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Title: Applying the CO_2 concentration-decay tracer-gas method in long term monitoring campaigns in occupied homes: identifying appropriate unoccupied periods and decay periods.

Structured Abstract.
Purpose: Ventilation is driven by weather conditions, occupant actions and mechanical ventilation, and so can be highly variable. This paper reports on the development of two analysis algorithms designed to facilitate investigation of ventilation in occupied homes over time.
Design / Methodology / Approach: These algorithms facilitate application of the CO_2 concentration-decay tracer-gas technique. The first algorithm identifies occupied periods. The second identifies periods of decaying CO_2 concentration which can be assumed to meet the assumptions required for analysis.
Findings: The algorithms were successfully applied in four occupied dwellings, giving over 100 ventilation measurements during a 6-month period for three flats. The specific implementation of the decay identification algorithm had important ramifications for the ventilation rates measured, highlighting the importance of interrogating the way that appropriate periods for analysis are identified.
Originality: Empirical investigations of ventilation in occupied dwellings rarely aim to investigate the variability of ventilation. This paper reports on analysis methods which can be used to address this gap in the empirical evidence.
Practical implications: The analysis algorithms provide robust, reliable and repeatable identification of CO_2 decay periods appropriate for ventilation rate analysis. The algorithms were coded in Python, and these have been made available via GitHub. As well as supporting future CO_2 tracer gas experiments, the algorithms could be adapted to different purposes, including the use of other tracer gases or exploring occupant exposure to indoor air pollution.

1. Introduction

People in the US and UK have previously been found to spend 50-70% of their time at home (Klepeis *et al.*, 2001; Kornartit *et al.*, 2010); indoor air quality (IAQ) can have serious implications for health (NICE, 2020). Home occupancy hours are likely to have risen during the Covid-19 pandemic (Gershuny *et al.*, 2021) and the increased risk of virus transmission in poorly ventilated spaces has also brought this issue to prominence (Bhagat *et al.*, 2020). While increasing ventilation rates can improve IAQ, it can also increase the energy consumption of building operation (ASHRAE, 2017), despite the need to reduce emissions to mitigate climate change (e.g. CCC (2020)). Ventilation strategies must balance energy and health considerations.

Ventilation results from indoor-outdoor pressure differences, driven by wind, temperature differences and fans. These result in variable ventilation rates, unless mechanical ventilation is strongly dominant. Passive tracer-gas methods measure average ventilation rate over extended periods, from two days (Bornehag *et al.*, 2005) to a month (Bekö *et al.*, 2016). This method cannot represent the variable ventilation rate experienced by occupants in systems not dominated by mechanical ventilation. Wallace *et al.* (2002) undertook ventilation measurements every 2-4 hours in an occupied house over a year, finding a mean ventilation rate of 0.65 ach and standard deviation of 0.56 ach (N~4600), illustrating the potential variability over extended periods. Bekö *et al.* (2016) applied several tracer gas methods in 5 occupied dwellings and found significant variability in the ventilation rate over daily periods. This included using the constant-concentration technique to measure every 3-4 minutes over 5 days during each season; they found standard deviations ranged 0.01-1.4 ach during the 5-day periods in individual homes. They highlight that this variability is significant because some pollution sources are likely to vary over similar time frames, with the combination of ventilation and pollution sources potentially impacting the IAQ experienced by occupants.

There is little empirical research regarding variation in ventilation over extended monitoring campaigns. Moreover, the research reported by Wallace *et al.* (2002) and Bekö *et al.* (2016) either took place in homes belonging to acquaintances of the authors or the authors themselves. Both studies required pumped gas sampling (bulky and noisy), potentially limiting the wider application of this method.

Penman (1980) developed the use of metabolic CO_2 as a tracer gas for ventilation measurement because this may be more acceptable to occupants than injecting tracer gases. Additionally, metabolic CO_2 negates the global warming concern of using gases such as SF_6 and perfluorocarbons (BSI, 2017). CO_2 is measurable using relatively inexpensive non-dispersive infra-red (NDIR) sensors. Numerous authors have applied this technique since Penman, particularly in schools and offices (Batterman, 2017), and the use of CO_2 as a tracer gas is described in several standards (e.g. BSI, 2017; ASTM, 2018). However, where CO_2 is used during occupied times its metabolic generation rate must be estimated. Standard assumptions about metabolic generation of CO_2 can lead to significant uncertainty in estimated ventilation rates (Persily and de Jonge, 2017). In dwellings it is common to apply such methods overnight, requiring knowledge or estimates of the number of people present and the hours of sleep. This is a potentially significant intrusion of privacy, particularly over an extended monitoring period.

The tracer-gas concentration-decay technique can be used with metabolic CO_2 after occupants leave the zone of interest. Guo and Lewis (2007) suggest the difficulty in accurately determining when a dwelling is occupied has limited the number of studies using this method. Roulet and Foradini (2002) monitored a single office-room and manually identified periods CO_2 decay, suggesting that prolonged periods of decreasing CO_2 indicate the absence of occupants. Guo and Lewis (2007) identified decay periods using occupant-reported daily log-sheets; however, occupant diaries may not always be accurate and increase the burden for participants (Bryman, 2004).

