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A study on the performance of metal oxide semiconductor (MOS) sensors for VOC measurement in residential setting

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ABSTRACT

This study investigated the performance of Metal Oxide Semiconductor (MOS) sensors for measuring Volatile Organic Compounds (VOC) in a residential environment. Previous research indicates that MOS VOC sensors can detect pollution events, making them potentially suitable for ventilation control. Our objective was to examine several MOS VOC sensors and determine their properties-sensitivity and hysteresis. We evaluated the cross-correlation among the sensors. We measured in a row house occupied by a family of four. We used a Photo Ionization Detector as a reference measurement. The tested sensors differed significantly in their sensitivity, meaning that they would not be directly interchangeable when used to control of mechanical ventilation airflow. The investigated sensors had small hysteresis, which is preferable. The cross-correlation between the CO_2 equivalent MOS VOC signal provided by one of the sensors and CO_2 measurements was weak, suggesting that the CO_2 equivalent cannot substitute the CO_2 signal. The results show that in ventilation control, a MOS VOC sensor can be utilized for detection of sudden VOC emissions related to human activities steering the airflow-boost signals. The control strategy must be adjusted according to the characteristics of the output signal provided by concrete sensor used.

HIGHLIGHTS

- The tested MOS VOC sensors differed in sensitivity. They are not directly interchangeable when used to control of mechanical ventilation airflow.
- The CO_2 equivalent signal had a weak correlation to actual CO_2 levels. CO_2 equivalent signal should not be used as surrogate for CO_2 concentration.
- Applying MOS VOC sensors for ventilation control requires individual adjustment of the control strategy.

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Residential ventilation; volatile organic compounds; metal oxide semiconductor; indoor air quality; cross-correlation function

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1. Introduction

Today's energy efficient buildings are airtight and need efficient ventilation to maintain high indoor air quality (IAQ). Smart ventilation (Durier et al., 2018) allows for continuous adjustment of ventilation airflow in time, and optionally by location, to provide the desired IAQ while minimizing energy consumption. Smart ventilation is slowly but steadily finding its way into new or renovated houses across Europe, the USA, and beyond. It is mostly the specific sub-type of smart ventilation, so-called Demand Controlled Ventilation (DCV) (Guyot et al., 2018), which is becoming increasingly popular even in the residential sector, where we would not expect it to be applied some decades ago. This is primarily due to technological advances in building control (digital and internet-enabled controllers, fans with continuous control of rotation speed) and IAQ sensing. Metal Oxide Semiconductor (MOS) sensors for measuring VOC represent such sensors (Herberger & Ulmer, 2012; Schütze et al., 2017). They offer the possibility to account for VOC emissions related to human presence, activities and other VOC sources that worsen IAQ. When used in DCV system, these sensors can ensure increased outdoor air supply rate during house-cleaning, cooking, etc. This represents a clear advantage in comparison to controlling DCV solely according to presence detection or CO_2 concentration.

These arguments support MOS VOC sensor technology, and ventilation manufacturers currently offer VOC-controlled DCV for residential applications. At the same time, some studies, like Won and Schleibinger (2011), describe the drawbacks. They mention a cross-sensitivity to moisture, low resolution, and inability to measure the concentration of individual chemicals. Generally, there is a large body of literature on MOS VOC sensors. We point the reader to the work of Chojer et al. (2020) and Ródenas García et al. (2022) for detailed information. However, the studies evaluating the field performance of MOS VOC are not that frequent. In laboratory conditions, Demanega et al. (2021) extensively evaluated low-cost environmental monitors, including MOS VOC sensors. They observed a strong correlation of sensor signals with the reference instruments (GrayWolf AdvancedSense Pro for TVOC) but a poor agreement concerning absolute values of VOC concentrations. Kolarik et al. (2023) applied cluster analysis to compare the behaviour of five commercially available MOS VOC sensors. The majority of the sensors responded in agreement with the reference measurements (Proton-Transfer-Reaction–Time-of-Flight Mass Spectrometer- PTR-ToF-MS). The cluster analysis revealed that the sensors from different manufacturers might react to various pollutants, and thus, their behaviour may alter depending on the pollutants emitted in the space. Moreno-Rangel et al. (2018) assessed a low-cost IAQ monitor's precision, accuracy, and usability in a residential environment (a bedroom). They observed a significant correlation with the reference instruments (GrayWolf IQ-410, TG-502 TVOC, and PC-3016A) regarding temperature, relative humidity, total volatile organic compounds (TVOC), and particulate matter ($PM_{2.5}$) data. However, the IAQ monitor underestimated temperature in average by 2.59 °C, relative humidity by 0.01% and TVOC by 22.12 ppb. $PM_{2.5}$ concentrations were overestimated by 1.4826 $\mu g\,m^{-3}$ in average. A study by Baur et al. (2021) investigated the potential and limits of MOS VOC sensors and applied calibration with randomized exposure and data-based models trained with advanced machine learning. The study included both laboratory calibration and field testing. In addition to monitoring normal ambient air, the authors conducted release tests with VOCs that were included in the laboratory calibration. Extensive laboratory-grade measurements were performed in parallel. The authors found a quantitative agreement between reference measurements (PID, thermo-desorption gas chromatography-mass spectrometry- TD-GC-MS and reducing compound photometer-GC-RCP) and the MOS VOC sensors. Sørensen and Kristensen (2024) applied low-cost sensors, including MOS VOC, to investigate concentrations of CO_2 and VOC in classrooms. The study demonstrated that low-cost sensors were useful for uncovering general trends regarding VOC dynamics.

As MOS VOC sensors find their way to ventilation control, there are attempts to use them as direct replacement of CO_2 sensors. Herberger et al. (2010) developed a sensor that uses data collected by Burdack-Freitag et al. (2009) correlating the measured VOC signal with human emission of CO_2. Consequently, the sensor concerts its output to the so-called CO_2 equivalent concentration. As CO_2 concentration became known to the public as an indicator of IAQ, the intention was that the building occupants would be able to interpret sensor signals more easily. There are few studies dealing with MOS VOC sensors ability to replace CO_2 sensors. Kolarik (2014) observed an agreement in the need for increased ventilation expressed consistently by VOC and CO_2 sensors during 49% of occupied time. During 11% of occupied time, only the VOC sensor indicated the need for increased ventilation. The study noted that replacing CO_2 with VOC sensors would lead to a significantly longer time with high airflow. Also, De Sutter et al. (2017) illustrated challenges related to the direct replacement of CO_2 sensors with VOC sensors. The results showed a notable increase in ventilation rates. These were associated with sharp peaks in the MOS VOC signals while the same set point was used for CO_2 and VOC control. The authors suggested a correction algorithm that would filter the VOC signal, but they did not demonstrate its application. Moreno-Rangel et al. (2018) showed that the CO_2 equivalent signal from the MOS VOC IAQ monitor was provided misleading CO_2 levels as indicators of ventilation. The CO_2 concentrations were underestimated by 147.08 ppm in average.

