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The gap between automated building management system and office occupants' manual window operations: Towards personalised algorithms

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ABSTRACT

This paper aims to demonstrate how knowledge acquired from occupants' manual window operations can be implemented into BMS automated window operation algorithms. Ten single-occupant offices were selected in a university building in the UK. More than 28,000 hourly data points on indoor and outdoor temperature and open window area (OWA) were analysed from 2015 to 2020. The BMS had adopted nine different automated window operation algorithms during the 5 years. The automated window algorithms could be manually overridden by the office occupants. Automated algorithms were compared against manual window operations. The results showed that the slope and gradient of the regression lines for occupants' manual window operations are smaller than automated operations. OWA of automated window operations increased 20% per 1 °C increase in indoor temperature, however, occupants opened windows 6–8% per 1 °C increase. Occupants react slower to temperature changes than assumed by BMS, which could be considered in BMS automated window operations.

1. Introduction

Occupant behaviour is a multidisciplinary research topic appearing in different sciences such as building, control technologies, computing and social sciences [1]. It is also a function of occupants' preferences for indoor environmental quality [2]. For example, thermal comfort can be achieved through occupants' adaptive behaviours such as opening/closing windows, adjusting clothing or changing seats [3]. Occupant thermal comfort has a significant impact on building operations and it is a major criterion to evaluate the performance of the building systems [4].

In the past, it was common for occupants to have a direct connection with building controls (e.g. windows and heating systems) [5], however, with the development of building management systems (BMSs), the level of manual control has changed [6,7]. Some BMSs still allow occupants to have a high level of interaction and can override the automated systems, whereas with others the interaction is largely limited, sometimes preventing occupants from even opening windows [8]. Increased complexity of automated or intelligent systems has been shown to have negative impacts on occupant comfort and satisfaction [9,10]. Several studies [11,12] have reported users and designers' misperceptions of the BMS as the common reasons for the failures of these systems. Many BMSs lack real-time input of dynamic factors including occupancy, occupant preferences, occupant actions and decisions [13]. One of the common problems with automated operations by the BMS is that the programmed algorithms are rarely defined based on knowledge of what occupants actually want [14].

In an efficient and comfortable building, an indoor environment control system needs to be developed to meet the demands of its occupants. A study by Kim et al. [15] recommends that the automated control algorithms embedded in the building systems should accurately estimate occupants ventilation behaviour. The increasing gap between building systems' automated actions and occupants preferences can change occupants' perceived level of control over building systems, often at the loss of occupant satisfaction, productivity, and comfort [10,16,17].

In the past 30 years, a high number of studies have been conducted to investigate office occupants' window-opening behaviour in the UK [18–25], Europe [23,26] and Asia [25,27]. Furthermore, several studies have considered occupant data or behaviours to improve building management systems and automated controls [4,13,28–30]. For example, the study by Klein et al. [13] implemented a multi-agent comfort and energy system (MACES) with input from a real-world building including occupant preferences and schedules to model alternative control of building systems and occupants. The results of this study showed a 12% reduction in energy consumption and a 5% improvement in occupant comfort as compared to the baseline control.

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Nomenclature

Algorithms	Operational Guidelines for Window Operation
Behaviour Gap	The gap between automated window operations by BMS and occupants' manual window operations
BEMS	Building Energy Management system
BMS	Building Management System
Dataset	Classification of Data by Months, Year and Office number and each classification is considered one dataset
Heating Season	October to March
IAQ	Indoor Air Quality
IEQ	Indoor Environment Quality
IoT	Internet of Things
Non-heating Season	April to September
Open Window Area (OWA)	The geometric free ventilation area created when a window is open
Ti	Indoor Temperature

The study by Batra et al. [28] investigated how electricity consumption within the buildings (plug loads, lighting and air conditioning) could be significantly improved using Occupancy-based Building Management Systems (Ob-BMS) [28]. The study by Jazizadeh et al. [4] included occupant-driven and personalised control of HVAC systems in their framework to provide higher levels of thermal comfort for occupants [4]. Another example is the study by Guillemin and Morel [30] that proposed a self-adapting control system for occupants' preferences through user input in the form of setpoints for thermal comfort. Also, the review paper by Dounis and Caraiscos [29] looked at how the development of intelligent control systems improved the efficiency of control systems for the management of the indoor environment including user preferences.

However, to the authors' knowledge, there is not any current research on the gap between automated operations by the BMS and occupants' window operations, which is referred to as the 'behaviour gap' in this study. Furthermore, there is a significant gap of knowledge on 'open window area (%)' in relation to indoor temperature in office buildings as previous studies have mainly considered the probability of windows being open or closed [19,20,22,23,25].

Occupants' behaviour is a key issue for building design optimisation and performance evaluation [31]. The goal for user-driven building controls is occupant satisfaction, for which thermal comfort is an important criterion [4]. Occupants' window operation behaviours reflect their perception of the Indoor Environment Quality (IEQ) and especially the thermal environment. Therefore, BMS automated window operations need to be personalised based on occupants' preferences to provide higher levels of comfort for them.

This study aims to develop operational algorithms for BMS automated window operations based on occupants' actual behaviours and preferences. The paper investigates:

- The gap and differences between automated window operations by BMS and office occupants' manual window operations (behaviour gap).
- Factors impacting occupants' manual window operations.
- Recommendations for improving BMS automated window operation algorithms.

2. Methodology

To investigate how occupants' manual window operations can be incorporated into BMS automated algorithms for window opening, data on both BMS automated window operations and occupants' manual window operations in a UK university building from November 2015 until December 2020 (5 years) were collected and analysed.

2.1. Building description

The building studied, called the Marine Building, is located on the University of Plymouth campus in the south-west of the UK. The building shown in Fig. 1, opened in 2012, provides a range of flexible research, educational, office and meeting spaces and houses specialist facilities and laboratories for marine research.

For this study, single-occupant offices, rather than double-occupancy and open-plan offices, were selected because occupants in single offices can have full control over windows based on their preferences, and therefore, operations can be higher [33,34]. Furthermore, occupants' manual operations in double-occupancy and open-plan offices can be influenced by other occupants' preferences in the workplace [35,36].

Therefore, ten single-occupant offices were selected, two located on the first floor (Fig. 2), six located on the second floor (Fig. 3) and two located on the third floor (Fig. 4). The offices located on the first floor (105 and 106) are oriented towards the south and the offices located on the second (203–208) and third floors (305 and 306) are oriented towards the north. The offices on the first floor are 7.9 m^2, on the second floor from 7.8–8.1 m^2 and on the third floor from 6.9–7.2 m^2.

Each office has one automated top hung window opening outward. The windows' size is 100 cm wide by 80 cm tall and is located 1 m above desk level. The total openable window area is 0.8 m^2. The windows in each office are controlled by the BMS, however, they can be overridden manually by a push button. The BMS automatically opens windows based on indoor temperature; a one-degree rise in indoor temperature (1 °C) increases the open window area by 20%. The starting indoor temperature for window opening set up by the BMS has varied over time and is investigated in the paper.

Each window has one single chain actuator which can control different open window area (%). When the chain is directed into a straight form, the window is pushed open and when it retracts into the casing, the window closes. The chain attached to the window is controlled and monitored by the BMS. However, the chain can be adjusted by occupants and the adjusted open window area (%) is fed back into the system and recorded by the BMS.

2.2. Data

In this study, the data on indoor and outdoor temperature as well as open window areas (%) recorded in the Marine Building was obtained from the University's Energy Management System called C3NTINEL [37]. More than 28,000 data points on open window area amongst a total of 190,000 data points (including closed windows) from the 10 single-occupant offices were obtained at one-hour intervals for more than five years (November 2015 until December 2020). Data were obtained during weekdays and office hours (9 am-5 pm) to investigate occupants' manual operations during typical occupancy.

2.3. Data analysis

The data is classified by office number, months, year, heating and non-heating seasons, time and floors. In this study, the heating season is classified from October to March and the non-heating season is classified as from April to September. Table 1 shows the classification of data by months, years and office numbers and each classification is considered to be one dataset. For example, data for 'January 2016, office 105' is considered one dataset and data for 'December 2020, office 305' is considered another dataset. As there are 62 months from November 2015 until December 2020 for every 10 offices, a total of 620 datasets (62*10) is presented in Table 1.

By plotting indoor temperature against the open window area (%) for each dataset (a total of 620 graphs), nine automated window operation

Fig. 1. Marine Building located on the University of Plymouth campus [32].

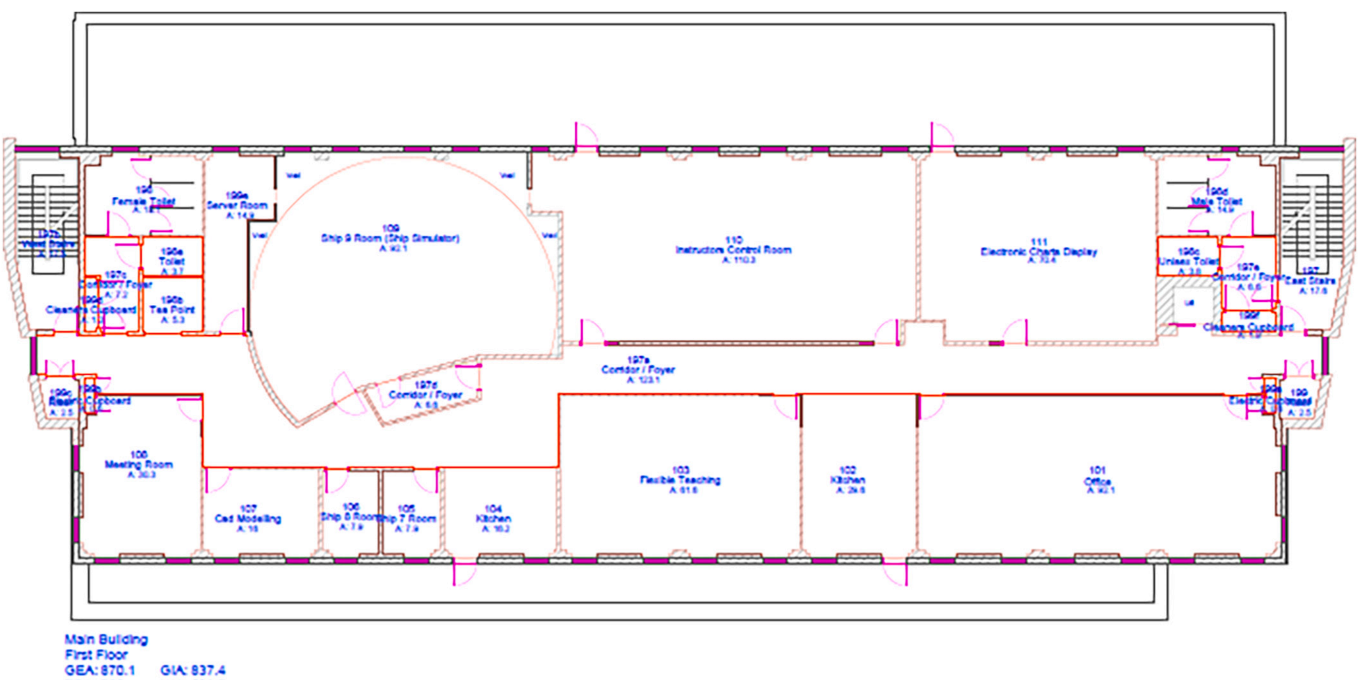

Fig. 2. South-facing offices studied on the first floor.

algorithms were identified. These were validated against the programmed algorithms outlined in the Building Operation and Maintenance Manual. Data that did not fit into these nine algorithms were considered to be occupants' manual operations. The data on 13 datasets were removed from the analysis due to faultiness, resulting in a total of 607 datasets (Table 1).

The statistical analyses used in this study are categorised into three main groups: 1) Descriptive, 2) Correlational (strength) and 3) Predictive (regression). The data were analysed using the Statistical Package for the Social Sciences (SPSS) 25 software [38].

