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Window operation behaviour and indoor air quality during lockdown: A monitoring-based simulation-assisted study in London

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Abstract

The Covid-19 outbreak has resulted in new patterns of home occupancy, the implications of which for indoor air quality (IAQ) and energy use are not well-known. In this context, the present study investigates 8 flats in London to uncover if during a lockdown, (a) IAQ in the monitored flats deteriorated, (b) the patterns of window operation by occupants changed, and (c) more effective ventilation patterns could enhance IAQ without significant increases in heating energy demand. To this end, one-year's worth of monitored data on indoor and outdoor environment along with occupant use of windows has been used to analyse the impact of lockdown on IAQ and infer probabilistic models of window operation behaviour. Moreover, using on-site CO_2 data, monitored occupancy and operation of windows, the team has calibrated a thermal performance model of one of the flats to investigate the implications of alternative ventilation strategies. The results suggest that despite the extended occupancy during lockdown, occupants relied less on natural ventilation, which led to an increase of median CO_2 concentration by up to 300 ppm. However, simple natural ventilation patterns or use of mechanical ventilation with heat recovery proves to be very effective to maintain acceptable IAQ.

Practical application: This study provides evidence on the deterioration of indoor air quality resulting from homeworking during imposed lockdowns. It also tests and recommends specific ventilation strategies to maintain acceptable indoor air quality at home despite the extended occupancy hours.

Keywords

Indoor air quality (iaq), occupant behaviour, window operation, building performance simulation, Covid 19 lockdown

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Introduction

The Covid-19 lockdowns across the globe mean that people spend much more time in their homes, where concentrations of several pollutants, including human associated particulate matter (PM), volatile organic compounds (VOCs), carbon monoxide (CO), and carbon dioxide (CO_2) can be several times higher than outdoor air, depending upon outdoor levels, building envelope air tightness and indoor sources, indicating a significant potential for detrimental health impacts.[1–3]

There are two factors that make CO_2 concentrations relevant to ventilation and IAQ standards: their relation to indoor levels of bioeffluents and associated odours (an important factor in perceived air quality and occupant satisfaction), and their relation to ventilation rates per person. Specifically, concentrations of CO_2 in occupied indoor spaces are often higher than concentrations found outdoors because people produce and exhale CO_2. Declining air change rates per person increase the magnitude of this indoor–outdoor difference in CO_2 concentration allowing for peak indoor CO_2 concentrations above outdoor levels to be used as rough, albeit imperfect indicators for outdoor-air ventilation rate per occupant.[4]

Direct health effects of CO_2 on humans have been reported at concentrations much higher than those found in normal indoor settings. For example, Lipsett et al.[5] suggest that CO_2 concentrations higher than 20,000 ppm cause changes in breathing. According to epidemiologic and intervention studies, higher levels of CO_2 within the range found in normal indoor settings (i.e. up to 5000 ppm), are associated with perceptions of poor air quality, increased prevalence of acute health symptoms (e.g. headache, poorer work performance, and increased absenteeism (e.g.).[6–8] It is debated whether these associations exist because the higher indoor CO_2 concentrations are correlated with higher levels of other indoor-generated pollutants which are the causative agents of the adverse effects.[9,10] Yet, as suggested by Chatzidiakou et al.,[11] CO_2 concentration can be used as a useful proxy for occupant-related contaminants.

Moreover, other studies have underlined the direct negative impacts of CO_2 on occupants, in the range of concentrations typically found in buildings. For example, Kajtar et al.[12] reported that controlled human exposures to CO_2 between 2000 ppm and 5000 ppm, with ventilation rates unchanged, were positively associated with perception of wellbeing and performance on some reading tasks. More recently, a study by Xu et al.[13] found that sleep quality was negatively affected by increasing concentrations of CO_2 up to 3000 ppm. Moreover, Mishra et al.[14] showed that with lower CO_2 levels, the number of awakenings throughout the night tended to decrease. Another study found that seven of nine aspects of work performance were significantly and negatively impacted by a CO_2 level of 2500 ppm.[15] It should be noted, however, that two small studies (one with 10 healthy college-aged volunteers and another with 25 similarly aged participants) presented findings that did not demonstrate an increase in physical symptoms or in a decline in office related tasks from levels of CO_2 (without bioeffluents) of up to 5000 ppm.[16,17]

In another strand of research, to address the challenges of modelling energy demand and IAQ with building performance simulation tools, understanding and modelling of occupants' operation of windows has gained momentum in the last two decades.[14,18,19] Specifically, a number of studies have introduced probabilistic models of window operation, which could explain the occupants' interactions with windows based on statistically significant indoor and outdoor environmental parameters.[20,21]

Arguably, the above-mentioned studies have become especially relevant as the extraordinary circumstances associated with the Covid-19 outbreak has resulted in unprecedented patterns of household occupancy. If people continue to spend more time at home following the 2020 global pandemic, it will be more critical to ensure that IAQ in houses meets the recommended standards without excessive energy use. To this end, the present study benefits from one-year's worth of monitored data to reveal the impact of the lockdown on IAQ and patterns of opening and closing windows by occupants. Moreover, the study deploys calibrated building performance simulation to investigate the potential of different ventilation strategies. For the purpose of the present paper, the monitoring-based study explores the concentrations of CO_2, PM_{10} and $PM_{2.5}$ and the simulation-based tests focus on CO_2 concentration as a proxy for IAQ.

Method

Monitored data

During the first enforced lockdown in London in spring 2020, the authors took advantage of remote access to a set of monitoring devices in eight occupied flats in East London, which were part of an investigation since before the outbreak (see Table 1). The flats were located within three buildings at two sites in a dense urban area near major, highly trafficked, roadways. Mean annual $PM_{2.5}$ levels in these locations is greater than 20–22 μg/m^3 and mean nitrogen dioxide levels can exceed 50 μg/m^3 according to publicly available monitoring at the sites by Imperial College London. The study used a dataset collected from July 2019 to June 2020 including solar irradiance, wind speed and wind direction, indoor and outdoor air temperature, relative humidity, concentrations of

Table 1. The monitoring equipment and specifications.

Parameter	Sensor	Range	Resolution	Accuracy
Temperature	Thermistor	–30.0°C to 65.0°C	0.1°C	±0.2°C at 20°C ±0.4°C for –5°C to 40°C
Relative humidity	Capacative	0.0%–100.0%	0.10%	±2% (0% to 90% RH) ±4% (0% to 100% RH)
CO_2	Non-dispersive infra-red (E + E Electronik)	0–5000 ppm	1 ppm	<±50ppm, +3%
Particulate Matter PM_1, $PM_{2.5}$, PM_{10}	Optical Particle Counter (Alphasense OPC-N2)	0.35 to 40 μm 0.00 to 500.00 μg/m^3	0.01 μg/m^3	Agreement with reference instruments: RMSE 2–6 μg/m^3 and R^2 values of between 0.75–1.0.
Occupancy	PIR (HOBO UX90)	82° detection angle, 0–10 m detection range	–	Associated with positioning and set-up
Window Opening	Magnetic Reed Switch – state data logger (Eltek GS34 or Lascar USB-5)	0–1 (open/closed)	–	Associated with positioning and set-up

CO_2, PM_{10} and $PM_{2.5}$ along with occupancy state in bedrooms and living rooms (as detected by PIR sensors) and operation of windows (as captured by contact sensors) at 5-min intervals.