The present paper's objective was to examine several commercially available MOS VOC sensors during operation in a realistic residential environment and determine their properties—sensitivity, linearity, and hysteresis- by comparing their signal with a reference measurement. The additional objective was to determine whether the signals from the sensors correlated with each other. Based on these results, the paper aimed to discuss the sensors' behaviour, when used for control of outdoor ventilation rates in residential mechanical ventilation systems.

2. Methods

2.1. Investigated sensors, the test house and measurement period

A MOS VOC sensor detects volatile organic compounds by measuring changes in the electrical resistance of a metal-oxide layer when exposed to gaseous contaminants. Table 1 summarizes the technical parameters of tested sensors. We investigated three

Table 1. Technical parameters of investigated sensors based on manufacturer data sheets (Appendix A lists the commercial names of the sensors and their manufacturers).

Abbreviation	A	B	C
Output (units)	VOC index [–][a]	Voltage [V]	$TVOC_{MOS}$ eq. [ppb][b] CO_2 eq. [ppm]
Sensing range	0–500 VOC index points; 0–1000 ppm ethanol equivalents	0–3.0 V DC; 1–30 ppm H_2	0–29,206 ppb $TVOC_{MOS}$ eq. 400–32,768 ppm CO_2 eq.
Measuring accuracy	± 15 VOC index points	N/A	N/A
Measurement interval/ response time	N/A/ $<$ 10 s	N/A	N/A
Power Supply	1.7–3.6 V DC	4.9–5.1 V DC	1.8–3.6 V DC
Communication	I^2C bus	0–3.0 V DC	I^2C bus
Warm-up time	N/A	N/A	20 min
Operation temperature range	−20 °C–55 °C	−10 °C–50 °C	−40 °C–85 °C
Operation humidity range	0%–80%, non-condensing	NA	10%–95%, non-condensing

[a]A built-in proprietary algorithm processes a raw sensor signal to obtain the VOC Index. The sensor manufacturer states the following: VOC Index visualizes VOC events on a logarithmic scale and relative to typical indoor gas composition during the recent 24 h. This means that level 'typical' refers to the typical conditions of the environment. The scale does not represent absolute concentrations.

[b]The sensor processes the raw signal into a VOC sum $TVOC_{MOS}$ and CO_2 equivalents. According to Salthammer (2022), the TVOC measured by MOS VOC sensors is not yet established in the literature. However, as the manufacturer calls the signal TVOC, we decided to use the abbreviation $TVOC_{MOS}$ for this paper. The algorithm for CO_2 equivalents is proprietary; the manufacturer states that CO_2 equivalents are determined based on the relationship between human production of VOC (bioeffluents) and CO_2.

different sensors from established manufacturers. When choosing the sensors, we have used our experience from a previous national project (Kolarik et al., 2018), where we studied MOS VOC sensors' response to pollution events simulated in a laboratory. That work showed challenges related to different types of output signals as well as absolute signal offset. Our current choice was driven by the intention to test sensors offering different ways to interpret the output—processed signal in a form of so called 'VOC index', analogue sensor signal and signal representing CO_2 equivalents. We purchased two specimens of each sensor and created two measuring sets. We integrated the sensors into one casing with a combined power supply. Arduino board with Wi-Fi module ensured wireless transfer of the measured data into a laptop equipped with the Lab View software connected to the same wireless network. We set the data logging interval to 1 min.

We used a portable photoionization gas detector (PID), Photo Check TIGER, for reference measurements. PID uses high-energy UV light to ionize VOC molecules and measures the resulting current. As the technology does not allow for selective measurements of particular VOCs, we abbreviate the signal provided by the instrument as $TVOC_{PID}$. TVOC is commonly used as a sum parameter in indoor air sciences; however, there exist several definitions of TVOC. We adopted the Salthammer (2022) approach, which indicated that the PID instrument measured the sum of VOC. The PID instrument was equipped with a 10.6 eV (eV - electronvolt) lamp, suitable for IAQ applications detecting compounds like Benzene, Toluene, Xylene, Formaldehyde, Acetone, Acetaldehyde, or Limonene. Before the measurements, we performed a custom calibration of the PID gas detector with 100 ppm of isobutylene (zeroing on zero gas mixture). The $TVOC_{PID}$ concentrations thus represented isobutylene equivalents. The

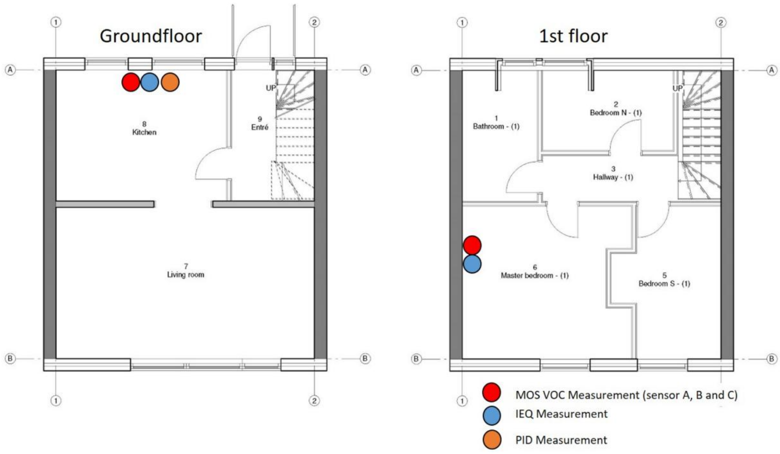

Figure 1. Placement of the sensors.

instrument had a detectable range of 1 ppb-20,000 ppm (minimum resolution 1 ppb or 0.001 mg/m^3 isobutylene at 20 °C and 1000 mbar) and accuracy ± 5% of a display reading. We did not use the PID measurements to describe the IAQ in the house. It served as a reference for evaluating the tested MOS VOC sensors.

Besides the MOS VOC signals, we also monitored standard indoor environmental quality (IEQ) parameters: room temperature (±0.3 °C 5–60 °C), relative humidity (±2% RH 20%–80% RH), and CO_2 concentration (non-dispersive infrared-NDIR, 400–2000 ppm, ±30 ppm ±3% of reading). We used internet-connected commercial indoor climate monitors providing measurements in 5-min intervals. In comparing MOS VOC signals and the IEQ variables, we averaged the 1-min MOS VOC data into 5-min intervals.

We have installed the sensor sets in a Danish row house occupied by a family of two adults and two children (elementary school age). We placed the sensor sets in two locations- a kitchen/dining room open to a living room and the main bedroom (Figure 1). Our intention was to measure continuously with MOS VOC sensors as well as with the PID monitor for about one year (September 2021—September 2022). However, as the measurements were conducted in a house occupied by real family, there were difficulties regarding the PID measurements. The continuously running PID instrument was relatively noisy, which disturbed the occupants of the house, so it was neither possible to measure during the whole period, nor measure in the bedroom. Moreover, some PID measurements were useless because the instrument was moved, exposed to strong source of VOC in proximity etc. During the initial screening of the measured data, we identified two usable periods. These periods were September-November 2021 and February-March 2022. As the we proceeded with the analysis, we identified suitable subsets of the aforementioned periods. For example, a two-week period with and without occupancy in the house. These subsets were used for the final analysis presented in the paper. The reader is referred to Table 2 for further details.

