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. 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 significantly higher CO_2 and PM_{10} concentrations. However, simple natural ventilation patterns or use of mechanical ventilation with heat recovery proves to be very effective to maintain acceptable IAQ.

Key Innovations

- Use of on-site CO_2 and window operation data to calibrate building energy models;
- Use of building performance simulation and novel metrics to assess occupant exposure to carbon dioxide.

Practical Implications

- Providing evidence on the deterioration of indoor air quality resulting from homeworking / imposed lockdowns.
- Recommending specific ventilation patterns to maintain acceptable indoor air quality despite the extended occupancy hours at home.

Introduction

The Covid-19 lockdowns across the globe mean that people spend much more time in their homes, where pollutant concentrations including particulate matter (PM), carbon monoxide (CO), carbon dioxide (CO_2), ozone (O_3) and volatile organic compounds (VOCs) can be several times higher than outdoor air, indicating a significant potential for detrimental health impacts.

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 exchange 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 indicators for outdoor-air ventilation rate per occupant (Persily and Dols 1990).

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. (1994) 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 5,000 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., Erdmann and Apte 2004; Federspiel et al. 2004; Milton et al. 2000). 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 (Mudarri 1997; Persily 1997). Yet, as suggested by Chatzidiakou et al. (2015), CO_2 concentration can be used as a good proxy for overall IAQ, with the exception of traffic-related pollutants.

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. (2012) 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. (2020) found that sleep quality was negatively affected by increasing concentrations of CO_2 up to 3000 ppm. Another study found that seven of nine aspects of work performance were significantly and negatively impacted by a CO_2 level of 2500 ppm (Satish et al. 2012).

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 analyse IAQ in eight flats prior to and during an imposed lockdown in London. 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. Thus, the study could use one-year's worth of monitored data collected from July 2019 to June 2020 to reveal the impact of the lockdown on IAQ and patterns of opening and closing windows by occupants. The dataset included solar irradiance, wind speed and wind direction, indoor and outdoor air temperature, relative humidity, concentrations of 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-minute 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.

The calibrated building energy model

The authors modelled one of the monitored flats in the building energy 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 for the walls, windows, ceilings and floors respectively. The building also employs mechanical ventilation with heat recovery (MVHR) that operates in the heating season.

The energy 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., Tahmasebi & Mahdavi 2013; Jain et al. 2020), the present study uses monitored CO_2 concentrations to calibrate a building model tailored for indoor air quality assessments. This poses further challenges for the calibration process, as the building model's reliability depends largely on the validity of the rather complex air flow network definition and the window operation assumptions. Besides, to the authors' knowledge, previous research has not established targets for the accuracy of calibrated building thermal performance models for IAQ predictions.

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 deployed to create real-year weather data for the purpose of model calibration using Elements software tool.

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 factor width for the open state of windows and interior doors, air mass flow through closed openings, occupants' activity level and CO_2 generation rate.

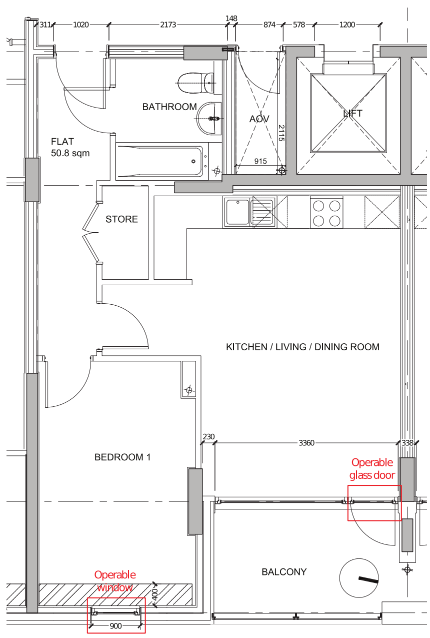

Figure 1: The floor plan of the flat and its openings.

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. It should be noted that, in this process the effective open area of windows is represented by the parameter called width factor for open state, while the height factor for open state is assumed to be 1.