The data analysis examined the impact of the lockdown at two scales. The first fortnight of lockdown was compared with the fortnight prior, to quantify the immediate impact of the lockdown. Then, to get a broader understanding of the overall effect, a 3-month period mid-lockdown has been compared with a 3-month period in the previous year with similar weather conditions.

Window operation analysis and modelling

Prior to modelling the occupant interactions with windows, three metrics are used to capture the key characteristics of window operation by occupants in pre-lockdown and lockdown periods:

- Overall fraction of open state [−]
- Median open state duration [h]
- Opening rate in occupied intervals [h^{-1}]

Addressing the state of windows, the first metric gives an overall picture of window openings and the second metric captures the typical duration of window opening instances. The third metric, however, encapsulates the opening actions and normalises them based on the duration of time when the room is occupied.[22]

To develop models of occupant behaviour, the authors examined a range of measured indoor and outdoor parameters in terms of their potential to explain the monitored window operation (Table 2). Thereby, to minimise multicollinearity, a pairwise correlation check was conducted as an initial variable selection process. Subsequently, using the non-correlated independent variables, logistic regression models of window opening and closing actions for all monitored windows were developed. This process involved estimating the regression coefficient (β_1) and intercept (β_0) in equation (1), where P is the probability of opening or closing windows and x refers to different independent variables. P-value was used to judge the statistical significance of each variable at 0.05 significance level.

$$P = \frac{\exp(\beta_0 + \beta_1 x)}{1 + \exp(\beta_0 + \beta_1 x)} \qquad (1)$$

Table 2. The parameters examined to explain occupants' operation of windows.

Parameter	Symbol	Unit
Indoor air temperature	T_{in}	°C
Outdoor air temperature	T_{out}	
Indoor relative humidity	RH_{in}	%
Outdoor relative humidity	RH_{out}	
Indoor $PM_{2.5}$ level	$PM2.5_{in}$	μg/m^3
Indoor PM_{10} level	$PM10_{in}$	
Outdoor $PM_{2.5}$ level	$PM2.5_{out}$	
Outdoor PM_{10} level	$PM10_{out}$	
Indoor CO_2 concentration	$CO_{2,in}$	ppm
Indoor total volatile organic compound	$TVOC_{in}$	

The calibrated building model

The authors modelled one of the monitored flats (flat 4) in the building simulation tool EnergyPlus 9.4. This is a 50.8 m^2 one-bedroom flat with one-sided ventilation through two east-facing windows in the bedroom and living room (see Figure 1). The building envelope is highly insulated with U-Values of 0.18, 0.92, 0.13 and 0.12 [$W/m^2.k$] for the walls, windows, ceilings and floors respectively. The building is also equipped with mechanical ventilation with heat recovery (MVHR). In the simulation test case number 7 (see next section), MVHR operates

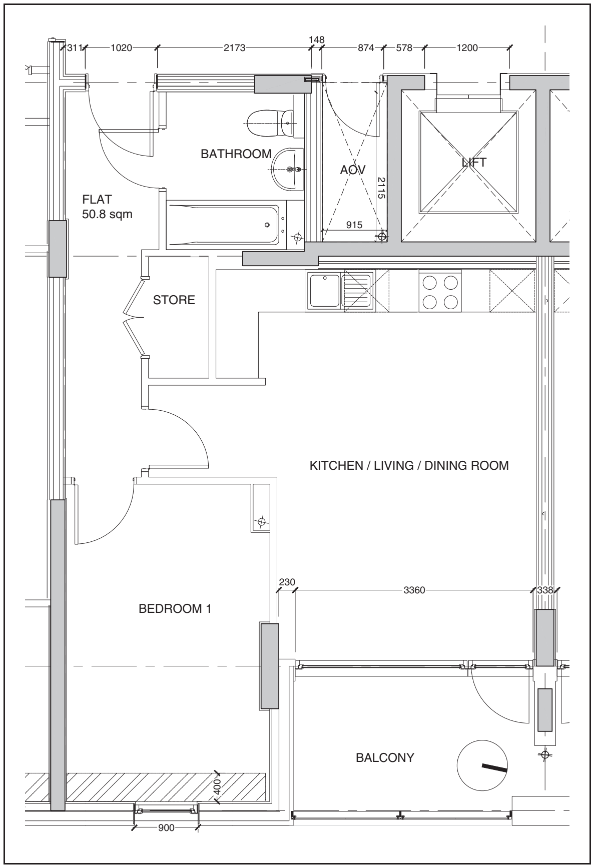

Figure 1. The floor plan of the modelled flat.

night and day in the heating season, providing 7 L/s.person outdoor air with a sensible heat recovery effectiveness of 0.75.

For the purpose of current study, the EnergyPlus building model is mainly indented to estimate indoor CO_2 concentrations under different ventilation scenarios. The model comprises of five thermal zones including bedroom, living room, store, corridor and bathroom. The airflow through the windows and across the zones is simulated using the multi-zone airflow network model of EnergyPlus. The walls, floor and ceiling, adjacent to the neighbouring flats, are assumed to be adiabatic.

Whereas previous efforts have predominantly relied on energy use data or monitored indoor temperatures to calibrate building thermal performance models (e.g.),[23,24] the present study uses monitored CO_2 concentrations directly to calibrate a building model tailored for indoor air quality assessments. More specifically, the following steps were carried out to prepare an initial thermal performance model of the flat for calibration:

- The calibration period was set to 15 July to 31 October 2019, during which time the MVHR system was not operating in the flat.
- Thermal properties of the building fabric elements and internal heat gain sources (other than occupants) were defined based on the best information available to the modellers.
- Monitored data on occupancy, window states and on-site outdoor CO_2 concentration from the calibration period were incorporated into the EnergyPlus model to reduce the number of unknown parameters in the underdetermined calibration problem.
- Hourly outdoor environmental data from the same period (including air temperature, air relative humidity, global, diffuse and direct irradiance along with wind speed and direction) were used to create real-year weather data for the purpose of model calibration.

