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Exploring the Indoor Air Quality in the Context of Changing Climate in Residential Buildings—Part A: Developed Measurement Devices of Low-Cost Sensors

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ABSTRACT

Indoor air quality (IAQ) is influenced by several parameters and the sources of indoor air pollutants are numerous (building materials, occupant behavior, HVAC systems, Outdoor air, etc.). Utilization of low-cost sensor devices for screening the indoor air pollution has notably drawn interest over the recent years. These systems are easy to access, portable, need low maintenance, and can provide real-time and continuous screening of target contaminants. The implementation of these systems to monitor the IAQ in real-time and for a long period of time, can support the study of indoor air pollutants trends and variations. In this paper, we present sensors performance needed for an indoor air use. For this reason, four multi-sensor devices are fabricated and developed to measure O_3, CO, NO, NO_2, $PM_{2.5}$, PM_{10}, as well as the temperature and humidity, in an experimental side by side performance evaluation by comparison with reference analyzers. The results showed a sufficient correlation of the measuring devices and the reference data considering the temperature and relative humidity. By the mean of Orthogonal regression method, the calibration equations were acquired for measuring parameters to enhance the IAQ monitoring devices performances. The results were examined on the basis of threshold limit value concentrations defined by European Commission indoor exposure limit values.

INTRODUCTION

Climate change will affect the pollutant levels in residential buildings (Nazzarof 2013). The essential need to provide residential buildings with acceptable Indoor Air Quality (IAQ) level and high energy performance has grown in recent years. Heatwaves and pollution peak events suggest that residential building design needs to address varying weather patterns caused by climate change. The main concern is obtaining a high level of IAQ and preserving thermal comfort while using less energy. The impacts of the IAQ on occupants' health, wellbeing and comfort demonstrate a key area and needs a comprehensive method wherein the multidisciplinary major environmental parameters are measured and evaluated at the same time. According to new data from WHO about 9 out of 10 people breathe air containing high levels of pollutants worldwide which is estimated in about 7million deaths per year (WHO 2020). On the other hand, generally, people spend nearly 90% of their time in indoor areas and consequently the impact of indoor conditions on health cannot be disregarded (Klepeis et al. 2001). Moreover, most of the indoor air contaminants are intangible to humans, which leads to occupants' unawareness of indoor air pollution. (Marios et al. 2011).

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Indoor air pollutants may include a wide variety of physical, biological or chemical, contaminants including CO, CO_2, VOCs, NOx, PM, and O_3 among others (González-Martín et al. 2020). It should be noted that CO_2 is not listed in the selected indoor pollutants by WHO, however it has been employed as a proxy of air ventilation where high CO_2 concentrations indicate poor ventilation, which might specify accumulation of indoor pollutants (Moreno-Rangel et al. 2018).

Measuring indoor pollutant levels is essential for a better perception and further assessment of IAQ (Ma et al.2020). While sophisticated measuring devices enable accurate determination of indoor pollutants, the expense and difficulty in application make them impractical for a broad range of missions. Low-cost sensors (LCS) monitoring devices provide dense temporal and spatial data measurement in a wider range of interior spaces. The literature and scientific articles on the LCS and indoor application are increasing. However, due to complex and multi-dimensional characteristic of IAQ and LCS studies, it is challenging to holistically track all studies being carried out.

Recognized approaches like gravimetry, chromatography, spectrometry, etc are able to deliver high temporal resolution data but these scientific devices are essentially designed for laboratory/stationary practice. Moreover, they need of expert operators and long results time and make them unsuitable for indoor air examinations (Abraham and Li 2014). These approaches are not time and cost efficient. Additionally, the precision of these utilities is superfluous for large-scale measurement campaigns, where determining of relative concentrations and their trends are main purposes. By the advances of LCSs in quality and operation, reliable devices with compact design and low-cost could be employed in holistic measurement/monitoring campaigns (bigger datasets), or any other required applications (Demanega et al. 2021). Low-cost gas sensors have various working principles including electrochemical sensors (Kumar et al. 2011), metal oxide (MOx) semiconductor sensors, IR sensors, photoionization detector (PID) and light scattering (Chojer 2020). Modern measurement devices based on LCSs, enable residential inhabitants to better perceive the IAQ. These devices usually employ online recording for the convenience of users. Still, there are few experimental performance information of LCS measuring devices available for indoor air applications. It should be noted that significant agreement with scientific instruments of many IAQ LCSs are due to experiments in the laboratory environments. The LCS calibration procedure has direct effects on precision, accuracy, and bias of sensors. It has been reported development or modification of calibration models can effectively increase the measurement accuracy (Moreno-Rangel et al. 2018; Liu et al. 2020; Falzone et al. 2020).