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 1 lists the calibration variables and their values in the initial and calibrated models and Table 2 gives the obtained error metrics for the estimated CO_2 concentrations by the initial and calibrated models in the bedroom and the living room.

In the absence of established accuracy targets for CO_2 concentration predictions (and without testing the model performance in a separate validation period), the error metrics seem to suggest that the calibration process has enhanced the model's reliability in this regard. Given that the current study incorporates monitored data on the operation of windows, in authors' view, the key parameter uncertainties contributing to the remaining discrepancy are the number of occupants in each room, wind pressure coefficients, as well as the effective opening area in each incidence of window opening.

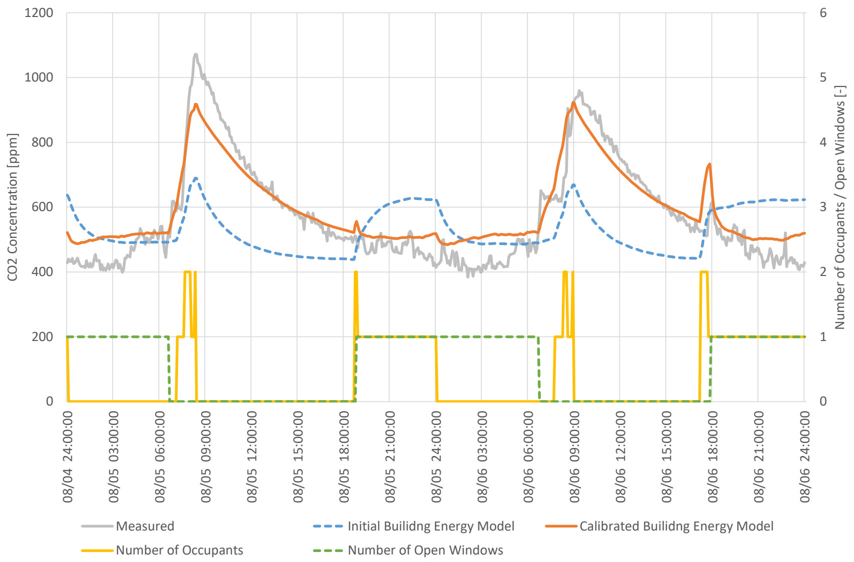

Figure 2: A two-day section of predicted living room CO_2 concentrations by the initial and calibrated building energy models in comparison with the measured values.

Table 1: Model inputs subjected to calibration.

Input parameters	**Initial model**	**Calibrated model**
Bedroom closed window air mass flow coefficient [kg/s.m]	0.001	0.0005
Living room closed window air mass flow coefficient [kg/s.m]	0.001	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

Table 2: 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

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 as normal occupancy), 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 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 litre/s.person outdoor air.

Performance metrics

To capture the occupants' exposure to 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.

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 setpoint 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). Comparing 3-month periods before and during lockdown, the data suggest that occupants have opened the windows less during the lockdown than before it. 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 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 by more than 200 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 on weekdays (as well as on weekends) in this period. This can be explained by the questionaries filled by the occupants, which reported more cooking incidences during lockdown, and in case of one participant, an increase in the use of candles.

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 high CO_2 concentrations (see Table 3, 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 Figure 7 and Figure 8, 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 3 and Figure 9, the selected natural ventilation strategy for a lockdown during a non-heating season (test number 3) seems to be very effective to maintain low levels of 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 3 and Figure 10). 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 use of mechanical ventilation with heat recovery. As can be seen in Table 3 and Figure 11, test number 7 demonstrates that a MHVR system (with a sensible heat recovery effectiveness of 0.75 and providing 7 litre/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.