Despite the widespread use of tracer gas decay methods, there is limited published detail of the systematic identification of periods for analysis. For example, Remion *et al.* (2019) note that the choice of final point in the decay can significantly impact estimated ventilation rate. In general, concerns over good mixing and the emergence of stable airflows in the initial period of the decay have led to waiting for a specified period before beginning the decay analysis (e.g. Wallace *et al.,* 2002; Cui *et al.,* 2015). However, the criteria applied in determining specific decay periods and the subsequent effect on calculated ventilation rates is often unclear.

The lack of reliable and repeatable methods for identifying unoccupied periods of decaying CO_2 limits the robust application of the metabolic CO_2 decay technique during extended monitoring campaigns in occupied homes. This article reports algorithms developed to address both issues. Section 2 outlines the CO_2 decay method and monitoring campaign. Sections 3 and 4 detail the occupancy and decay identification algorithms respectively. Section 5 presents the case study results and Section 6 discusses the uncertainty of the measured ventilation rates. The final section discusses possibilities for future research and applications for the methods and analysis algorithms.

2. Analysis outline and monitoring technique

2.1. CO_2 decay technique

Tracer gas methods use a specific gas to `tag' the airflow in a volume of air and analyse this using the continuity equation, as well as the injection rate and concentration of tracer gas in the measured zone. Several assumptions are made in single-zone tracer-gas analysis, including the uniform distribution of tracer gas and that the measured space is adequately represented by a single zone exclusively exchanging air with the outdoors. Implementing the concentration decay method requires setting tracer source term to zero (occupants must be absent if CO_2 is used), and the relationship between tracer concentration and time is given by (Liddament, 1996):

$$\mathrm{C(t)} = \mathrm{C_0} \exp(-\mathrm{At}) , \qquad (1)$$

where *C(t)* is the concentration of tracer gas at time *t* and C_0 is the concentration at *t = 0. A* is the air change rate *(A = Q/V)*, *Q* is the volume flow rate, *V* is the effective volume of the measured space. If CO_2 is used, concentration is replaced by ΔCO_2, the concentration difference between indoors and outdoors (ASTM, 2012).

2.2. Monitoring campaign

Results are presented from several monitoring campaigns. As the analysis technique is the focus of this paper, only brief details of the dwellings are reported, with greater emphasis on the data collected.

Four flats (A-D) in one building were monitored in London (England), CS2, an office building converted to domestic use in 2015. The flats had 1 or 2 occupants and were either 1-bedroom or studio-flats with floor area 30-40m^2. Ventilation was provided by trickle vents, openable windows, and continuous mechanical extract. Measurements took place June 2019 - January 2020. Eltek-GD47 sensors recorded CO_2 concentration, temperature, and relative humidity every five minutes externally and in all rooms except the bathroom. The sensors have an *accuracy* of 50ppm + 3% of the measured value, however the absolute value of the concentration is not critical since ΔCO_2 is used in the calculation of ventilation rate (Etheridge, 2012). Empirical tests showed that the *precision* of the concentration measurement was 5.4ppm, further details are provided by Few (2021). The response time is not reported by the manufacturers; however, recordings respond to being moved from indoor to outdoor concentrations within the 5 minute measurement frequency. Eltek-AQ110 sensors were placed in all kitchens, recording pollutant concentrations as well as the parameters recorded by the Eltek-GD47s. Sensors were placed 1.0m-1.5m above the floor on surfaces such as tables and counter-tops outside the breathing zone of the occupants, out of sunlight and away from heat sources. HOBO-UX90-001M event-logging magnetic proximity sensors were placed on all doors and almost all windows (one side of some double casement windows were monitored).

Additionally, an unoccupied case study dwelling, UTH, in Loughborough (England) was studied: built in the 1930's, 3-bedroom semi-detached, with suspended timber floors, cavity walls and retrofitted throughout with double glazing and trickle vents. Eltek-GD47 sensors were used as above. Measurements focussed on characterising single-room ventilation rates in one upstairs and one downstairs room with their doors closed. During investigation of each room 3 or 4 sensors were placed around that room, and 3 or 4 additional sensors were placed in the middle of other rooms in the dwelling. A battery-operated HOBO-MX1102A sensor measuring CO_2, temperature and humidity every five minutes was installed in an outdoor utility room of the neighbouring house (also unoccupied). This sensor had a stated accuracy of 50ppm + 5% of the measured value, and response time of 1 minute to 90% in airflow of 1 m/s, the empirically determined precision was 7.6 ppm. The door to this utility room was very poorly fitting and it was assumed that the air in this space represents the outdoor CO_2 concentration. As above, HOBO-UX90-001M event loggers were installed on the front, back and measurement room doors. Measurements took place November 2018 - February 2019.