This study has considered the linear regression for the relationship between manual window operations and indoor temperature for two main reasons; to compare manual window operations with automated operations as automated algorithms were based on the linear relationship between open window area (%) and indoor temperature and to provide more information on how much the windows were open. Although logistic regression models could provide information on the probability of windows being open or closed in response to indoor temperature, they cannot be applied to continuous variables. Therefore, open window area (%) as a continuous variable from 0 to 100% would need to be split into two groups of open (1) and closed (0) windows, which would decrease the detailed information on open window area (%). This study improves the state of art on window models moving beyond open and closed window state models and focusing on how much the windows are open.

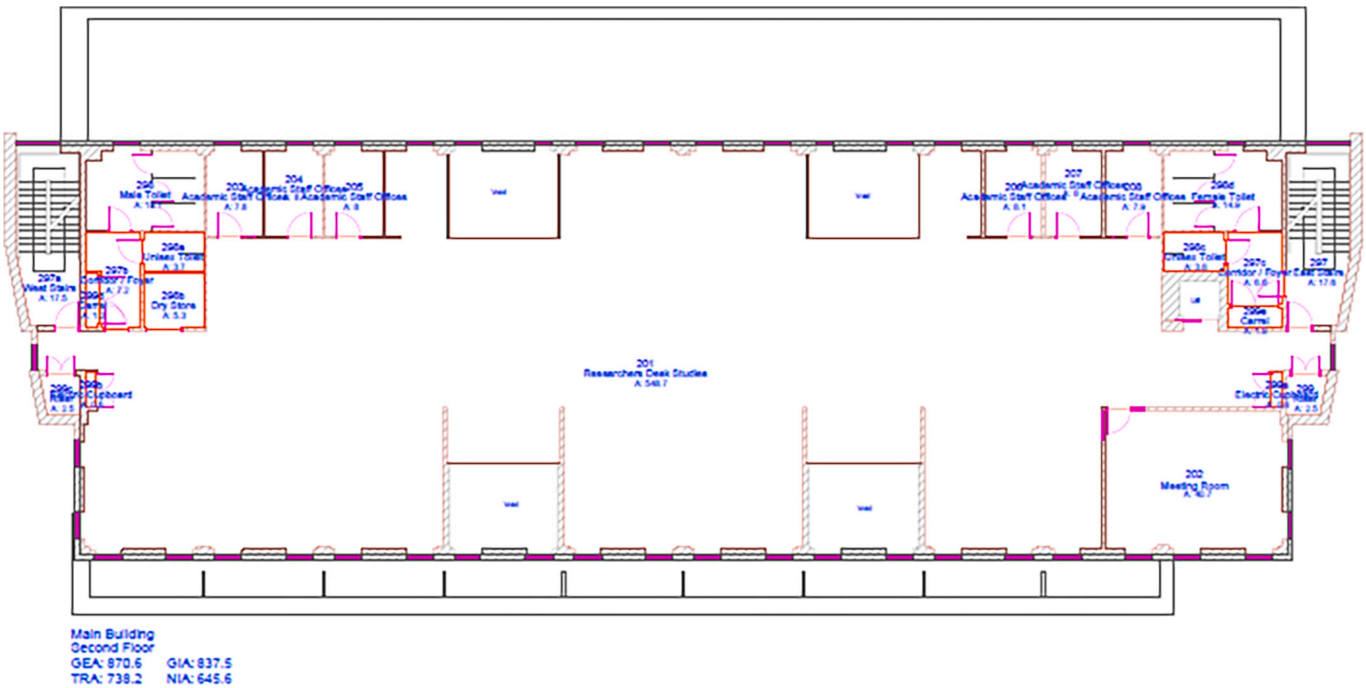

Fig. 3. North-facing offices studied on the second floor.

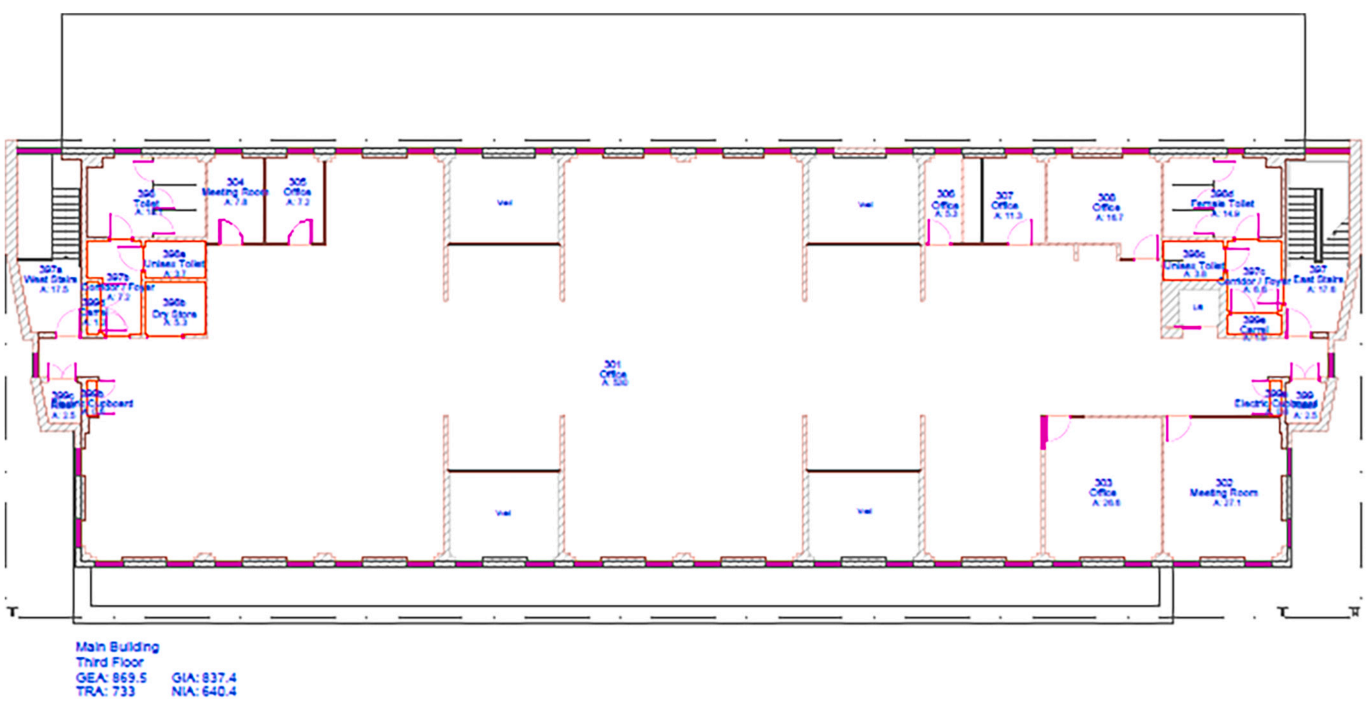

Fig. 4. North-facing offices studied on the third floor.

2.4. Overview of the data

This study is focused on open window behaviour (BMS automated and manual occupant behaviour), therefore, the overview does not include data related to closed windows. Fig. 5 shows the frequency of round-up outdoor temperature (°C) from November 2015 until December 2020. Outdoor temperatures between 19 and 21 °C have the highest frequency.

Fig. 6 shows the frequency of round-up indoor temperature, with the temperature of 24 °C having the highest frequency.

Fig. 7 shows the frequency of round-up open window area (%) for the open window data, with open window area (%) of 10–20% having the highest frequency. Classifications of open window area (%) in Fig. 7 does not include the first number in the category, for example, for category (0–10], 0 is not included. The number of closed windows due to its large frequency (more than 160,000) is not presented in Fig. 7.

Table 1
Distribution of the use of Algorithms 1–9 for different datasets by Office, Month and Year.

Floors. Offices	First Floor		Second Floor						Third Floor	
Month. Year	105	106	203	204	205	206	207	208	305	306
11.15	2	2	1	2	1	1	1	1	1	1
12.15	2	2	1	1	1	1	1	1	1	1
1.16	2	2	1	1	1	1	1	1	1	1
2.16	2	2	1	1	1	1	1	1	1	1
3.16	2	2	1	1	1	1	1	1	1	1
4.16	2	2	1	1	1	1	1	1	1	1
5.16	2	2	3	3	3	3	3	3	3	3
6.16	2	2	1	1	1	1	1	3	4	1
7.16	2	2	5	5	1	1	1	1	4	4
8.16	2	2	1	1	1	1	1	1	4	4
9.16	2	2	1	1	1	1	1	1	4	4
10.16	2	2	1	1	1	1	1	1	1	1
11.16	2	2	1	1	1	1	1	1	1	1
12.16	2	2	1	1	1	1	1	1	1	1
1.17	2	2	1	1	1	1	1	1	1	1
2.17	2	2	1	1	1	1	1	1	1	1
3.17	2	2	1	1	1	1	1	1	1	1
4.17	2	2	1	1	1	1	1	1	1	1
5.17	2	2	1	1	1	1	1	1	1	1
6.17	2	2	1	5	1	1	5	1	5	5
7.17	2	2	1	1	1	1	1	1	1	1
8.17	2	2	1	1	1	1	1	1	1	1
9.17	2	2	1	1	1	1	1	1	1	1
10.17	2	2	1	1	1	1	1	1	1	1
11.17	2	2	1	1	1	1	1	1	1	1
12.17	2	2	1	1	1	1	1	1	1	1
1.18	2	2	1	1	1	1	1	1	1	1
2.18	6	2	1	1	1	1	1	1	1	1
3.18	6	2	1	1	1	1	1	1	1	1
4.18	6	2	1	1	1	1	1	1	1	1
5.18	6	2	1	1	1	1	1	1	1	1
6.18	1	1	1	1	1	1	1	1	1	1
7.18	2	2	4	4	4	4	4	4	1	1
8.18	E	2	1	4	4	4	1	4	1	1
9.18	E	2	1	1	1	1	1	4	1	1
10.18	E	2	1	1	1	1	1	1	1	1
11.18	E	2	1	1	1	1	1	1	1	1
12.18	E	2	1	7	1	7	1	1	1	1
1.19	E	2	1	1	1	6	1	1	1	1
2.19	E	1	1	1	1	7	1	1	1	1
3.19	E	1	1	7	1	7	1	1	1	1
4.19	E	8	7	7	1	7	1	7	7	7
5.19	E	1	7	7	1	7	1	7	1	1
6.19	E	1	1	1	1	1	1	1	1	1
7.19	9	1	7	7	7	7	7	7	7	7
8.19	9	8	7	7	7	7	7	7	7	7
9.19	9	8	7	7	7	7	7	7	7	7
10.19	9	1	7	7	1	7	1	1	1	1
11.19	8	1	7	7	1	7	1	1	1	1
12.19	E	1	7	7	1	7	1	1	1	1
1.2	1	1	7	7	1	7	1	1	1	1
2.20	1	1	1	1	1	7	1	1	1	1
3.20	1	1	1	1	1	7	1	1	1	1
4.20	1	1	1	1	1	1	1	1	1	1
5.20	1	1	1	1	1	1	1	1	1	1
6.20	1	1	1	1	1	1	1	1	1	1
7.20	E	1	7	7	7	7	7	7	7	7
8.20	8	1	7	7	7	7	7	7	7	7
9.20	8	1	7	7	7	7	7	7	7	7
10.20	8	1	1	7	1	7	1	1	7	1
11.20	8	1	1	7	1	1	1	1	1	1
12.20	1	1	1	1	1	1	1	1	1	1

Each cell is considered one dataset.
1 = Algorithm 1, 2 = Algorithm 2, … and 9 = Algorithm 9.
*E = Error in Recording.