Table 2. Overview of the measurement periods used for the analysis.

Chapter	Analysis	Measurement period	Description
3.1	Visual assessment of sensor signals, cross-plots	17.10.2021 – 31.10.2021	Two-week period comprising house with occupancy as well as empty house. Data for kitchen.
3.2	Determination of characteristic curves	7.3.2022 – 12.3.2022	Period with simultaneous measurements of MOS VOC and PID. Data for kitchen.
3.3	Determination of sensor hysteresis	11.3.2022	This day was selected because occupants performed house-cleaning. Therefore, the data included distinct build-ups and decays due to emissions from cleaning detergents etc. Data for kitchen.
3.4	Cross-correlation analysis	17.10.2021 – 31.10.2021	Two-week period comprising house with occupancy as well as empty house. Data for kitchen.
3.5	Relation between CO_2 and CO_2-equivalent signal	17.10.2021 – 31.10.2021 7.3.2022 – 12.3.2022	Both periods used for previous analyses were included. Data from bedroom and kitchen.

2.2. Data processing

2.2.1. Data normalization

As each studied sensor provided a different output signal, we normalized these signals to avoid the influence of the absolute value of each observation. Each observation was normalized against the difference of its maximum value and minimum value, as shown in Equation (1):

$$y = (x - \min(x))/(\max(x) - \min(x)) \tag{1}$$

Where x is the i-th observation in the measured data and y is the i-th normalized observation for the sensor signal. Normalization was conducted separately for each of the analysed periods. We used only the normalized data in our analyses.

2.2.2. Determination of characteristic curves

A so-called characteristic curve describes sensor's properties. Fahlen et al. (1992) determined characteristic curves by exposing sensors to a set of steady-state concentrations of a known VOC in ascending and descending order. It is thus a relationship between a known reference signal and the signal from an evaluated sensor. In the present paper, we further developed their approach using continuous data measured in the field, rather than steady-state concentrations from laboratory. We established characteristic curve by fitting the linear regression model to the data with PID measurements as independent and MOS VOC data as dependent variables. Thus, the slope of the relationship represented the sensor's sensitivity. The R^2 value for the linear model indicated the linearity of the sensor. As the character of the signal response was not known for all tested sensors, we decided to use only linear fit to demonstrate the approach. When evaluating sensors with other types of response (logarithmic, exponential, power law) the appropriate form of the characteristic curve can be fitted. We deal with this issue in more detail in Section 4.2.

2.2.3. Determination of hysteresis

To evaluate hysteresis, we selected one-day measurements from the data. We fitted a linear regression model to build-up and decay periods separately. Consequently, we expressed the hysteresis as a mean distance from the two regression lines. We used the obtained linear models to determine such distance to predict the MOS VOC signal for three distinct reference signal levels (150, 250, and 350 ppb isobutylene equivalent). The mean difference between such predictions for build-up and decay determined the hysteresis.

2.2.4. Correlation analysis, CO_2 equivalent signal and the CO_2 measurements (sensor C)

We applied Justo Alonso et al. (2022) approach to determine a correlation among the signals from tested MOS VOC sensors and a correlation between the CO_2 equivalent signal provided by sensor C and the absolute CO_2 measurements by the NDIR sensor. We used a cross-correlation function (CCF) to calculate a correlation between two time series (sensor measurements), considering different time lags (Madsen, 2007). As the time series are inherently auto-correlated, using Pearson's coefficient to determine their correlation is inappropriate. Justo Alonso et al. (2022) showed that the pre-whitening process removes the auto-correlation and separates the actual correlation between time series. Following the procedure described in detail by Justo Alonso et al. (2022), we applied the Autoregressive Integrated Moving-Average Model (ARIMA) to remove the trend in one of the investigated time series. This would describe the time series without auto-correlation (up to white noise residuals). Consequently, we applied such a model to the second time series and calculated CCF for the residuals of the first time series. Finally, we determined the values of the second time series transformed using the AIRMA model. The result of such analysis is the CCF plot depicting the correlation between the studied time series in the time lags. Time lag resolution is corresponding to one 'time unit', matching the sampling frequency of the original time series, therefore it is 1 min in our data. Pearson's coefficient in the particular time lag represents the correlation. Correlation in time lag 0 indicates that the studied variables change simultaneously. The correlation in higher time lags suggests that the change of the first variable precedes the change of the second.

3. Results

Table 2 summarizes the measurement periods used for analyses presented in the paper. Despite the original plan, we were not able to conduct continuous PID measurements, as these were disturbing the family occupying the house. Therefore, we conducted PID measurements during short periods lasting only several days. During initial screening of the data, one of them was selected for the analysis. We performed most of the analyses on data from kitchen, as in this space the sensors were exposed to emissions from larger variability of sources. In the bedroom, the emissions were more uniform- mostly human bioeffluents. Moreover, it was not possible to conduct PID measurements in the bedroom, which disqualified the data for determination of characteristic curves and hysteresis.

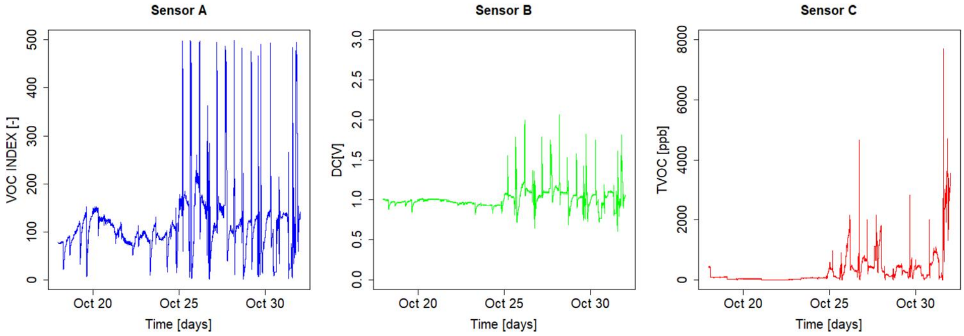

Figure 2. Absolute signal of the tested MOS VOC sensors placed in the kitchen for two weeks in October 2021 (the house was unoccupied during the first week).