3. Occupancy Algorithm

To systematically identify periods of data appropriate for concentration decay analysis, two separate algorithms were developed. The first, described here, separated the monitored data into occupied and unoccupied subsets. The second, described in Section 4, identified periods of decaying ΔCO_2 meeting the assumptions detailed above and for the calculation of ventilation rates. Python scripts for implementing these algorithms and a sample dataset are available (github.com/jessicafew/CO2-decay-analysis).

While there are few examples of robust methods for determining when a building is occupied for ventilation measurement, there is much literature regarding building occupancy more generally. Chen *et al.* (2018) reported that a wide variety of sensors have been used for indicating occupancy, including: passive infra-red, smart meters, CO_2 concentration, cameras, WiFi, Bluetooth and others. Chen *et al.* (2018) found that different types of sensor can be used to compensate for the shortcomings related to others, so best results are often obtained when sensors are combined. Dedesko *et al.* (2015) used beam-break sensors and CO_2 concentration to estimate the number of people passing in or out of a room. The beam-break data provides information regarding the specific time that the space is entered or exited, while the CO_2 concentration was used to estimate the total number of people present over longer time scales. The present work uses CO_2 concentration, door and window state sensors, all of which were required for insights into ventilation rates.

The occupancy status algorithm (OSA) developed in this research has similar principles to Dedesko *et al.* (2015). Figure 1 illustrates the flow chart of the decision making process used by the occupancy algorithm. The dwelling is occupied if any internal doors or windows change state between the front door closing and the next time it opens. If none of the doors or windows change position but the CO_2 rises significantly, then the dwelling is also likely to be occupied (or another significant source of CO_2 is present, which precludes use of the decay method). The first 30 minutes of CO_2 data are disregarded if the period under investigation is sufficiently long, after which good mixing is assumed. Further information regarding the testing and improvements to the OSA are reported by Few and Elwell (2019).

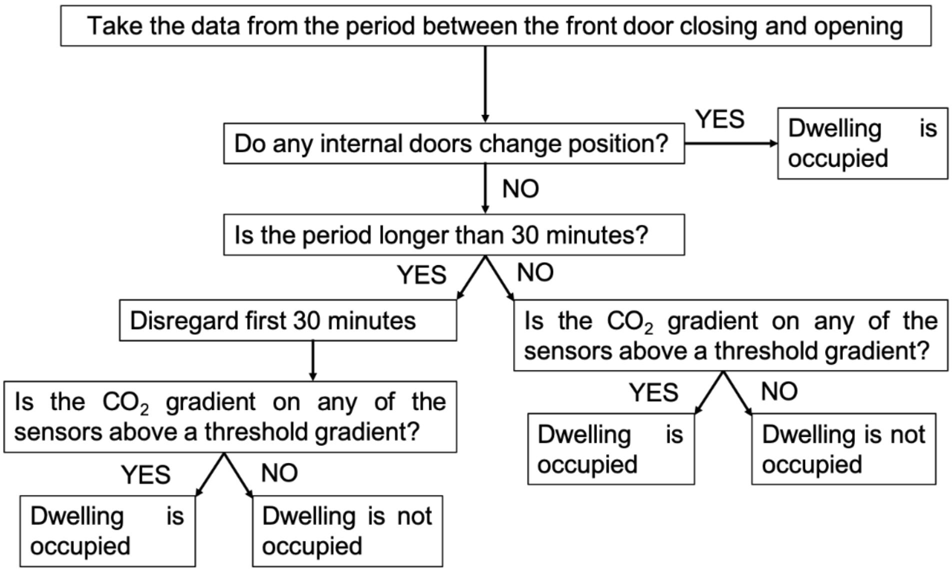

Figure 1. Flow chart of the decision making of the occupancy status algorithm.

4. Decay identification algorithm.

The data classified as unoccupied by the OSA were passed to a decay identification algorithm to identify appropriate periods for analysis, the following steps were taken:

a) Identify when the CO_2 is spatially homogeneous.
b) Smooth the mean ΔCO_2 data and identify periods which are monotonically decreasing
c) Remove data where the mean ΔCO_2 is below a minimum threshold value
d) Apply minimum and maximum duration limits
e) Reject decays if the external CO_2 varies over a threshold limit

The implementation of these criteria has implications for the decays identified and the ventilation results, as discussed below, and thresholds may be adjusted as appropriate for different scenarios. The steps above refer to the mean ΔCO_2 in the measured zone, for CS2 this was the mean of all sensors in the flat, whereas for UTH this was the mean of the sensors in the room of interest.

4.1. Spatial homogeneity

Application of Equation 1 requires that the tracer gas is homogenously distributed within the measured zone. During co-location of the sensors at CS2 and in-situ estimation at UTH, the standard deviation of recorded concentration differences was 10-20 ppm. Therefore, 95% of the concentration differences were within 40 ppm of the mean at the upper limit. ASTM (2018) recommend that the measured space can be assumed to be spatially homogenous if samples of ΔCO_2 agree within 10%. Given the precision of our sensors during co-location periods, this requirement was excessively strict at low ΔCO_2 concentrations. As a result, the space was classified as adequately spatially homogeneous if the ΔCO_2 concentrations were within the larger of 40 ppm or 10% of each other. The spread in ΔCO_2 concentrations measured by different sensors was accounted for in the estimate of ventilation rate uncertainty, discussed further in Section 6.