3. Results

3.1. BMS automated and occupants' manual window operations

The BMS has adopted nine algorithms for the automated operation of windows during the 5 years and two months included in this study. Among these nine algorithms, Algorithm 1 kept the windows closed regardless of the indoor temperature. The other eight automated window operation algorithms are presented in Fig. 8 and they differ significantly in their response to indoor temperature, with Algorithm 3 commencing window opening at an indoor temperature of 17 °C and Algorithm 5 starting at an indoor temperature of 26 °C. Algorithms are

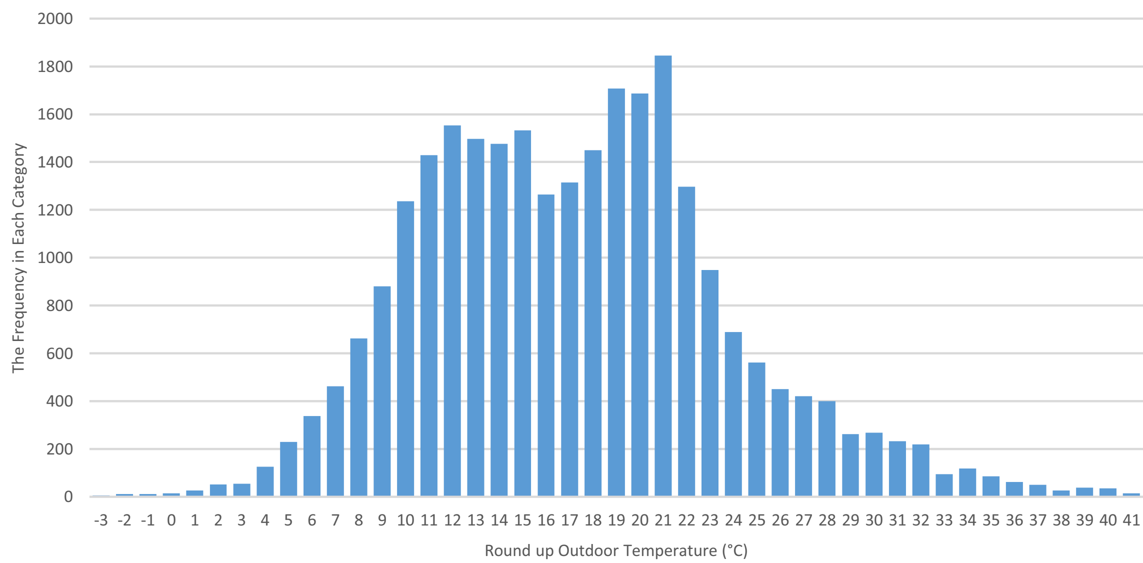

Fig. 5. The frequency of round-up outdoor temperature (°C).

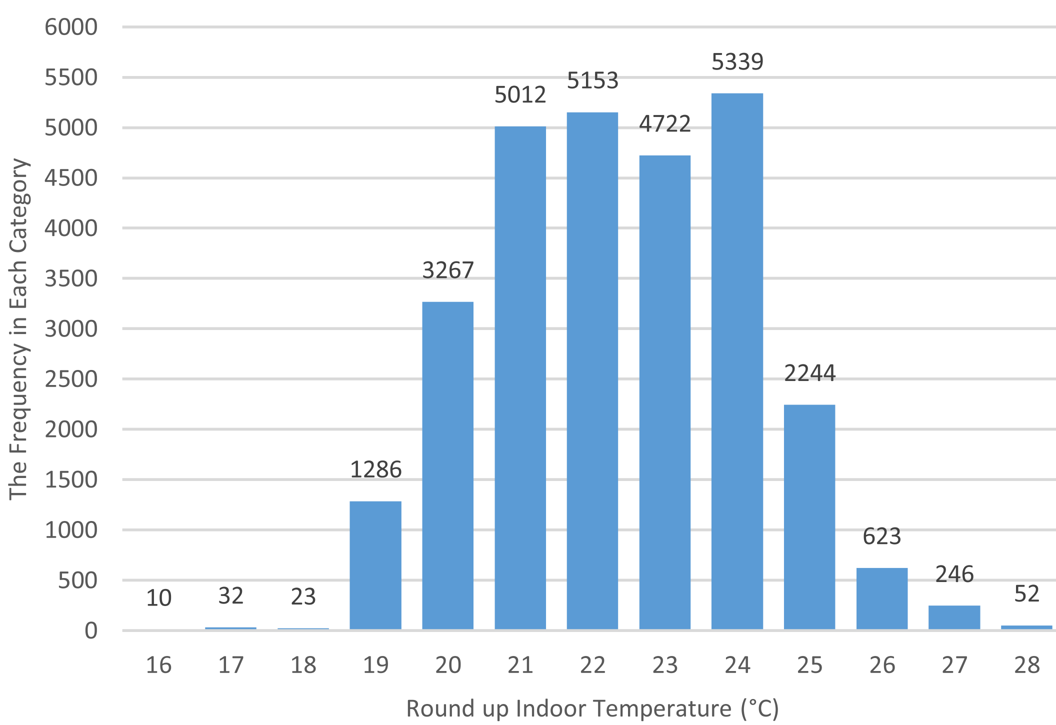

Fig. 6. The frequency of round-up indoor temperature (°C).

numbered based on the time (month and year) that they were first used by the BMS, with Algorithms 1 and 2 initially used in 2015, Algorithms 3, 4 and 5 first being used in 2016, Algorithm 6 initially used in 2018 and Algorithms 7, 8 and 9 first being used in 2019.

3.1.1. Algorithm 1

Algorithm 1 was the most frequent control mode algorithm that kept all the windows closed and was used in 409 datasets (Tables 1 and 2). This algorithm was primarily used on the second and third floors. However, the occupants chose to manually override Algorithm 1661 times to open the closed windows. Fig. 9 shows the relationship between occupants' choice of open window area (%) and indoor temperature, which suggests that 13% of their window opening behaviour can be explained by indoor temperature ($R^2 = 0.13$). As Algorithm 1 keeps all windows closed, it could be perceived as a manually controlled mode, where occupants decide when to open the windows based on their preferences. Occupants opened windows to 20% at 20 °C increasing to 70% at 28 °C. In other words, the behaviour gap between automated operation by the BMS and the occupants' preferred open window area is between 20 and 70%.

3.1.2. Algorithm 2

In Algorithm 2 (Fig. 10), the windows are kept closed below the temperature of 19 °C. The windows opened to 10% open window area at 19 °C and were fully opened to 100% at 24 °C or above. This algorithm was used in 67 datasets on the first floor (Tables 1 and 2). Although the

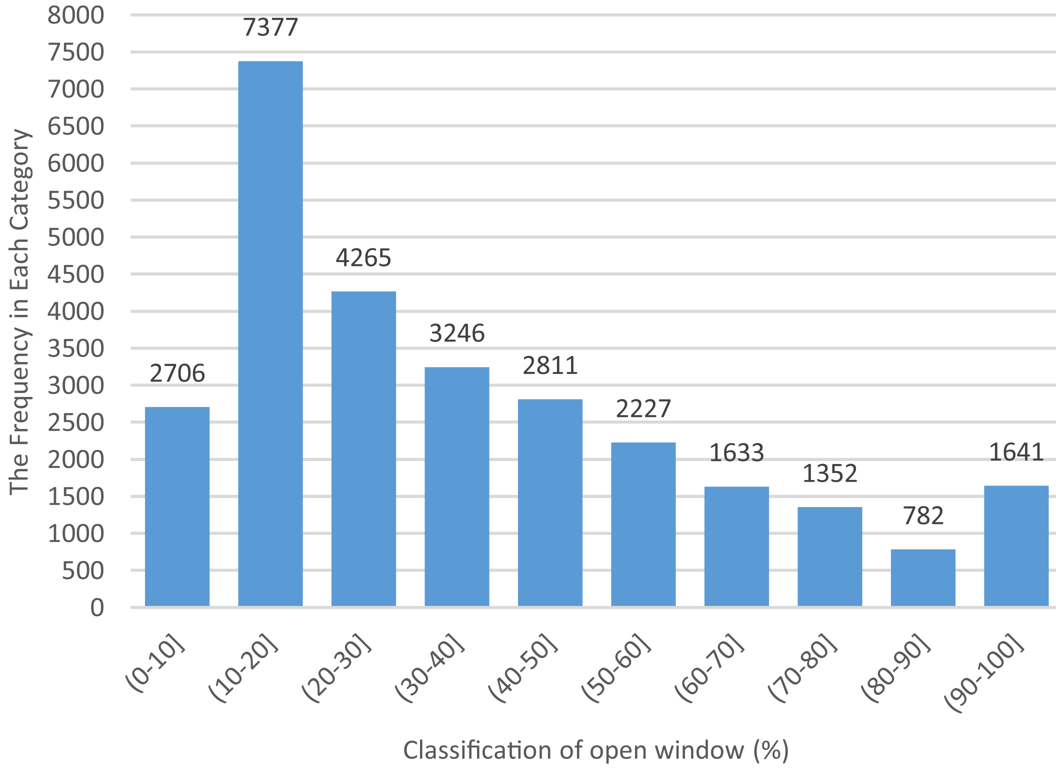

Fig. 7. The frequency of classifications of open window area (%).

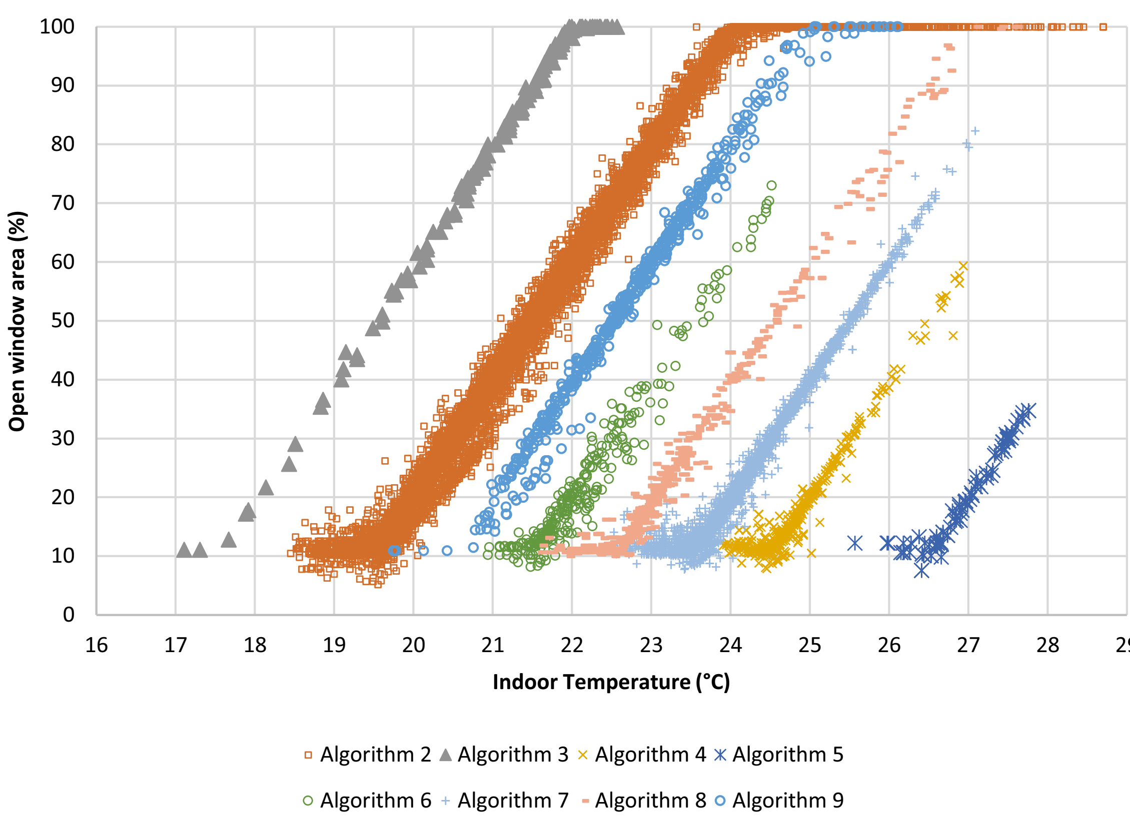

Fig. 8. Eight automated window operation algorithms.

Table 2
Number of datasets and occupants' adjustments for each algorithm.

Algorithms	Number of datasets	Number of occupants' adjustments
1	409	661
2	67	2709
3	9	9
4	18	51
5	6	21
6	5	81
7	81	1137
8	8	129
9	4	200
Error	13	–
Total	620	4998

regression line for automated control suggests that almost all operations are explained by the indoor temperature ($R^2 = 0.94$), the regression line for the manual operations suggests that 27% of the occupants' open window area (%) could be explained by the indoor temperature. It was evident that the behaviour gap for Algorithm 2 increased as internal temperature increased; the gap was less than 10% at 20 °C, however, it was more than 40% at 25 °C.

