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Doi: 10.53412/jntes-2022-1-4

## OCCUPANCY IMPACT ON THE INDOOR AIR QUALITY OF THE MONITORED OPEN-OFFICES

**Abstract:** *Humans spend 90% of their time indoors therefore proper air quality in buildings is crucial for human health and productivity. The problem with poor air quality is usually found in buildings with no mechanical ventilation. Contrary, modern office buildings, which are usually equipped with mechanical ventilation, are often over-ventilated. The reason is usually related to lower-than-designed buildings' occupancies. In the context of a pandemic, the occupancy of the buildings has significantly decreased, meanwhile the ventilation systems often operate at the design air flow rates thus causing a waste of energy. The paper presents long-term occupancy and CO<sub>2</sub> concentration monitoring results for 4 office buildings. All of the buildings showed very low occupancies and over-ventilation of the rooms. Seeking to decarbonize the buildings sector much is done to strengthen the requirements for energy efficiency of buildings, but the results of the study prove once more that the potential of better building energy using systems management is still unexploited.*

**Keywords:** *monitoring, office buildings, ventilation, occupancy*

### Introduction

Overall, buildings account for 36% of global energy demand and 37% of energy-related CO<sub>2</sub> [1]. To meet the EU's climate objectives, the building sector will need to achieve 60% greenhouse gas (GHG) emissions reductions by 2030 and fully decarbonise by 2050. Unfortunately, Europe is not on track: buildings still account for 40% of the EU's total energy consumption and 36% of CO<sub>2</sub> emissions [2].

Heating, ventilation and air conditioning (HVAC) systems are the most consuming service worldwide (38%), both in residential (32%) and tertiary (47%) sectors [3], but today, people spend up to 90% of their time in an indoor environment, therefore energy efficiency in buildings cannot be reached at the cost of thermal comfort or indoor air quality (IAQ).

It is well known that IAQ has a significant impact on health, well-being, and human performance. The most common indoor air pollutant is CO<sub>2</sub> and it is commonly used as a metric of IAQ [4]. To ensure a minimum ventilation rate to guarantee proper IAQ countries have established different requirements for indoor CO<sub>2</sub> concentrations [5], but it is commonly assumed that when the CO<sub>2</sub> level is higher than 1000 ppm, it indicates that the room is polluted and it can lead to poor well-being, health, and productivity [6]. The main source of CO<sub>2</sub> in the room is its occupants. Their presence in the building determines: 1) when the building needs to be ventilated and 2) how much it needs to be ventilated to satisfy the required IAQ level.

Occupancy (demand) based ventilation is a key solution to optimise energy consumption related to ventilation. Here different sophisticated, artificial intelligence-based methodologies are developed and proposed by scientists already for some years. E.g. novel image-based occupancy positioning system

for demand-oriented ventilation [7], different neural network-based methods [6, 8], deep vision-based ventilation control, which could properly maintain the indoor CO<sub>2</sub> concentration with 24-35% lower ventilation rates compared to traditional ventilation control strategies [9]. As Khan et al. [10] have concluded, even design airflow for HVAC sizing could potentially be reduced using actual occupancy information. Even taking into account that Covid-19 pandemic has brought upfront significant changes in buildings IAQ to minimize the spread of viruses [11], demand-controlled ventilation is still considered a key solution to keep buildings safe and energy efficient, just more novel CO<sub>2</sub>-based demand-controlled ventilation strategies can be applied [12, 13].

Intelligent use of energy within buildings is a recent trend of research studies and is the goal of Building Energy and Comfort Management systems, which requires a proper understanding of the interaction between occupants and building systems [14] as well as a sufficient amount of data to train the prediction models and to keep high reliability. As Xie et al. (2021) have noted, data is the soul of the digitalisation and intelligentisation of buildings [15]. And here also can be added, that occupancy data is also very important when simulating buildings' energy performance during the design phase, as it enables to decrease Energy Performance Gap when buildings start to operate. Precise building occupancy patterns and activities input data enable to achieve a very good agreement between real energy consumption and simulated one [16].