4.2. Smoothing

The unoccupied and spatially homogeneous data were smoothed using a moving average to reduce the impact of noise in identifying periods of monotonically decreasing ΔCO_2. Figure 2 shows the decays identified when different amounts of smoothing are applied. Without smoothing none of this data is identified as appropriate for ventilation rate analysis. The algorithm is increasingly able to identify decays associated with small decreases in ΔCO_2 as the amount of smoothing is increased. This allows more decays to be identified when ventilation rates are low. However, decays with low signal-to-noise ratios may also be identified, such as the decays in Figure 2 after 14:00 when smoothing is applied over 25 minutes. For our analysis, smoothing was applied over 15 minutes to balance these issues.

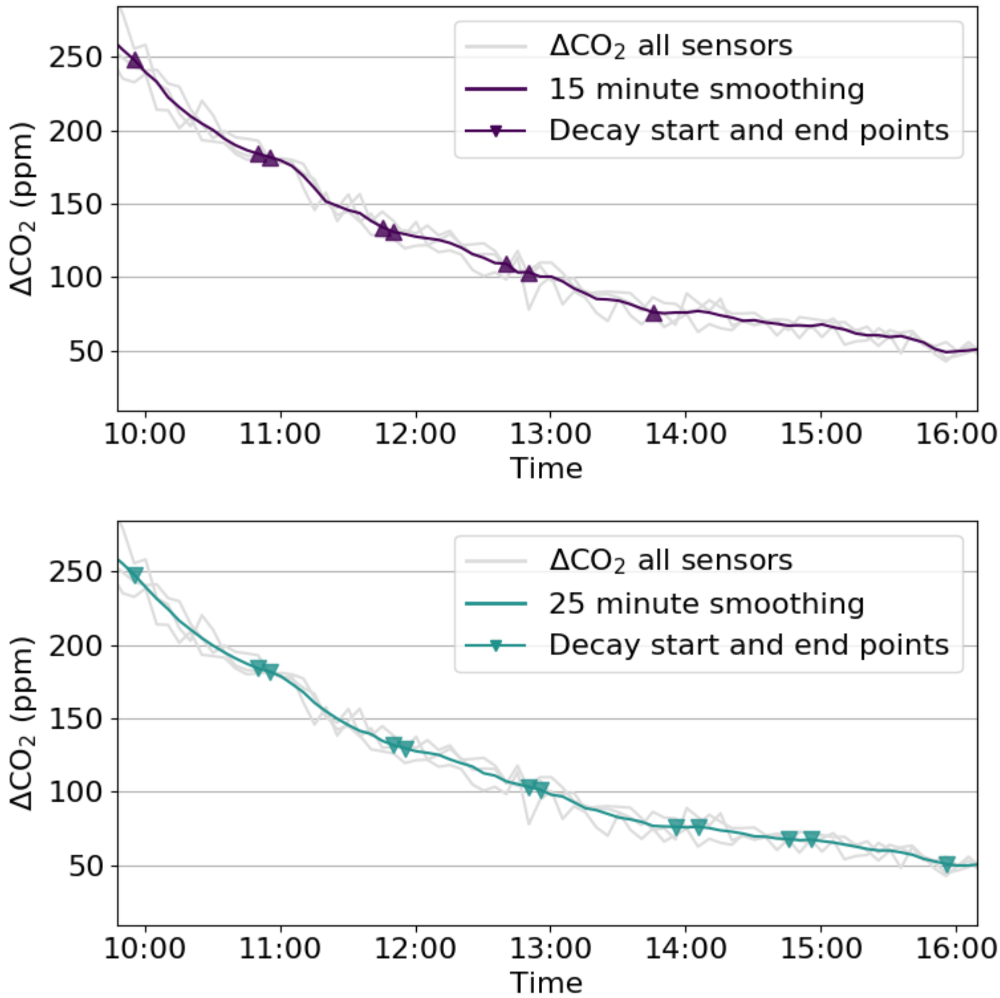

Figure 2. ΔCO_2 concentration during an unoccupied period, showing the decays identified when different amounts of smoothing are applied to mean ΔCO_2.

4.3. Minimum ΔCO_2 threshold

The decay identification algorithm includes a minimum ΔCO_2 threshold, below which data are disregarded due to low signal-to-noise ratio. This threshold accounts for the precision of the sensors, in addition to the potential for leakage between adjacent zones. For example, data from unoccupied times in Flat D at CS2 occasionally revealed possible leakage between adjacent dwellings, in such cases the mean ΔCO_2 was ~50ppm. Similar artefacts were uncommonly found for other flats, with magnitude likely related to the extent of leakage, pathways, occupancy patterns and ventilation rates.