The objective of this study is to evaluate the performance of four IAQ monitoring devices based on LCSs, designed by SAM-ULiège (Sensing of Atmospheres and Monitoring Laboratory, University of Liège) especially CO, NO, NO_2, O_3, $PM_{2.5}$ and PM_{10}, in residential buildings. For this aim, test results from four fabricated devices are compared to the data of reference analyzers from a wallonia public institute (ISSeP - Institut Scientifique de Service Public). ISSeP is responsible for operating the official air quality stations networks on behalf of the AWAC (Walloon Air and Climate Agency) according to the ambient air European directive. Their certified automatic analyzers are as follows:

- for NO/NOx, a certified analyzer APNA 370 from Horiba (chemiluminescence)
- for O_3, a certified analyzer from Horiba, the APOA370 (UV Absorption)
- for CO, an IR certified analyzer
- for PM, EDM180 from GRIMM company.

This study equivalences the specifications of fabricated four indoor-air measuring devices and investigates their modules in detail. Since the development of these devices has been part of the OCCuPANt project (Impacts of climate change on the indoor environmental and energy performance of buildings in Belgium during summer, University of Liege project 2020) they are named and refered as OCT in this study. Lastly, field calibration equations are presented to enhance the trueness of OCT devices relative to reference analyzers.

MATERIAL AND METHODS

The performance evaluation of LCSs was carried out from 2nd Oct 8:30 local time to 31th Oct 2020 23:30 for CO, NO, NO_2, O_3, $PM_{2.5}$ and PM_{10} in Val-Benoît, Liège, Belgium. The sensors were located at a height of 2m at the same place than the reference analyzers (Lenartz 2021). Figure 1 shows the OCT designed devices based on low cost electrochemical and light scattering sensors. Table 1 presents their main specifications. The data logging was set to measure the parameters all together in each minute. The meteorological data including the temperature, relative humidity, wind speed and direction were recorded and employed to contextualize the data, to confirm that different conditions were characterized.

Figure 1 Schematic of OCT IAQ measuring devices.

Table 1. Specification of Sensors Included in OCT Devices

Sensors	Provider	Concentration	Temp ˚C
$PM_{2.5}/PM_{10}$	Light scattering Sensirion SPS30	0-1000 µg/m^3(±10)	10 - 40
O_3	EC -Alphasense O_X-B431	1-20 ppm (±2)	-30 - 40
NO	EC Alphasense B4	2-20 ppm (±2)	-30 - 40
NO_2	EC Alphasense B43F	2-20 ppm (±2)	-30 - 40
CO	EC Alphasense B4	2-1000 ppm (±2)	-30 - 50
VOC(Planned)	PID -AMETEK MOCON – Blue	0.5 ppb - 2 ppm	-20 - 60

Regarding the measurement of O_3, it should be mentioned that EC (Alphasense) employs both an oxidant sensor (O_X-B431) for the total of O_3+NO_2 and a single NO_2 sensor (B43F) at the same time to quantify the levels of O_3. The NO_2-B43F sensor excludes the O_3 by a MnO_2 strainer (conversion of ozone to oxygen) and thus the value of O_3 can be calculated by Equation 1 as follows:

$$O_3 = OX_{B431} - NO_{2_{B43F}} \qquad (1)$$

Statistical analysis

Data treatment is performed in MATLAB software. Firstly, the input of 85280 data logs were averaged by a time interval of 30 minutes (1423 half an hourly averages points per contaminant for each device) since the reference (ISSeP) data had been recorded in the form of a half hourly mean. In the next step, 1423 input values of each test contaminant were divided randomly into 1138 (80%) and 285 (20%) pairs for calibration and validation datasets, respectively.

The K–S test (Kolmogorov–Smirnov examination) disapproved the hypothesis of normal distribution. Due to synchronized real-time measurement process, a monotonic relationship is observed. Since Spearman's correlation (r_s) measures the strength and direction of monotonic association between variables, it was used to define the correlation between variables of paired OCTs.

When examining whether samples originate from the same distribution, the nonparametric Kruskal–Wallis approach is applied. Hence, for comparison of the four IAQ devices, the Kruskal–Wallis test by ranks was performed to detect if there were statistically meaningful differences among them. In the next step, field calibration formulations were determined with an orthogonal regression analysis (Späth 2014) with the ISSeP reference data. The validation dataset is used in order to assess the correctness of the sensors outputs after applying calibration equation. The obtained values after applying the calibration improvement are compared with the reference analysers by the Bland–Altman method (validation stage). The Bland-Altman technique (mean-difference and limits of agreement (LOA) plot) is applied to evaluate the difference between two measurements within 95% LOA from the mean difference (1.96 of the standard deviation (SD) (Falzone et al. 2020; Moreno-Rangel et al. 2018).