To produce a more reliable building model, the key input parameters governing the air flow model and CO_2 generation were subjected to calibration. These were opening factors for the open state of windows and interior doors, air mass flow through closed openings, and occupants' activity level and CO_2 generation rate. As given in Table 3, for the initial model, the opening factors and air mass flow through closed openings were set based on the values in DesignBuilder software library for medium-tight openings and cracks. The initial activity level value was assumed based on the modeller's estimation, and the initial occupant carbon dioxide generation rate was set to EnergyPlus default value. Subsequently, an iterative process of minimizing the errors in the predicted CO_2 concentrations was conducted. Two error metrics, namely Mean Bias Error (MBE) and Root Mean Square Error (RMSE) captured the model predictive potential in the calibration period. The authors also largely benefitted from visualizations of model predictions in the process, so that the resulting calibrated model could better predict the patterns of CO_2 decay and build-up in different rooms.

Figure 2 illustrates a 2-day section of the estimated CO_2 concentrations in the living room obtained from the initial and calibrated building models compared with the monitored concentrations. Table 3 lists the calibration variables and their values in the initial and calibrated models and Table 4 gives the obtained error metrics for the estimated CO_2 concentrations by the initial and calibrated models in the bedroom and the living room.

Building simulation test cases

Using the calibrated thermal performance model, the authors examined a number of occupancy and ventilation scenarios to get a better picture of the impact of lockdown on IAQ and the mitigating potential of different ventilation strategies. To this end, two occupancy patterns were considered, namely a common home occupancy schedule before the outbreak (referred to

Table 3. Model inputs subjected to calibration.

Input parameters	Initial model	Calibrated model
Bedroom closed window air mass flow coefficient [kg/s.m]	0.0001	0.0005
Living room closed window air mass flow coefficient [kg/s.m]	0.0001	0.02
Bedroom window width factor for open state [–]	0.05	1
Living room window width factor for open state [–]	0.05	0.6
Corridor door width factor for open state [–]	0.025	1
Living room occupant activity level [W/person]	99	115
Occupant carbon dioxide generation rate [m^3/s-W]	3.82E–08	6.00E–08

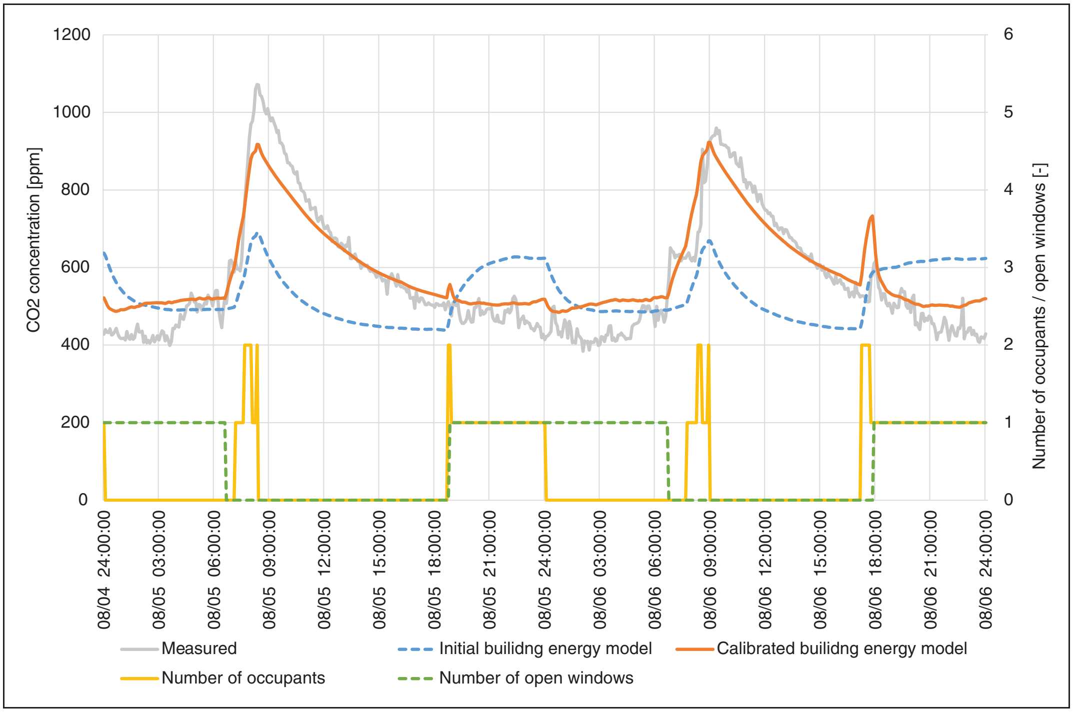

Figure 2. A two-day section of predicted living room CO_2 concentrations by the initial and calibrated building energy models in comparison with the measured values.

Table 4. Errors from the initial and calibrated models.

Error metrics	Initial model	Calibrated model
Bedroom MBE [ppm]	–245	60
Living room MBE [ppm]	–86	–42
Bedroom RMSE [ppm]	511	318
Living room RMSE [ppm]	270	189

as normal occupancy, in this case involving 2 occupants in the flat from 18:00 to 8:00 (+1) on weekdays and from 13:00 to 10:00 (+1) on weekends), and a constant full occupancy (referred to as lockdown occupancy). In terms of ventilation, a worst case scenario of no window operation, two effective patterns of natural ventilation in free-running and heating seasons, and use of MVHR system were studied. Thus, the simulation-based study involved the following simulation test cases:

1. Non-heating season, normal occupancy, no window operation or mechanical ventilation
2. Non-heating season, lockdown occupancy, no window operation or mechanical ventilation
3. Non-heating season, lockdown occupancy, bedroom window open for 1 hour in the morning, living room window open in waking hours
4. Heating season, normal occupancy, no window operation or mechanical ventilation
5. Heating season, lockdown occupancy, no window operation or mechanical ventilation
6. Heating season, lockdown occupancy, 1 to 2 windows open for 15 min every 4 waking hours

7. Heating season, lockdown occupancy, MVHR providing 7 L/s.person outdoor air.

Building performance metrics

To capture the occupants' exposure to relatively high levels of CO_2 concentration, the following building performance metrics were obtained for each simulation test:

- Peak CO_2 concentration in each room [ppm]
- Sleeping time CO_2 above 2500 [%]: This is the percentage of sleeping hours in the bedroom with CO_2 concentrations above 2500 ppm.
- Active time CO_2 above 2500 [%]: This is the percentage of occupied hours in the living room with CO_2 concentrations above 2500 ppm.

The threshold of 2500 ppm is set based on the aforementioned study by Satish et al.[15] on the impact of low to moderate CO_2 concentrations on human decision-making performance. While, for bedrooms, Mishra et al.,[14] as an example, suggest a CO_2 threshold close to 1150 ppm (beyond which sleep of healthy young adults may start getting compromised), for the purpose of the current study we utilized a single threshold for both rooms. Furthermore, to study the implications of different ventilation strategies for building energy use, the building heating energy load in kWh/m^2 was estimated for each heating season test case. A heating set-point of 22°C has been used when calculating the heating energy load.

