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Uncertainty and sensitivity analyses applied to a dynamic simulation of the carbon dioxide concentration in a detached house

Jean-Louis Bouvier¹ · Stéphanie Bontemps¹ · Laurent Mora¹

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Abstract

This paper aims to study the variability of indoor CO₂ concentration due to occupant behaviour and physical parameter uncertainties. A case study, conducted in a mechanically ventilated detached house, is presented with an uncertainty and sensitivity analysis (Monte Carlo method with a Latin hypercube sampling). Uncertainties related to occupant behaviour are described by combining four types of scenarios: occupation, generation of CO₂ per person, indoor doors, and outdoor windows' openings. The uncertainty analysis showed that despite an acceptable average room CO₂ concentration, large variations, due to input parameter uncertainties, are observed in CO₂ instantaneous concentrations. Moreover, during occupied periods, average value is relatively important (higher than 1300 ppm). Occupants spent around 30% of the time at CO₂ concentrations over 1500 ppm. Large output uncertainties are reached on the cumulative CO₂ concentration and time fraction spent over 1500 ppm. The sensitivity analysis highlights the strong influence of the parameters related to bedrooms (number of occupants, night generation of CO₂) and of the kitchen extracted airflow rate. It also shows that low-level air change rates in bedrooms are mainly caused by an incorrect air distribution in the building. Potential solutions to reduce both concentrations and uncertainties are discussed.

Keywords Uncertainty analysis · Sensitivity analysis · Mechanical exhaust ventilation · Indoor air quality · Occupant behaviour · Residential buildings

Introduction

In the current energy context, energy efficiency measures tend towards the reduction of ventilation and leakage airflow rates in buildings. Indoor air quality (IAQ), which can be affected by this reduction, is also a major preoccupation. Indeed, IAQ is an essential element of occupant comfort and health [1]. Unlike temperature, it is rarely measured, and thus, users can only rely on their perception. Moreover, it is difficult for occupants to control IAQ for a long period, especially in winter when the fact that opening windows enters in conflict with thermal comfort and energy savings. Consequently, quantifying IAQ variability in buildings is highly important. This variability can be quantified by an uncertainty and sensitivity analysis.

Although uncertainty and sensitivity analyses have been conducted by many authors on building energy performances [2–11], few publications discuss the effect of input parameter uncertainties on residential building indoor air quality. Laverge et al. [12] compared different mechanical exhaust ventilation systems in accordance with five standards on five different dwelling typologies. A probability-based approach was considered for several input variables (such as façade orientation, CO₂ production by occupants, number of occupants, and occupancy schedules). A Monte Carlo approach was used with 100 simulations. This study reveals that for the Belgian, Dutch, and French standards, occupation time with an excess CO₂ concentration higher than 1000 ppm is less than 5%. The authors demonstrated the high importance of air transfer grilles between rooms to reach a satisfactory airflow rate distribution. They also showed the weak importance of boundary conditions (e.g., wind speed and direction) in case of relatively small size trickle ventilators (as in the British, French, and ASHRAE standards). This conclusion is consistent with another study, where different ventilation strategies were compared [13].

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This study showed that the performance of controlled air-supply opening size systems is less affected, by variable conditions such as climate or occupancy, than systems with controlled air exhaust. A sensitivity analysis was conducted by Richieri et al. [14] to assess the impact of the envelope airtightness on airflow patterns. The authors reported that poor airtightness can modify the airflow pattern in the house and can also lead to a fraction of the air entering the house by air inlets lower than 30% (and infiltration higher than 70%) for a mechanical exhaust ventilation system.

Das et al. [15] conducted a sensitivity analysis on particulate matter ($PM_{2.5}$) concentration in a single-storey flat with natural ventilation in England. A Latin hypercube sampling method as well as a linear regression and various sensitivity tests were used. The study pointed out the principal influent parameters on $PM_{2.5}$ concentration in the flat (i.e., internal deposition rate, infiltration rate, ambient external concentration, window opening, $PM_{2.5}$ generation rate, and indoor temperature). Hyun et al. [16] investigated the uncertainty of the air change rate in a naturally ventilated building using the Monte Carlo method with a Latin hypercube sampling. The results indicate that uncertainty is high and that influential parameters are related to weather conditions (wind velocity and outdoor temperature), occupant behaviour (window opening area), and model parameters (discharge coefficient, flow exponent, local terrain constant, and wind velocity profile exponent). These publications demonstrate the growing interest in residential building indoor air quality particularly under uncertainty. However, some studies considered closed windows and indoor doors [12, 14], did not integrate input uncertainties [14], or were performed on a natural ventilation system [15, 16].

The objective and the novelty of this paper are to conduct an uncertainty and sensitivity analysis on a mechanically ventilated detached house to investigate the variability of indoor CO_2 concentration due to occupant behaviour and physical parameter uncertainties. This way, the most influent parameters on indoor CO_2 concentration will be identified. Their value should be known and measured as much as possible to limit the variability on the results and to improve the accuracy of building simulation results. Furthermore, the best practices to reduce the indoor CO_2 concentration could be deduced by identifying actions on the most influent parameters. An original approach is used for the input parameter uncertainties related to occupant behaviour by combining four types of scenarios: occupation (time and occupancy level), generation of CO_2 per person, and indoor doors and outdoor windows openings. This analysis is based on the Monte Carlo method with a Latin hypercube sampling (LHS).

We are aware that carbon dioxide (CO_2) concentration does not provide a complete indication of IAQ [17]. Indeed, it does not describe various phenomena (such as absorption/

desorption and deposition) nor constant or occupant-independent sources (such as emissions from building materials and furniture). However, CO_2 has the advantage of capturing the dynamic effect of occupant contaminant generation. Used by many authors [12, 16, 18, 19], it also has the advantage of being a good indicator for bio-effluents acceptance [17] and consequently for the ventilation efficiency to exhaust this indoor pollution.