RESULTS

CO. The data of the four OCT devices were compared to those from the reference analyzers from ISSeP. The data analysis presented that the CO measurements were highly correlated ($r_s = 0.73\ to\ 0.8,\ p < 0.001$). As it is shown in Figure 2 (a), it was revealed that OCTs averagely underestimated CO concentration (average (avg) $= -0.016$, 95% confidence interval from 0.05 to -0.01 mg/m^3). Information of variability between OCTs is essential for the practical reliability of devices. Examination of the CO data from OCT devices presented a very high uniformity ($r_s = 0.96\ to\ 0.98,\ p < 0.001$) and low variability of (avg $= 0.004$ mg/m^3, from 0.003 to 0.005 mg/m^3) among the CO measurements.

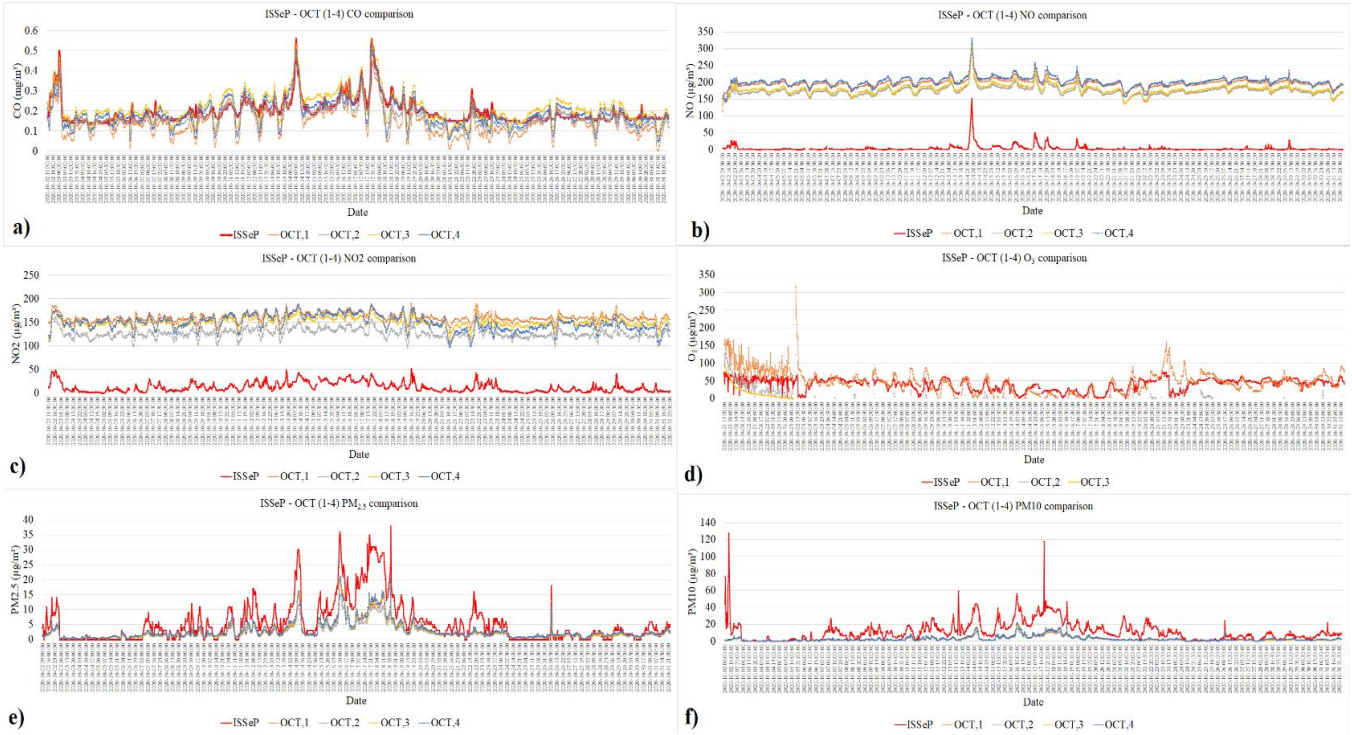

Figure 2 Measurment results of OCT device and ISSeP: (a) CO (b) NO (c) NO_2 (d) O_3 (e) $PM_{2.5}$ (f) PM_{10}