The goal of this paper is to demonstrate based on long-term measurements of 4 modern office buildings how occupancy changed within recent years and accordingly, how it has influenced the IAQ measured in terms of CO<sub>2</sub>.

## Methodology

The research is based on long-term (not less than 3 months) measurements performed in 4 office buildings in Vilnius (Lithuania). All the buildings are built after 2005 and have energy efficiency certificates – 3 buildings had energy efficiency label class “B” and one building had label class “D”. They also have mechanical balanced air ventilation systems with heat recovery.

The monitoring time covered before the pandemic, total lockdown, and post-pandemic periods. The generated sample data in different buildings varied from 2653 to 7819.

The occupancy was measured using Table Air double-check motion sensors (PIR) which were mounted under the tables. They calculated how many people are in the room and the time that employees spend at their workplaces. The sensor's laser detected movement and the temperature sensor confirmed that an employee was sitting at the current workplace.

The CO<sub>2</sub> concentration was measured with the weather station HOBO MX1102A every 5 min. The data were processed to obtain hourly values for occupancy and CO<sub>2</sub> concentrations for all of the measured periods and each week separately.

**TABLE 1.** Monitored buildings properties

Building	Energy efficiency label	Year of construction/ useful area	Predicted (certificated) energy consumption	Actual normalised heating energy consumption
B_1	B	2017/2405 m <sup>2</sup>	43	59
B_2	B, LEED GOLD	2017/22 164 m <sup>2</sup>	19	56
B_3	D	2008/6567 m <sup>2</sup>	128	114
B_4	B	2014/4107 m <sup>2</sup>	26	174

TABLE 2. Monitoring periods and equipment

Building	Monitoring period	Occupancy	CO <sub>2</sub> concentration	Sample data (hourly values)
B_1	From 05/01/2021 to 27/11/2021 <i>From total lockdown to the post-quarantine period</i>	<i>Table Air sensor</i> Motion sensor (PIR): - Heat sensor - Data transfer 4.0LE - WiFi 2.4 GHz	Weather station HOBO MX1102A: - Measurement range from 0 to 5000 ppm - Error ±50 ppm	7819
B_2	From 15/07/2019 to 23/12/2019 <i>Before pandemic</i>			3862
B_3	From 07/04/2022 to 28/04/2022 From 05/05/2022 to 30/07/2022 <i>Post-quarantine</i>			2653
B_4	From 2021/12/16 to 2022/05/13 From 2022/06/06 to 2022/08/31 <i>Post-quarantine</i>			5381

## Results

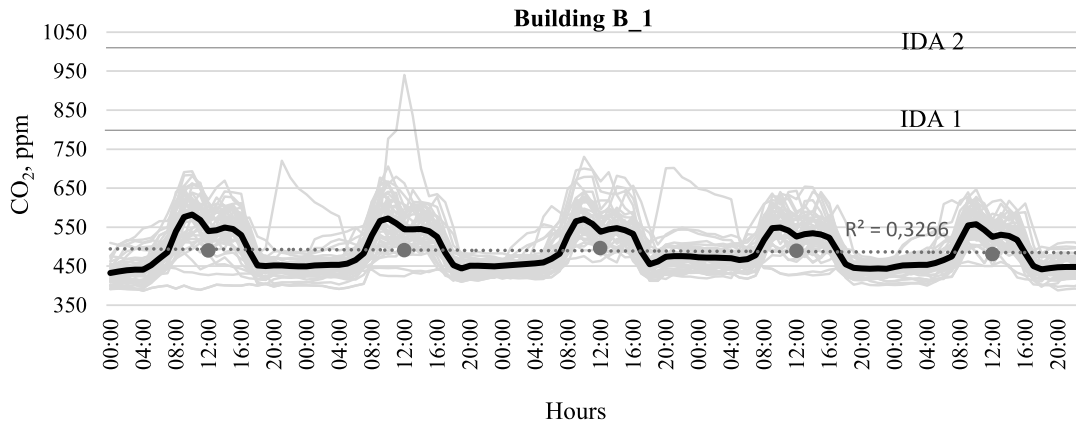
**Occupancy monitoring results.** The monitored occupancy in buildings has shown just slightly different numeric results, despite that measurements were performed at different pandemic conditions, e.g. building B\_2 was measured before the pandemic, and therefore higher occupancies were expected in this building. Meanwhile building B\_1 measurement period includes different periods of the pandemic, from total lock-down to the post-quarantine period. Buildings B\_3 and B\_4 measurements already include a period, which can be considered as post-quarantine, as the specific time of the end of the pandemic is not defined. Therefore we may state, that measured periods enable us to have a view of building occupancies in different situations. The variation of the maximum measured occupancies within the buildings is in a range of 0.48-0.7 (the highest value was measured in building B\_3). But these values do not reflect typical occupancies, it just shows that actual occupancies within the long-term measurements never reached even half of the design values. When analysing average weekly occupancies during the measured periods for monitored buildings it is noticed that the highest daily peak occupancies are found on Mondays varying from 0.15 to 0.38 (highest values are for building B\_3 and lowest for B\_1). The gathered occupancies are provided in Table 3.