The definition of an acceptable CO_2 concentration as well as its impact on health and cognitive functions is not fixed [1, 20]. The level selected as a limit (acceptance and comfort) in the present paper is 1500 ppm, based on the recommendation of Satish et al. [21] and on the German standard DIN 1946-2 [22]. This value is in accordance with the ANSI/ASHRAE Standard 62.1 [23] that indicates that a CO_2 concentration lower than about 700 ppm above outdoor will satisfy a substantial majority of visitors entering the room with respect to human bio-effluents (body odour).

In recent years, the number of relatively cheap indoor climate measuring instruments, that can detect CO_2 , is increasing rapidly in private households. Thus, improving the knowledge of CO_2 in dwelling is a relevant subject for occupants to be able to interpret the importance of their measurements.

The first part of this paper defines the methodology and tools used for sampling and for sensitivity and uncertainty analysis. The modelling approach, including a description of the case study and input parameters, as well as the indicators used to characterise indoor CO_2 concentration are detailed in the following part. Finally, the results, which consist of both an uncertainty and a sensitivity analysis, are presented.

Methodology

With the objective of investigating the variability of indoor CO_2 concentration, the following methodology is applied. The Monte Carlo method is selected, because both uncertainty and sensitivity analyses can be performed with this method. First, the modelling approach and input parameters as well as related uncertainty distributions are defined (“[Case study and modelling](#)”). Uncertainties on occupancy schedule, doors and windows opening, and closing times are considered for occupant behaviour variability. Uncertainties on physical parameters include building characteristics such as air leakage and air inlet areas, building parameters such as ventilation flow rate, temperature set point, heater power, and wind pressure coefficients. Afterwards, the Latin hypercube sampling (LHS) method is used to build a sample of model input parameters. Among the different methods available, LHS sampling method has been chosen, since it allows exploring the input parameter space with a relatively reduced sample size. This method is particularly convenient to get a



quick estimate of sensitivity indices when a few number of parameters has been selected and model evaluation cost is high [24, 25]. The sampling process is the generation of a set of model input parameters that will be used to perform the Monte Carlo analysis. For constant physical parameters, values from the sampling are used directly in the simulation. Occupant behaviour scenarios are also constructed from this sample that provides time and level variables. There are no fixed criteria for the sample size depending on the number of parameters. Some authors recommend that sample size should be at least the number of parameters multiplied by a factor of 4/3 [16] or 3/2 [26, 27]. The chosen size of the sample is here 500 for 178 parameters. LHS is implemented in Python with a matrix generated by the software R [28].

Once the simulations run, using the defined indicators (“Indicators of indoor CO₂ concentration”), results are processed to conduct an uncertainty and sensitivity analysis. Uncertainty is characterised by means of graphical analysis (relative frequency and cumulative probability graphs) and by the calculation of average and standard deviation values for the defined indicators. A global sensitivity analysis is carried out to study the influence of input parameters variability on indoor CO₂ concentration indicators. It consists of a simultaneous variation of all input parameters on their whole variation interval. Standardised regression coefficients (SRC) are chosen to rank and quantify the effects of

input parameters on indoor CO₂ concentration indicators [29]. They are calculated by a linear regression with the least square method. A sign is added to the SRC depending on the sign of the associated regression coefficient. The coefficient of determination (R^2) is used to evaluate the validity of the linear regression [3, 10]. Figure 1 describes the methodology and software used.

Case study and modelling

Case study

The chosen case study (Fig. 2) is based on the N2 house of the Fraunhofer Institute in Holzkirchen (Germany) used in the IEA Annex 58 [30].

Although no CO₂ concentration measurements were performed, this house is selected because of the availability of building characteristics that are presented in a previous paper [32]. Some modifications have been performed. In this study, the house is considered to be in Bordeaux (France) using TMY3 weather data from IWEC (International Weather for Energy Calculations). The ventilation system is adapted to the French standard (Fig. 3) [33, 34]. Only the ground floor is studied. A constant temperature (equal to indoor set point) is fixed as a boundary condition for the cellar and the attic.

Fig. 1 Methodology and software used

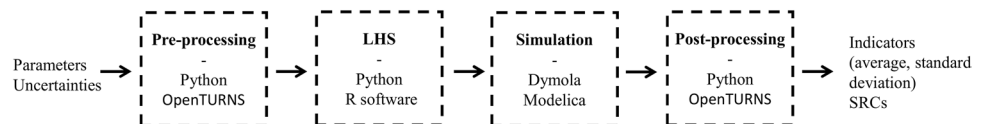
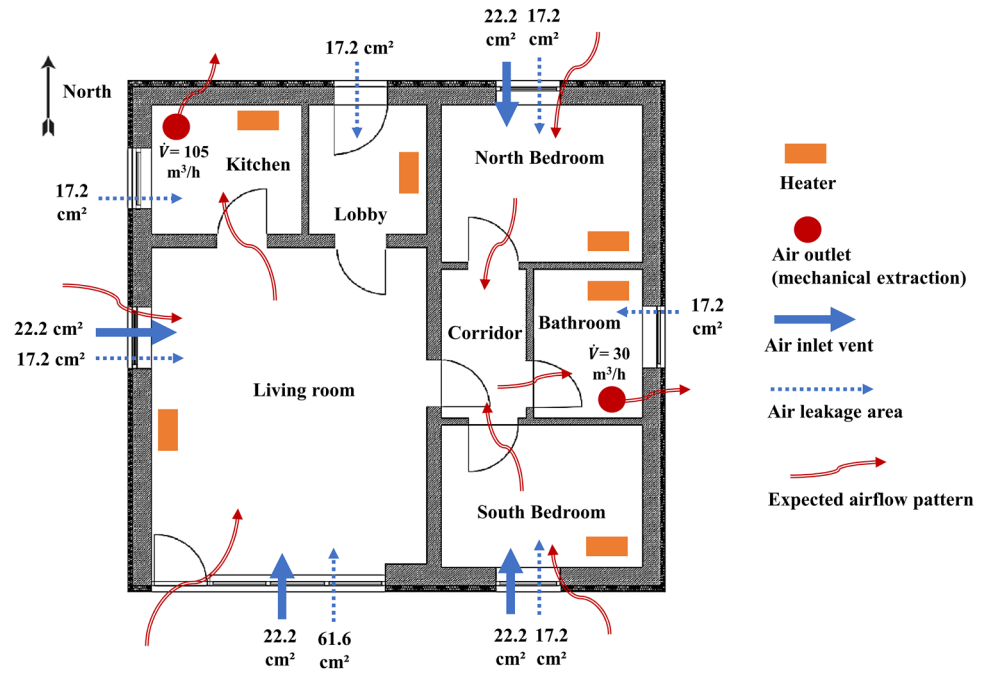