Results and discussion

Monitored air quality and window operation

The monitored data – not surprisingly – revealed a substantial increase of occupancy levels in the studied flats especially on weekdays, as shown in Figure 3. Nonetheless, rather unexpectedly, occupants have relied less on natural ventilation (Figure 4). Table 5 suggests that during the lockdown period occupants have opened the windows for far shorter periods of time (a mean value of 2.9 versus 4.9 h) resulting in a lower overall fraction of open window state (21.7% versus 32.3%). While this can be partly explained by the slightly higher outdoor temperatures in the selected pre-lockdown period, the data from the fortnights around the lockdown (with very similar weather conditions) confirms the decreased level of night-time natural

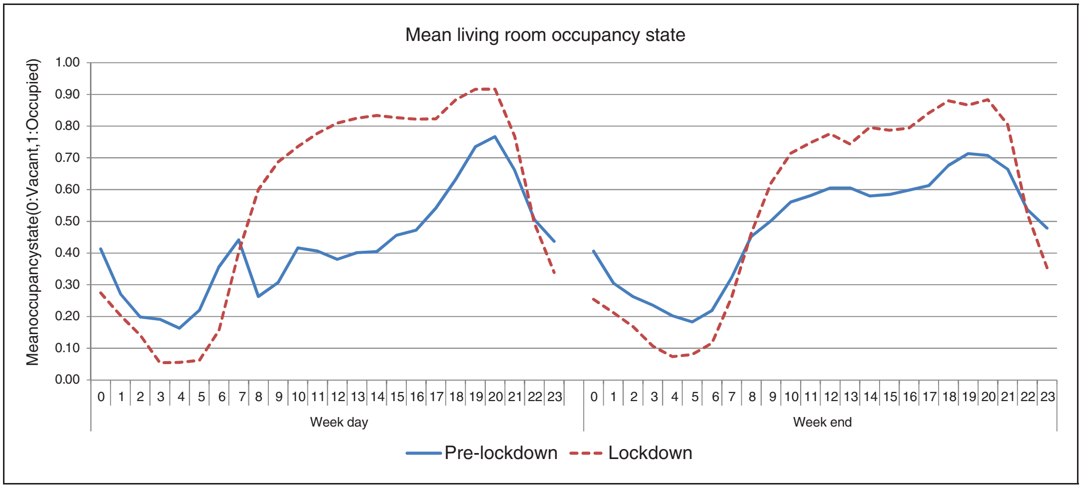

Figure 3. Mean living room occupancy state on weekdays and weekends of two 3-month periods prior to and during lockdown.

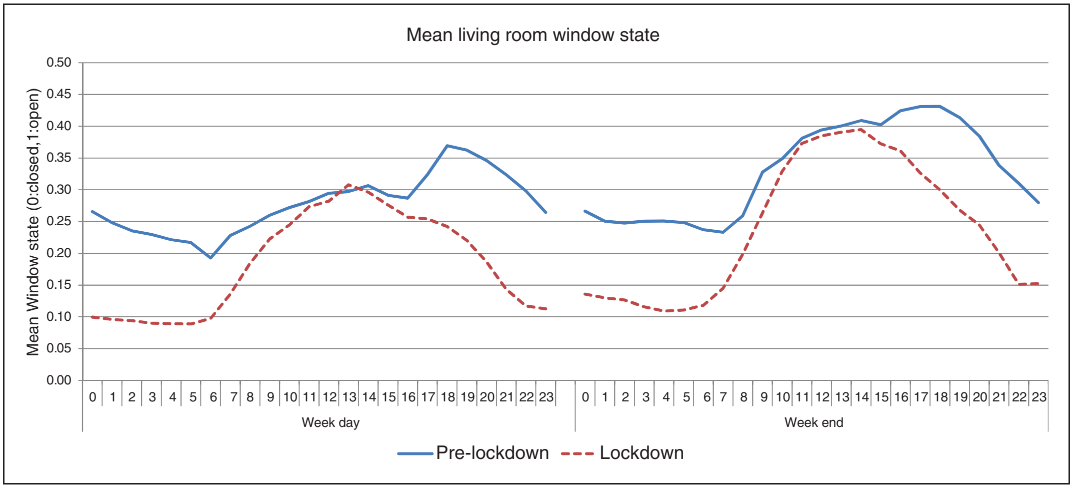

Figure 4. Mean living room window state on weekdays and weekends of two 3-month periods prior to and during lockdown.

Table 5. Window operation metrics.

Window number	Overall fraction of open state [%]		Median opening duration [h]		Opening action rate [h^{-1}]	
	Pre-lockdown	Lockdown	Pre-lockdown	Lockdown	Pre-lockdown	Lockdown
Flat 1 W1	12.9%	6.6%	11.8	8.6	0.007	0.008
Flat 1 W2	39.8%	24.2%	12.0	10.7	0.032	0.035
Flat 2 W1	53.6%	13.5%	0.1	0.1	0.061	0.105
Flat 2 W2	67.6%	39.5%	0.7	0.6	0.109	0.101
Flat 3 W1	21.1%	11.1%	2.3	0.8	0.062	0.082
Flat 3 W2	42.3%	16.0%	2.9	1.3	0.057	0.094
Flat 4 W	42.9%	42.3%	5.7	0.5	0.105	0.178
Flat 5 W1	3.2%	4.0%	0.5	0.3	0.057	0.075
Flat 5 W2	47.3%	11.9%	12.8	2.1	0.029	0.027
Flat 5 W3	54.1%	31.5%	12.3	3.0	0.037	0.043
Flat 6 W	11.3%	14.5%	2.3	1.8	0.042	0.078
Flat 7 W	19.7%	48.4%	3.2	3.2	0.141	0.090
Flat 8 W1	2.6%	1.0%	0.7	6.0	0.002	0.003
Flat 8 W2	34.3%	38.7%	1.7	1.6	0.117	0.179
Mean	32.3%	21.7%	4.9	2.9	0.061	0.078
Standard deviation	20.6%	15.6%	5.0	3.3	0.042	0.054

ventilation by occupants. The outcome of this higher occupancy and lower natural ventilation can be clearly seen in Figure 5, which shows that the living room median CO_2 concentration has increased up to 300 ppm at specific hours. Figure 6 also reveals that, despite the lower outdoor PM_{10} concentrations on weekdays during the lockdown, indoor PM_{10} concentrations rose

