Do Spatially Distributed Sensor Measurements Provide Better Representation of Indoor Environment than Single Sensor Measurements? A Mechanically Ventilated Office Space Case Study

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ABSTRACT

Most existing office buildings are equipped with indoor environmental quality (IEQ) sensors that are connected to the Building Management System (BMS) and provide feedback to the heating, ventilation and air-conditioning (HVAC). Unfortunately, they are often installed in locations selected based on practical reasons rather than for reliable representation of IEQ at actual workplaces. This leads to a difference in the IEQ sensed by the BMS and the occupants, resulting in increased complaints and decreased occupant satisfaction. This paper investigated whether additional sensors spatially distributed in mechanically ventilated office spaces provided a better representation of IEQ than originally installed BMS-connected sensors providing single sensor measurements. Two mechanically ventilated office spaces were equipped and monitored with additional sensors from January to May 2019. Indoor temperature and CO_2-concentration were measured with sensors located at the perimeter and the interior of the office spaces. Statistical analysis (confidence intervals and p-value) was used to determine whether the difference in sensor measurements between the two locations was significant. The results showed that the temperature measured at the perimeter was significantly lower (1-1.7 °C) than the temperature measured at the interior of the office space. Overall, the difference in the measured CO_2-concentration at the monitored locations was statistically insignificant (< 162 ppm). The results suggest that whereas one CO_2 sensor seems sufficient to adequately represent IEQ at the office spaces, at least two temperature sensors should be deployed in 20 – 210 m^2 office spaces with mixing ventilation and a 0.33 window-to-wall ratio. Additional analysis showed that accounting for the actual IEQ at the office spaces can be associated with increased energy demand. Using the sensor measurements at the perimeter for HVAC control can increase heating energy use by 0.4 – 40%, depending on the climate zone and building type.

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INTRODUCTION

International Standards such as EN-16798-2 (2019) suggest that long-term evaluation of indoor environmental quality (IEQ) in buildings can be performed with measurements acquired at representative locations, including different orientation and thermal load conditions. Long-term measurements can be typically acquired from sensors connected to the Building Management System (BMS). However, such sensors are typically located on the interior walls away from workplaces to avoid any obstructions or disturbances to the measurements (Madsen et al. 1990; Borier et al. 2019). Various studies questioned the fact that such sensor location can reliably represent the IEQ sensed by the occupants. For example, Clear et al. (2017) pointed out that tension between occupants and facility managers can arise as occupants dismiss the validity of measurements if these do not represent the reality they convey. Fisk et al. (2010) also pointed out that field studies on CO_2-based demand control ventilation provided neither the required energy saving nor the necessary ventilation air rate due to the poor accuracy of sensors and their inappropriate location. Borier et al. (2019) and Madsen (1990) also discussed that the location of BMS sensors or thermostats used for heating, ventilation and air-conditioning (HVAC) control can greatly impact the energy use of the HVAC.

Studies by Tushar et al. (2018) and Aryal et al. (2019) point towards low-cost wireless sensor technologies, Internet of Things (IoT), to provide a better representation of IEQ in office spaces. These wireless sensor technologies can provide capabilities such as high temporal resolution and flexibility regarding placement. There might be a greater advantage in deploying low-cost sensors for long-term and high temporal-spatial measurements to reflect the long-term variability in indoor environmental parameters instead of expensive BMS sensors providing single sensor measurements (Parkinson et al. 2019). Contrarily, many authors are concerned with the accuracy of the low-cost sensors as they can impact the reliability of IEQ assessment (Kolarik and Olesen 2015; Mylonas et al. 2019).

The objective of the study presented in this paper was to determine whether additional temperature and CO_2 sensors spatially distributed in mechanically ventilated office spaces provided a better representation of the indoor temperature and CO_2-concentration than single sensor measurements.