**CO<sub>2</sub> monitoring results.** The results of the CO<sub>2</sub> concentrations measured in 4 buildings are provided in Figures 1-4. The separate grey lines in the figures present weekly variations and the black lines present average weekly curves from Monday to Friday. Orange lines mark the limits of the levels of indoor air quality – IDA 1 (high quality, when CO<sub>2</sub> concentration is less than 400 ppm above the outdoor air concentration) and IDA 2 (average quality, when CO<sub>2</sub> concentration is 400-600 ppm above the outdoor air concentration). It is assumed that outdoor air CO<sub>2</sub> concentration is 400 ppm, accordingly, IDA 1 corresponds to up to 800 ppm and IDA 2 – up to 1000 ppm.

TABLE 3. Measured occupancies

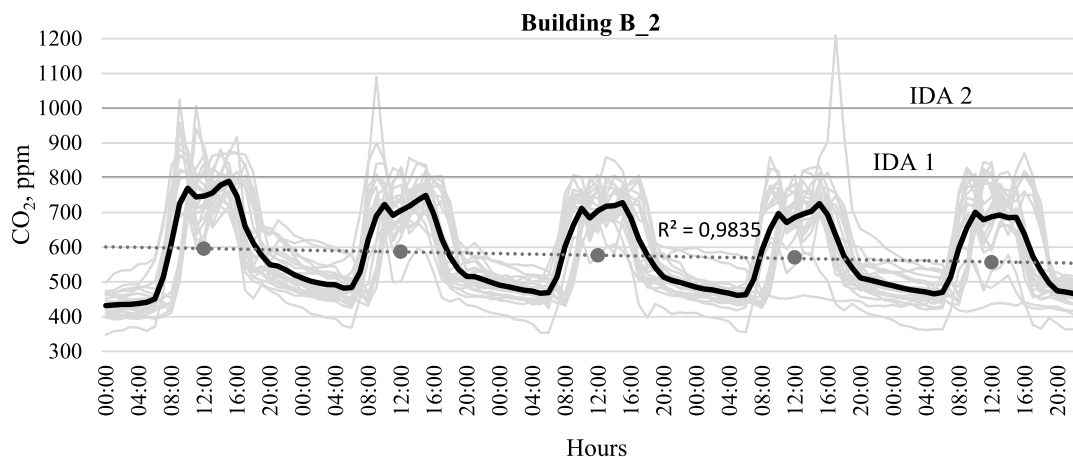
Building	Maximum occupancy measured within the period	Average daily peak occupancy				
		Monday	Tuesday	Wednesday	Thursday	Friday
B_1	0.4	0.15	0.13	0.14	0.11	0.12
B_2	0.4	0.28	0.24	0.19	0.22	0.21
B_3	0.7	0.38	0.31	0.33	0.29	0.16
B_4	0.48	0.18	0.19	0.14	0.10	0.12

**Building B\_1** (Fig. 1). It is seen that air quality in building B\_1 nearly all the time corresponds to IDA 1 quality and is even better. Just once, when the occupancy was 0.4, the concentration was higher and almost reached the limit of IDA 2. An average peak concentration is **less than 600 ppm**. So most of the time room is over-ventilated. This is related to very low occupancies of the room, which are mainly influenced by changes in user behaviours and switching to remote work even after quarantine ended.