Fig. 2 South view of the house [31]



Fig. 3 Ground floor plan (modified from [31])



Model

The simulation is carried out for a period of 7 days during winter (from December 18 to December 24). This period has been chosen, because in winter, windows are usually opened less often, potentially leading to higher indoor pollutant concentration from internal sources [15]. It is performed in Dymola (Modelica language) using the validated *Modelica Buildings* library [35, 36]. A multi-zone approach with one zone per room is applied. The modelling methodology is detailed in a previous paper [32]. The Dymola built-in Esdirk45a solver is used with a tolerance of 10^{-6} . Input parameters described in the following sections are pre-processing before being entered in the model (Fig. 1). Model outputs consist of the room CO_2 concentrations that are used to compute the indicators of indoor CO_2 concentration defined in “Indicators of indoor CO_2 concentration”.

Constant and modelling parameters

Ventilation system: air leakage area

Fresh air is supplied to the building from air inlets located in the two bedrooms and in the living room. Air leakage through the building envelope and window openings also contribute to fresh air supply. Stale air is mechanically extracted in the kitchen and the bathroom (Fig. 3). The constant extracted flow rates are set to $105 \text{ m}^3/\text{h}$ (kitchen) and $30 \text{ m}^3/\text{h}$ (bathroom) according to the French regulation [33, 34].

French regulation also requires that the fresh airflow rate entering the building by vents and infiltration, at a rated pressure difference of 20 Pa, should be at least equal to the extracted flow rate. For this type of building, the prescribed inlet flow rate, under a pressure difference of 20 Pa, is $60 \text{ m}^3/\text{h}$ in the living room and $30 \text{ m}^3/\text{h}$ in each bedroom [37]. Using the Bernoulli's equation [35]

$$\dot{V} = C_d A \Delta P^m \sqrt{2/\rho}, \quad (1)$$

where \dot{V} is the airflow rate (m^3/s), C_d is the discharge coefficient (–), A is the air inlet area (m^2), ΔP is the pressure difference (Pa), m is the flow coefficient (–), and ρ is the air density (kg/m^3). Considering $C_d = 0.65$ and $m = 0.5$ (large crack [35]), it leads to an air inlet area of 44.4 cm^2 for the living room and of 22.2 cm^2 for each bedroom.

n_{50} (air exchange through the building envelope at a 50 Pa pressure difference) measured value is 1.62 air changes/hour (ac/h). A global air leakage area is computed with $C_d = 0.65$ and using [38]:

$$A = \dot{V} \frac{\sqrt{\rho/(2\Delta P)}}{C_d}. \quad (2)$$

Then, this area is distributed (Table 1) in each room proportionally to windows and doors perimeters [32].

Concerning the air circulation in the building, the French regulation recommends an undercut of 2 cm for the kitchen door and of 1 cm for the other doors [37].



Table 1 Leakage areas

	Air leakage area (cm ²)
Whole ground floor	165.1
Living room (windows 2 and 3)	61.6
Living room (window 1)	17.2
Bathroom	17.2
South and north bedroom	17.2
Kitchen, lobby	17.2

Doors and windows

Doors and windows are modelled with the *DoorDiscretize-Operable* model included in the *Airflow* package of the *Modelica Buildings* library [35].

The inlet air area and the air leakage area are both included in the windows closed area (Fig. 3). The following parameters are used [14, 35, 39]:

- Kitchen and Bathroom windows : $C_d=0.65$ and $m=0.65$ (closed), $C_d=0.65$ and $m=0.5$ (open).
- Other windows (including inlet air area) and doors: $C_d=0.65$ and $m=0.5$ (closed or open).

Other parameters

The indoor air temperature set point is fixed to 20 °C [40]. An ambient external CO₂ concentration of 400 ppm is assumed. It is equal to the mean yearly value measured in Paris [41]. This value is also close to 380 ppm assumed by Hyun et al. [16] in Seoul and to the range 340–460 ppm used by Calì et al. [42] in Aachen, Germany. The electric

heater power is fixed to 2000 W [30]. The wind pressure coefficient at zero wind incidence angle (C_{p0}) is considered equal to 0.6 [43].

Scenarios

Four types of scenarios are defined: occupation, generation of CO₂ per person, indoor doors and outdoor windows openings.

Occupation

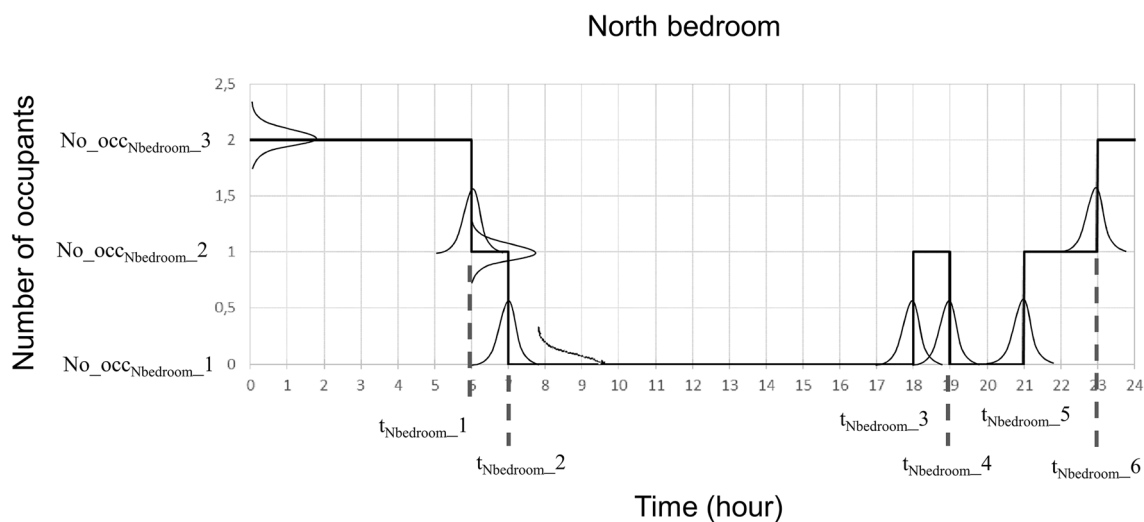
A deterministic schedule is fixed for each room. This schedule, similar for all the days of the week, is based on a family of four people (2 adults and two teenagers), and it is based on time and number of occupants variables (respectively, $t_{Nbedroom}$ and $No_occ_{Nbedroom}$ in Fig. 4).