3.1.3. Algorithm 3

In Algorithm 3 (Fig. 11), the windows were closed below the temperature of 17 °C. The windows opened to 10% at 17 °C and 100% at 22 °C. This algorithm was used in nine datasets on the second and third floors in 2016 (Tables 1 and 2). Unlike the automated control ($R^2 = 0.99$), the regression line for the occupants' manual window operations suggested that 39% of the occupants' open window area could be explained by the indoor temperature ($R^2 = 0.39$). The behaviour gap for Algorithm 3 increased with increasing indoor temperature from 45 to 55%.

3.1.4. Algorithm 4

For Algorithm 4 (Fig. 12), the windows were shut below the internal temperature of 24 °C, opening to 10% at 24 °C and 60% at 27 °C. This algorithm was used in 18 datasets on the second and third floor in 2016 and 2018 (Tables 1 and 2). Unlike Algorithms 2 and 3, the regression line for the occupants' manual operation was above that of the automated operation with automated operations occurring at higher temperatures. The behaviour gap was 40–50% for Algorithm 4. The regression line for the occupants' manual operation suggests that 10% of the occupant's open window area can be explained by the indoor temperature ($R^2 = 0.10$).

3.1.5. Algorithm 5

For Algorithm 5 (Fig. 13), the windows were closed below 26 °C, with windows automatically opening to 10% at 26 °C and 40% at 28 °C. This algorithm was used in 6 datasets on the second and third floors in 2016 and 2017 (Tables 1 and 2). Like Algorithm 4, the regression line for the occupants' manual operation was above the automated operation. The behaviour gap was 70–80% for Algorithm 5 with the regression line indicating that 48% of the occupant's opening behaviour could be explained by the indoor temperature ($R^2 = 0.48$).

3.1.6. Algorithm 6

For Algorithm 6 (Fig. 14), the windows were kept closed below 21 °C and were automatically opened to 10% at 21 °C and opened to 70% at 24.5 °C. This algorithm was used in 5 datasets (Tables 1 and 2). The behaviour gap was less than 20% under Algorithm 6 with the occupants' manual operations undertaken under Algorithm 6 being the closest to the automated operations. The regression line for the occupants' manual operations suggests that 32% of the occupant's open window area could be explained by the indoor temperature ($R^2 = 0.32$).

3.1.7. Algorithm 7

For Algorithm 7 (Fig. 15), the windows were closed below 22.5 °C and automatically opened to 10% at 22.5 °C and 80% at 27 °C. This algorithm was used in 81 datasets (Tables 1 and 2) which was the most frequent algorithm after Algorithm 1 in which windows remain closed. The regression line suggests that 16% of the occupant's open window area can be explained by the indoor temperature ($R^2 = 0.16$). Similar to Algorithm 2, the behaviour gap increased with higher internal temperatures; the gap was around 10% at 24 °C, however, it is more than 35% at 26 °C.

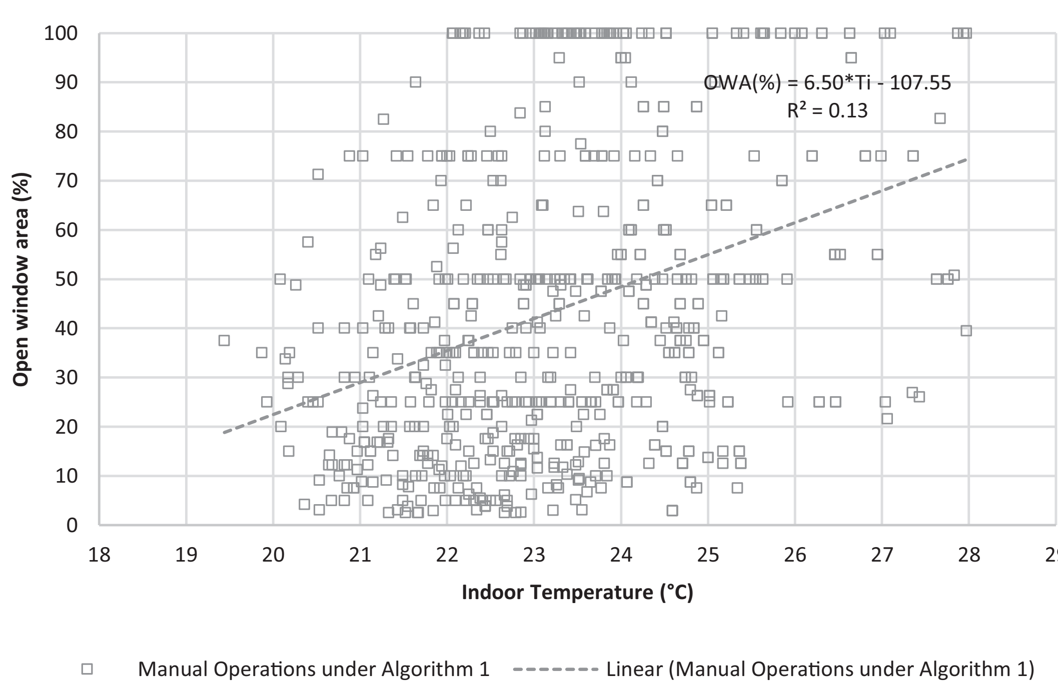

Fig. 9. Occupants' manual window operations in response to indoor temperature under Algorithm 1.

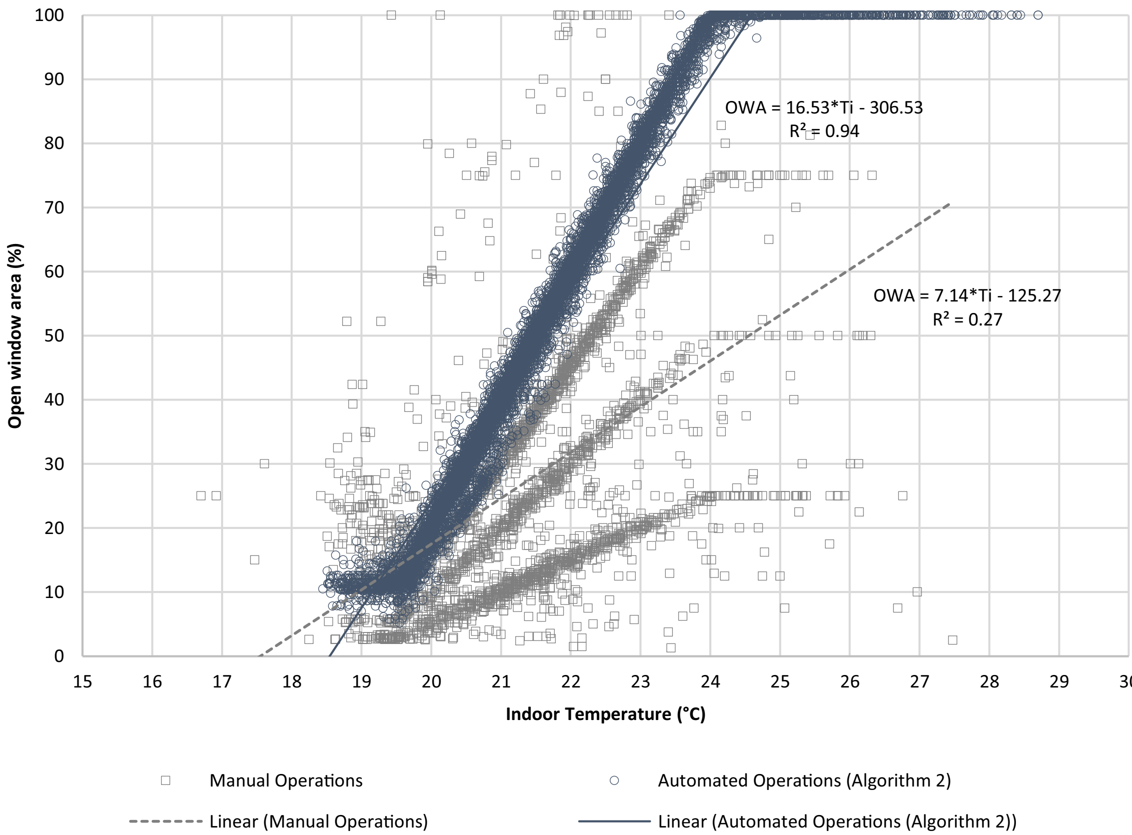

Fig. 10. Behaviour gap under Algorithm 2.

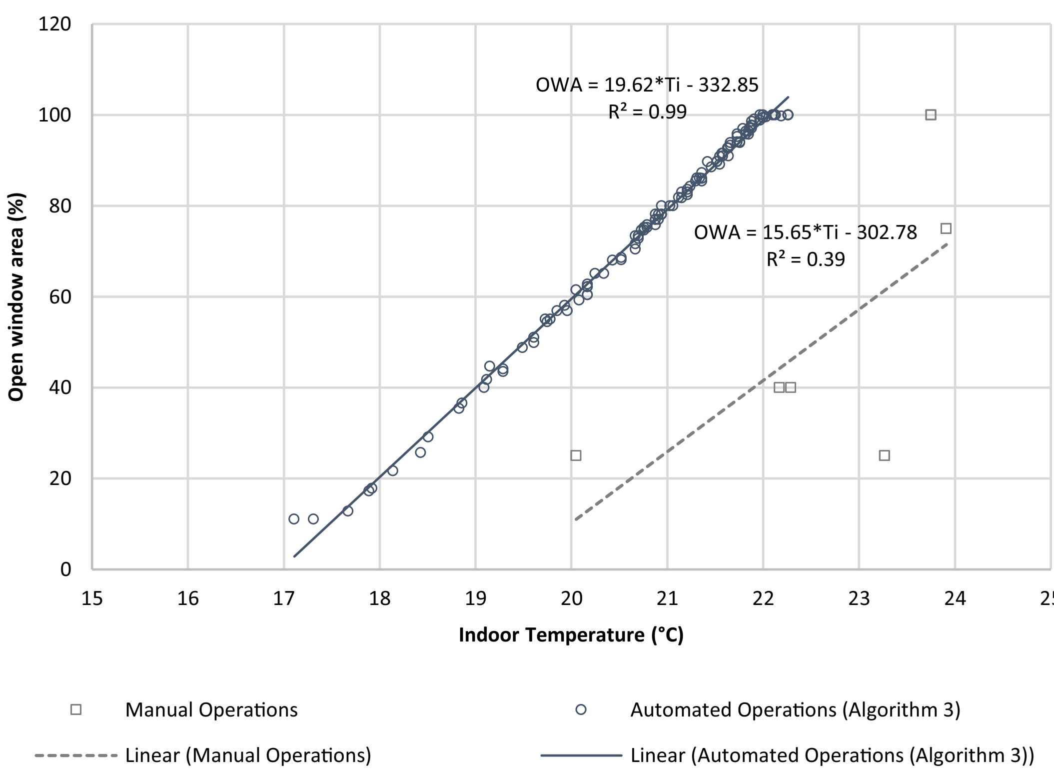

Fig. 11. Behaviour gap under Algorithm 3.