At times when air is exchanged with adjacent spaces which have CO_2 concentration higher than the measured dwelling, the results will be systematically shifted towards lower ventilation rates (and vice versa for lower concentrations). However, without extensive monitoring in neighbouring properties it is not possible to robustly differentiate between this and low air exchange with outdoors. A threshold of 50 ppm was chosen for our study to negate significant bias due to leakage from adjacent flats.

4.4. Decay length

It is assumed that the ventilation rate is constant over the period during which the tracer gas concentrations are fitted to an exponential decay. The length of decays vary considerably in the literature, from minutes (Cui *et al.*, 2015) to 8-hours in an extreme case (Parsons, 2014).

The minimum decay length combined with the ΔCO_2 concentration at the start of the decay determine the maximum measurable ventilation rate: no decays are recorded when the time for ΔCO_2 to fall below the minimum threshold is shorter than the minimum decay length. However, the sampling rate (5 minutes in our case) limits the number of data points available in any given time. In our study, increasing the minimum decay time beyond 40 minutes significantly reduced the number of decays in one dwelling where windows were frequently open, biasing the results towards lower ventilation rates. Reducing the minimum decay time to 20 minutes increased the number of decays identified, but the degrees of freedom were reduced to two: the fit was readily influenced by noisy signals. An empirically determined minimum decay length of 40 minutes was therefore implemented.

Long decays are more likely to be affected by changes in conditions, which was investigated using the Durbin-Watson statistic. A result tending towards 0 indicates systematic correlation between successive residuals and a result tending towards 4 indicates systematic anti-correlation (Hughes and Hase, 2010). A Durbin-Watson value of 2 suggests that the model describes the data well. Figure 3 shows the Durbin-Watson statistic against length of decay for Flat D at CS2 indicating increasing correlation with decay time. Etheridge and Sandberg (1996) suggest wind speeds and pressures averaged over approximately an hour may be considered constant for the purposes of analysing ventilation driving forces. For our analysis, long decays were split into a series of hour-long decays, with the final decay in a series up to 90 minutes long or split into two equal length decays if 90- 120 minutes. Figure 3 shows that after imposing the maximum decay length there is generally less correlation of residuals, suggesting a better fit of the model to the data.

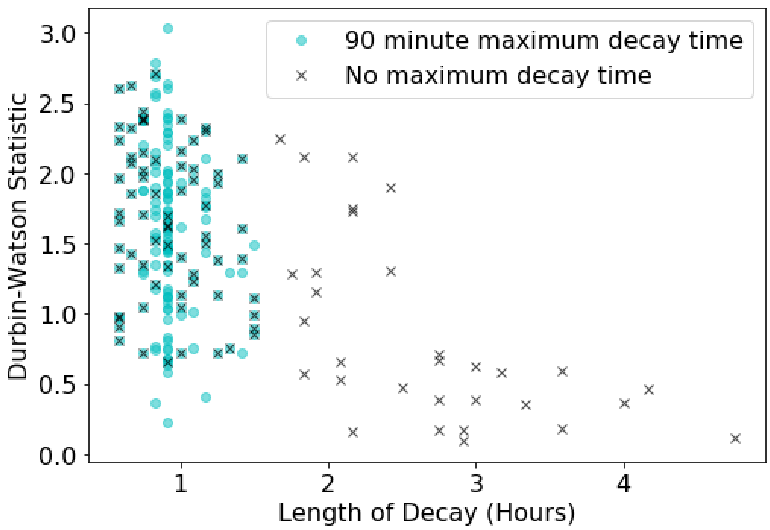

Figure 3. Durbin-Watson statistic against length of decay when decays are limited to a maximum period of 90 minutes and when there is no maximum decay time. Data from Flat D at CS2.

4.5. External CO_2 variation

CO_2-based analysis substitutes the tracer gas concentration with the concentration difference between inside and outside. It is often assumed that external CO_2 concentration is constant and ΔCO_2 varies only with internal CO_2 concentration. However, the urban CO_2 dome, whereby CO_2 concentrations vary diurnally and seasonally, is an established phenomenon in atmospheric science (Xueref-Remy *et al.*, 2018).

For 40 measurements at UTH, ΔCO_2 was calculated using an assumed constant external CO_2 concentration and using measured external CO_2. The difference in resulting ventilation rates was over 0.1 ach for 32% of measurements: significant in terms of frequency of occurrence, and interpretation of the ventilation rate. Figure 4 shows an example with varying external CO_2 concentration, impacting ventilation measurement. The impact of variation in external CO_2 concentration depends on factors including the concentration difference during the decay, the `true' ventilation rate and the rate of change of external CO_2 concentration. A limit of 40ppm variation in external CO_2 during the decay and the previous hour was applied. 4-46% of decays were rejected after applying this requirement across the dwellings studied, highlighting the importance of external concentration measurement during extended campaigns.