**FIGURE 1.** Weekly  $CO_2$  concentrations variation for open-office of the building B\_1

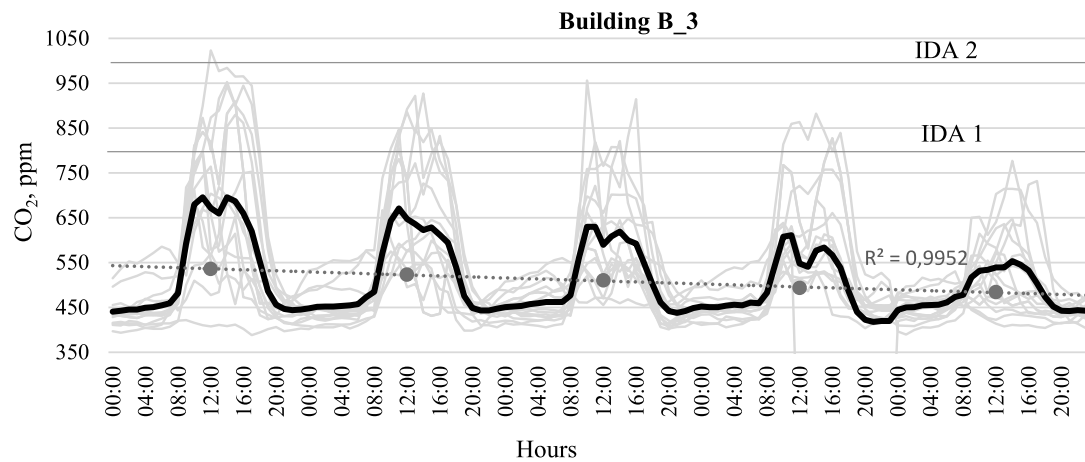
**Building B\_2** (Fig. 2). Building B\_2 was monitored before the pandemic, therefore low occupancies here are related to other reasons than remote work. The open office is an engineering office where employees have no personal workstations and do not sit in the office permanently, as they have to travel a lot and because of that reason workstations are often unoccupied. It is seen that air quality in the building B\_2 most of the time is between the IDA 1 and IDA 2 categories, most of the time is around the IDA 1 category, but looking at averaged curve – concentration is usually below 800 ppm. Here energy saving potential of the ventilation system is smaller compared to building B\_1, but seeking to save energy, switching to IDA 2 category can give higher savings, especially taking into account that the same occupant does not stay for the whole day in the office, there is no need to keep IDA 1 category.



**FIGURE 2.** Weekly  $CO_2$  concentrations variation for open-office of building B\_2

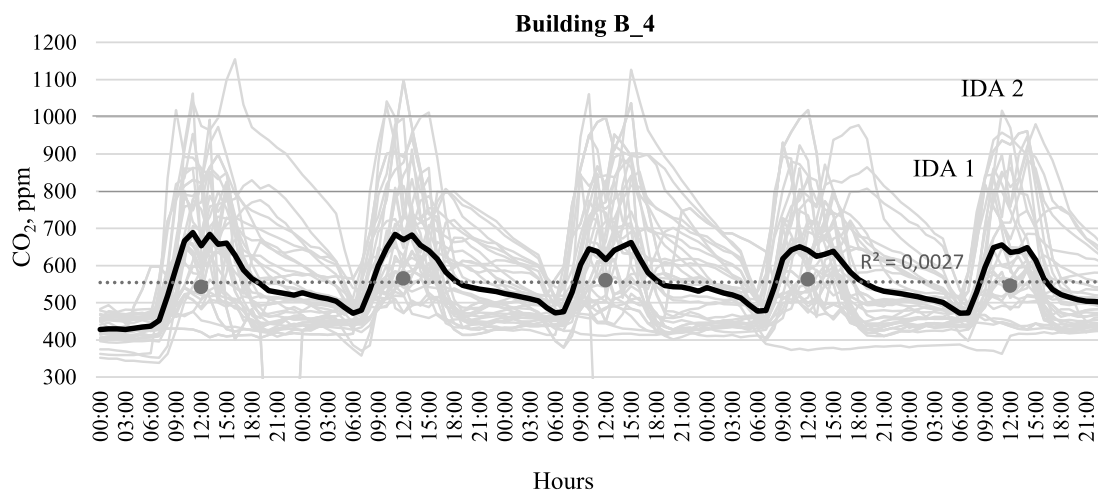
**Building B\_3** (Fig. 3). Building B\_3 was monitored during a post-quarantine time, the occupancy of the building stayed very low, and here, we may see how the pandemic has changed the occupancy as most occupants were working remotely even when quarantine ended. What is specific about that building is that higher  $CO_2$  fluctuations within each working day can be noticed, e.g. each week is very different (grey curves). Hence, similar to the other buildings, occupancies are higher at the beginning of the week and lowest on Fridays. Indoor air quality is nearly 100% sufficient –  $CO_2$  concentration between

