study to establish occupant behaviour models to gain understandings of occupants' thermostat and window use behaviours in multi-occupant spaces for which the control algorithms can be further improved.

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