Figure 3 (a) illustrates the relationship between the CO levels of ISSeP and OCT calibrated dataset by the apply of best Orthogonal regression model. The best fit results in a R^2 of 0.79 and the CO equation generated by regression is:

$$CO(ISSeP) = 0.033 + 0.963\ CO(OCT) \qquad (6)$$

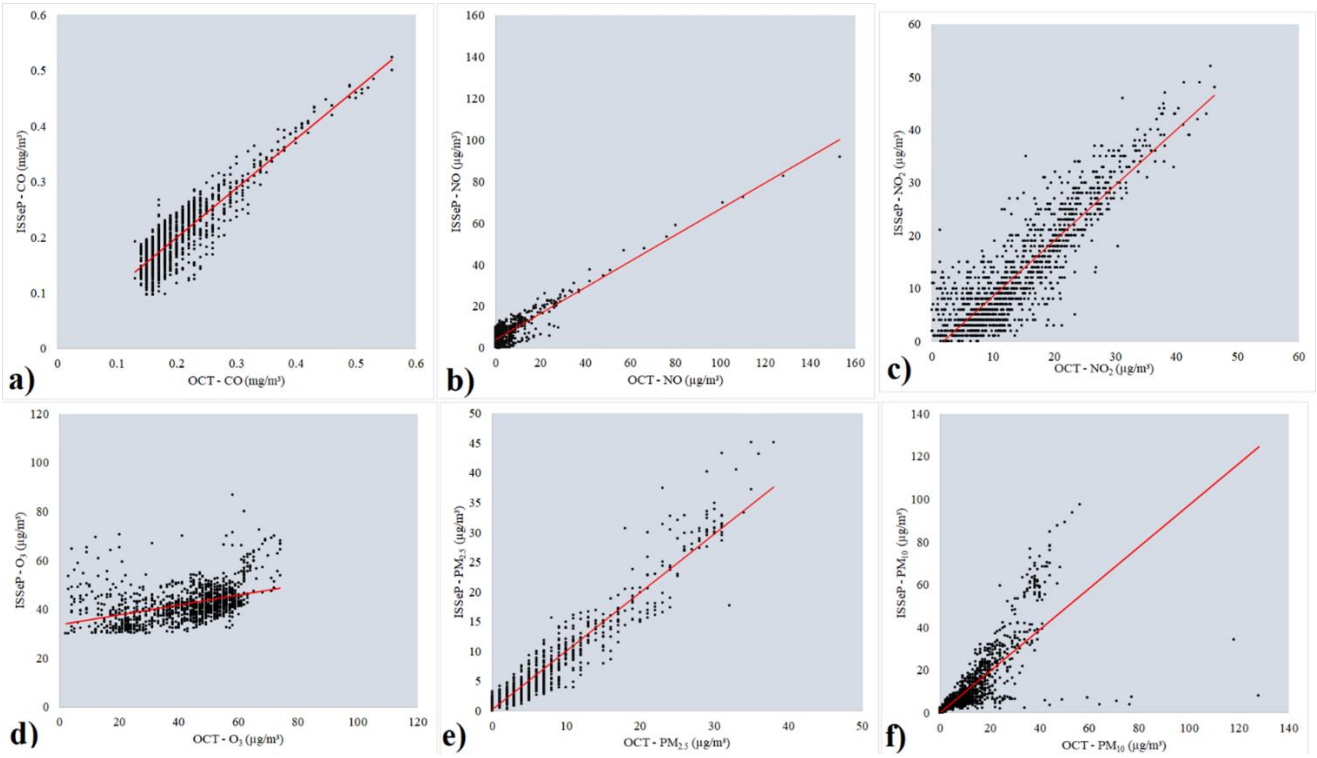

Figure 3 Comparision of calibrated OCT data with the ISSeP, for: (a) CO (b) NO (c) NO_2 (d) O_3 (e) $PM_{2.5}$ (f) PM_{10}

Figure 4 (a) also presents the Bland–Altman analysis for the comparison of four calibrated sensor devices with the reference analiser after applying the calibration modification in the validation stage. It presents the mean difference between the ISSeP and the OCT CO calculated measurements (-2.34E-10 mg/m^3 with the LOA of –0.055 to 0.055 mg/m^3 at a 95% confidence interval). The number of 48 points (3.5 %) of the dataset were beyond of the LOA (42 higher than the upper LOA and 6 less than the lower LOA).

This range is meaningfully far below the European Commission (EC) Exposure Limit Values (ELVs) for CO which is about 10 mg/m^3 (Maximum daily, 8-hour mean, 2005).