METHODS

Case study description and sensor setup

Two office spaces (210 m^2 and 225 m^2) in two Danish office buildings were selected as case studies – denoted Case Building I and II. Both spaces had a mechanical ventilation system designed as mixing ventilation and operated as variable-air-volume. Air was distributed via ceiling-mounted diffusers. Supply temperature was centrally controlled, and the ventilation airflows during occupied hours varied from 0.8 to 1.1 m^3/s. The spaces had an estimated thermal mass of 120 Wh/K per m^2 and 0.33 window-to-wall ratio. Figure 1 shows the office layout and the sensor distribution in both office spaces. Case Building I was controlled and monitored as two adjacent open-plan office zones. Ventilation, heating and cooling were provided from the same single duct ventilation, so-called all-air system. Case Building II was a mix of small open-plan (25-110 m^2) and single office spaces (20 m^2). Ventilation and cooling were provided from the ventilation system, while heating was provided via radiators located below windows, a so-called mixed system.

Two types of commercially available IoT devices were temporarily deployed in each case building. The IoT device mounted on the wall (Figure 1) had an accuracy of ± 0.3 °C and ± 50 ppm for the temperature and CO_2 sensors. The IoT device placed on some of the occupants' desks or shelves (Figure 1) had an accuracy of ± 1 °C for the temperature sensor, and it did not measure CO_2. The BMS sensors installed in both buildings were used for HVAC control. The BMS sensors in Case Building I had an accuracy of ± 0.5 °C and ± 40 ppm for the temperature and CO_2 sensors. The BMS sensor in Case Building II only measured the temperature and had an accuracy of ± 0.3 °C. The sensor accuracy was obtained from the manufacturers' datasheets. The temperature sensors were in a casing, measuring a combination of radiant and air temperature. None of the sensors was exposed to direct sunlight. Note that a sensor located at the perimeter, in the middle of a room or near the interior wall was denoted sensor A, B or C (Figure 1).

In a preliminary experiment, the IoT sensors from Case Building II were placed together on a table in the northeast open-plan office space (Figure 1b) for nine days to determine the difference in sensor measurement when exposed to the same indoor environment. The observed differences were up to 0.8 °C (95th percentile) for measured temperature and up to 150 ppm (95th percentile) for measured CO_2. These differences were related to the measurement uncertainties among the different sensors. Moreover, the IoT and BMS sensors were placed at different heights (Figure 1). However, preliminary spot measurements in the office spaces showed that the vertical temperature variation (from 0.75 m to 1.5 m) was negligible (> 0.3 °C). Two sensors, the temperature sensor C2 in Case Building I (Figure 1a) and the CO_2 sensor A4 in Case Building II (Figure 1b), showed highly different measurement values than the nearby sensors. Since nothing in the surrounding indoor environment (e.g., exposure to direct sunlight or higher occupant density) could explain the observed differences, they were likely caused by measurement error. Thus, the sensors were excluded from the data analysis.

Figure 1 (a) Left: Case Building I and (b) Right: Case Building II. Type and location of sensors. The net floor area is shown on the floor plans. Both office spaces had a ceiling height of 2.7 meters.

Data collection and processing

The IoT and BMS sensor measurements (except BMS measurements in Case Building II) were logged every 5 minutes and automatically stored in a database. This was not possible for the BMS sensors in Case Building II; thus, the data were manually extracted every day over two weeks. The temperature and CO_2 measurements used in the data analysis for Case Building I were from January to May. The temperature measurements for Case Building II were from April to May, and the CO_2 measurements were from March to May. The measurements were processed as follows:

1. All sensor values less than or equal to zero or equal to "NA" were removed.
2. The data was aggregated to 15 minutes timestep to align timestamp across sensor measurements.
3. Constant sensor readings due to faulty sensor signals were removed from the dataset. They were identified and removed by calculating if the sensor measurements had a daily standard deviation of zero.
4. Data analysis for CO_2 measurements only included data collected during occupied hours (Monday to Friday 06:00 – 17:00).