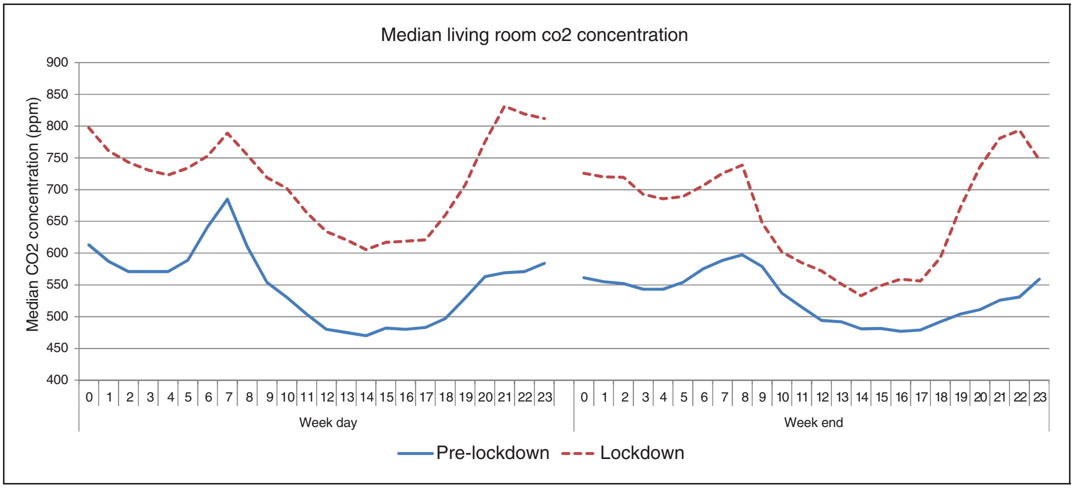

Figure 5. Median living room CO_2 concentration on weekdays and weekends of two 3-month periods prior to and during lockdown.

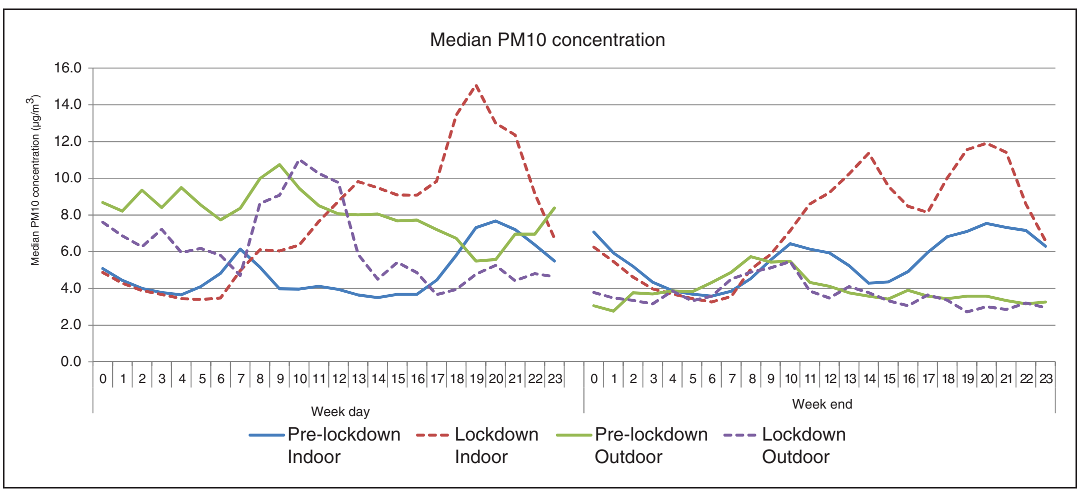

Figure 6. Median indoor and outdoor PM_{10} concentration on weekdays and weekends of two 3-month periods prior to and during lockdown.

on weekdays (as well as on weekends) in this period.

Window operation driving factors

Before identifying the main driving environmental factors behind the operation of windows by occupants, the correlation analysis detected highly correlated parameters of T_{in} and T_{out}, RH_{in} and RH_{out}, $PM_{2.5,in}$ and $PM_{10,in}$, and $PM_{2.5,out}$ and $PM_{10,out}$. Therefore, to minimise multicollinearity, the subsequent variable selection procedure (based on statistical significant test) was applied to a subset of measured parameters including T_{in}, RH_{in}, $CO_{2,in}$, $PM2.5_{out}$, $PM_{2.5in}$, and $TVOC_{in}$.

Table 6 summarizes the results of the statistical significance test. It gives the fraction of 14 monitored windows in 8 studied flats, where each independent variable is statistically significant to explain the opening and closing actions. These fractions clearly suggest that indoor temperature is the main driving factor for opening and closing windows in both pre-lockdown and lockdown periods. In contrast, the variables representing indoor air quality do not explain the operation of windows in the majority of flats. Given the rather similar significance fractions in the pre-lockdown and lockdown periods, one can argue that the thermal comfort-driven

Table 6. The statistical significance fraction of different environmental parameters to explain window opening and closing actions across the studied flats.

	Significance fraction for window opening		Significance fraction for window closing	
Independent variable	Pre-lockdown	Lockdown	Pre-lockdown	Lockdown
T_{in}	78.6%	78.6%	57.1%	71.4%
RH_{in}	21.4%	50.0%	28.6%	7.1%
$CO2_{in}$	42.9%	42.9%	35.7%	35.7%
$PM2.5_{in}$	35.7%	35.7%	35.7%	14.3%
$PM2.5_{out}$	21.4%	21.4%	28.6%	14.3%
$TVOC_{in}$	21.4%	21.4%	28.6%	14.3%

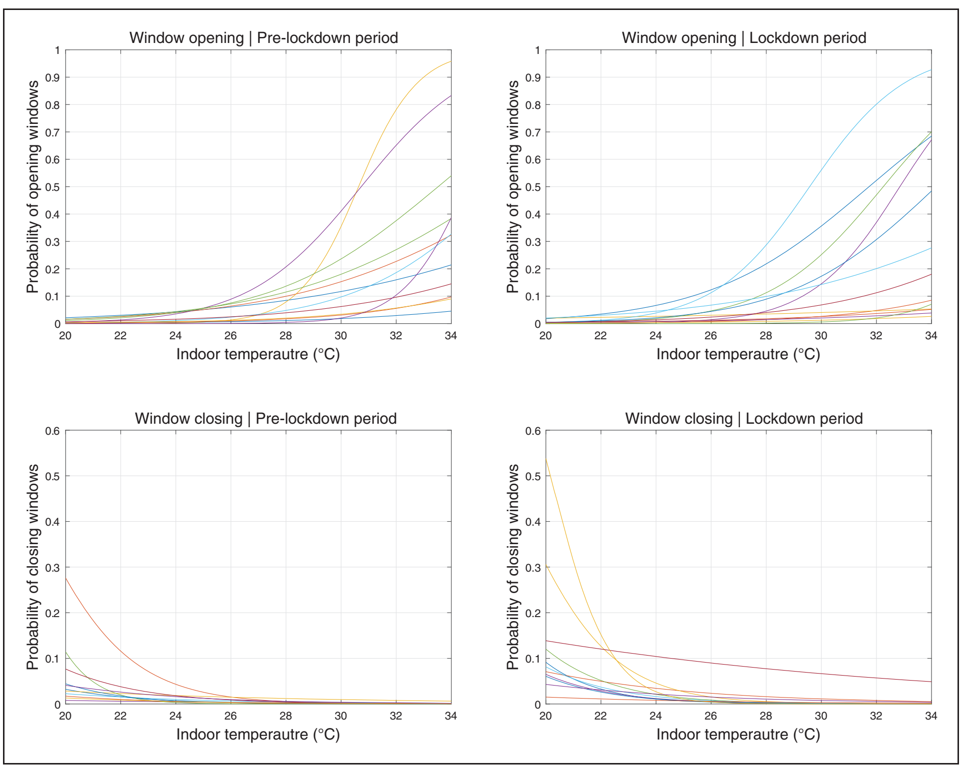

Figure 7. Window opening and closing models.

window operation behaviour of occupants has not changed during the lockdown.