IDA 1 and IDA 2 categories. From averaged curves, it can be seen that CO<sub>2</sub> concentrations are **lower than 600 ppm** thus obviously showing a waste of energy and insufficient control of the ventilation system as it does not correspond to the real demand.



**FIGURE 3.** Weekly CO<sub>2</sub> concentrations variation for open-office of building B\_3

**Building B\_4** (Fig. 4). Building B\_4 was monitored also during a post-quarantine time, and the situation with the occupancy is very similar to building B\_3. The occupancy curves are very similar to all of the buildings, but the CO<sub>2</sub> concentrations have different curves than for the other buildings, the concentration stays higher even during unoccupied hours, this tendency is seen during the winter time when more employees were working remotely compared to spring and summer months. So concentration peaks at 6:00 p.m. can not be explained by occupancies, just by some changes in ventilation system management. Nevertheless, the air quality was nearly always kept at a sufficient level – between IDA 1 and IDA 2. According to average curves depending on the weekday, it is not exceeding 700 ppm. Here, similar to building B\_3 variations of concentration is more difficult to predict compared to buildings B\_1 and B\_2.



**FIGURE 4.** Weekly CO<sub>2</sub> concentrations variation for open-office of the building B\_4

Figures 1-4 demonstrate variations of CO<sub>2</sub> concentrations within different weeks and average weekly concentrations, it is beneficial to look at how often concentrations stay in a certain range and this is shown in Figure 5. For all of the buildings prevailing range of concentrations is 401-500 ppm. But most of those hours can be explained with the limitations of the study, as non-working hours are not excluded here. But if looking at Figures 1-4 it is seen that such values are also found during occupied periods with

low occupancies. Again, similarities in distributions can be seen between buildings B\_3 and B\_4 (they both are scientific administrative buildings, and the other two buildings – are engineering offices).