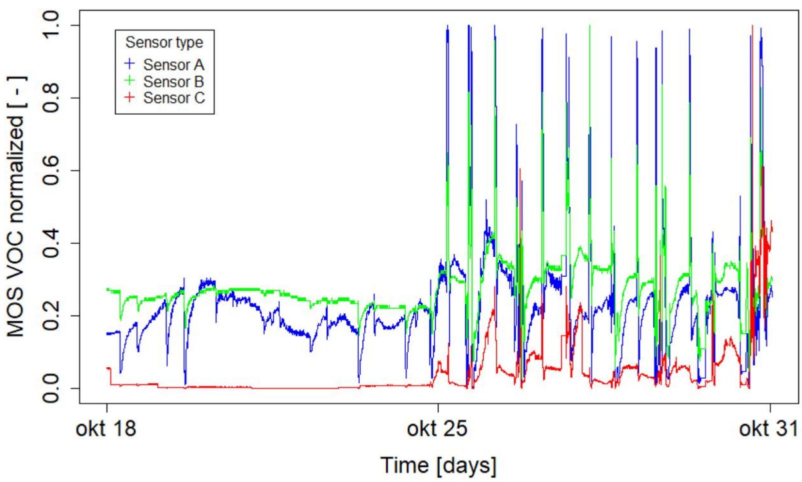

Figure 3. Normalized signals of the tested MOS VOC sensors placed in the kitchen for two weeks in October 2021 (the house was unoccupied during the first week).

3.1. Long term data

Figure 2 gives an example of non-normalized sensor signals from the kitchen. The figure illustrates a typical signal variability when the house was empty and occupied. There is a clear difference in the signal amplitude regardless of the sensor type.

Figure 3 shows the same period as Figure 2 but displays normalized data. It is possible to see that even though the trend in amplitude of the signals is the same for empty and occupied house, there is a clear difference in the character of the signal. The signal from sensor C is almost zero when the house is empty. On the contrary, signals from sensors A and B still represent some development, and despite the difference in amplitude of the build-ups and delays, there seems to be an agreement between these two signals. During the occupancy period, sensor A appears to have the largest fluctuations.

Figure 4 represents a cross plot of normalized signals of the MOS VOC sensors placed in the kitchen for the same period, as presented in Figures 2 and 3. The figure

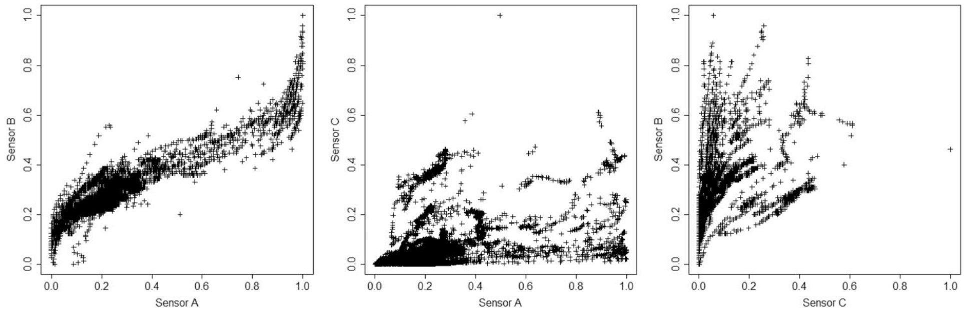

Figure 4. Cross-plot of normalized signals of the tested MOS VOC sensors placed in the kitchen for two weeks in October 2021 (the house was unoccupied during the first week).

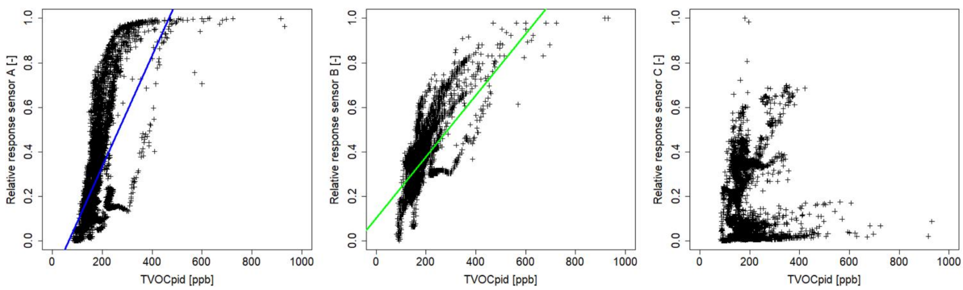

Figure 5. Characteristic curves for tested sensors determined for continuous parallel measurements with MOS VOC sensors and the PID monitor (7.3.2022–12.3.2022); regression line is not depicted for sensor C as the R^2 value does not indicate a linear relationship.

allows for graphical comparison of the relationships among the studied sensors. It is clear from the figure that there was a consistent relationship between sensor A and B responses. The relationship was much weaker comparing sensors A and B with sensor C. Figure 4 shows only two weeks, but the patterns were similar through the analysed periods. Detailed statistical analysis is described in the next section.

3.2. Characteristic curves

Figure 5 represents characteristic curves determined using measurements from 7.3.2022 until 12.3.2022. We selected this period because it contained consistent and undisturbed $TVOC_{PID}$ measurements. The figure depicts the linear regression fit to the data in the case of sensor A (blue) and sensor B (green). In the case of sensor C, the variance explained by the linear model was too low to consider the linear relationship between the sensor C signal and the reference $TVOC_{PID}$ signal. Table 3 summarizes the sensitivity values and R^2 values of the linear regression models for particular sensors. It is clear from the table and Figure 5 that the response of sensor C did not show any meaningful relation to the reference signal. Therefore, sensor C did not seem to represent the changes in TVOC concentration as determined by the reference instrument during the analysed period.

Table 3. Sensitivity and linearity of the tested sensors.

	Sensitivity (95% conf. int.)[a]	R^2[b]
Sensor A	$2.497{\cdot}10^{-03}$ ($2.432{\cdot}10^{-03}$, $2.562{\cdot}10^{-03}$)	0.40
Sensor B	$1.383{\cdot}10^{-03}$ ($1.350{\cdot}10^{-03}$, $1.416{\cdot}10^{-03}$)	0.44
Sensor C	$7.413{\cdot}10^{-05}$ ($2.042{\cdot}10^{-05}$, $12.78\ 10^{-05}$)	0.0007

[a]The sensitivity- determined as a slope of the linear fit between the MOS VOC sensor signal and the reference signal ($TVOC_{PID}$).
[b]The variance explained (R^2) of the linear fit between the MOS VOC sensor signal, and the reference signal ($TVOC_{PID}$) determined the linearity of the MOS VOC sensors.

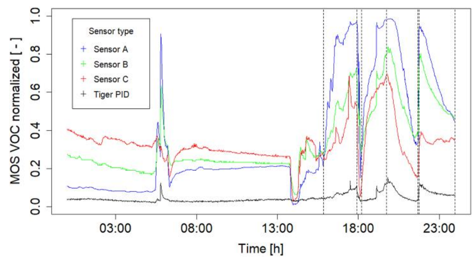

Figure 6. Data used for evaluation of hysteresis. Vertical dashed lines indicate selected build-up and decay periods during afternoon cleaning activities in the house.