Window operation models

Given the dominance of indoor temperature to explain window operation across the monitored flats, for the purpose of the current study, only indoor temperature-based univariate models of window opening and closing actions are presented in Figure 7. Moreover, the estimated coefficients of these models are given in Table 7. These models give the probability of opening and closing windows at different indoor temperatures in the studied flats. As can be seen clearly in Figure 7, the window opening and closing trend remains the same in the pre-lockdown and lockdown periods: People are more likely to open windows at higher indoor temperatures and close them at lower indoor temperatures. However, the resulting models suggest that at any given indoor temperature, it is slightly more likely for occupants to close the windows during the lockdown.

Table 7. The estimated coefficients for univariate window opening and closing models.

		Opening model				Closing model			
		Pre-lockdown		lockdown		Pre-lockdown		lockdown	
Window	Coef.	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Flat 1 W1	b0	–28.54	9.49E–26	–20.46	2.20E–07	0.39	9.19E–01	–3.14	4.07E–01
	b1	0.93	1.79E–17	0.62	4.93E–04	–0.24	1.26E–01	–0.08	6.61E–01
Flat 1 W2	b0	–4.94	8.64E–04	–7.01	1.43E–04	–2.08	5.14E–02	–1.94	2.84E–01
	b1	–0.02	7.96E–01	0.08	3.98E–01	–0.14	5.65E–03	–0.13	1.27E–01
Flat 2 W1	b0	–15.11	6.06E–17	–15.64	1.91E–26	16.47	4.47E–18	10.29	8.21E–16
	b1	0.49	1.28E–09	0.49	8.71E–15	–0.93	2.46E–27	–0.56	1.54E–24
Flat 2 W2	b0	–9.34	6.35E–16	–17.03	2.64E–35	0.34	7.37E–01	6.05	3.88E–05
	b1	0.26	2.76E–07	0.58	3.68E–22	–0.21	3.90E–06	–0.44	9.37E–12
Flat 3 W1	b0	–13.53	3.76E–33	–10.89	1.01E–16	5.00	6.47E–04	7.26	2.83E–06
	b1	0.38	8.39E–16	0.28	1.46E–06	–0.37	1.18E–09	–0.46	1.74E–11
Flat 3 W2	b0	–9.79	1.79E–16	–12.85	6.17E–24	6.44	2.77E–06	5.95	9.64E–05
	b1	0.24	5.30E–06	0.38	1.04E–11	–0.48	4.33E–15	–0.42	6.58E–10
Flat 4 W	b0	–7.44	1.25E–16	–10.85	2.47E–28	4.13	1.44E–04	8.67	1.53E–20
	b1	0.18	5.06E–06	0.34	5.53E–14	–0.38	1.83E–14	–0.55	1.20E–36
Flat 5 W1	b0	–11.09	7.25E–17	–9.14	5.17E–16	–1.74	1.28E–01	–0.19	8.05E–01
	b1	0.24	4.54E–06	0.18	1.72E–04	–0.04	3.68E–01	–0.08	1.68E–02
Flat 5 W2	b0	–12.51	1.29E–09	–10.29	9.54E–08	1.91	1.52E–01	6.10	2.33E–04
	b1	0.30	3.13E–04	0.20	2.03E–02	–0.30	2.27E–07	–0.44	2.67E–09
Flat 5 W3	b0	–11.08	8.83E–10	–8.85	5.08E–09	0.32	8.00E–01	–0.94	3.74E–01
	b1	0.26	4.90E–04	0.17	1.36E–02	–0.23	1.71E–05	–0.16	7.18E–04
Flat 6 W	b0	–8.31	3.55E–07	–12.89	2.93E–32	9.72	1.89E–04	1.26	2.54E–01
	b1	0.11	6.67E–02	0.31	1.08E–14	–0.53	1.79E–07	–0.19	1.72E–05
Flat 7 W	b0	–9.02	1.98E–68	–5.37	2.39E–46	–1.34	1.90E–02	–3.98	1.80E–13
	b1	0.24	4.24E–32	0.07	3.80E–08	–0.11	1.06E–05	–0.03	2.56E–01
Flat 8 W1	b0	–29.33	1.79E–03	–24.33	1.12E–03	16.77	3.47E–01	18.88	4.15E–02
	b1	0.85	1.73E–02	0.64	2.26E–02	–0.83	2.41E–01	–0.94	1.61E–02
Flat 8 W2	b0	–11.19	1.72E–39	–8.04	1.94E–28	1.69	1.88E–02	0.43	5.44E–01
	b1	0.33	1.32E–18	0.21	1.43E–11	–0.24	1.67E–13	–0.18	1.07E–08

Simulation-based investigations

Firstly, considering the worst-case scenarios, the simulation results suggest that the extended occupancy hours during a lockdown can significantly increase occupants' exposure to CO_2 (see Table 8, tests number 1, 2, 4 and 5). For example, during a lockdown in the heating season, occupants could face CO_2 concentrations of above 2500 ppm for almost 90% of the time that they spend in the living room, compared to only 33% with a normal occupancy pattern. As illustrated in Figures 8 and 9, the impact of lockdown occupancy on CO_2 levels can be seen clearly in both the living room and bedroom, even though the bedroom occupancy patterns are assumed to be identical in the normal and lockdown scenarios.

Secondly, as can be seen in Table 8 and Figure 10, the selected natural ventilation strategy for a lockdown during a non-heating season (test number 3) seems to be very effective to reduce CO_2. In the living room, the CO_2 concentrations never exceed the 2500 ppm threshold. In the bedroom, this happens for less than 2 percent of occupied time, even though the windows in both the bedroom and living room are assumed to be closed during the sleeping time.

Thirdly, although the natural ventilation pattern suggested for the heating season relies on much shorter window openings (test number 6), it manages to noticeably reduce the CO_2 levels (see Table 8 and Figure 11). That is, the living room CO_2 concentrations never reach the threshold of 2500 ppm and the bedroom CO_2 levels exceed this level for only 29% of sleeping hours. However, unsurprisingly, while this window operation during the heating season improves IAQ considerably, there is also an adverse effect on heating demand for this highly-insulated flat (a heating load of 6.55 kWh/m^2 for months of January and February compared to that of 0.95 kWh/m^2 when windows remained closed in these months). Needless to say, this challenging trade-off between IAQ and heating energy demand, is one of the key arguments for greater

Table 8. The simulation tests and the obtained IAQ and thermal performance metrics.