Generation of CO₂ per person

The generation of CO₂ per person is defined on two periods of the day to take into account a low-level night activity. Metabolic rate is assumed to be 1.5 MET (Metabolic Equivalent of Task) between 6 h and 22 h (daytime) and 0.9 at night [44, 45]; this corresponds, respectively, to a CO₂ generation of 0.39 and 0.23 l/min [23]. These values are in the same range as the previous studies [19, 46, 47] (Fig. 10 in Appendix).

Indoor doors and outdoor windows

Indoor doors and outdoor windows are considered to be closed by default. Doors are set as opened (with a mean opening fraction of 0.8) for a typical period of 5 min when

**Fig. 4** Schedule for the occupancy of the North bedroom

the number of occupants in the room is changing. Windows are also opened for 5 min following a determined schedule. The opening is performed using two time variables, one for the opening and another one for the closing.

Uncertainties

Constant parameters

In this study, only the uncertainties that would have a possible impact on CO₂ concentration are considered. Average and standard deviation values for the design and physical parameters are presented in Table 2. They are chosen according to the literature [2, 3, 6, 40, 41]. Truncated normal distributions bounded between $\pm 2\sigma$ are generated with the OpenTURNS software [48]. The number of this type of parameters is equal to 25.

Table 2 Uncertainty of design and physical parameters

	Average (μ)	Standard deviation (σ)
Windows, doors dimensions	0.935, 1.11, 1.23, 1.54, 1.98, 2.37 m	1 cm
Kitchen door undercut dimension	2 cm	0.5 cm
Other doors undercut dimension	1 cm	0.25 cm
Ventilation flow rate	30, 105 m ³ /h	10%
Air inlet area	22.2 cm ²	10%
Leakage area	17.2, 61.6 cm ²	25%
Wind pressure coefficient at zero wind incidence angle (C_{p0})	0.6	0.1
Ambient external CO ₂ concentration	400 ppm	10%
Indoor temperature	20 °C	1 °C
Electric heater power	2000 W	10%

Table 3 Uncertainty of the occupant behaviour parameters

	Average (μ)	Standard deviation (σ)
Time (doors, windows opening/closing)	0 to 24 h	5 min
Time (occupation, generation of CO ₂ by person)	0 to 24 h	30 min
Fraction of the door or window closed	0	2.10^{-6}
Fraction of the door or window open	0.8	0.1
Generation of CO ₂ by person	0.39 and 0.23 (l/min)	10%
Number of occupants (bedroom)	0, 1, 2	0.25
Number of occupants (other room)	0, 1, 2, 4	0.5

Scenarios

An uncertainty distribution is set for each time and occupancy-level variable (respectively, $t_{Nbedroom}$ and $No_{occ-Nbedroom}$ in Fig. 4) [49]. In the sampling process, different values for all variables are fixed following the chosen uncertainty distribution. Then, for each simulation, a different scenario is randomly built. The result, after the sampling process, is presented in Fig. 11 (“Appendix”).

An uncertainty distribution is also set for each time and opening fraction variable of indoor doors and outdoor windows. The indoor doors schedule is linked to changes in the deterministic occupancy schedule. Doors and windows schedules (after the sampling) are presented in Figs. 12 and 13 (“Appendix”).

Average and standard deviation values for occupant behaviour parameters used in the scenarios are presented in Table 3. A negligible standard deviation is set for the fraction of the door or window closed (0) to prevent a constant opening fraction that would lead to an important opening area. As for the design and physical parameters, truncated normal distributions bounded between $\pm 2\sigma$ are generated. However, with this distribution, negative values are obtained for the zero value of the number of occupants. Either setting a truncated distribution between 0 and $+2\sigma$ or replacing the negative values by zero could solve this issue. We choose the second solution to limit the mean value that will not be in both cases equal to zero [as it can be observed in Fig. 11 (“Appendix”)]. The number of occupant behaviour parameters is equal to 153.

Indicators of indoor CO₂ concentration

Several indicators and criteria can be used for the characterisation of indoor CO₂ concentration [50]. We selected three indicators: the average CO₂ concentration, the time fraction spent over a limit concentration, and the cumulative CO₂ concentration.

Three different average CO₂ concentrations are considered: room and house CO₂ concentrations (CO_{2,r}, CO_{2,av,r}),



occupied room and house CO_2 concentrations ($\text{CO}_{2,r,\text{occ}}$, $\text{CO}_{2,\text{av},r,\text{occ}}$), and CO_2 concentration averaged by occupant ($\text{CO}_{2,\text{av},\text{occ}}$).