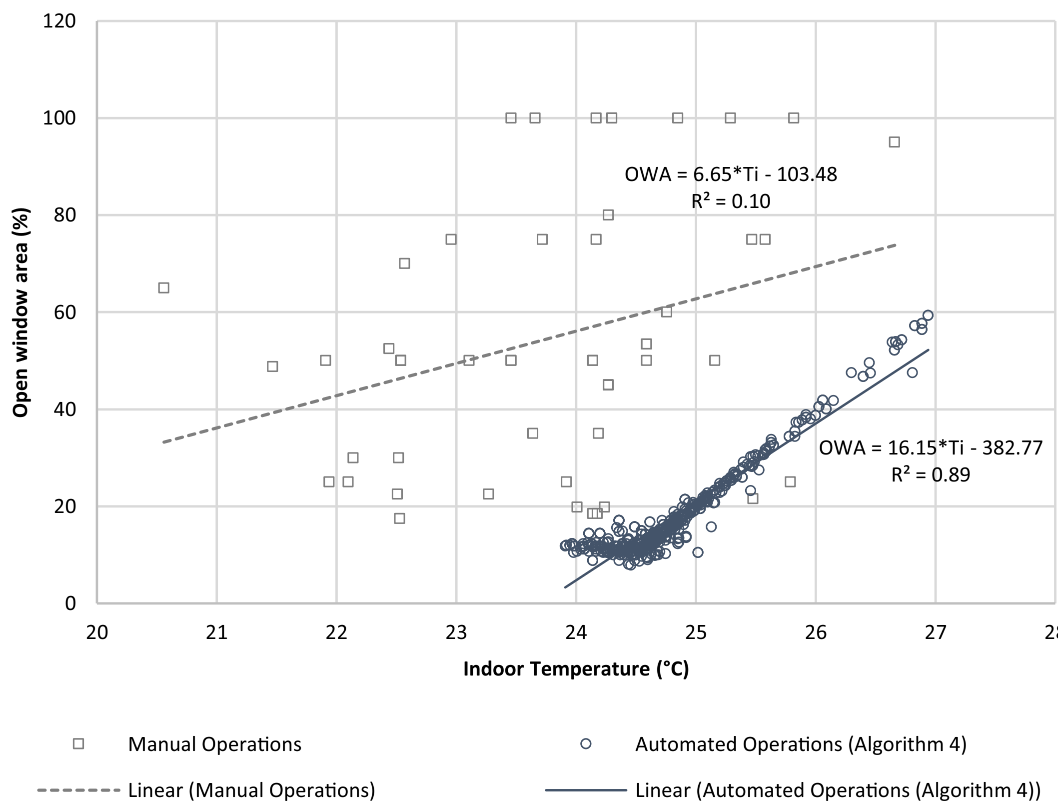

Fig. 12. Behaviour gap under Algorithm 4.

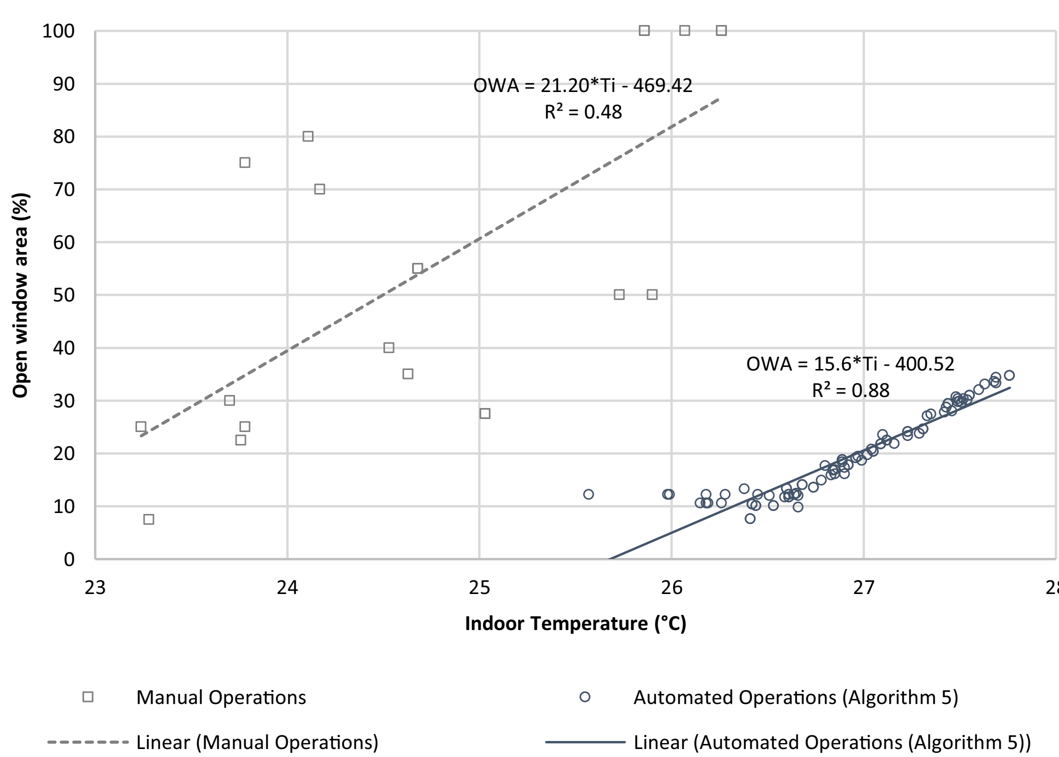

Fig. 13. Behaviour gap under Algorithm 5.

3.1.8. *Algorithm 8*

For Algorithm 8 (Fig. 16), the windows are closed at internal temperatures below 22 °C, opening to 10% at 22 °C and 100% at 27 °C. This algorithm was used in 8 datasets on the first floor in 2019 and 2020 (Tables 1 and 2). The occupants' manual operations suggested a desire for a lower open window area (%) in response to indoor temperature. Similar to Algorithms 2 and 7, the behaviour gap increased as indoor temperature increased; the gap was around 10% at 23 °C, rising to

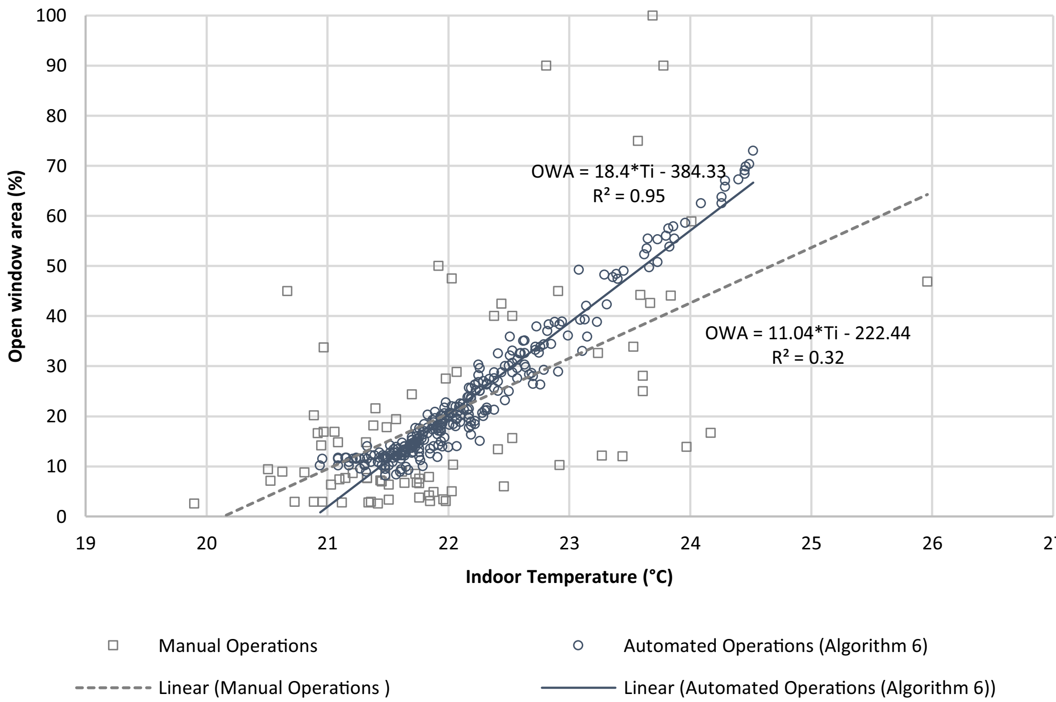

Fig. 14. Behaviour gap under Algorithm 6.

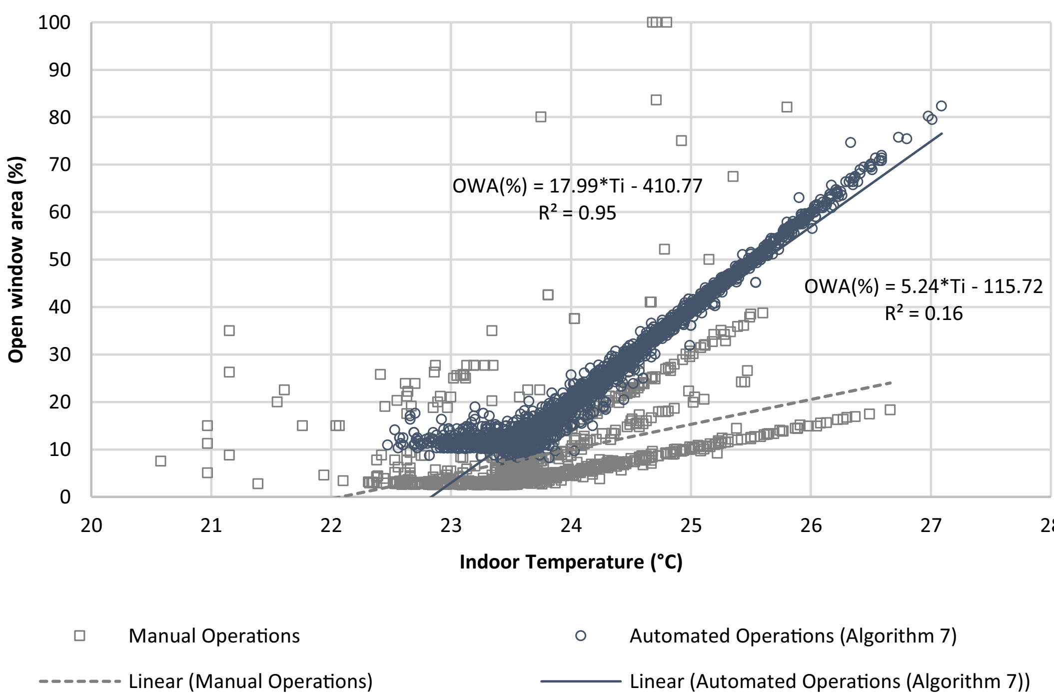

Fig. 15. Behaviour gap under Algorithm 7.

around 60% at 26 °C. The regression line for the occupants' manual operations suggests 17% of the open window area is explained by indoor temperature ($R^2 = 0.17$).

3.1.9. Algorithm 9

For Algorithm 9 (Fig. 17), the windows were kept closed below 20.5 °C and automatically opened to 10% at 20.5 °C and fully opened at 25 °C or above. This algorithm was used in 4 datasets in office 105 in 2019 (Tables 1 and 2). Like Algorithms 2, 7, 8 and 9, the behaviour gap increased with higher internal temperatures. For Algorithm 9, the behaviour gap was less than 10% at 21 °C, however, was around 60% at 25 °C. The regression line suggests 21% of the occupant's choice of open window area is explained by indoor temperature ($R^2 = 0.21$).

3.1.10. Summary of behaviour gaps and occupants' manual window operations

The most uncomfortable algorithm according to the occupants' manual data would be Algorithm 5 which had the largest behaviour gap

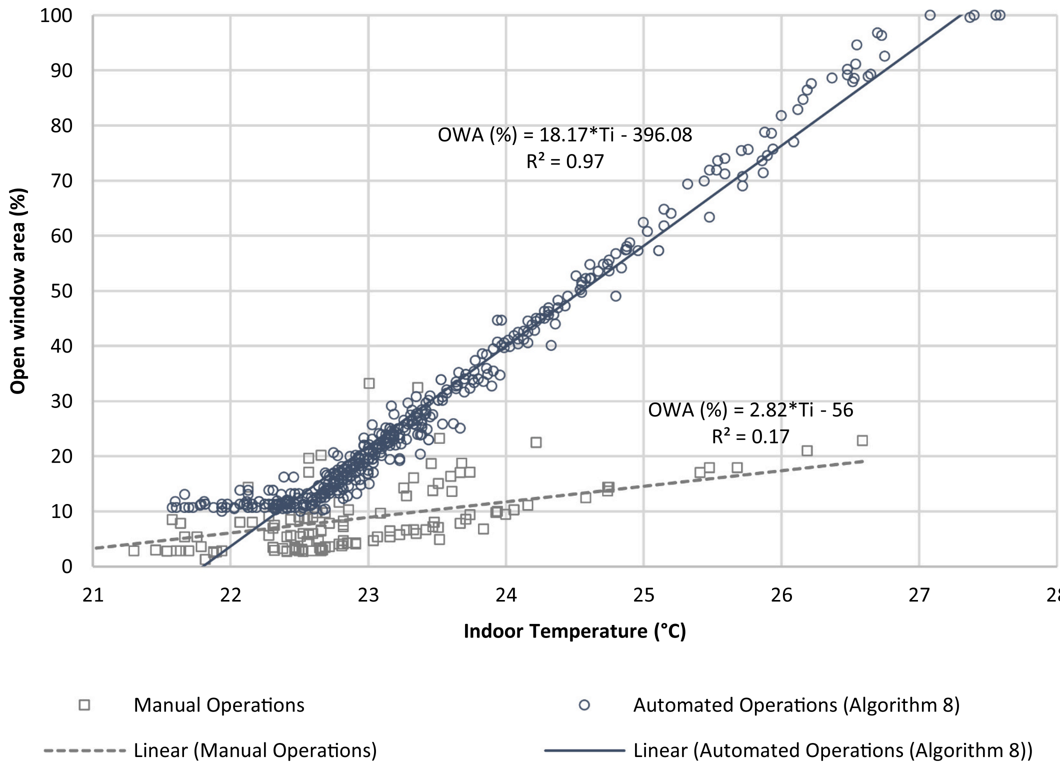

Fig. 16. Behaviour gap under Algorithm 8.