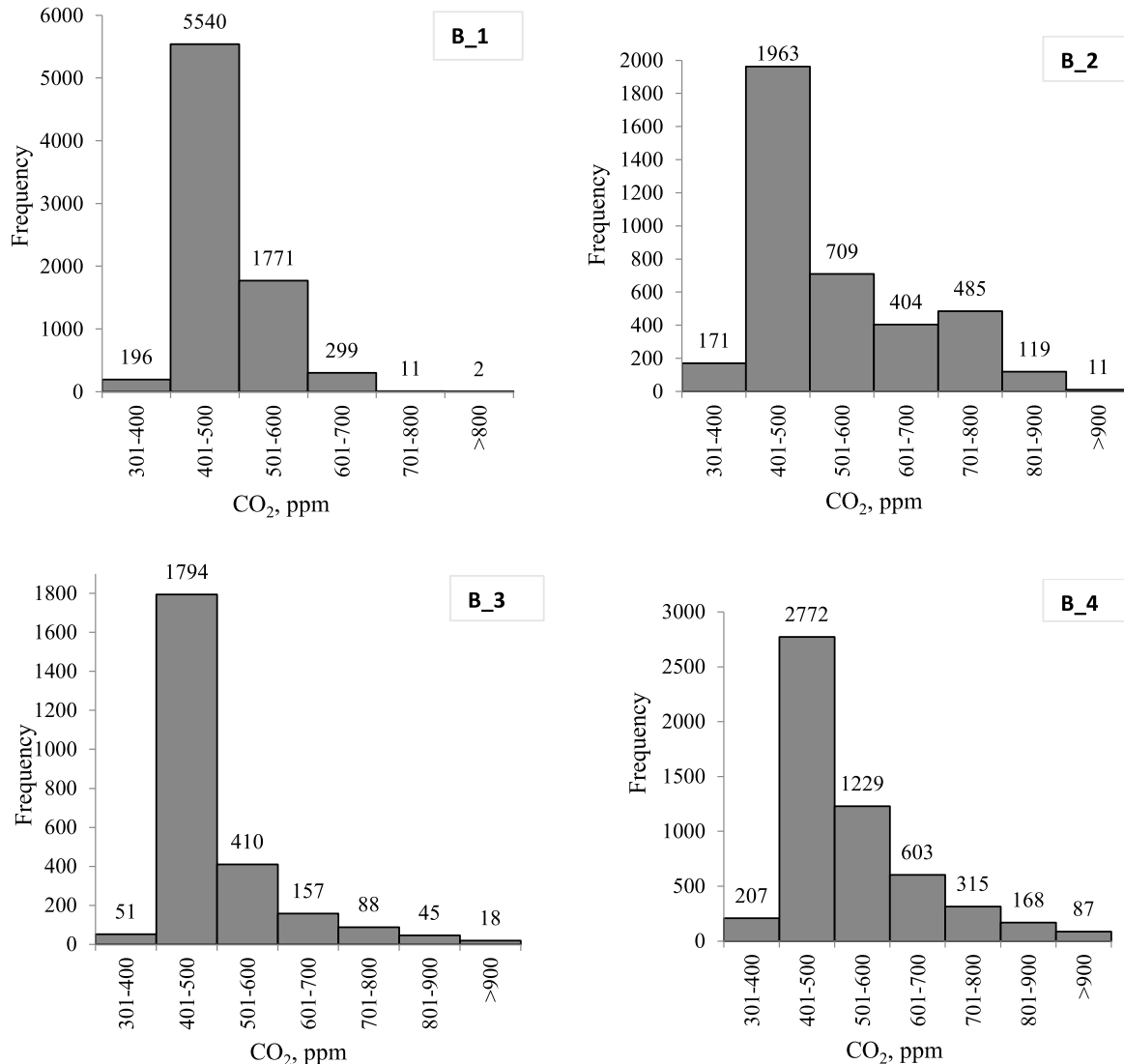


FIGURE 5. Frequencies of CO<sub>2</sub> concentrations

## Conclusions

Globally, the office sector is going through a period of change exacerbated by COVID-19 lockdowns, law changes, flexible working, and structural factors and these realities must be taken into account already now. The performed analysis of long-term measurement data just proved that and enabled to make the following conclusions:

1. Real occupancies in 4 measured buildings within different conditions were much lower than design values and for 3 buildings they even did not reach 50%. The pandemic resulted in a change in office work culture and this number became even lower.
2. As ventilation demand in offices is calculated according to maximum occupancies (100%) it means that in some offices already in the design phase systems are designed for excessive air volumes. Therefore more flexibility is needed in the design phase when calculating air volumes (take into account more realistic occupancies, occupancies schedules must take into account specifics of the office, lower required airflow values per person could be considered, invest in demand-controlled ventilation, etc.).

3. If no demand controlled (e.g. according to CO<sub>2</sub> concentrations) ventilation systems are applied, energy is wasted for over-ventilation.
4. In existing buildings with BMS systems, occupancy or resulting CO<sub>2</sub> concentration monitoring prediction using Artificial Intelligence-based models (e.g. Machine Learning) could be a key solution to more efficient energy usage in ventilation systems.

#### Acknowledgment

This research was funded by a grant (No. S-MIP-20-62) from the Research Council of Lithuania (LMTLT).

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