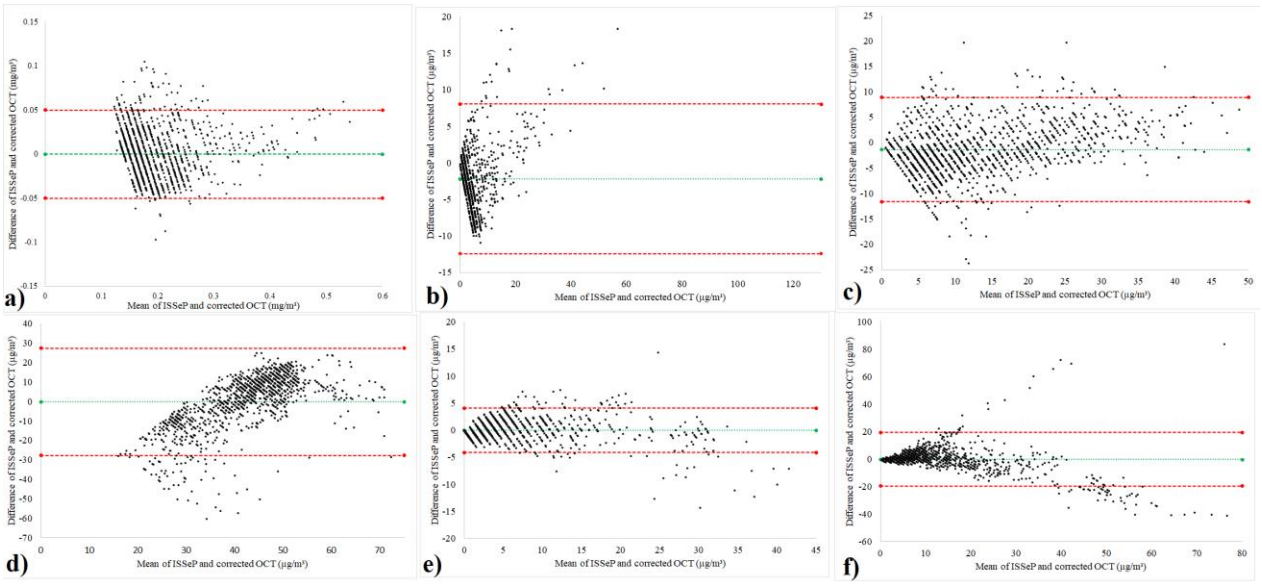

Figure 4 Bland–Altman plot for validation datasets: (a) CO (b) NO (c) NO_2 (d) O_3 (e) $PM_{2.5}$ (f) PM_{10}

NO. The data analysis presented that the NO measurements were weakly correlated ($r_s = 0.3\ to\ 0.39,\ p < 0.001$) by the four OCT and the ISSeP monitors. As it is shown in Figure 2 (b) a shift of the values was detected between OCT and ISSeP measurements, as long as the OCT overestimated the NO levels by average of 185.47 μg/m³, from 171.17 to 199.42 μg/m³. Investigation of the four OCTs revealed a very high uniformity ($r_s = 0.96\ to\ 0.98,\ p < 0.001$) and high difference regarding (avg $= 195.51\ \mu g/m^3$, from 157.16 to 229.55 μg/m³) of the NO reference data. Figure 3 (b) illustrates the relationship between the ISSeP and OCT calibrated NO levels determined by the Orthogonal regression model. The best fit results in a R^2 of 0.75 and the NO regression output modeled is:

$$NO(ISSeP) = 0.033 + 0.963\ NO(OCT) \quad (7)$$

Figure 4 (b) depicts the Bland–Altman analysis for the ISSeP NO measurements by the corresponding best fit determined by the Orthogonal regression for the validation dataset from the four OCT measurement devices. It presents the mean difference between the ISSeP and the OCT NO calculated measurements (-2.19 μg/m³ with the LOA of -12.14 to 8.03 μg/m³ at a 95% confidence interval). The number of 28 points (2.8 %) of the dataset were beyond of the LOA (28 higher than the upper LOA).