First, the average room and house CO_2 concentrations are calculated for the whole period (1 week):

$$\text{CO}_{2,r} = \frac{\sum_{t=t_0}^{t_{\text{end}}} \text{CO}_{2,r}^t \Delta t}{t_{\text{end}} - t_0} \quad (3)$$

$$\text{CO}_{2,\text{av},r} = \frac{\sum_{r \in n_{\text{room}}} V_r \text{CO}_{2,r}}{\sum_{r \in n_{\text{room}}} V_r} \quad (4)$$

with n_{room} , the total number of rooms in the house, CO_2 , the CO_2 concentration (ppm), N_{occ} , the number of occupants, Δt , the time step, V_r , the room volume, t_0 and t_{end} , respectively, the start and stop time of the simulation.

Second, the average room and house CO_2 concentrations are computed considering only the occupied rooms:

$$\text{CO}_{2,r,\text{occ}} = \frac{\sum_{t=t_0}^{t_{\text{end}}} \varepsilon \text{CO}_{2,r}^t \Delta t}{\sum_{t=t_0}^{t_{\text{end}}} \varepsilon \Delta t} \quad (5)$$

with $\varepsilon = 0$ if $N_{\text{occ}} \leq 0.5$ and $\varepsilon = 1$ if $N_{\text{occ}} > 0.5$:

$$\text{CO}_{2,\text{av},r,\text{occ}} = \frac{\sum_{r \in n_{\text{room}}} V_r \text{CO}_{2,r,\text{occ}}}{\sum_{r \in n_{\text{room}}} V_{r,\text{occ}}} \quad (6)$$

with $V_{r,\text{occ}}$, the occupied room volume. If a room is not occupied ($N_{\text{occ}} \leq 0.5$) during the whole period, neither its CO_2 concentration nor its volume is taken into account in the average.

Third, the occupant average CO_2 concentration is calculated considering the whole period:

$$\text{CO}_{2,\text{av},\text{occ}} = \frac{\sum_{t=t_0}^{t_{\text{end}}} \sum_{r \in n_{\text{room}}} \text{CO}_{2,r}^t * N_{\text{occ}}^t}{\sum_{t=t_0}^{t_{\text{end}}} \sum_{r \in n_{\text{room}}} N_{\text{occ}}^t} \quad (7)$$

The time fraction spent by an occupant over a limit concentration (l_1) is defined as

$$f_{t,c>l_1} = \frac{\sum_{t=t_0}^{t_{\text{end}}} \sum_{r \in n_{\text{room}}} N_{\text{occ}}(\text{if } \text{CO}_{2,r}^t > l_1)^t \Delta t}{\sum_{t=t_0}^{t_{\text{end}}} \sum_{r \in n_{\text{room}}} N_{\text{occ}}^t \Delta t} \quad (8)$$

The cumulative CO_2 concentration (in ppm.h) is the number of hours when CO_2 concentration is over a limit (l_1) multiplied by the excess CO_2 above this limit [51]:

$$\text{CO}_{2,\text{cum}>l_1} = \sum_{t=t_0}^{t_{\text{end}}} \frac{\sum_{r \in n_{\text{room}}} N_{\text{occ}}(\text{if } \text{CO}_{2,r}^t > l_1)^t * (\text{CO}_{2,r}^t - l_1) \Delta t}{\sum_{r \in n_{\text{room}}} N_{\text{occ}}(\text{if } \text{CO}_{2,r}^t > l_1)^t} \quad (9)$$

Results and discussion

Uncertainty analysis

Rooms CO_2 concentration

The average number of occupants in the house is 2.96. The repartition of occupants over the presence period in the house and for the 500 simulations is 27% in the north bedroom, 24% in the south bedroom, 28% in the living room, 11% in the kitchen, and 10% in the bathroom. Figure 5 presents the average (solid line), 5th and 95th percentiles (dotted lines) CO_2 concentrations in each room for the 500 simulations.

We can observe, in Fig. 5, relatively high CO_2 concentrations (> 1500 ppm), particularly in the bedrooms. Indeed, the major part of output airflow rate air is extracted in the kitchen (105 out of 135 m^3/h , Fig. 3). However, due to the leaks and floor geometry, only a small fraction of this flow rate is coming from the bedrooms. The concentration difference between both bedrooms is mainly due to a dominant wind coming from South–East direction (Fig. 6) that causes an increase in the south bedroom inlet flow rate during the first 6 days. On the 7th day (from 144 h), a North–West wind leads to a lower pressure on the south bedroom walls and consequently to a lower inlet flow rate that conducts to high CO_2 values. The opening of the north bedroom window at night has a relatively low influence (< 350 ppm) on the concentration. The corridor concentration is often elevated due to a dilution from the bedrooms. The peaks in concentration in the lobby are due to dilution from the living room under unfavourable wind direction.

The fast CO_2 concentration drops are principally related to window openings (for example, in the morning in the bedrooms). High amplitudes between 5th and 95th percentile values are observed. For example, the concentration in the north bedroom at 30 h is varying between 2300 and 4600 ppm depending on input parameters. Moreover, the intervals between the 5th and 95th percentiles are different among the rooms with a highest value in the north bedroom.

In Table 4, the average room CO_2 concentration varies from 694 ppm in the living room to 1236 ppm in the north bedroom. The house volume average is 849 ppm. The highest average and standard deviation values are reached in the bedrooms and the bathroom. From these results, the ventilation system seems to provide an acceptable indoor CO_2 concentration to the occupants. However, these relatively low average values are mostly explained by the fact that the house is almost empty during the daytime. Considering only the occupied periods (Table 5), average values