Data analysis and evaluation

The distributions of each sensor measurement were checked for normality using a QQ-plot. Since the plot showed that the distribution of the measurements differed from a normal distribution, a non-parametric hypothesis test was used in the data analysis. The Wilcoxon Signed-rank test was applied to the dataset for each case building to determine if there was a statistically significant (significance level, $\alpha = 0.05$) difference among the sensor measurement distributions over the entire measurement period. This was investigated for the measured indoor temperature (denoted *Ti*) and measured CO_2-concentration (denoted CO_2). Since the analysis was performed as a piece-wise comparison (Benavoli et al. 2016), the Bonferroni corrected significance level ($\alpha_{bonferroni}$) for the two-sided hypothesis test was applied.

As hypothesis testing on large datasets can result in a small p-value because of minor differences, e.g., due to measurement uncertainties (Kim 2015), an additional evaluation using the confidence interval was performed to address this problem (Lee 2016). The confidence interval (denoted $Conf_\theta$) for the median difference between two sensor measurements (denoted $\Delta\theta_{median}$) was determined. $Conf_\theta$ was calculated as the upper/lower non-parametric confidence interval according to (Hollander et al. 2014) for the $\alpha_{bonferroni}$.

As previously described, the measurement uncertainty for the sensors was 0.8 °C for indoor temperature and 150 ppm for CO_2-concentration. Consequently, $\Delta\theta_{median}$ was significant if the null-hypothesis was rejected (p-value < $\alpha_{bonferroni}$) and $Conf_\theta$ was greater than 0.8 °C for temperature and 150 ppm for CO_2. The statistical package rstatix version 0.7.0 (Kassambara 2020) for R (R Core Team 2020) was used in the data processing and analysis steps.

RESULTS

Indoor temperature

Figure 2 shows the boxplot of the indoor temperature measurements for each sensor in Case Building I and II. The grand median of all temperature measurements for Case Building I and II was 23.4 °C and 24.6 °C, respectively.

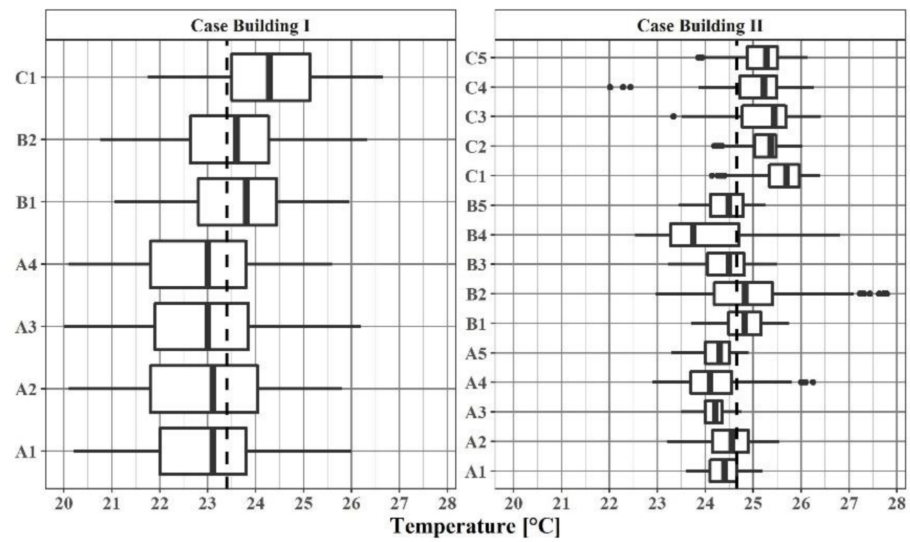

Figure 2 Boxplot of the indoor temperature measurements for all sensor locations in each case building. The horizontal line is the grand median temperature of all measurements.