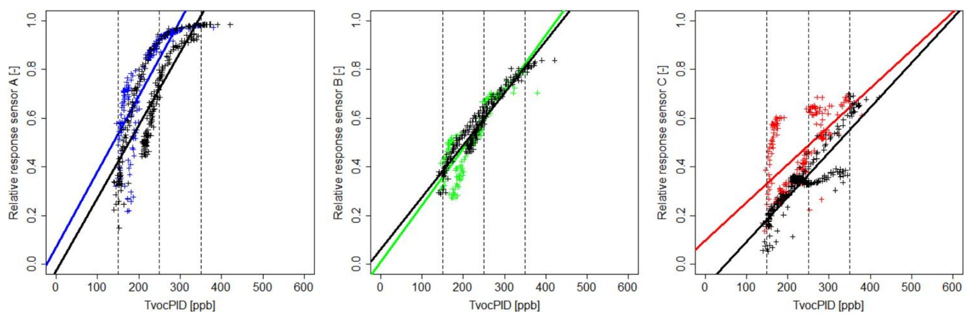

Figure 7. Separated build-up, decay periods, and corresponding linear fits for the three tested sensors. The build-up is depicted in colour, the decay in black; vertical dashed lines indicate distinct reference signal levels of 150, 250, and 350 ppb isobutylene equivalent used to determine hysteresis.

3.3. Hysteresis

Analysis of the hysteresis required the separation of build-up and decay periods. This is a relatively easy task in laboratory conditions when sensors are exposed to controlled pollution events. However, with the field data, the analysis was more demanding. For this paper, we analysed the sensors' hysteresis on data from one particular day, Friday, 11.3.2022. After 15:00, the whole family gathered at home and started cleaning the house. This initiated excitement of the sensor signals suitable for separating decay and build-up periods. Figure 6 shows the normalized data.

Figure 7 illustrates the hysteresis of the three investigated sensors for the tested period. The determined hysteresis was 0.123, 0.014, and 0.121 for sensors A, B, and C, respectively. The hysteresis was generally rather low, at 12.3%, 1.4%, and 12.1% of the measuring range, which is preferable. Sensors A and C had comparable hysteresis, while sensor B showed practically no hysteresis.

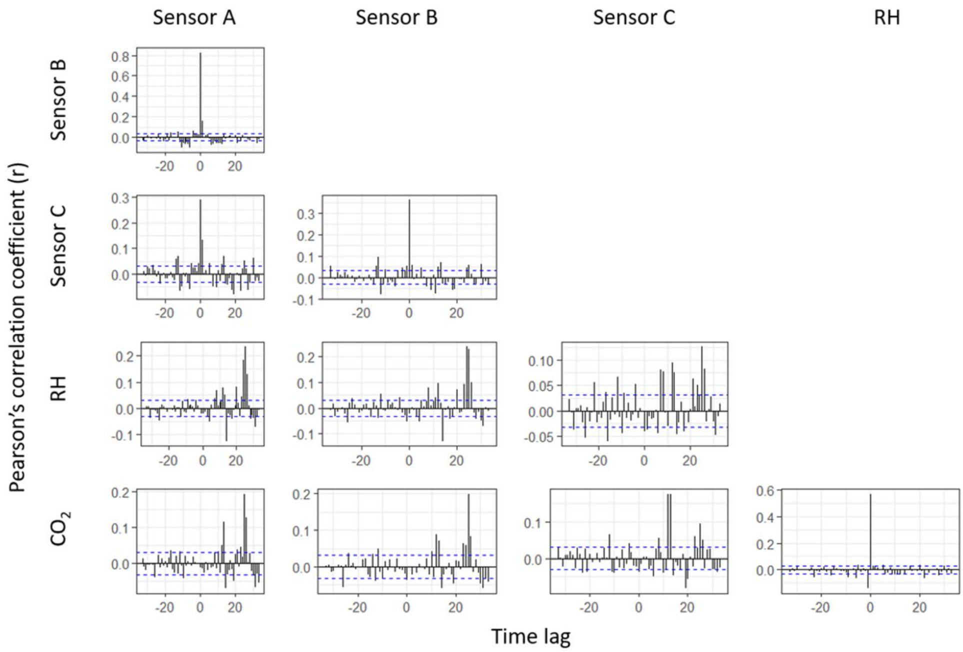

Figure 8. A cross-correlation function (CCF) is represented between the normalized signals from investigated MOS VOC sensors, CO_2, and relative humidity measured in the kitchen. The y-axis represents Pearson's correlation coefficient (*r*) for the particular signals in the respective time lag. Blue dashed lines represent a 95% interval for *r*.

For sensors A and B, the sensitivity determined using a longer period (Figure 5) was comparable to that determined during one-day measurements. The output of sensor C output had a very weak relationship to the reference also during one-day measurements.

3.4. Relation among the MOS VOC, CO_2, and humidity measurements

Cross-plots presented in Figure 4 visually indicate the relationship between the investigated sensors. To better describe the relationship between the sensors, we conducted a correlation analysis using the cross-correlation function (CCF). Figure 8 depicts the results corresponding to the period shown in Figure 2 (two weeks in October 2021). We determined the CCF for the MOS VOC sensors and the CO_2 and relative humidity signals. It is visible that the CCF confirms the results based on the cross-plots (Figure 4). The signals for sensors A and B were strongly correlated in the time lag zero with $r = 0.8$. The correlation between sensor C and sensors A and B was weak, with $r = 0.3$. There were also correlations in other time lags that reached over 95% confidence interval. None of these correlations had $r > \pm 0.1$. The latter results confirm the weak relationship between the sensor C and the remaining sensors. For all the sensors, there was a weak but significant correlation to relative humidity (r approx. 0.2) in higher time lags. More specifically, at time lag 25. This demonstrates that all the sensors were only very weakly sensitive to changes in relative humidity and that there was a considerable delay between the increase of the

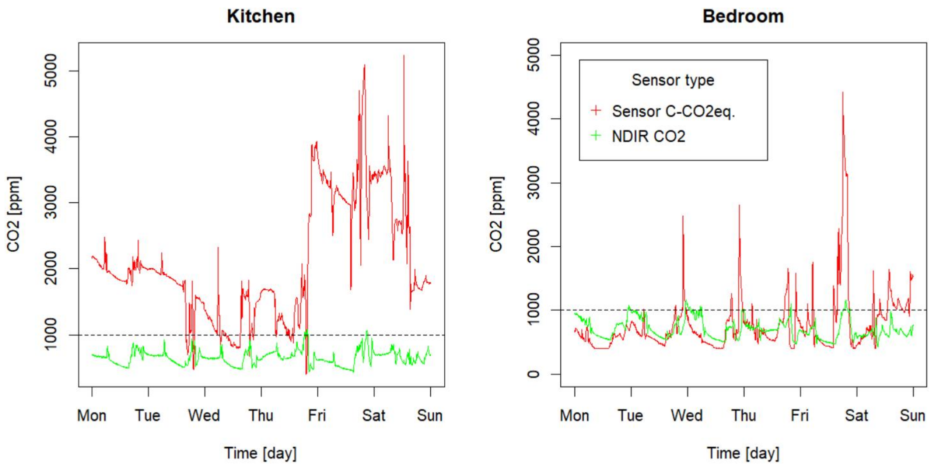

Figure 9. Comparison of CO_2 and CO_2 equivalent signal for measurements in the kitchen (left) and bedroom (right). Data from March 2022.