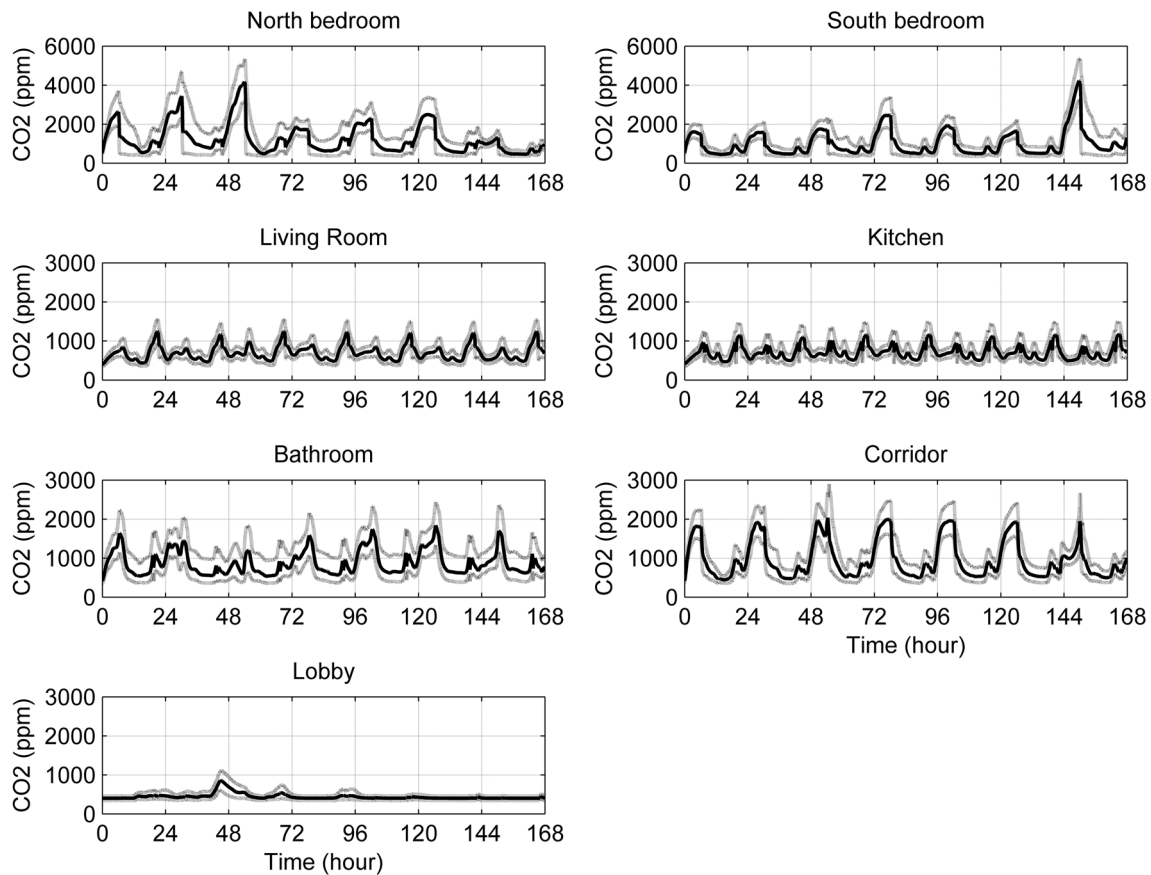


Fig. 5 Average (solid line), 5th and 95th percentiles (dotted lines) CO₂ concentrations in each room

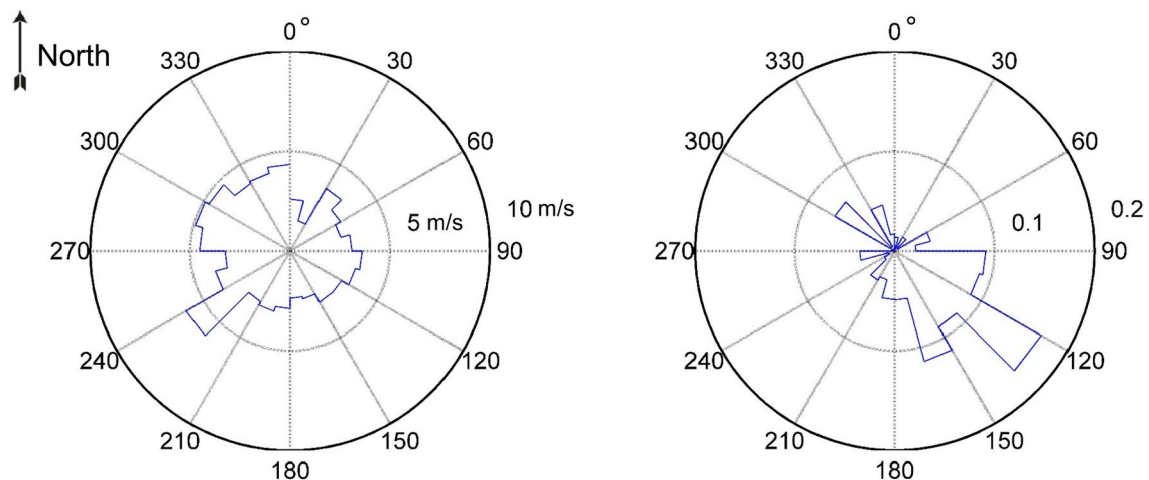


Fig. 6 Wind rose: Speed distribution (m/s) (left) and frequency distribution (right) for the studied week in Bordeaux (France)

are higher with problematic concentrations (> 1500 ppm) reached in the bedrooms. Thus, the ventilation system does not provide, during the occupied period, an adequate fresh airflow rate to maintain an average concentration below 1500 ppm in the bedrooms. Several authors also mentioned

frequent high indoor CO₂ concentrations in bedrooms. Koffi et al. [18, 52], in a deterministic multi-zone model study, also observed an elevated CO₂ concentration (48% of the occupancy duration spent at a concentration higher than 2460 ppm) in the bedroom occupied by two adults



Table 4 Average and standard deviation of the weekly average room CO₂ concentrations

Average room CO ₂ concentrations (ppm) (CO _{2,r} , CO _{2,av,r})	Average (μ)	Standard deviation (σ)	Standard deviation (σ) in %
North bedroom	1236	222	18.0
South bedroom	999	163	16.3
Living room	694	69	9.9
Kitchen	706	77	10.9
Bathroom	881	169	19.2
Volume average	849	79	9.3

Table 5 Average and standard deviation of the weekly average occupied room CO₂ concentrations

Average occupied room CO ₂ concentrations (ppm) (CO _{2,r,occ} , CO _{2,av,r,occ})	Average (μ)	Standard deviation (σ)	Standard deviation (σ) in %
North bedroom	1760	258	14.7
South bedroom	1585	196	12.4
Living room	858	102	11.9
Kitchen	872	115	13.2
Bathroom	1344	244	18.2
Volume average (not considering empty rooms)	1168	101	8.6

with a similar ventilation system. Jensen et al. [53] noted, during a 10-day field test, that 31% of CO₂ concentration measurements were higher than 1560 ppm in the bedroom of a mechanically ventilated house. Laverge et al. [54] also measured average CO₂ concentrations above 1200 ppm above ambient in bedrooms of mechanically ventilated

houses and the average reported bedrooms concentration has a similar profile, as shown in Fig. 5.