Figure 3 presents the results of the statistical analysis as a matrix plot. The displayed values are the median temperature difference between two sensor locations, specifically derived by subtracting the measurement values of the sensors displayed on the x-axis from the values of the sensors displayed on the y-axis. Colored points indicate whether the difference was significant (p-value < $\alpha_{bonferroni}$ and $Conf_{Ti}$ > 0.8 °C). In Case Building I, the difference in indoor temperature measurements between sensor C1 and sensors A and B2 were statistically significant and ranged from 1.2 to 1.7 °C. In Case Building II, the differences in indoor temperature measurements were statistically significant among, e.g., sensor C and A located in the same zones (except for zone 2) and sensor C4 and B4. The median temperature difference for these sensors ranged from 1 to 1.9 °C.

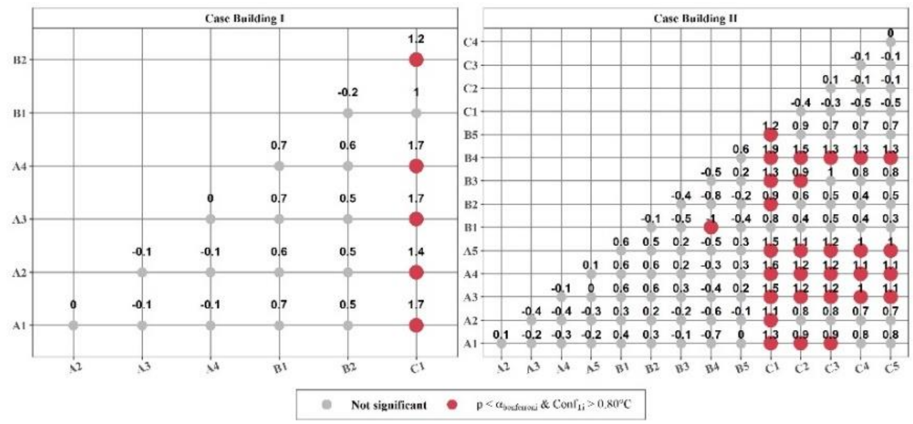

Figure 3 Matrix plot displaying if the median temperature difference between two sensors (bold text above each point) was significant (red) or not (grey). $\alpha_{bonferroni} = 0.0018$ (Case I) and $\alpha_{bonferroni} = 0.00048$ (Case II).

CO_2-concentration

Figure 4 shows the boxplot of the CO_2 measurements for each sensor during occupied hours. The grand median of all CO_2 measurements was close to 600 and 500 ppm for Case Building I and II, respectively. The median for most of the boxplots for each sensor was near the grand median. Only the difference in CO_2 measurements between sensors A2 and A4 in Case Building I were statistically significant. Here, the median difference was 155 ppm. For the remaining sensors in both buildings, the difference in CO_2 measurements was insignificant, and their values ranged from 1 to 109 ppm.

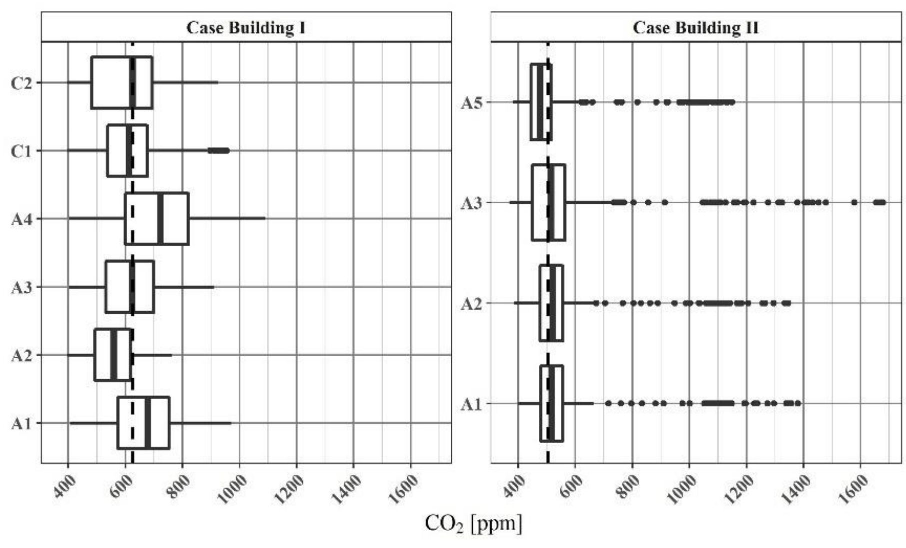

Figure 4 Boxplot of CO_2 measurements for all sensors in each building. The horizontal line is the median CO_2-concentration for all measurements.