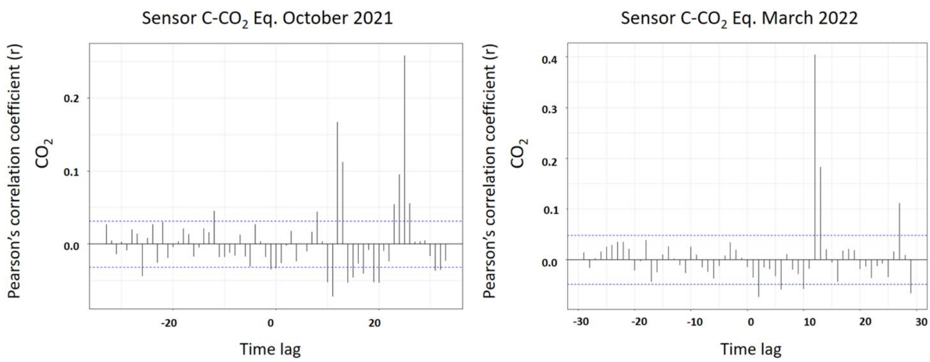

Figure 10. Representation of a cross-correlation function (CCF) between the normalized signals from the CO_2 sensor and CO_2 equivalent signal by Sensor C in the kitchen. Left: data from October 2021; Right: data from March 2022. The y-axis represents Pearson's correlation coefficient (r) for the particular signals in the respective time lag. Blue dashed lines represent a 95% interval for r.

two signals. Considering the correlation between CO_2 and MOS VOC signals, the results were similar to those regarding relative humidity—a weak correlation in high time lags. The strong correlation ($r = 0.6$) between CO_2 and relative humidity at time lag zero suggests that these two variables increased simultaneously. Such a common increase corresponds to the occupancy patterns in the house; when the occupants arrived from work and school, the CO_2 concentration increased. At the same time, they probably started preparing food and performing other activities related to moisture emissions.

3.5. CO2 and CO_2 equivalent signals

Besides the $TVOC_{MOS}$ signal, sensor C also offered a so-called CO_2 equivalent. Figure 9 compares CO_2 and CO_2 equivalent signals measured in the kitchen and bedroom during one week in March 2022. In the bedroom, the CO_2 equivalent signal closely followed the CO_2 measurements, though with noticeable overshoots. This pattern, however, was not observed in the kitchen. Human bioeffluents were the primary source of pollution in the bedroom, while most of the other pollutants were emitted in the kitchen. The kitchen was directly connected to the living room, and the occupants, when not sleeping, spent most of their time there. The data shows that when a stronger pollution event excited the sensor C, its CO_2 equivalent signal drifted from the actual CO_2 values.

Figure 10 represents the CCF for CO_2 and CO_2 equivalent signals in the kitchen for the two periods presented in the paper (October 2021 and March 2022). The correlation between the CO_2 and the CO_2 equivalent signals is relatively weak. The r values over the 95% confidence interval can be seen in higher time lags for both periods. In the data from October 2021, including one week with an empty house, the r reaches just over 0.25 in the time lag 25. In the second period, where the house was continuously occupied, the r reaches 0.4 in time lag 12. These r values suggest weak positive correlation. The fact that it appears in higher time lags means that there is a delay (25 and 12 min respectively) between the concentration changes detected in the two analysed signals. The weak correlation suggests that the MOS VOC sensors offering CO_2 equivalent measurements should not be used to substitute CO_2 sensors. A carefully tuned control algorithm should accompany their application. Herberger et al. (2010) introduced the CO_2 equivalent to help non-expert users understand and interpret sensor signals. However, our data show that in actual conditions with many other VOC emissions than human bioeffluents, CO_2 and CO_2 signals can hardly be considered correlated.

4. Discussion

4.1. Usability for control

All tested sensors demonstrated the ability to react to pollution events in the house. The signal from sensor C seemed to be least correlated to the reference PID measurements in the kitchen. Moreover, the correlation between the signal from sensor C and the response of the other two investigated sensors was weak, too. Analysis using cross-correlation function-CCF revealed the similar results. Utilization of sensor A as well as sensor B in ventilation control would lead to comparable control actions. Despite the differences in sensitivity and the offset in normalized signals, the two sensors seemed to react to the same pollution sources. The performance of sensor C contrasted with that. The most probable reason for such a difference is that the active layer of the sensor C was sensitive to different mixture of VOCs. The results of Kolarik et al. (2023) similarly showed that depending on the type of exposure, there were differences between the studied sensors. Some were clustered together, indicating their response had similar patterns, while others were placed in different clusters. Thus, their response had dissimilar patterns. The authors estimated that there probably were different 'driving' compounds for particular sensors. Kolarik et al. (2023) did not analyse CO_2 equivalent signals. However, the signal from four out of five tested MOS VOC sensors was clustered with the signal from the NDIR CO_2 sensor during exposure to human bioeffluents. In this case, humans were the only source of pollution in the test room. With the exposure to pollution from cleaning, two MOS VOC sensors showed different patterns. The results of the present study are not directly comparable to those of Kolarik et al. (2023). However, considering both studies, it seems that MOS VOC sensors, as can CO_2 sensors, can detect occupancy. At the same time, their signal correlates weakly to the actual CO_2 measurements unless humans represent the exclusive pollution source. The challenge concerning demand control ventilation (DCV) in residential setting is depicted in Figure 9. De Sutter et al. (2017) also observed 'overventilation' when using CO_2 equivalent signals while keeping original set-point values in their study. From Figure 9, it is clear that one should not apply the same set point (representing absolute measured concentration) when using CO_2 or CO_2 equivalent signals, respectively. Using a set point of 1000 ppm for a system utilizing a MOS VOC sensor measuring CO_2 equivalents would lead to almost constantly boosted airflow in the kitchen (90.8% of boost time in the kitchen compared to 1.2% of boost time with control based on NDIR CO_2 sensor). On the other hand, in the bedroom, such a set point would lead to several periods with boosted airflow (16.8% of time compared to 5.4% of time with control based on NDIR CO_2 sensor) when using CO_2 equivalents, but generally, the control would be comparable to the one based on CO_2. De Sutter et al. (2017) suggested several methods for signal processing to avoid overventilation (e.g. peak shaving, vertical shift, etc.). Moreno-Rangel et al. (2018) also observed disagreement between CO_2 and CO_2 equivalents. Demanega et al. (2021) pointed out notable differences in absolute values of the sensor signals, even though they did not deal with CO_2 equivalents. It should be mentioned that the caution is needed even when using controllers working with concentration gradients, rather than concentration levels. Figure 9 indicates that in the kitchen, concentration gradients differed significantly between CO_2 and CO_2 equivalent signals. In the current work, we did not focus on defining control algorithms, but our data demonstrate the peculiarity of the CO_2 equivalent signals, which must be considered in practice.