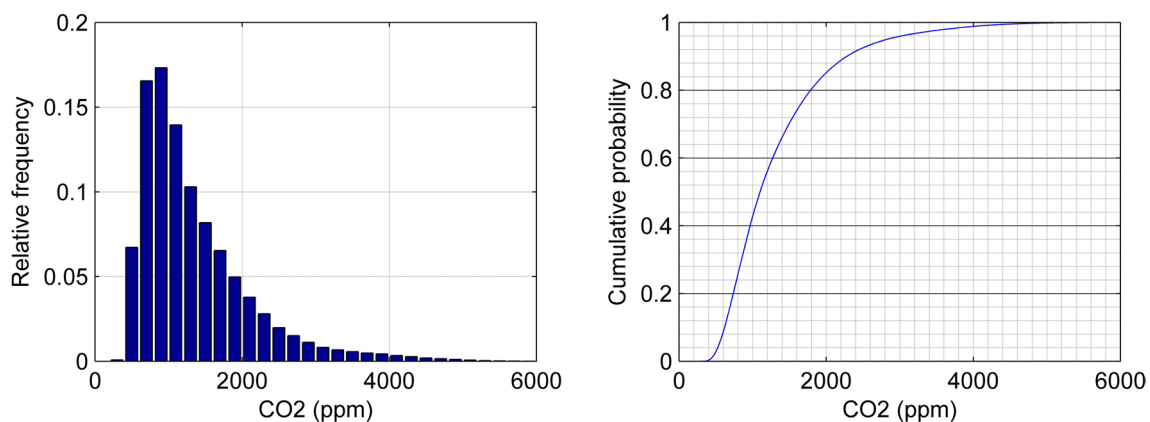
Instantaneous CO₂ concentration by occupant

Figure 7 presents the relative frequency and cumulative probability of the instantaneous CO₂ concentration for all the occupants of the 500 simulations. It shows a relatively large dispersion of the concentration with a probability of 0.4 for an occupant to be exposed to a CO₂ concentration below 1000 ppm and of 0.7 below 1500 ppm. Furthermore, concentrations higher than 5000 ppm are reported. Lower values are reported by Laverge et al. [12] in a numerical study comparing different standards conducted on 150 m² dwellings located in Belgium. These lower values compared to the present study can be explained by differences in the building configurations and occupation scenarios.

Average occupant CO₂ concentration, time fraction, and cumulative CO₂ concentration

The average occupant CO₂ concentration (CO_{2,av,occ}), time fraction spent over 1500 ppm ($f_{t,c>1500}$), and cumulative CO₂ concentration over 1500 ppm (CO_{2,cum>1500}), defined in “Indicators of indoor CO₂ concentration”, are computed for each simulation of 1 week. The relative frequency and cumulative probability of the average occupant CO₂ concentration (CO_{2,av,occ}) and time fraction spent over 1500 ppm are presented in Figs. 8 and 9.

In Fig. 8, the average occupant CO₂ concentration is between 950 and 1900 ppm. Due to averaging, this interval is logically smaller than the instantaneous concentration (Fig. 7). Therefore, the use of average indicators should be done cautiously, because it can hide important disparities. In Fig. 9, we can observe a large variability of the results with 10–50% of an occupant week spent at a CO₂ concentration

**Fig. 7** Relative frequency and cumulative probability of CO₂ concentration for all the occupants of the 500 simulations

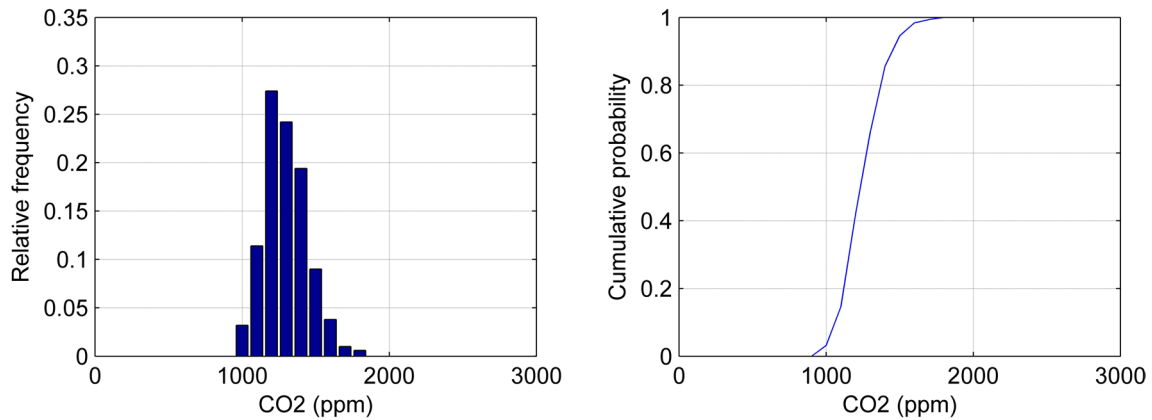


Fig. 8 Relative frequency and cumulative probability of weekly average occupant CO₂ concentration