DISCUSSION

The results showed a significant difference between the indoor temperature measured for sensors C (interior) and sensors A (perimeter) for both case buildings. Overall, no significant temperature difference was observed among the sensors at the perimeter, in the middle of a room and between sensors at the perimeter and in the middle of the room. The results showed that the measured temperature at the perimeter was 1-1.70 °C (a mean of 1.4 °C) lower than the temperature measured at the interior. In general, these results are in line with previous studies such as Kim et al. (2019). They observed an average temperature difference of 0.5 °C with a spread of 0.8 °C between sensors at the workstations and BMS sensors mounted on the interior wall in an open-plan all-air office space.

There was no significant difference among the CO_2 sensors at the monitored locations except between sensor A2 and A4 for Case Building I. The insignificant difference in CO_2 measurements was likely because of the mixing ventilation utilized in both case buildings. Previous studies such as Pantazaras et al. (2018) and Pei et al. (2019) obtained similar results. However, Fisk et al. (2010) conducted a field study in which they observed a significant spatial variation in CO_2-concentration (> 200 ppm). They explained that it was caused by the inhomogeneous occupancy distribution in the room. The variation in the occupancy density might also explain the significant difference between sensor A2 and A4 (Figure 1a: four workstations directly near A4 compared to two workstations near A2).

Ideally, for reliably representing the indoor environment sensed by the occupants, temperature sensors should be placed near occupants' workstations. However, the occupants might perceive this sensor location as inconvenient because the sensor can be "in the way". Therefore, the sensors risk being obstructed, disconnected or moved (Gilani and O'Brien 2017). Since most workstations in an open-plan office are located near windows and a few near the interior wall, the study provides the following recommendations. At least two temperature sensors should be deployed per zone in office spaces with similar characteristics and HVAC control as the studied office spaces. One sensor should be located at a zone's interior and another at its perimeter to represent the thermal environment adequately. Since the office spaces utilized mixing ventilation, had a generally consistent occupancy distribution and relatively high, uniformly distributed airflow during office hours, a single CO_2 sensor per zone would be adequate to represent the indoor condition. This also agreed with the recommendation by Mahyuddin and Awbi (2012). One temperature sensor is sufficient in single-occupant office spaces, as it can be mounted on the exterior wall near the occupant. CO_2 sensors can be placed at the interior wall to avoid being a nuisance to the occupants.

The temperature measured at the perimeter was on average 1.4 °C lower than the temperature measured at the interior of the monitored office spaces. For example, according to the CBE Thermal Comfort Tool ASHRAE-55 (Hoyt et al. 2019) (Predictive-Mean-Vote method, airspeed = 0.1 m/s and relative humidity = 50%), the thermal sensation of an occupant (1.2 metabolic rate) seated at a room's interior (21 °C) or perimeter (19.6 °C) was "Slightly cool" in both conditions for occupants wearing 0.6 clo and "Neutral" and "Slightly cool", respectively, for occupants wearing 0.9 clo. The clo-values were estimated based on observations during the preliminary experiments. It is well-known that the thermal sensation greatly depends on occupants' clothing and metabolic rate as well as other factors such as physiological conditions (Wang et al. 2018). However, the example illustrated that temperature sensors should be located near occupants' typical work area to represent the conditions they sense reliably. This is important if the intention is to use the measurements for evaluating whether the thermal environment meets indoor environmental requirements; as a foundation for an objective discussion between occupants and building operating managers about the thermal conditions (Clear et al. 2017); or for controlling the HVAC according to occupants' perceived indoor environment.