NO_2. The statistical analysis showed that the NO_2 measurements from the four OCT devices and the ISSeP NO_2 showed a good correlation ($r_s = 0.706\ to\ 0.824,\ p < 0.001$). As it is depicted in Figure 2 (c) very high variability was detected between OCT and ISSeP measurements, as long as the OCT overestimated the NO_2 levels by average of 134.66 μg/m³, from 114.57 to 149.21 μg/m³. Study of four OCT devices presented a very high uniformity ($r_s = 0.9\ to\ 0.96,\ p < 0.001$) and high variance (avg $= 138.21\mu g/m^3$, from 88.67 to 247.28 μg/m³) between the different NO_2 sensors. Figure 3 (c) illustrates the relationship between the ISSeP and OCT calibrated NO_2 levels by the Orthogonal regression model. The best fit results in a R^2 of 0.78 and the NO_2 regression equation is:

$$NO_2(ISSeP) = -172.41 + 1.14\ NO_2(OCT) \quad (8)$$

Where NO_2 is the concentration (μg/m³). Figure 4 (c) depicts the Bland–Altman analysis for the ISSeP NO_2 measurements by the corresponding best fit determined by the Orthogonal regression for the validation dataset from the four OCT measurement devices. It presents the mean difference between the ISSeP and the OCT NO_2 calculated measurements (-1.39 μg/m³ with the LOA of -11.64 to 8.85 μg/m³ at a 95% confidence interval). The number of 75 points (5.7 %) of the dataset were beyond of the LOA (40 higher than the upper LOA and 35 less than the lower LOA). This range is much less than the EC defined ELV for NO_2 equal to 200 μg/m³ (1-hour mean, 2010).

O_3. Investigation of the O_3 measurement by the OCT devices and the ISSeP reference data revealed that the OCT O_3 concentrations varied from those of ISSeP. Figure 2 (d) presents a low correlation ($r_s = 0.22\ to\ 0.67,\ p < 0.001$) was identified. The OCTs overrated the O_3 levels (avg $= 1.9\mu g/m^3$, from -3.2 to 7.8 μg/m³). Investigation of the four OCT datasets presented a low but notable uniformity ($r_s = -0.18\ to\ 0.9,\ p < 001$) and a moderate variance (avg $= 27.41\ \mu g/m^3$, from 21.39 to 31.28 μg/m³) between the O_3 measurements. Figure 3 (d) illustrates the relationship between the ISSeP and OCT calibrated O_3 levels from the Orthogonal regression model. The best fit results in a R^2 of 0.16 and the regression formulation of O_3 is:

$$O_3(ISSeP) = 30.0328 + 0.23866\ O_3(OCT) \quad (9)$$

Where O_3 is the concentration (μg/m³). Figure 4 (d) depicts the Bland–Altman analysis for the ISSeP O_3 measurements by the corresponding best fit determined by the Orthogonal regression for the validation dataset from the four OCT measurement devices. It presents the mean difference between the ISSeP and the OCT O_3 calculated measurements (-0.188 μg/m³ with the LOA of -27.78 to 27.4 μg/m³ at a 95% confidence interval). The number of 65 points (5.2 %) of the dataset were beyond of the LOA (65 less than the lower LOA). This range is remarkably less than the defined EC ELV for O_3 equal to 120 μg/m³ (Maximum daily, 8-hour mean, 2010).

PM2.5. The measurements of particulate matters from the four OCT devices and the ISSeP reference analyzers were very highly correlated ($r_s = 0.93\ to\ 0.95,\ p < 0.001$) to each other. As it is shown by Figure 2 (e) the OCT underestimate $PM_{2.5}$ values (avg $= -3.2\ \mu g/m^3$, from -2.76 to -2.47 µg/m³). The examination of the four OCT monitors revealed a very high uniformity ($r_s = 0.99,\ p < 001$) and a small variance (avg $= 8.19 \mu g/m^3$, from 8.43 to 9.64 µg/m³) among $PM_{2.5}$ measurements. Figure 3 (e) illustrates the relationship between the ISSeP and OCT calibrated $PM_{2.5}$ levels from the Orthogonal regression model. The best fit results in a R^2 of 0.91 and the $PM_{2.5}$ regression equation is:

$$PM_{2.5}(ISSeP) = -1.57 + 3.08\ PM_{2.5}(OCT) \quad (10)$$

Where $PM_{2.5}$ is the concentration (µg/m³). Figure 4 (e) depicts the Bland–Altman analysis for the ISSeP $PM_{2.5}$ measurements by the corresponding best fit determined by the Orthogonal regression for the validation dataset from the four OCT measurement devices. It presents the mean difference between the ISSeP and the OCT $PM_{2.5}$ calculated measurements (-0.017 µg/m³ with the LOA of -4.1 to 4.07 µg/m³ at a 95% confidence interval). The number of 69 points (5.3 %) of the dataset were beyond of the LOA (40 higher than the upper LOA 29 less than the lower LOA). This range is much less than the defined EC ELV for $PM_{2.5}$ which is 25 µg/m³ (yearly, 2010).

PM_{10}. It should be mentioned that the sensor does not measure PM10 but a correction factor is applied by the producer on the PM2.5 measurements.