As discussed, the difference in proportions of the absolute signals produced by MOS VOC sensors brings the problem of selecting the right set point. For example, it

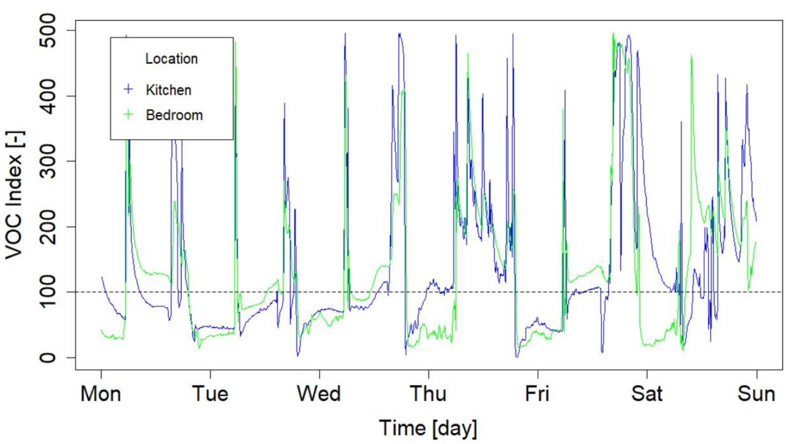

Figure 11. Comparison of VOC Index signal from Sensor A for measurements in the kitchen and bedroom. Data from March 2022.

is impossible to use the same set point value for a system utilizing CO_2 equivalents as if the sensor measuring CO_2 was used (Laverge et al., 2015). The manufacturer of sensor A has approached the problem mentioned above by using the so-called 'VOC Index.' This measure, calculated continuously using the raw signal from the MOS VOC sensor, uses an algorithm that normalizes the signal using a running mean from the last 24 hours. Plotting the sensor A signal as not normalized VOC Index for the kitchen and bedroom during the same period (one week in March 2022) in Figure 11 reveals how different the signal is from the CO_2 equivalent signal by sensor C and CO_2 concentrations measured by the NDIR sensor depicted in Figure 9.

The manufacturer assigns a value of 100 for the VOC Index as the average VOC concentration 'intensity'. Intensity denotes that the MOS VOC sensor can only measure relative values, not absolute concentrations. With such an approach, the ventilation control can work with set points in the form of VOC Index values. As the VOC Index is related to the history of the signal the highest benefit can be obtained when using the sensors in systems with room-based control. One MOS VOC sensor per room providing VOC Index accounting for development of pollutant concentrations would ensure distribution of airflow according to demand of particular rooms. However, most in most residential ventilation systems, the airflow is controlled on dwelling level. In this case, sensors placed in each room can provide signal to a decision algorithm. Thus, the airflow to whole dwelling would be controlled according to the room with the highest VOC Index. It is also possible to place the sensor in the exhaust duct leading to the air-handling unit, this is possible in both centralized and decentralized systems. However, as the exhaust duct gathers all air from the dwelling, such solution would not provide the correct picture of the air pollution in particular rooms, as also elaborated by Abdul-Hamid et al. (2014). Nowadays, many commercially available MOS VOC sensors do not offer signal processing in a form like the VOC Index described above. Here, the designer of the control algorithm needs to provide such processing to ensure robust and stable control.

4.2. Limitations and future work

4.2.1. PID as a reference instrument

Utilization of the PID instrument as a reference measurement in this study had its limitations. The device has a broad detectable range. Therefore, when measuring in an ordinary dwelling, the measured values were mainly at the lower end of the detectable range. This low sensitivity to residential emissions and the high sensitivity of the MOS VOC sensors led to high variance in the characteristic curves. Figure 6 shows that under usual pollution patterns in the house, the normalized PID signal stayed at about 20% of the measurement range established from the whole dataset. At the same time, using the PID as a reference enabled the comparison of the tested sensors, and the results agreed with the cross-correlation analysis results. Proton-Transfer-Reaction–Time-of-Flight Mass Spectrometer (PTR-ToF-MS) enabling continuous real-time monitoring of individual VOC down to ppt concentrations would be a more suitable method for reference measurements, see Kolarik et al. (2018, 2023). However, its application in practice is complicated due to the high cost and high demands on the qualifications of the operating staff.

4.2.2. Utilization of min-max normalization

We have chosen to use min-max normalization in our data analysis. The motivation for this choice was that as investigated sensors produced their output using different units/scales, there was a need to normalize the data to one scale to allow meaningful comparison. We have chosen min-max normalization based on our experience from previous studies (Kolarik et al., 2023). The main advantages supporting our choice were range consistency (all data scaled to interval 0–1), computational simplicity and easy interpretation of the scaled data. Interpretation is a very important issue. As the MOS VOC sensors utilize relative measurement, comparing actual value under exposure to a certain pollutant (or mixture of pollutants), to the signal range achieved during the whole measuring campaign, helps to understand the sensors' behaviour/ sensitivity to different pollutants. We are aware of the likely issues related to this normalization strategy. They can include possible amplification of noise and errors in the data or danger of skewing data due to outliers caused by errors or anomalies. For more details, the reader is referred to work by Mazziotta and Pareto (2022). However, it is our assessment that the selected normalization did not affect the analyses we performed. To ensure that, we have additionally applied so-called robust scaling. Robust scaling typically employs the median and the interquartile range (IQR) instead of the mean and standard deviation for normalization. This method is robust to outliers and can be used even if the data is not normally distributed. Applying robust scaling did neither change the parameters of the characteristic curves nor the R^2 values for the linear fit.

4.2.3. Utilization of linear regression for characteristic curves

We determined the characteristic curves based on approach by Fahlen et al. (1992). In their work, they tested sensors' linearity by assessing the deviation between the values measured by the tested sensor and the linear fit to the concentrations of the reference VOC mixture. We extended this approach by using measurements of reference concentrations as a time series rather than steady state concentration levels. As the actual characteristics of the tested sensors may be unknown in practice, using a linear fit seems to be an obvious first step when determining the relationship between reference measurement and the sensor signal. In some cases, the manufacturers provide information regarding characteristics of their sensors. In such cases, it is more appropriate to use a relationship provided by the manufacturer. However, it can make comparison of sensors from different manufacturers difficult. The manufacturer of sensor A provides a logarithmic relationship to recalculate VOC index output to isobutylene concentration (Sensirion, 2023); see Equation (2).

$$TVOC_{isobutylene} = (ln(501 - VOC_{index}) - 6.24)\cdot(-878.53)\left[\mu g/m^3\right] \quad (2)$$

Where $TVOC_{isobutylene}$ is isobutylene concentration or concentration is isobutylene equivalent and VOC_{index} is the output signal from sensor A.