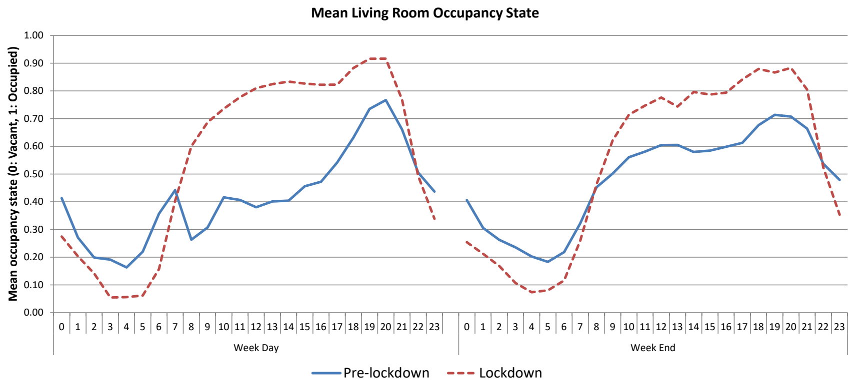

Figure 3: Mean living room occupancy state in two 3-month periods prior to and during lockdown.

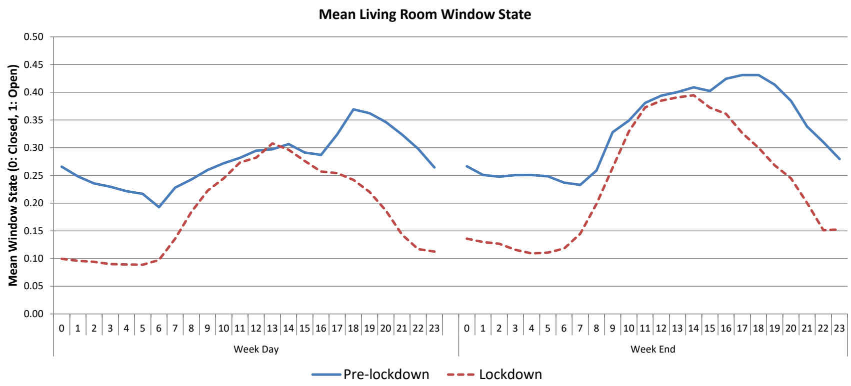

Figure 4: Mean living room window state in two 3-month periods prior to and during lockdown.

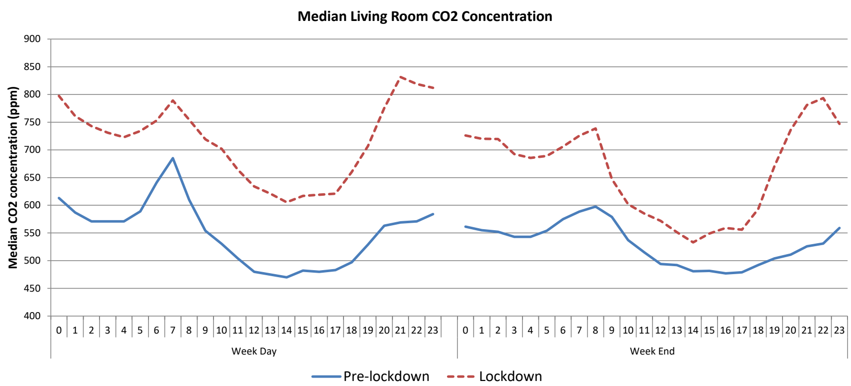

Figure 5: Median living room CO_2 concentration in two 3-month periods prior to and during lockdown.

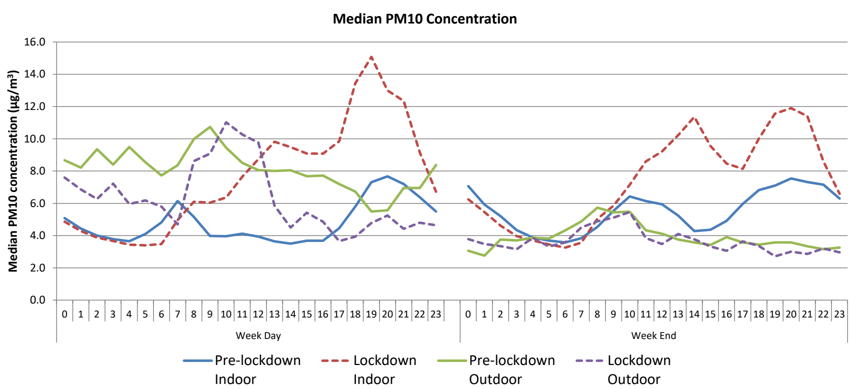

Figure 6: Median indoor and outdoor PM_{10} in two 3-month periods prior to and during lockdown.