Test no.	Run period	Occupancy pattern	Window opening pattern	MVHR [L/s.pers]	Bedroom peak CO_2 conc. [ppm]	Living room peak CO_2 conc. [ppm]	Sleeping time above 2500 ppm [%]	Active time above 2500 ppm [%]	Heating Load [kWh/m^2]
1	Apr–May	Normal	No window opening	–	4942	4272	60.5	20.0	–
2		Lockdown	No window opening	–	5195	5038	78.3	65.1	–
3			Bedroom win. open 1 hour in morning Living room win. open in waking ours	–	2715	1478	1.6	0.0	–
4	Jan–Feb	Normal	No window opening	–	4540	3552	64.6	32.7	1.96
5		Lockdown	No window opening	–	5236	4643	86.4	89.9	0.95
6			1 to 2 windows open for 15 minutes every 4 waking hours	–	3090	2024	28.8	0.0	6.55
7			No window opening	7.0	1250	1326	0.0	0.0	3.79

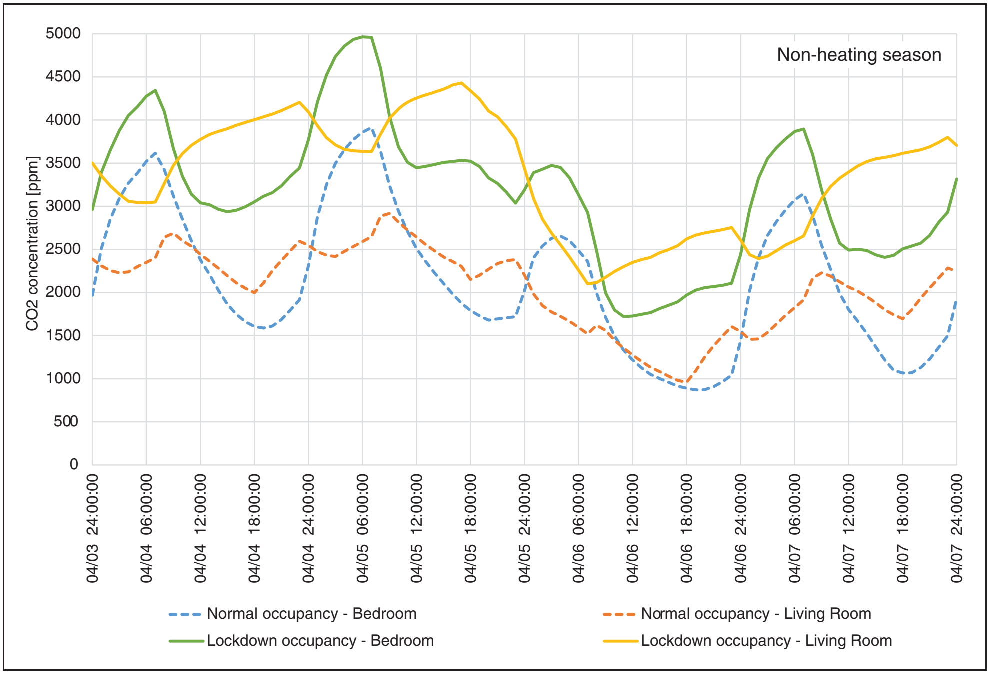

Figure 8. A 4-day section of simulation tests 1 & 2 – Worst-case CO_2 concentration in non-heating season without window operation and mechanical ventilation for normal and lockdown occupancy patterns.

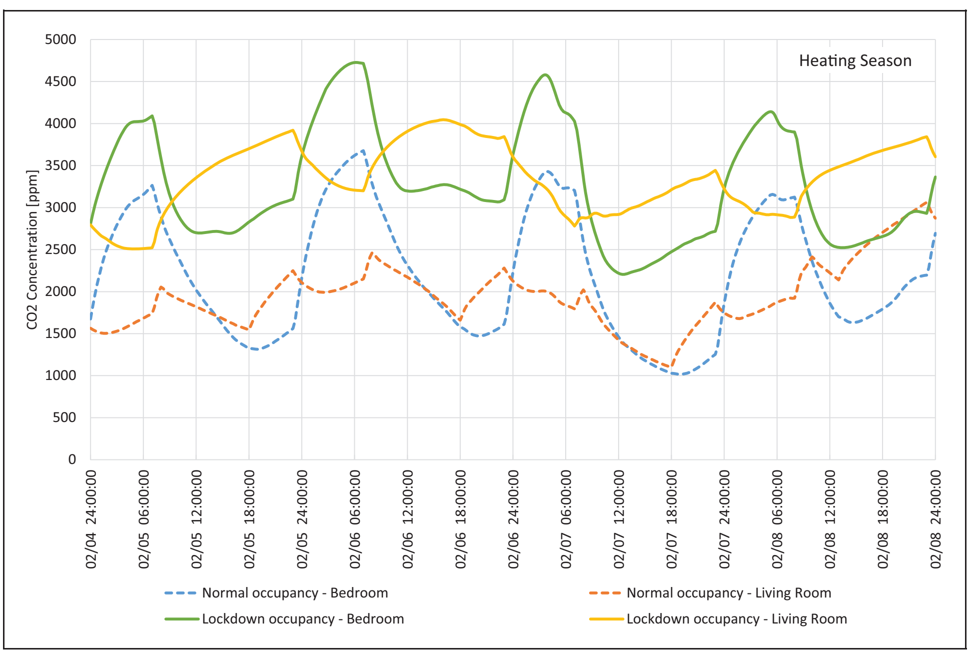

Figure 9. A 4-day section of simulation tests 4 & 5 – Worst-case CO_2 concentration in heating season without window operation and mechanical ventilation for normal and lockdown occupancy patterns.