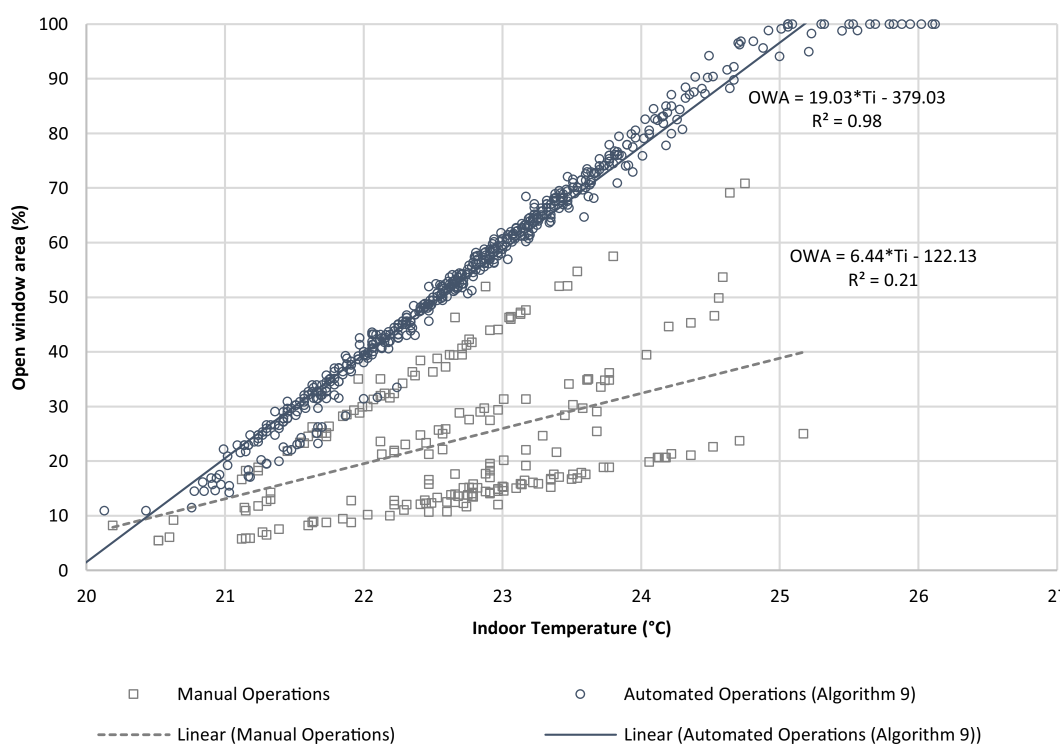

Fig. 17. Behaviour gap under Algorithm 9.

(70–80%). The most comfortable would be Algorithm 6 with the smallest behaviour gap (less than 20%). Furthermore, indoor temperature explains occupants' manual window opening from 10% (for Algorithm 4) to 48% (for Algorithm 5). Therefore, more than 50% of occupants' window opening behaviour cannot be explained by indoor temperature.

Table 1 shows the distribution of the algorithms for different datasets over different months of the year from 2015 to 2020 for different offices.

Table 2 shows the number of datasets for each algorithm according to Table 1 and the number of occupant's manual adjustments for different algorithms. It is evident that occupants have operated windows more often when the BMS operated under Algorithm 2. The next part of the paper is focused on occupants' manual operation of windows.

3.2. Occupants' manual window operations according to floor level and season

It is important to consider the potential impact of office differences (such as orientation and floor level) and seasonal changes on occupants' window operations, to help propose the most appropriate automated window operation algorithm based on occupants' preferences.

In this study, offices on the same floor level have the same orientation and approximately the same area (m^2) (± 0.3 m^2). Offices on the same floor were grouped to see if the floor level impacted the number of occupants' manual window operations. The number of datasets and occupants' window adjustments for different floors and seasons are presented in Table 3. The proportion between the number of datasets and occupants' window adjustments shows that occupants operate windows more significantly on the first floor compared to the second and third floors.

Table 4 shows the correlation between open window area (%), indoor temperature and outdoor temperature for different floors. Table 4 suggests that the relationship between open window area and indoor temperature is stronger than its relationship with outdoor temperature. The relationship was significant for the first and third floors (sig = 0.00), however, there was no relationship for the second floor (sig = 0.582).

To propose an algorithm based on occupants' preferences for heating and non-heating seasons, data for the second floor can be removed as open window area (%) did not show any relationship with indoor temperature according to Table 4 (Sig = 0.582). The correlations between indoor temperature and open window area (%) for the first and third floors during heating and non-heating seasons are presented in Table 5. There is only one dataset for the third floor during heating seasons (October 2020, Office 305, Table 1), therefore, no correlation is presented for it in Table 5.

Figs. 18 and 19 show the scatter plot of indoor temperature and open window area (%) for the first floor during heating and non-heating seasons. The regression lines show that there is not a significant difference between open area (%) in response to indoor temperature during heating and non-heating seasons. The maximum difference between open window area (%) for the same temperature during heating and non-heating seasons was 6%. As there is not a significant difference between open area during heating and non-heating seasons, data for these seasons would be considered altogether for proposing an algorithm for the first floor.

Figs. 20 and 21 show the scatter plot of indoor temperature and open window area (%) due to manual operations on the first and third floors, respectively. This data could be used to propose automated window operation algorithms based on occupants' preferences for the offices on the first and third floors.

Three differences can be highlighted by comparing the regression lines in Figs. 20 and 21.

1. Around 20% of the open window area (%) can be explained by indoor temperature on the first floor, however, this decreases to 5% on the third floor.
2. Open window area (%) in response to indoor temperature is 3–7% higher for the first floor compared to the third floor (Table 6).
3. Most importantly, window opening starts to occur at higher temperatures on the third floor. While occupants' window opening mostly starts at 18.5–19 °C on the first floor, the opening starts at 22 °C on the third floor (Table 6).

Figs. 20 and 21 and the last two columns in Table 6 can suggest control algorithms for the first and third floors based on occupants' response to indoor temperature. For the first floor, windows are

Table 3
The number of datasets and occupants' window adjustments for different floors and seasons.

Floors	Seasons	Number of Datasets	Number of occupants' window adjustments	Proportion (%)
First Floor	Heating	57	1862	32.7
	Non-heating	54	1245	23.1
Second Floor	Heating	24	495	20.6
	Non-heating	66	957	14.5
Third Floor	Heating	1	2	2.0
	Non-heating	25	435	17.4

Table 4
The correlation between open window area (%), indoor temperature and outdoor temperature for different floors.

Floor Plans	Spearman's Correlation between OWA (%) and ...	Indoor Temperature	Outdoor Temperature
First Floor	Correlation Coefficient	0.461**	0.162**
	Sig. (2-tailed)	0.000	0.000
Second Floor	Correlation Coefficient	0.014	0.047
	Sig. (2-tailed)	0.582	0.078
Third Floor	Correlation Coefficient	0.358**	0.158**
	Sig. (2-tailed)	0.000	0.001

Table 5
Correlation between indoor temperature and open window area (%) for the first and third floors during heating and non-heating seasons.

Floor Plans	Spearman's Correlation Coefficient between indoor temperature and OWA (%)		
First Floor	Heating	Correlation Coefficient	0.477**
		Sig. (2-tailed)	0.000
	Non-heating	Correlation Coefficient	0.340**
		Sig. (2-tailed)	0.000
Third Floor	Non-heating	Correlation Coefficient	0.262**
		Sig. (2-tailed)	0.000

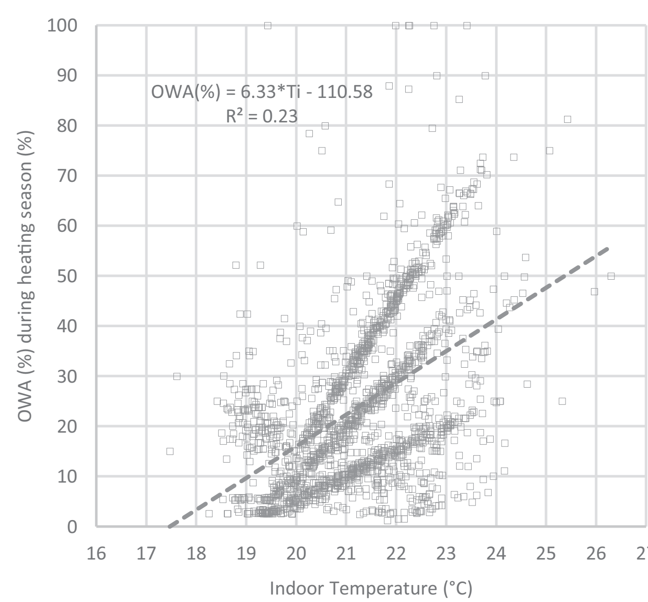

Fig. 18. Scatter plot of indoor temperature and OWA (%) for the first floor during heating seasons.

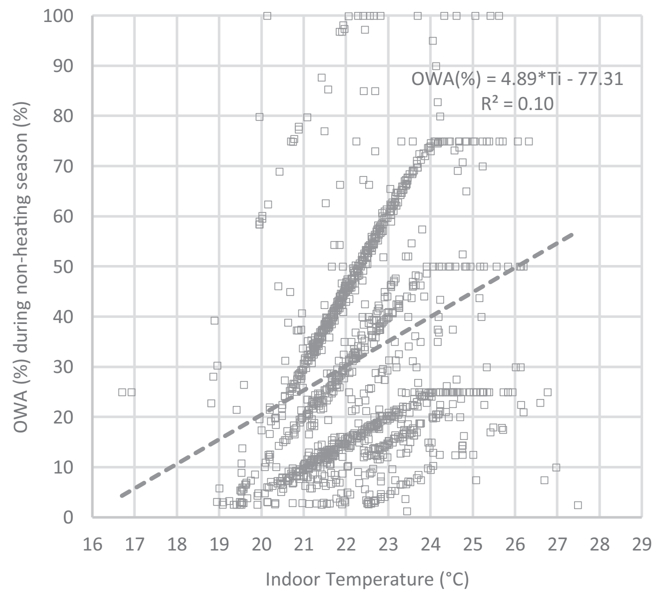

Fig. 19. Scatter plot of indoor temperature and OWA (%) during non-heating seasons.

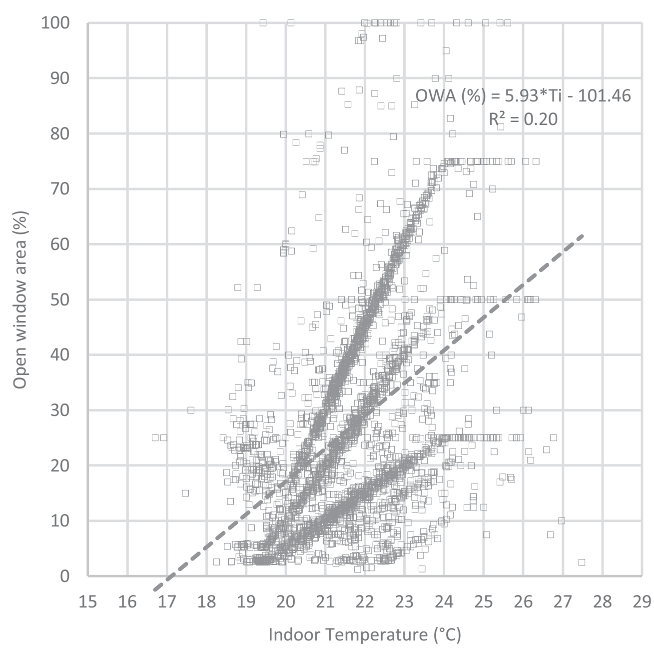

Fig. 20. Scatter plot of indoor temperature and OWA (%) for the first floor.

recommended to open at a lower temperature (around 10% at a temperature of 19 °C) and for the third floor, windows are recommended to open at a higher temperature (around 20% at a temperature of 22 °C). For both floors, OWA is recommended to increase 6–8% for a 1 °C increase in indoor temperature.