The statistical analysis showed that the PM_{10} measurements from the four OCT monitors and the ISSeP were highly correlated ($r_s = 0.86\ to\ 0.88,\ p < 0.001$) to each other. As it is depicted by Figure 2 (f) the analysis of the measurements showed that the OCT underestimated PM_{10} concentrations (avg $= -8.63\ \mu g/m^3$, from -9.09 to -8.33 µg/m³). The study of four OCT datasets presented that there was a very high uniformity ($r_s = 0.99,\ p < 001$) and a small variance (avg $= 2.87\ \mu g/m^3$, from 2.33 to 3.12 µg/m³) between the different PM_{10} sensors. Figure 3 (f) illustrates the relationship between the ISSeP and OCT calibrated PM_{10} levels by the Orthogonal regression model. The best fit results in a R^2 of 0.57 and the regression model of PM_{10} is:

$$PM_{10}(ISSeP) = -2.12 + 4.77\ PM_{10}(OCT) \quad (11)$$

Where PM_{10} is the concentration (µg/m³). Figure 4 (f) depicts the Bland–Altman analysis for the ISSeP PM_{10} measurements by the corresponding best fit determined by the Orthogonal regression for the validation dataset from the four OCT measurement devices. It presents the mean difference between the ISSeP and the OCT $PM_{2.5}$ calculated measurements (-0.06 µg/m³ with the LOA of -19.63 to 19.5 µg/m³ at a 95% confidence interval). The number of 69 points (5.3 %) of the dataset were out of the LOA (51 higher than the upper LOA 18 less than the lower LOA).

This range is almost equal to the EC ELV for PM_{10} which is 50 µg/m³ (24 hours, 2005). The number of data points on which the PM_{10} levels surpassed the 50 µg/m³ is about an average of 0.38%. At last, the correlation between the calibration and validation datasets were favorably accredited. Both presented a sufficient agreement on the PM_{10} levels higher than 50 µg/m³.

DISCUSSION

In this very first step, the accuracy of lab-made devices for measurement of pollutants (CO, NO, NO_2, O_3, $PM_{2.5}$, PM_{10}) during a side-by-side performance evaluation by comparison with reference analyzers is investigated. Calibration was not performed in the lab by using synthetic gases but by comparison with reference analyzers (from Scientific Institute of Public Service of Wallonia, ISSeP). To achieve best results, specific calibration equations should be derived for each device. The validation outcomes presented that there was correct agreement between the reference analyzer data and those of the OCT devices for some pollutants, after applying correction of the sensor outputs by using the regression equations. However, the O_3 sensors (Alphasense O_X-B431) were not as precise as expected even after correction with the calibration equation. It is probably related to the way these sensors work. In order to enhance the quality of O_3 measurement, the zero offset, the sensitivity (nA/ppm) and temperature dependence of the NO_2 sensors (B43F) and the O_3 one (B431) have to be checked in laboratory before usage.

After correction thanks to the calibration, the OCT devices presented a very good agreement with the ISSeP analyzers, for CO ($r_s = 0.73\ to\ 0.8$), NO_2 ($r_s = 0.70$ to-0.82), $PM_{2.5}$ ($r_s = 0.93\ to\ 0.95$) and PM_{10} ($r_s = 0.86\ to\ 0.88$) data. The NO concentration was overestimated by an average of 185.47 µg/m³. The generated regression fits for CO, NO, NO_2 and $PM_{2.5}$ decreased the variance among the measurements sufficiently and enhanced their performances in comparison with ISSeP which led to R^2 values equal to 0.79, 0.75, 0.78 and 0.91, respectively. The absence of an exact O_3 detector resulted in wrong results. Nevertheless, outcomes indicated that it has not influenced the performance of the other detectors. Thus, OCTs can be utilized in future research experiments and free running ventilation indoor environments. The results revealed that OCT devices based on LCSs, can detect ELV exceedance by high contaminant peaks. It is noteworthy to be mentioned that Wi-Fi communication with a physical as well as a cloud storage, make the OCT a user-friendly gadget to assess the IAQ in wider temporal and spatial dimension, in comparison with commonly used methods. Implementation of several devices in a measurement campaign and applying calibration modifications increase the accuracy and precision of the measurements.

According the OCT calibration results, it was revealed that less than 5% of the CO, NO, NO_2, O_3, $PM_{2.5}$ and PM_{10} values were beyond the LOA range when the range was set to ±1.96 SD of the difference. Variability of the fraction of concentrations higher than ELVs was mostly insignificant and was considered to be improbable to make drastic alteration in the IAQ evaluation.