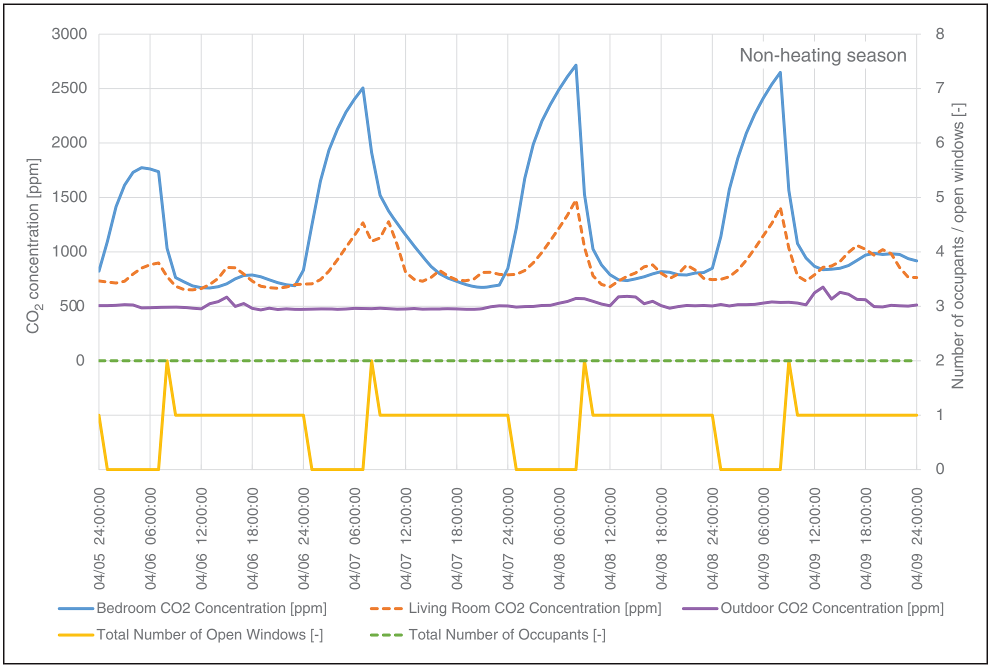

Figure 10. A 4-day section of simulation test 3 – Monitored outdoor and predicted indoor CO_2 concentrations in non-heating season with lockdown occupancy pattern and opening of 1 to 2 windows during the day.

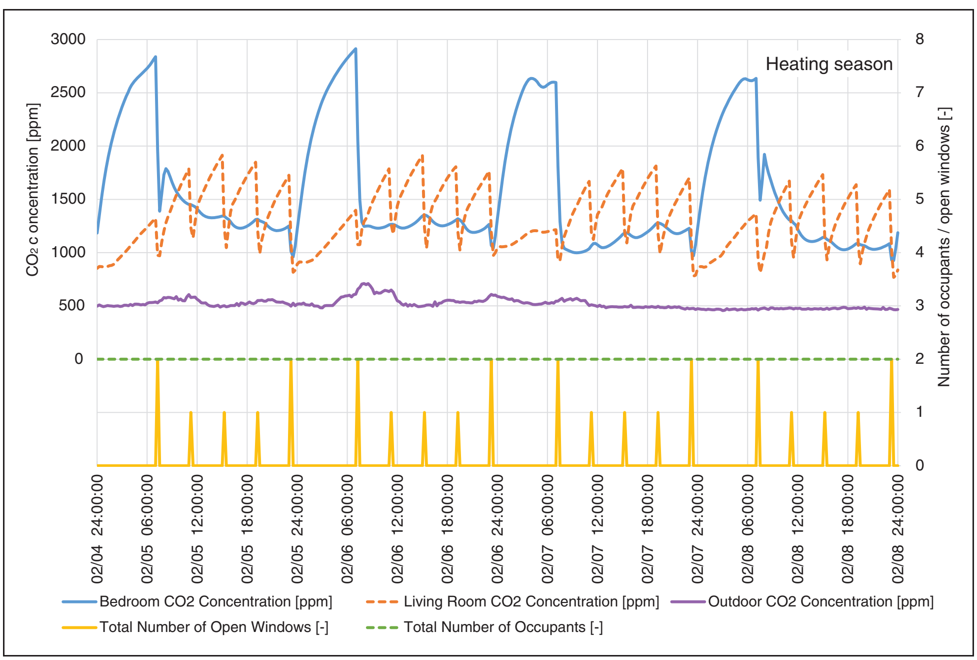

Figure 11. A 4-day section of simulation test 6 – Monitored outdoor and predicted CO_2 concentrations in heating season with lockdown occupancy pattern and daytime opening of 1 to 2 windows for periods of 15 min every 4 h.

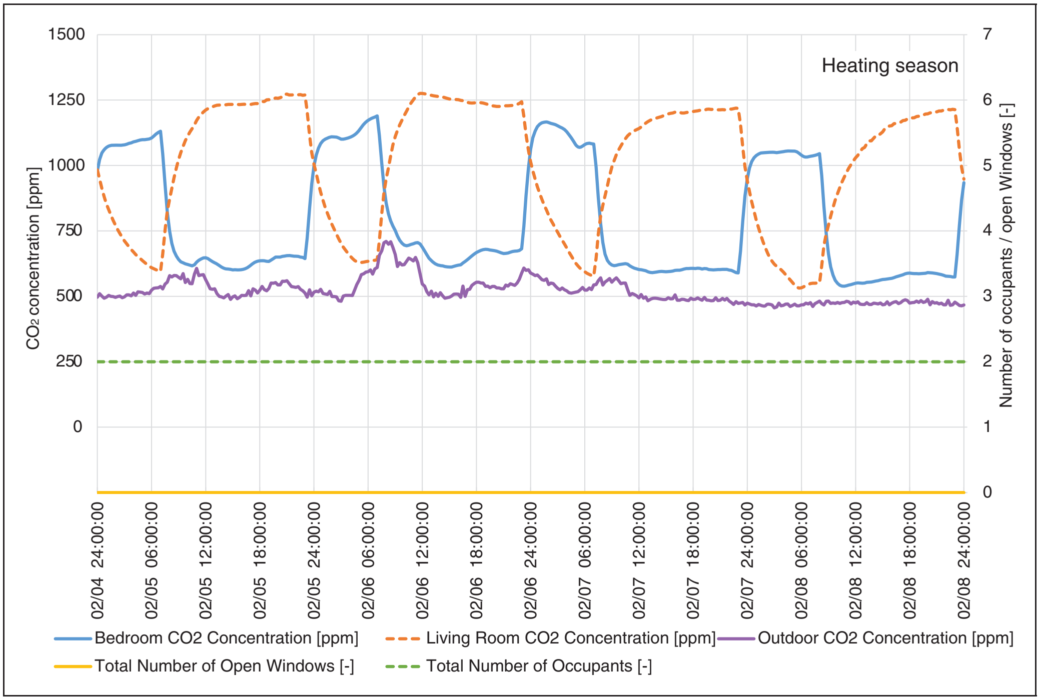

Figure 12. A 4-day section of simulation test 7 – Monitored outdoor and predicted CO_2 concentrations in heating season with lockdown occupancy pattern and operation of MVHR delivering 7 L/s.person outdoor air.

use of mechanical ventilation with heat recovery. As can be seen in Table 8 and Figure 12, test number 7 demonstrates that a MHVR system (with a sensible heat recovery effectiveness of 0.75 and providing 7 L/s.person outdoor air), can maintain the CO_2 concentrations in both rooms below 1400 ppm. It also reduces the heating demand by more than 40% compared to the solution based on natural ventilation in test number 6.

Conclusion

This paper has shown that with the changing home occupancy patterns after the Covid-19 outbreak, indoor CO_2 concentrations can rise significantly. At the same time, the results of the study suggested that the main environmental driving factor for window operation in both pre-lockdown and lockdown periods was indoor temperature. Nonetheless, the natural ventilation strategies tested on a flat with one-sided openings and the use of MVHR proved to be very effective to maintain acceptable IAQ at home.

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