3.3. Comparison between BMS automated window operation algorithms and occupants' manual window operations

All the BMS algorithms identified in Sections 3.1.1–3.1.9 are presented in Table 6 and compared with the proposed algorithms based on the occupants' manual window operations on the first and third floors (Figs. 20 and 21). Comparing algorithms together shows that Algorithm 3 started to automatically open the windows at the lowest indoor

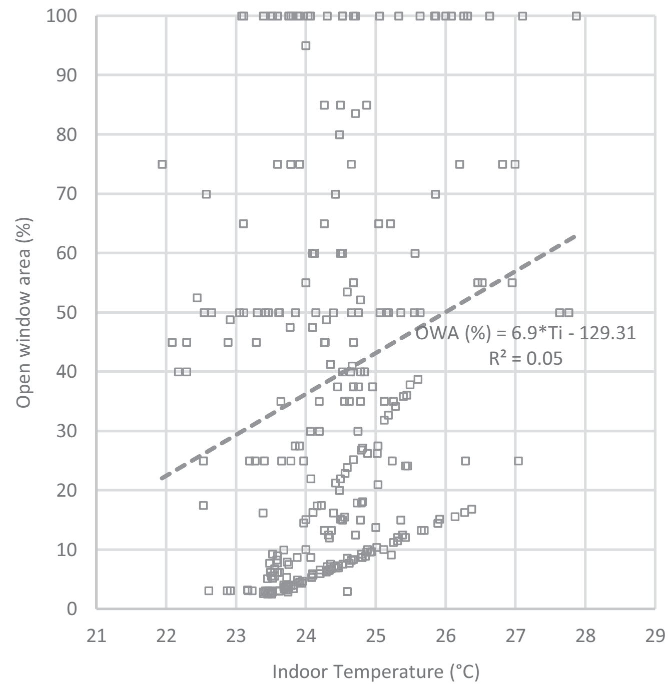

Fig. 21. Scatter plot of indoor temperature and OWA (%) for the third floor.

temperature (17 °C) and Algorithm 5 at the highest indoor temperature (26 °C).

The comparison between the BMS automated algorithms and occupants' manual window operations highlights three main differences in terms of the indoor temperatures that windows are opened, the maximum open window area (%) and the rate of changes in the open window area (%).

1) According to Table 1, Algorithms 2, 6, 8 and 9 are used for the first floor, however, occupants' window opening temperature on the first floor is lower than all these algorithms (Table 6). Also, Algorithms 3, 4, 5 and 7 are used for the third floor (Table 1), however, occupants' window opening temperature on the third floor is lower than three of these algorithms (4, 5 and 7).
2) Unlike several BMS automated window operation algorithms (2, 3, 8 and 9), the maximum open window area (%) based on the occupants' manual operations on the first and third floors never reaches 100% even at high indoor temperatures (27–28 °C).
3) Most importantly, Table 6 suggests that for a one-degree increase in temperature (1 °C), open window area (%) increases 20% for all BMS algorithms. However, occupants react to a one-degree increase in temperature by increasing the open window area by only 6–8%.

4. Discussion

4.1. Behaviour gap

The behaviour gap can be discussed from two main aspects; open window area (%) in response to indoor temperatures for each BMS automated window operation algorithm and the rate of changes in open window area (%).

The behaviour gap is different under different algorithms (70–80% for Algorithm 5 and less than 20% for Algorithm 6). For four algorithms (2, 7, 8 and 9), the behaviour gap increased as indoor temperature increased. This suggests that occupants' behaviour in response to indoor temperature (especially at higher temperatures) is very different from what is assumed by the automated window operations by the BMS. As can be seen in Figs. 10–17, the slope of the regression lines for the

Table 6
Comparison of all BMS automated window operation algorithms and proposed algorithms based on occupants manual window operations.

Indoor Temperature Range	The range of Open window area (%) for Each BMS automated window operation Algorithm								Algorithms of Open window area (%) based on Occupants' manual Operations (Figs. 20 and 21)	
	1	2	3	4	5	6	7	8	9	First Floor	Third Floor
<17	0	NI	NI	NI	NI	NI	NI	NI	NI	NI	NI
17–17.5	0	NI	10	NI	NI	NI	NI	NI	NI	NI	NI
17.5–18	0	NI	10–20	NI	NI	NI	NI	NI	NI	3–5	NI
18–18.5	0	NI	20–30	NI	NI	NI	NI	NI	NI	5–8	NI
18.5–19	0	10	30–40	NI	NI	NI	NI	NI	NI	8–11	NI
19–19.5	0	10	40–50	NI	NI	NI	NI	NI	NI	11–14	NI
19.5–20	0	10–20	50–60	NI	NI	NI	NI	NI	NI	14–17	NI
20–20.5	0	20–30	60–70	NI	NI	NI	NI	NI	NI	17–20	NI
20.5–21	0	30–40	70–80	NI	NI	NI	NI	NI	10–20	20–23	NI
21–21.5	0	40–50	80–90	NI	NI	10	NI	NI	20–30	23–26	NI
21.5–22	0	50–60	90–100	NI	NI	10–20	NI	NI	30–40	26–29	NI
22–22.5	0	60–70	100	NI	NI	20–30	NI	10	40–50	29–32	22–26
22.5–23	0	70–80	NI	NI	NI	30–40	10	10–20	50–60	32–35	26–30
23–23.5	0	80–90	NI	NI	NI	40–50	10	20–30	60–70	35–38	30–33
23.5–24	0	90–100	NI	NI	NI	50–60	10–20	30–40	70–80	38–41	33–36
24–24.5	0	100	NI	10	NI	60–70	20–30	40–50	80–90	41–44	36–40
24.5–25	0	100	NI	10–20	NI	NI	30–40	50–60	90–100	44–47	40–43
25–25.5	0	100	NI	20–30	NI	NI	40–50	60–70	100	47–50	43–47
25.5–26	0	100	NI	30–40	NI	NI	50–60	70–80	NI	50–53	47–50
26–26.5	0	100	NI	40–50	10	NI	60–70	80–90	NI	53–56	50–53
26.5–27	0	100	NI	50–60	10–20	NI	NI	90–100	NI	56–59	53–57
27–27.5	0	100	NI	NI	20–30	NI	NI	100	NI	NI	57–60
27.5–28	0	100	NI	NI	30–40	NI	NI	NI	NI	NI	60–64

NI = This Temperature not included in the BMS automated window operation algorithm or algorithms based on occupants' manual window operations.
Confidence Interval = ±5%.

occupants' manual window operations is always smaller than the slope for automated window operations by the BMS. The regression slope is a measure of sensitivity to temperature changes [39], therefore, occupants are not as sensitive to temperature changes as assumed by the BMS. Furthermore, the gradient of the regression lines for occupants' manual window operations is shallower (except Algorithm 5) than that for automated operations. The gradient of the regression equation for linear models is inversely proportional to the adaptability of the building occupants [40]. A shallow gradient shows that subjects adapt more effectively to room temperature [40,41] and accordingly their behaviours do not change quickly. Furthermore, occupants' choice of open window area in response to a one-degree increase in temperature was 6–8%, which is less than for automated window operations by the BMS (20%). This confirms that occupants are less sensitive and react slower to temperature changes and are more adaptable to the indoor environment.

4.2. Factors impacting occupants' manual window operations

The results show that occupants' manual window operations are related to environmental factors such as indoor temperature and outdoor temperature (Tables 4). Indoor and outdoor temperatures are found as paramount factors influencing window opening and closing in several previous studies [18,19,26,42]. However, indoor temperature is found to be a more important factor in this study.

Also, occupants operated windows more significantly on the first floor compared to the second and third floors. This can be explained by the south orientation of offices on the first floor and the lower outdoor wind speed for offices located on lower floors. Orientation impacts solar heat gains and temperature variations [21], therefore, occupants operate south-facing windows on the first floor more frequently to adjust to the variations. Several other studies have suggested wind speed as a driver for closing the windows because the sensation of drafts can cause discomfort [21,43]. Wind picks up speed when its travel is not obstructed, therefore, wind movement is more likely to become strong and cause heat loss and noise when the building is higher [21]. As wind becomes stronger at the higher levels, windows are less adjusted on the third floor compared to the first floor.

Furthermore, around 20% of the open window area (%) can be explained by indoor temperature on the first floor, however, this number decreases to 5% on the third floor. This confirms that the impact of other environmental variables (for example wind) on window operation is more significant on the third floor than on the first floor. Furthermore, indoor temperature explains less than 50% of occupants' manual window operations for different algorithms which suggests occupants' window opening could be impacted by other environmental variables such as CO_2. Overall, occupants' manual window operation is shown to be correlated with environmental variables (such as indoor and outdoor temperature and potentially CO_2 level and wind speed), and building-related factors such as floor level and orientation.

Results show that occupants' manual window operations for the same office are different under different algorithms. For example, Algorithm 2, 6, 8 and 9 are used for Office 105, however, the occupant's manual window operations are different under different algorithm (Figs. 10, 14, 16 and 17). This applies to all offices and it is mainly because when BMS automatically opens the windows at a certain indoor temperature, occupants react to it by increasing or decreasing the open window area (%) in comparison to the degree/ percentage that it was already open. Several studies have underlined the impact of the previous state of windows on occupants' window operations [22,43–45], however, this study highlights the impact of automated window operations by the BMS on occupants' manual window operations. This explains why there is not a significant difference between open window area (%) in response to indoor temperature during heating and non-heating seasons as several algorithms such as 2 and 7 are used for both heating and non-heating seasons and they impact occupants' window operations similarly.

Considering the impact of the BMS algorithms on occupants' manual window operations, it is very important to consider occupants' manual operations under Algorithm 1, which kept all windows closed regardless of the indoor temperature. Occupants' manual window operations for Algorithm 1 is separated into heating and non-heating seasons. As can be seen in Figs. 22 and 23, there is a significant difference between occupants' manual window operations and indoor temperature during heating and non-heating seasons. While open window area (%) increases with indoor temperature during the non-heating season, open window

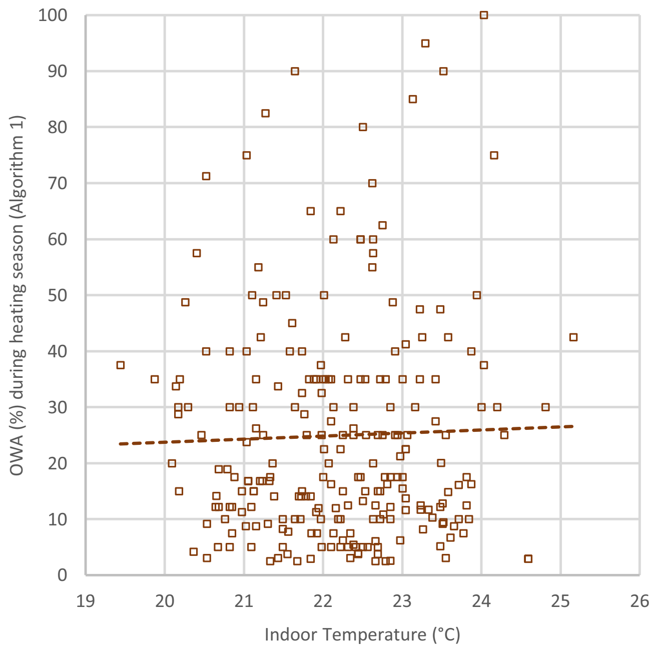

Fig. 22. Scatter plot of indoor temperature and OWA (%) during the heating season (Algorithm 1).