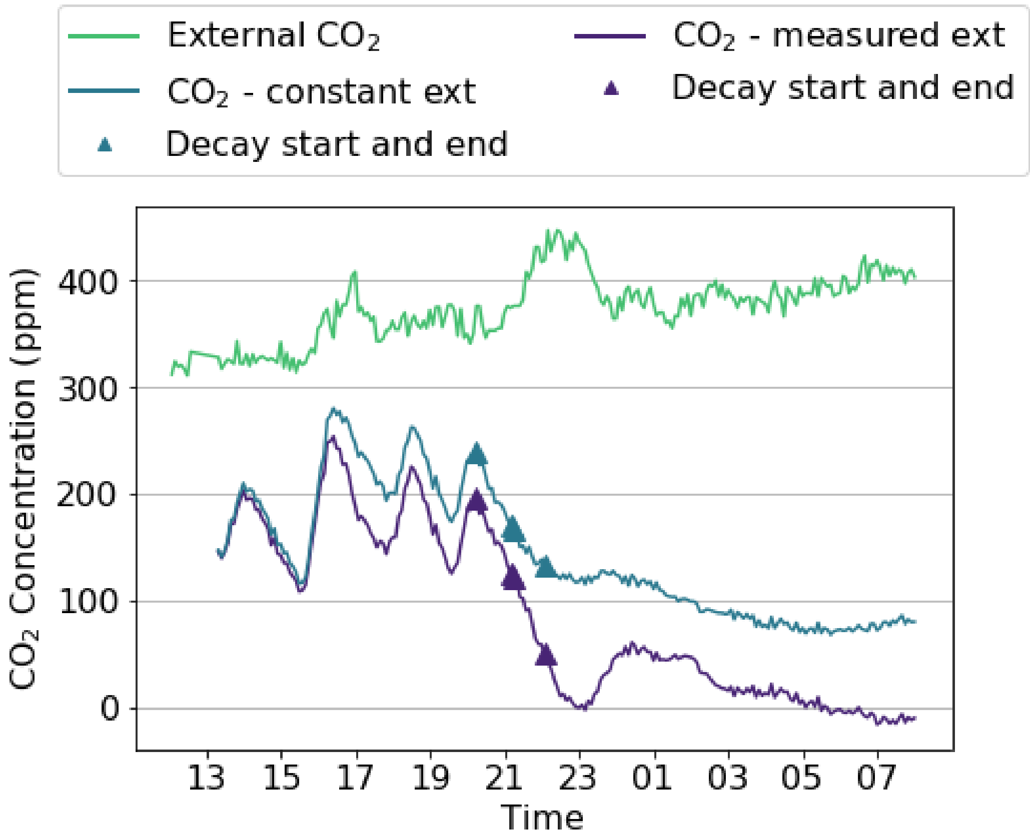

Figure 4. ΔCO_2 calculated using a constant value for the external CO_2 and the measured external CO_2 concentration. The measured external CO_2 concentration is shown in this figure. The ventilation rates calculated during the two periods identified differed by over 0.2 ach with these different methods.

5. Combining occupancy algorithm and decay identification and analysis

The methods presented in Sections 3 and 4 were used to identify periods suitable for decay analysis, resulting in over 100 ventilation measurements for Flats B, C and D at CS2. 29 decays were recorded at Flat A, where windows were usually open, leading to little build-up of CO_2. Figure 5 illustrates the implementation of the method over a two-day period for Flat C at CS2. Results were categorised according to the configuration of doors and windows during the decay period. Figure 6 shows the ventilation rates measured in the four most common configurations for one flat, the proportion of occupied time with that configuration and the weather conditions during measurement periods. The additional detail afforded by this method compared to previous work enables new insights to be drawn. It also supports the use of CO_2 as a tracer gas in long-term measurement studies due to the identification of occupancy status and automatic identification of suitable decay periods. Future research is discussed in Section 7; the uncertainty of the results is discussed in Section 6.