Moreover, the impact of sensor location on HVAC energy use was investigated. The increase or decrease in heating energy use was estimated for an HVAC controller using either the temperature sensor located at a room's interior or perimeter (Table 1). The estimated difference in energy use was based on the ranges derived by a simulation study conducted by Hoyt et al. (2015) averaged across seven outdoor climates (ASHRAE climate zones 1-5 and 7) and six building types (vintage and ventilation control strategy). The increase in heating energy use was estimated relative to a 21 °C fixed temperature setpoint. The temperature measured with sensors at a room's perimeter was on average 1.4 °C lower than the temperature measured at the interior. If the sensors at the perimeter were used for HVAC control, heating energy use would increase by 0.4-40%, depending on the climate zone and building type.

Table 1. HVAC Heating Energy Use for Different Sensor Location

Strategy: Using the sensor located at the	**Measured temperature**	**Heating energy use mean and range[a]**
Interior	21 °C	-
Perimeter	19.6 °C	13%, 0.4% - 40%

[a]Mean, min. and max. energy use across climate zone and building vintage type estimated using the values from Table 3 by Hoyt et al. (2015).

As the study's dataset spanned from January to May and thus only represented the thermal conditions during winter and spring, cooling energy use was not investigated. Temperature variations may be different during summer, .e.g., due to increased solar heat gain. Using a sensor located at the room's perimeter for HVAC control might increase cooling energy use (Borier et al. 2019).

Having additional sensors in an office space can support occupants to identify workstations that match their preferred indoor conditions. This is particularly useful in office spaces with flexible seating. For example, Sood et al. (2020) developed a smartphone app in which occupants could monitor and rate the indoor environment of a workstation as well as book the workstation if it matched their preferences.

A final remark to sensor location was related to the application of IoT sensors. In the case study, the low-cost IoT sensors were deployed to collect long-term measurements in the office spaces at locations not monitored by the BMS sensors. The measurements from both IoT and BMS sensors revealed that there was a spatial variability in temperature measurements. Thus, the current practice of only providing a single temperature sensor in an open-plan office space or mounting a sensor at the interior of a space was insufficient to represent the indoor condition sensed by occupants seated at the perimeter of a space. Compared to the existing BMS sensors, the main advantage of the deployed IoT sensors was the ability to place them anywhere in the space without any restrictions due to wiring or costly retrofitting solutions. Therefore, IoT sensors can be suitable during the re-commissioning of existing buildings regarding the installation cost and time spent setting up the IoT sensors. However, a critical limitation with both IoT and existing BMS sensors in the building was related to the sensor accuracy. These sensors are seldomly calibrated like a scientific instrument is done. The inaccuracy of these sensors led to conservative thresholds (0.8 °C and 150 ppm) used in deciding if a difference in measurement between two sensors was due to changes in the indoor environment or sensor inaccuracy. Consequently, the precision and accuracy of sensors should be improved, specifically for CO_2 sensors.

CONCLUSION

Significant spatial temperature variations were observed in two office spaces in two office buildings. Contrarily, no significant spatial variation was observed for CO_2-concentration. Consequently, a single CO_2 sensor per ventilated zone utilizing mixing ventilation would be sufficient to represent the indoor air quality. In contrast, additional sensors deployed at the perimeter of a space measured temperatures significantly lower than the BMS-connected sensors mounted on the interior wall. Thus, additional temperature sensors would provide a better representation of the indoor conditions sensed by the occupants, typically seated at the perimeter of a space. However, using the sensor measurements at the perimeter for HVAC control might increase heating energy use by 0.4-40%, depending on the climate zone and building type. Future work should include more case buildings during at least a year and monitor occupants' thermal comfort to identify if the spatial variations can explain any differences in occupants' thermal comfort levels.

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