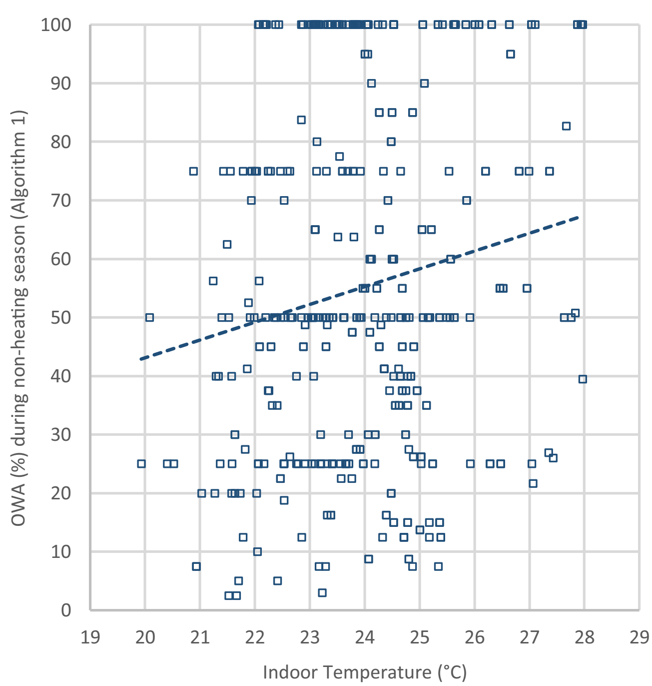

Fig. 23. Scatter plot of indoor temperature and OWA (%) during the non-heating season (Algorithm 1).

area (%) stays constant (23–28%) during the heating season. During the non-heating season, the open window area (%) increases from 40% to 70% while temperature changes from 20 to 28 °C. The impact of seasonal changes on occupants' manual window operations is highlighted in several other studies [23,46,47].

4.3. Window operations by the BMS

Automated window operations by the BMS can be discussed in terms of their current efficiency and future further improvement.

4.3.1. Effective aspects

One of the effective aspects of the BMS in this building is that it lets occupants override automated operations if they want to. This provides occupants with perceived control over the indoor environment which impacts their comfort and satisfaction level. The importance of perceived control on occupants' overall comfort is highlighted in several studies [5,14].

The results in Table 1 show an improvement in BMS automated window operations over time. Algorithms 2 and 3 were used in 2015–2018 but they were later replaced with Algorithms 7, 8 and 9 in 2019–2020 to reduce the behaviour gap between BMS automated window operations and occupants' manual window operations. In other words, the BMS tends to open windows less in response to indoor temperature during the last two years. Furthermore, there is a clear difference between algorithms used for the offices on the first floor (2, 6, 8 and 9) with south orientation and algorithms used for the second and third floors (3, 4, 5 and 7) with north orientation. Also, Algorithm 1 which keeps all windows closed is mostly used on the second and third floor. These suggest that the BMS has considered the impact of building-related differences such as orientation and floor level to some extent on automated window operation.

4.3.2. Recommendations for BMS automated window operation Algorithms

Based on the results and discussion, recommendations can be suggested to improve the automated window operations by BMSs.

- It is recommended to modify programmed algorithms outlined in the Building Operation and Maintenance Manual based on control algorithms suggested for first and third floors to reflect occupants' preferences and improve BMS operations. Windows are recommended to open at a lower temperature on the first floor compared to the third floor and OWA is recommended to increase 6–8% instead of 20% for a 1 °C increase in indoor temperature.

Occupants' manual window operations were found to be correlated with indoor temperature on the third floor, however, not correlated on the second floor. Window operations on the second floor might therefore be related to other environmental variables such as CO_2 level or Indoor Air Quality (IAQ). On the other hand, algorithms used for offices on the second and third floors (3, 4, 5 and 7) are the same while offices are located on different floors.

- The BMS in this study operates based on indoor temperature, which used to be an essential metric for occupancy thermal comfort and is still the most common variable used for controlling the operation of buildings. However, it is recommended that future BMSs consider other environmental variables such as CO_2 alongside indoor temperature to provide higher levels of IAQ. Several studies have shown that CO_2 concentrations determine occupants' perception of air freshness and stuffiness [48–51], therefore, CO_2 level and IAQ could be used as other stimuli for automated opening of windows. As suggested in the study by Klein et al. [13], with CO_2 sensors, it would also be possible to track when the building is partially occupied and adjust the window open area accordingly.

- BMSs need to consider building-related differences (floor level and orientation) and seasonal changes to propose the most effective algorithm for dataset automated window operations.

4.4. Future studies

The appearance of the Internet of Things (IoT) in the last decade has provided a wealth of data for the optimisation of BMSs based on personal comfort. The application of IoT will become the normal practice in the future development of smart buildings [52]. 'Smart/intelligent' buildings that have a wide range of distributed IoT sensors throughout buildings and provide data inputs to the BMS could provide better control over the indoor environment. Several studies have highlighted the role of IoT on energy efficiency in smart buildings [53–56], the control of electric appliances in smart environments [57] and commercial buildings' HVAC systems [58], however, their role in optimising and personalising window operation algorithms has not been investigated. The study by Jia, et al. [52] confirms that a mature adoption of IoT technologies in the building industry is not yet recognised.

Real-time IoT sensors can track dynamic variations in IEQ and trends in occupants' behaviours. Thus, by pairing real-time weather/occupant data with the BMS, window operation algorithms can be optimised to address occupants' preferences. The BMS would be able to continue updating its window operation algorithms based on occupants' changing their individual preferences or the occupant themselves changing (i.e. a new person in the office with different preferences).

IoT sensors could help maintain an optimal indoor environment quality not only based on indoor temperature but other variables. For example, CO_2 sensors can show when the room is occupied and the space requires further ventilation to maintain indoor air quality. Capitalising on motion data, the occupancy of different offices can be assessed. For example, occupancy might be assumed as 9 am-5 pm, however, for the one occupant starting at 8 am, the relevant adjustments can be made to their office. These highlight the importance of future studies focusing on feeding BMSs with real-time building data to modify automated window operation algorithms based on each individual and office.

With global warming, extreme weather events and rises in outdoor temperature are expected to occur more frequently and with higher intensity [59,60], therefore the relationship between window opening and outdoor temperature might change. For example, the study by Tahmasebi and Mahdavi [61] shows that in extreme summer conditions, the probability of opening windows decreases when outdoor temperature increases. Therefore, future studies are encouraged to consider how automated and manual window operation algorithms might change as a result of increased outdoor temperature due to global warming.

4.5. BMS system architecture

To reduce the behaviour gap and increase occupants' satisfaction with automated window operation algorithms, the study proposes a BMS system architecture (Fig. 24) based on the results of this study (Sections 4.2 and 4.3) and the recommendations for future studies (Section 4.4).

5. Conclusion

This paper aims to bridge the gap between automated window operations by the BMS and occupants' manual window operations and personalise automated window operation algorithms based on occupants' preferences. Data on BMS automated window operations and occupants' manual window operations were collected in a UK university building from November 2015 until December 2020. Ten single-occupant offices were selected and more than 28,000 data points on open windows were analysed.

In total, nine BMS automated window operation algorithms were identified in this study and data that did not fit into these nine algorithms was marked as occupants' manual operations. Based on occupants' manual window operation, personalised algorithms for the first and third floors are proposed.

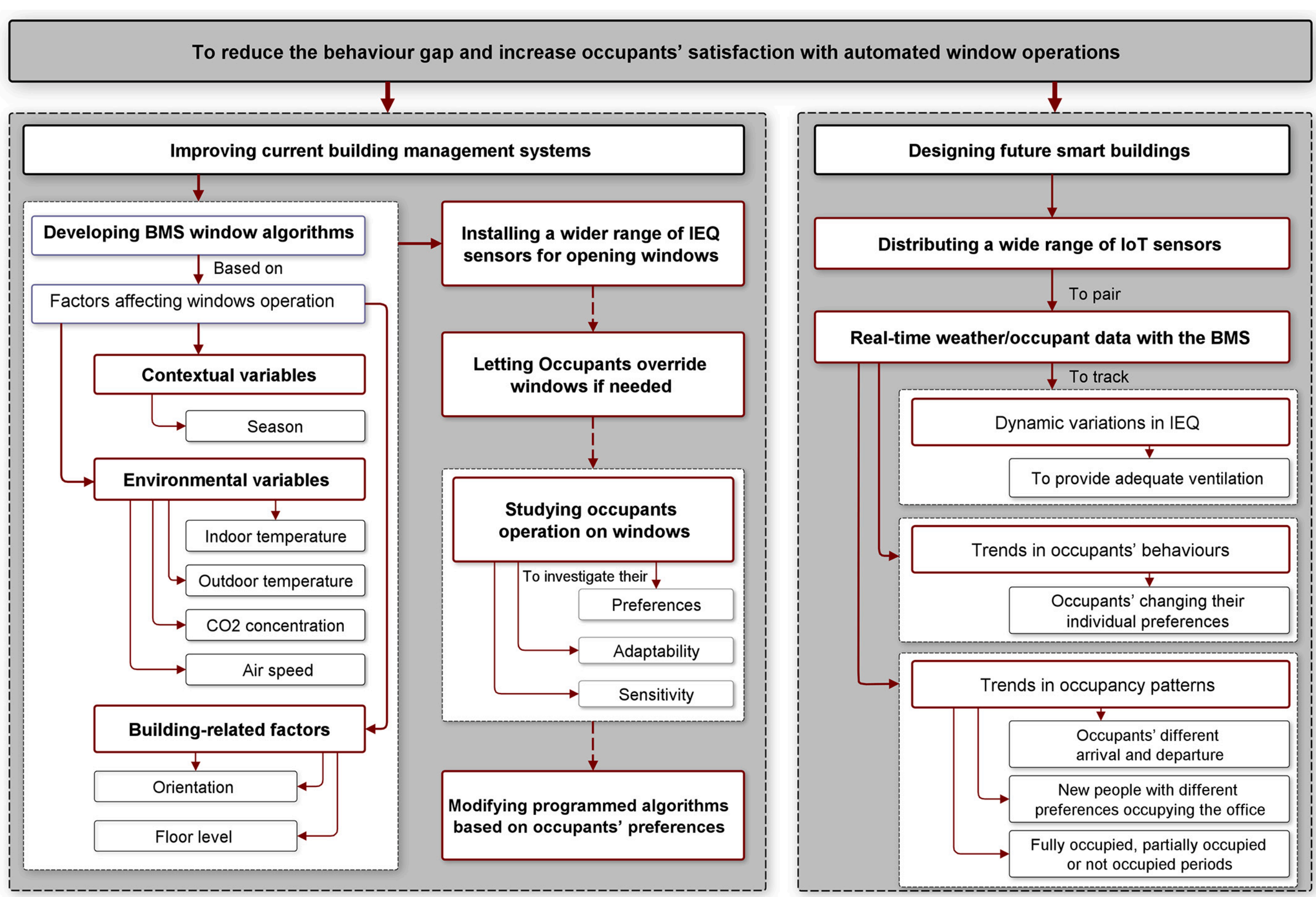

Fig. 24. Proposed BMS system architecture to reduce the behaviour gap and increase occupants' satisfaction.

Significant differences can be observed between automated window operations by the BMS and personalised algorithms. For example, for a one-degree increase in indoor temperature (1 °C), open window area (%) increases 20% for all the BMS algorithms. However, occupants react to a one-degree increase in temperature by increasing the open window area by only 6–8%. Furthermore, the window operation behaviour gap is different under different algorithms which suggests that the occupants' behaviour is very different from what is assumed by the automated operations by the BMS. Occupants are less sensitive and react slower to temperature changes and are more adaptable to the indoor environment.

One of the effective aspects of the BMS in the studied building is that it lets occupants override automated window operations. However, the BMS can be improved by considering building-related differences (floor level and orientation) and linking to other environmental variables such as CO_2 level to track occupancy, improve IEQ and increase ventilation during times of high occupancy. BMS could be revised based on occupants' manual window operations to consider occupants preferences.

The implication of this study is to reduce the behaviour gap, increase occupants' satisfaction with the automated window operation algorithms and alleviate perceived thermal discomfort.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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