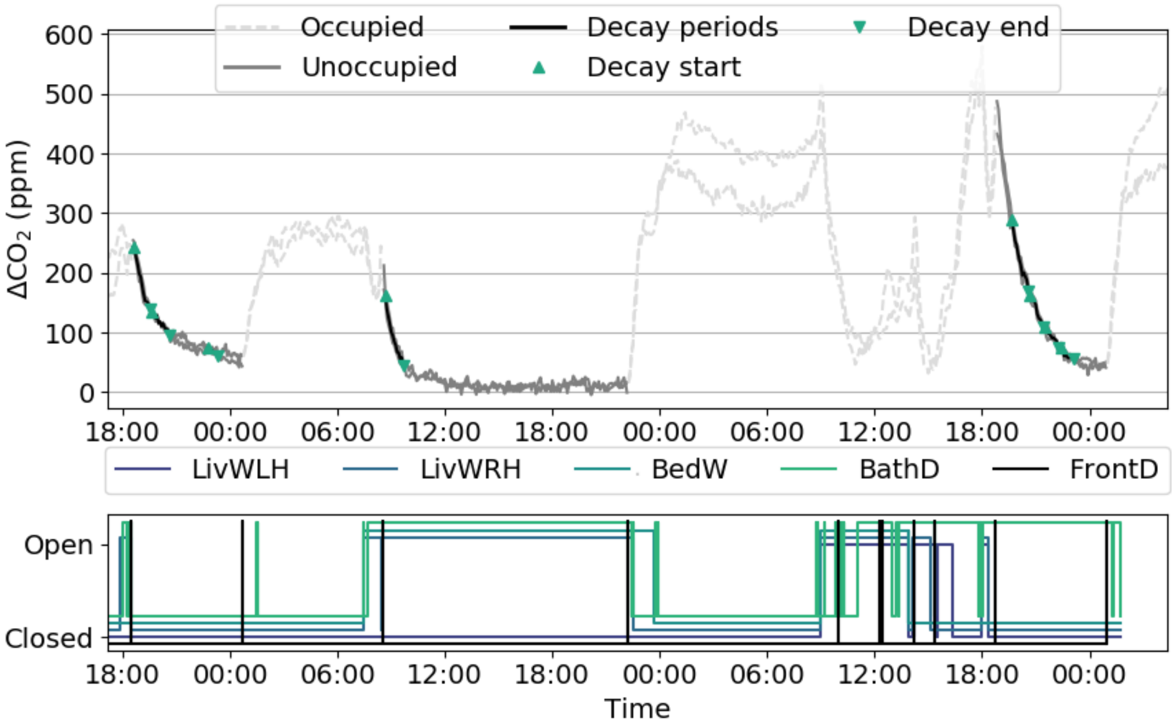

Figure 5. Example two-day period from CS2, the top figure shows ΔCO_2 data with periods identified as occupied and unoccupied, and periods used for ventilation measurement. The bottom figure shows the door and window opening data. The legend for the doors and windows uses the following abbreviations: Liv = living room, Bed = bedroom, Bath = bathroom, W = window, LH = left hand, RH = right hand, D = door.

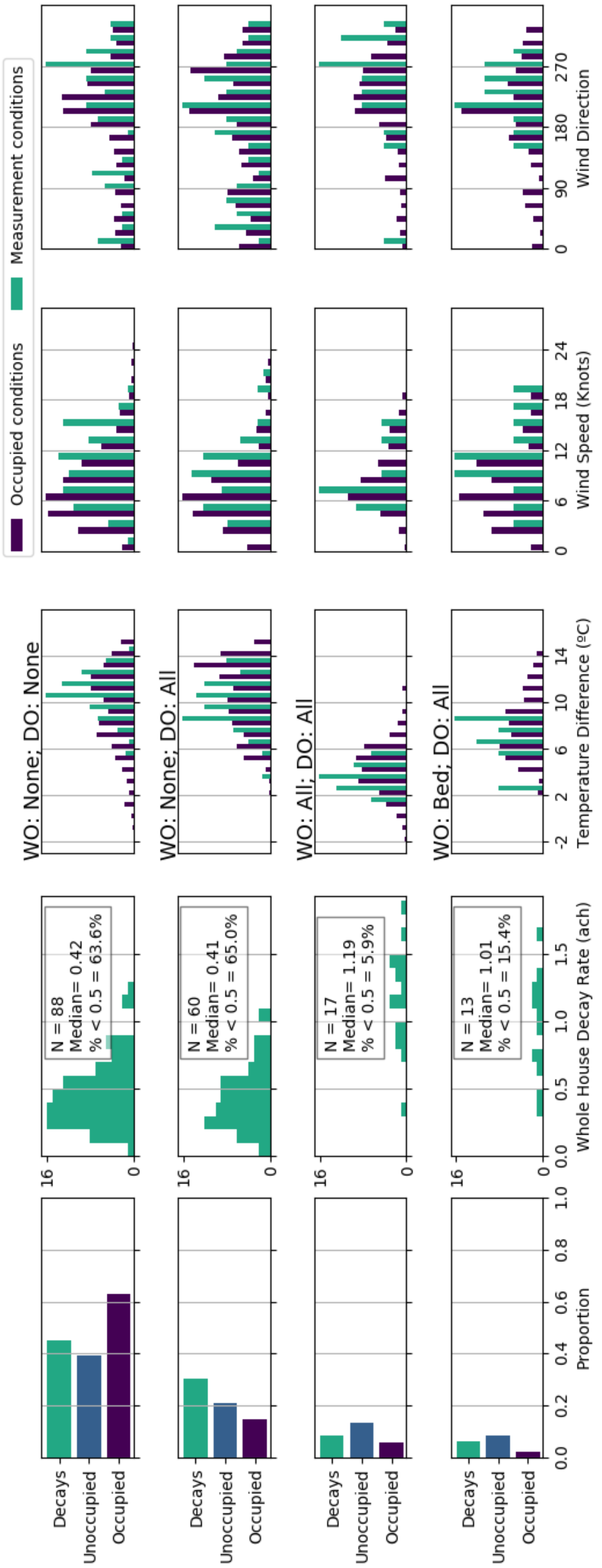

Figure 6. Results for the four most common configurations of doors and windows from Flat C at CS2. For each configuration the proportion of measurements, unoccupied time and occupied time recorded is shown in the left figure; the distribution of measured ventilation rates in the second left figure; the distribution of temperature differences, wind speed and wind direction during occupied and ventilation measurement periods are shown in the final three plots.