Table 3. 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

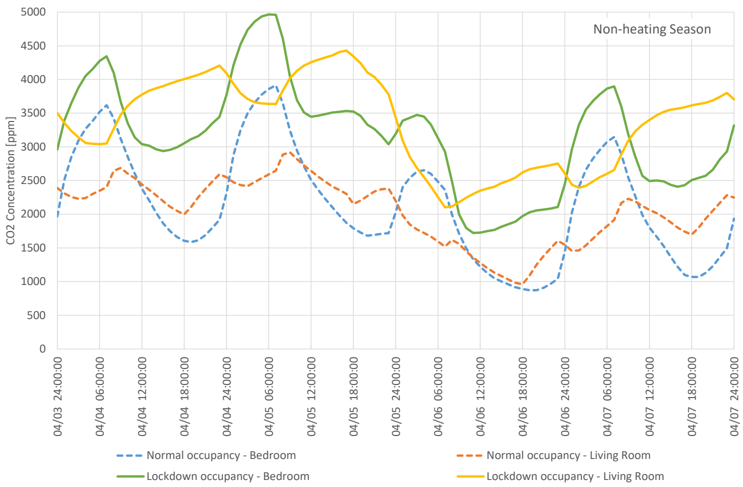

Figure 7: A 4-day section of simulation tests 1 &2 –Worst-case CO_2 concentration in non-heating season without window operation and mechanical ventilation for normal and lockdown occupancy patterns.

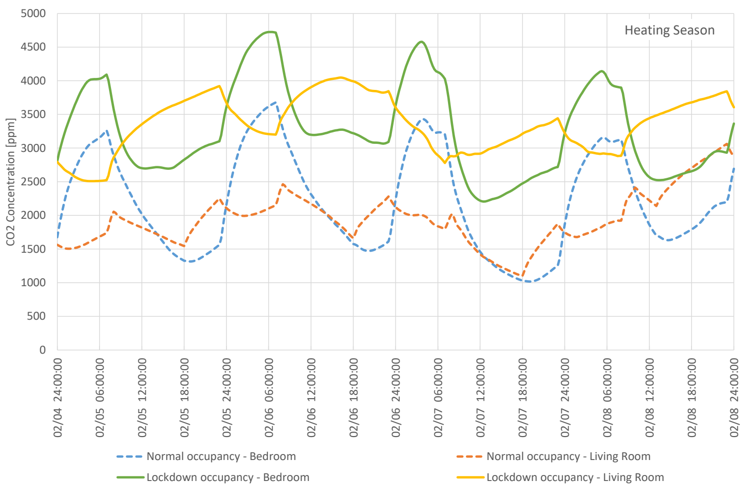

Figure 8: A 4-day section of simulation tests 4 &5 –Worst-case CO_2 concentration in heating season without window operation and mechanical ventilation for normal and lockdown occupancy patterns.

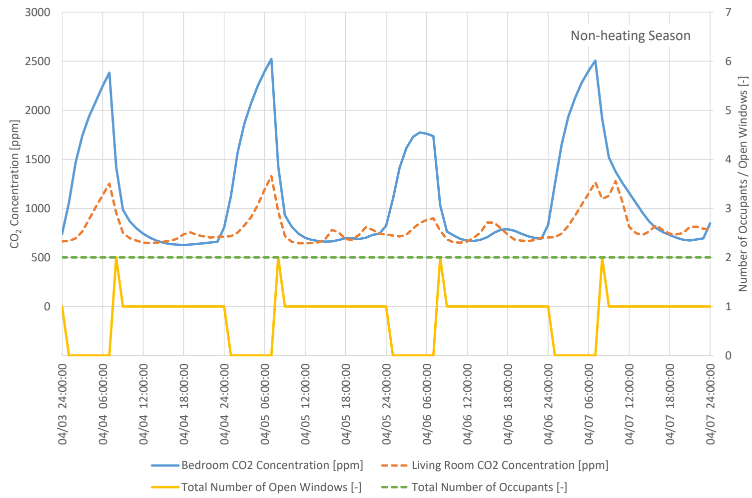

Figure 9: A 4-day section of simulation test 3 – Predicted CO_2 concentration in non-heating season with lockdown occupancy pattern and opening of 1 to 2 windows during the day.