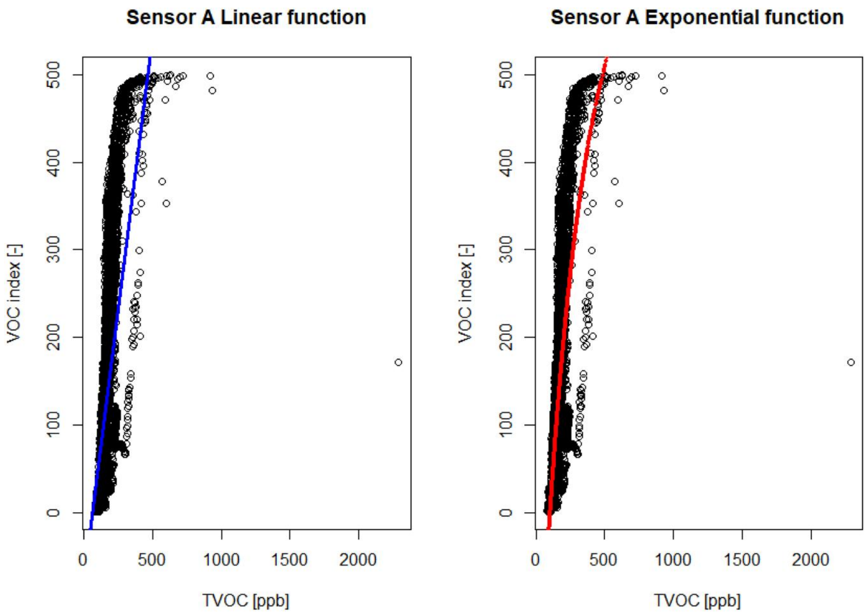

Figure 12. Comparison of data fit using linear function (left) and exponential function (right) to the data measured by Sensor A.

To evaluate the goodness of fit provided by linear model in comparison to the model provided by the manufacturer, we have used the relationship (2) to determine an exponential model predicting VOC_{index} for given isobutylene equivalent concentrations. We have fitted the model to the measured data. The results can be seen in Figure 12. Comparison between linear and exponential fit to the data revealed that the linear model had the variance explained $R^2 = 0.40$ (see Table 2) while the exponential model resulted in variance explained $R^2 = 0.49$. Thus, application of the model provided by the manufacturer explained 10% more of the variance in the measured data.

4.2.4. Sensor hysteresis

In the present paper, we evaluated the sensors' hysteresis based on only one-day measurements. We base our approach on the one by Fahlen et al. (1992); however, they exposed the sensors to steady-state pollution levels in a test chamber. We used a 'dynamic' approach to evaluate the hysteresis from real-life measurements. Such an approach brings a challenge in identifying suitable decay and build-up periods. In future analyses, the hysteresis determination should include several days of distribution through the whole dataset. This procedure can indicate whether the hysteresis remained consistent.

4.2.5. Other remarks

Correlation studies focused on indoor environmental quality parameters often use the Pearson correlation coefficient directly without pre-whitening the analysed time series. As discussed in detail by Justo Alonso et al. (2022), such an approach can result in an unrealistically high correlation due to auto-correlation within each series. We studied de-trended correlations by pre-whitening our data to remove the auto-correlation bias. The results of our correlation analysis confirmed the trends indicated by visually examining cross-plots concerning the relation among the studied MOS VOC sensors. Moreover, the visualization of cross-correlation in higher time lags can be useful in exploring the effect of indoor environmental parameters, e.g. relative humidity, on assessed sensor signals.

VOC emissions from building materials and furniture can increase under elevated temperatures (Xiong et al., 2016). However, we did not include the temperature into our correlation analysis, because the temperature conditions were rather stable. For the period used for establishing the characteristic curves, the mean temperature ± SD was 21.3 ± 0.8 °C with quartile range (20.8, 21.9)°C.

Recent research on the calibration of MOS VOC sensors utilizes multiple regression models and deep learning algorithms (Schütze et al., 2017; Hong et al., 2023; Robin et al., 2021). Such methods provide calibration models using multiple laboratory-grade measurements conducted parallel to the MOS VOC monitoring. These methods significantly improve the performance of MOS VOC sensors or even enable selective monitoring of individual compounds. However, their application in residential ventilation is still a question of the future. As practitioners in the field usually cannot utilize laboratory-grade measurement instruments, our work did not focus on calibration procedures but rather on a simple method to compare the performance of different MOS VOC sensors.

Future work regarding MOS VOC sensors should focus on suitable signal processing algorithms and the possibility of their practical use in residential ventilation systems. Considering new work defining harm from indoor pollutants by Morantes et al. (2024), combining MOS VOC sensors with sensors measuring particulate matter (especially $PM_{2.5}$) should receive attention.

5. Conclusions

Our study assessed three commercially available MOS VOC sensors exposed to indoor environmental conditions in a row house. The tested sensors differed significantly in terms of their sensitivity, which we determined using reference PID measurements. For the two sensors (denoted A and B) there was an apparent relationship between their output signals, which was confirmed by analysis employing a cross-correlation function. This suggests that the sensors reacted to similar pollutants. However, aforementioned differences in sensitivity suggest that these sensors would not be directly interchangeable when used for control of airflow in residential ventilation.

The third tested sensor (denoted C) presented a weak relationship to the reference measurements - in the analysed data, the sensor signal did not correspond to the $TVOC_{PID}$ concentrations represented in isobutylene equivalents. Moreover, sensor C also had a weak correlation to the remaining sensors. This does not disqualify the sensor C per se; it just indicates that the control engineer cannot expect the same behaviour from sensors by different manufacturers.

The investigated sensors had small hysteresis, which is preferable, but we conducted on a relatively small sample of measurements. Analysis of a broader range of build-up and decay periods is needed to confirm the results.

The CO_2 equivalent signal by MOS VOC sensor presented, in general, a weak correlation to CO_2 measurements. There were large discrepancies between the two signals in the kitchen where the human bioeffluents were not the main pollution source. The discrepancies in the bedroom seem smaller, but the correlation was also weak.

The study results indicate that the characteristics of the MOS VOC sensors need to be properly considered in control algorithms. Based on our results, we do not recommend the designers and/or ventilation systems' manufacturers to rely on CO_2 equivalent concentrations as a surrogate for CO_2 levels in the dwelling. In ventilation control strategies, a MOS VOC sensor can be utilized for detection of sudden VOC emissions related to human activities steering the airflow-boost signals. Our results show that MOS VOC sensors from different manufacturers are not directly interchangeable, and the control strategy must be adjusted according to the output signal provided by the sensor used. Furthermore, recent developments in low-cost sensors measuring particulate matter (PM) bring a new perspective to using MOS VOC sensors. As PM represents by far the highest health risk for humans, one can expect that low-cost PM sensors will soon make their way into residential ventilation control. However, this does not necessarily rule out the MOS VOC sensors. Future research should focus on controls that effectively combine those two.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the corresponding author, Jakub Kolarik, upon reasonable request.

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Appendix A

Table A1 summarizes the names and manufacturers of the tested sensors.

Table A1. Commercial names and manufacturers of the investigated sensors.

Sensor	Commercial name	Manufacturer
A	SGP40	Sensirion AG
B	EM 8100	Figaro Engineering Inc.
C	CCS811	ScioSense B.V.