6. Uncertainty in measured ventilation rates

Quantifiable, unquantifiable and unknown effects all contribute to uncertainty in measurement (JCGM, 2008). In this case, important unquantifiable uncertainties include definitional uncertainty, uncertainty arising from an imperfect translation between the concept of ventilation and the measurand, and the possibility of flows from adjacent spaces. The quantifiable uncertainty is briefly presented here.

The ventilation rate, calculated according to Equation 1, and fitted using a weighted least squares algorithm has uncertainty (Hughes and Hase, 2010):

$$\alpha_m = \sqrt{\frac{\sum_i w_i}{\sum_i w_i \sum_i w_i x_i^2 - (\sum_i w_i x_i)^2}}\,, \qquad (2)$$

where α_m is the uncertainty in the gradient of the least squares fit (the ventilation rate), $w_i = 1/\alpha_i^2$ where α_i is the uncertainty in the dependent variable of the i^{th} point in the fit (the uncertainty in $ln(\Delta CO_2)$), the summations are over all data points in the least squares fit, and x is the independent variable (time elapsed since the start of the decay).

The uncertainty in mean ΔCO_2 due to spatial inhomogeneity and due to sensor uncertainties were calculated separately, propagated to uncertainty in $ln(\Delta CO_2)$ and combined assuming independence. Few (2021) gives full details of this calculation. Across the case studies the mean combined uncertainty was 9-13% of the measured value.

7. Discussion & Conclusions

Empirical ventilation research generally either measures average ventilation rates over days or weeks, or takes a small number of `snapshot' measurements over minutes or hours. Neither of these approaches support a detailed understanding of the ventilation rates that occupants experience since ventilation is highly variable due to changes in driving forces and occupant actions. This paper reported two analysis algorithms to facilitate research investigating the variability of ventilation rates in occupied dwellings using the CO_2 decay technique.

The occupancy status algorithm (OSA) identified periods when the dwellings were unoccupied, the second algorithm subsequently identifies periods of ΔCO_2 decay for single-zone ventilation rate measurement. The decay identification algorithm imposed conditions to ensure that the method's assumptions were adequately satisfied: spatial homogeneity of CO_2 concentration, minimum ΔCO_2 concentration, limits on the minimum and maximum decay time and on the variation of external CO_2 concentration. The latter resulted in rejecting 4%-46% of decays, highlighting the importance of coincident external CO_2 measurement, particularly where measurements take place over an extended period.

The method was applied to analyse data from four illustrative case studies, three of which recorded over 100 measurements of ventilation over a 6-month period. This enabled investigation of the varying nature of ventilation rate, its relation to occupants' use of the property and detailed insights into the use of doors and windows. This method enables metabolically generated CO_2 to be used as a tracer gas in long-term monitoring studies, without significant researcher burden. This enables detailed studies of ventilation rates in occupied dwellings, addressing a current gap in empirical evidence. Such research will support improvements to policy and practice to deliver healthy living environments at low energy cost and improve the translation between empirical measurement, laboratory testing and modelling of ventilation.

Research has often used a single value to describe ventilation in relation to health outcomes (Sundell *et al.*, 2011; Fisk, 2018). Differences in door and window configurations between occupied and unoccupied states could lead to significant differences in ventilation rate, but only the former is likely to have health implications. McGrath *et al.* (2017) modelled personal exposure to indoor pollutants for different occupants with various indoor pollution locations, source strengths, door closures and occupant location profiles. They found that some occupants were exposed to significantly more pollution than others in the same dwelling. Similarly, Bekö *et al.*, (2016) argued that temporal variations in pollutant sources are often not adequately addressed by ventilation standards, requiring that particular ventilation rates are met at all times in all spaces. The method presented here enables the characterisation of door and window configurations during occupied and unoccupied periods, and links this to ventilation rates observed in those configurations, enabling greater insight into the impact of ventilation rates on health outcomes.

The method and code published from this work can be modified to support a range of research purposes. For example, interzonal flows may be studied using the internal door positions in relation to CO_2 concentrations. The decay identification algorithm may be applied to use gases such as SF_6, or gases monitored for IAQ purposes (e.g. VOCs, PMs, NO_2 or humidity). Conversely, the OSA could be used to support empirical investigations where differences between occupied and unoccupied conditions are of interest, such as exposure to pollutants or overheating, including estimating the location of occupants within the building using CO_2 concentration. The method developed in this work enables the study of ventilation and IAQ as they vary over time, space and configurations of windows and doors to address an important gap in the empirical evidence relating to conditions in occupied dwellings.

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