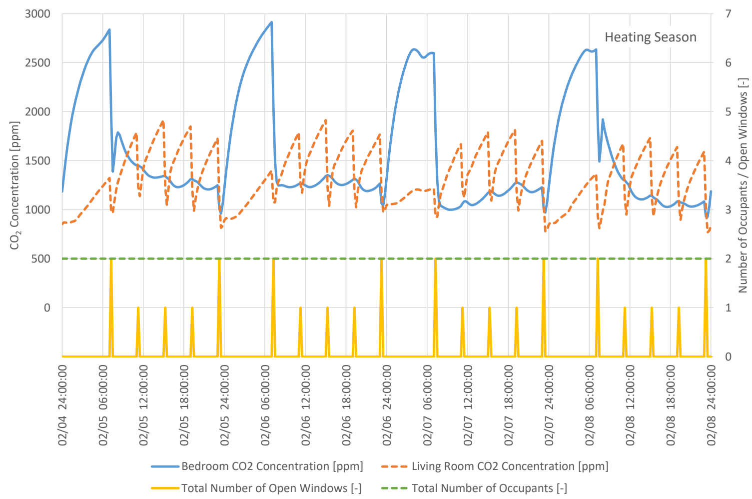

Figure 10: A 4-day section of simulation test 6 – Predicted CO_2 concentration in heating season with lockdown occupancy pattern and daytime opening of 1 to 2 windows for periods of 15 min every 4 hours.

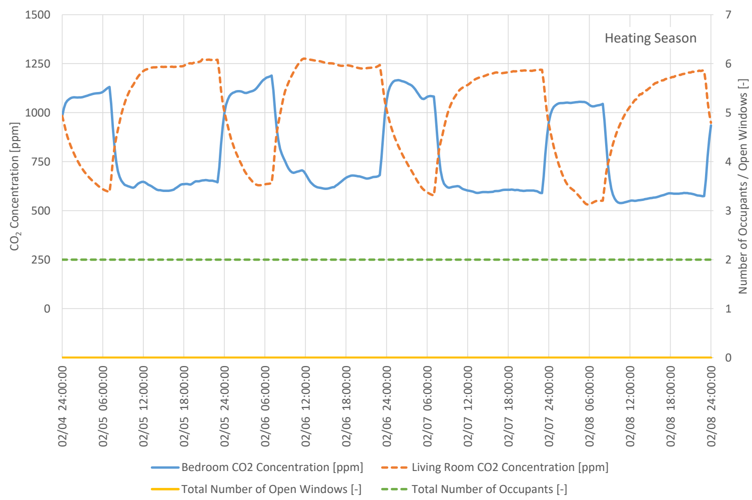

Figure 11: A 4-day section of simulation test 7 – Predicted CO_2 concentration in heating season with lockdown occupancy pattern and operation of MVHR delivering 7 litre/s.person outdoor air.

Conclusion

This paper has shown that with the changing home occupancy patterns after the Covid-19 outbreak, the indoor pollutant concentrations can rise significantly. However, the natural ventilation strategies tested on a flat with one-sided openings, and deploying MVHR proved to be very effective to maintain acceptable IAQ at home. Therefore, it is particularly important that the households are made aware of the benefits of sufficient air exchange rates and the environmental control possibilities at their disposal to enhance IAQ. The research team will further investigate the observed interactions of occupants with windows and the associated driving factors to arrive at tailored models of window operation for post-pandemic residential buildings.

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