CONCLUSION

The results indicated that the OCTs could provide appropriately results for IAQ study in residential buildings. It is important to experimentally evaluate the accuracy of LCS to study their reliability and correctness. The OCT monitoring devices based on LCSs, will provide extensive indoor air data for inhabitants which ensure the adoption of correct strategies to deal with bad IAQ. Furthermore, the effects of occupant's behaviour on IAQ and the efficiency of natural (free running) or mechanical ventilation can be determined. Thus, OCTs can be utilized in future research experiments and free running ventilation indoor environments. The results revealed that OCT devices based on LCSs, can detect ELV exceedance by high contaminant peacks. It is noteworthy to be mentioned that Wi-Fi communication with a physical as well as a cloud storage, make the OCT a user-friendly tool to assess the IAQ in wider temporal and spatial dimension, in comparison with classical methods. Implementation of several devices in a performance evaluation and applying calibration modifications increase the accuracy and precision of the measurements.

Thanks to these results, an indoor air measurement campaign is now organized in residential buildings (both naturally ventilated and mechanical ones), simultaneously with outdoor air measurement. Heat events and proxy data linked to climate change (CC) are considered to establish some relations between IAQ and CC. This measurement campagin will be presented in a following paper. The information provided in this study can support the basics of research on how climate change affects the IAQ in residential buildings by considering outdoor environmental data in future studies

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REFERENCES

Abraham, S., & Li, X. 2014. A cost-effective wireless sensor network system for indoor air quality monitoring applications. *Procedia Computer Science*, *3*4:165-171.

Chojer, H., Branco, P. T. B. S., Martins, F. G., Alvim-Ferraz, M. C. M., & Sousa, S. I. V. 2020. Development of low-cost indoor air quality monitoring devices: Recent advancements. *Science of The Total Environment*, 12:138385.

Demanega, I., Mujan, I., Singer, B. C., Anđelković, A. S., Babich, F., & Licina, D. 2021. Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. *Building and Environment*, 187:107415.

Falzone, C., Romain, A. C., Broun, V., & Gérard, G. 2020. PM2. 5 low-cost sensor perfomance in ambient conditions. *New perspectives in Environmental Information Systems: Transport, Sensors, Recycling*, 129-138.

González-Martín, J., Kraakman, N., Pérez, C., Lebrero, R., & Muñoz, R. 2020. A state-of-the-art review on indoor air pollution and strategies for indoor air pollution control. *Chemosphere*, 128376.

Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer, P., ... & Engelmann, W. H. 2001. The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *Journal of Exposure Science & Environmental Epidemiology*, 11: 231-252.

Kumar, A., Singh, I. P., & Sud, S. K. 2011. Energy efficient and low-cost indoor environment monitoring system based on the IEEE 1451 standard. *IEEE Sensors Journal*, 11:2598-2610.

Lenartz, F., Dury, M., Bergmans, B., Hutsemékers, V., Broun, V., Brose, C., & Guichaux, S. Antilope, a portable low-cost sensor system for the assessment of indoor and outdoor air pollution exposure. *Frontiers in Sensors*, 10.

Liu, M., Barkjohn, K. K., Norris, C., Schauer, J. J., Zhang, J., Zhang, Y., ... & Bergin, M. 2020. Using low-cost sensors to monitor indoor, outdoor, and personal ozone concentrations in Beijing, China. *Environmental Science: Processes & Impacts*, *22*:131-143.

Ma, N., Aviv, D., Guo, H., & Braham, W. W. 2021. Measuring the right factors: A review of variables and models for thermal comfort and indoor air quality. *Renewable and Sustainable Energy Reviews*, 135:110436.

Monn, C. 2001. Exposure assessment of air pollutants: a review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended particulate matter, nitrogen dioxide and ozone. *Atmospheric environment*, 35:1-32.

Moreno-Rangel, A., Sharpe, T., Musau, F., & McGill, G. 2018. Field evaluation of a low-cost indoor air quality monitor to quantify exposure to pollutants in residential environments. *Journal of Sensors and Sensor Systems*, *7*:373-388.

Nazaroff, W. W. 2013. Exploring the consequences of climate change for indoor air quality. Environmental Research Letters, 8:015022.

OCCUPANT Project, 2020, http://www.occupant.uliege.be/ , Accessed April 2021.

Späth, H. 2014. Mathematical algorithms for linear regression. Academic Press, 260-298.

Tsakas, M. P., Siskos, A. P., & Siskos, P. A. 2011. Indoor air pollutants and the impact on human health. Chemistry, Emission Control, Radioactive Pollution and Indoor Air Quality, 447-484.

World Health Organization (WHO), https://www.who.int/news-room/air-pollution, Accessed April 2021.