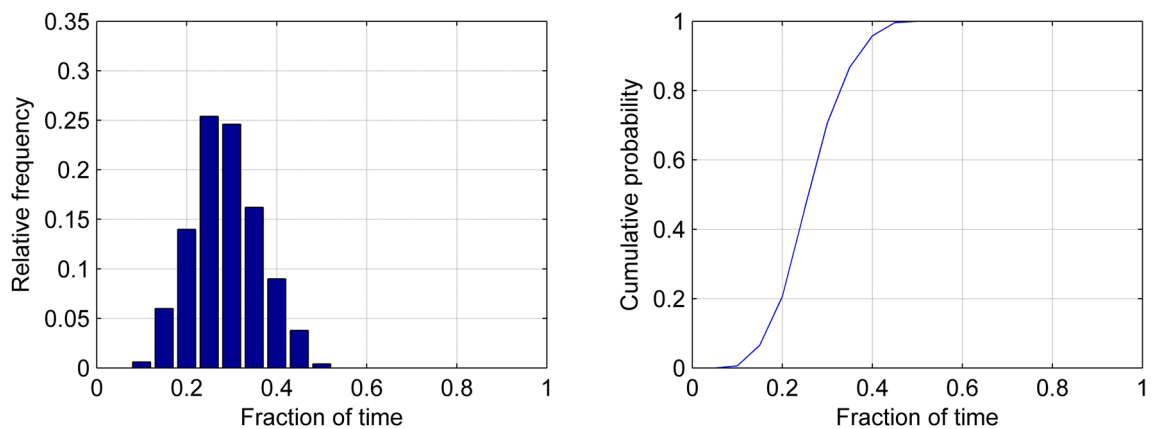


Fig. 9 Relative frequency and cumulative probability of time fraction spent over a CO₂ concentration of 1500 ppm

Table 6 Average and standard deviation of the output indicators

	Average (μ)	Standard deviation (σ)	Standard deviation (σ) in %
Average occupant CO ₂ concentration (ppm) ($CO_{2,av,occ}$)	1349	144	10.7
Time fraction spent over 1500 ppm (-) ($f_{t,c>1500}$)	0.31	0.08	24.4
Cumulative CO ₂ concentration over 1500 ppm (ppm.h) ($CO_{2,cum>1500}$)	77,895	27,150	34.9

over 1500 ppm. This shows that, for some input parameter configurations, important periods of discomfort can occur.

Table 6 shows the average and standard deviation of some indoor CO₂ concentration indicators. The average occupant CO₂ concentration (1349 ppm) is higher than the occupied room volume average (1168 ppm). This means that rooms, where concentrations are important are occupied by more than one person ($N_{occ} > 0.5$). Indeed, this first indicator describes more precisely the concentration to which occupants are exposed. It can be noted the high standard deviations of both the time fraction spent over

1500 ppm and the cumulative CO₂ concentration. These are mainly due to high CO₂ concentration variations that can be observed in Fig. 5. These two unaverage indicators are, furthermore, related to safety (due to the possible cumulative effect of exposure to high CO₂ concentration) and comfort (taking into account concentration higher than 1500 ppm) [50]. Therefore, providing a guaranty that the cumulative CO₂ concentration and the time fraction spent by an occupant above a certain concentration are below a limit value is challenging with uncertain input parameters.



Table 7 SRCs and R^2 coefficient for the average north and south bedrooms CO_2 concentration

CO_2 Weekly average – Occupied room ($\text{CO}_{2,r,occ}$) North Bedroom			CO_2 Weekly average – Occupied room ($\text{CO}_{2,r,occ}$) South Bedroom		
Parameter	Mean value	SRC (%)	Parameter	Mean value	SRC (%)
No_Occ North Bedroom	2	20.4	No_Occ South Bedroom	2	34.1
Generation of CO_2 by person (night)	0.23 l/min	14.1	Generation of CO_2 by person (night)	0.23 l/min	21.0
Leakage area Liv. Room	$6.16 \cdot 10^{-3} \text{ m}^2$	10.0	Leakage area South Bedroom	$1.72 \cdot 10^{-3} \text{ m}^2$	– 7.3
Extracted flow rate (Kitchen)	105 m^3/h	– 9.0	Door undercut dimension	0.01 m	– 4.8
No_Occ North Bedroom	1	5.5	Ambient CO_2 concentration	400 ppm	3.3
Leakage area North Bedroom	$1.72 \cdot 10^{-3} \text{ m}^2$	– 4.2	Leakage area Liv. Room	$6.16 \cdot 10^{-3} \text{ m}^2$	3.3
$R^2 = 0.95$			$R^2 = 0.97$		

Table 8 SRCs and R^2 coefficient for the average living room and kitchen CO_2 concentration

CO_2 Weekly average – Occupied room ($\text{CO}_{2,r,occ}$) Living Room			CO_2 Weekly average – Occupied room ($\text{CO}_{2,r,occ}$) Kitchen		
Parameter	Mean value	SRC (%)	Parameter	Mean value	SRC (%)
No_Occ Liv. Room	2	27.1	No_Occ Kitchen	1	27.6
Ambient CO_2 concentration	400 ppm	14.7	Ambient CO_2 concentration	400 ppm	9.8
Generation of CO_2 by person (day)	0.39 l/min	11.4	Generation of CO_2 by person (day)	0.39 l/min	7.9
No_Occ Liv. Room	0	– 6.5	No_Occ Liv. Room	0	6.5
Occupation time Liv. Room	20 h	– 4.4	No_Occ Liv. Room	2	5.1
Extracted flow rate (Kitchen)	105 m^3/h	– 3.3	Occupation time Kitchen	20 h	3.3
$R^2 = 0.88$			$R^2 = 0.90$		

These first results show that although acceptable average room CO_2 concentration values can be observed, high concentrations are reached temporally in some rooms and average values considering the occupant are also elevated (higher than 1300 ppm). Thus, for some input parameter configuration, discomfort can often be felt. As a result of the input parameter uncertainties, elevated amplitudes between 5th and 95th percentiles values are observed in instantaneous concentrations. The time spent by an occupant at a CO_2 concentration over 1500 ppm is around 30%, which is important. We also highlight that large output uncertainties can be reached, especially on unaverage indicators (cumulative CO_2 concentration and time fraction spent by an occupant over a limit concentration). These results show the importance of the choice of input parameters or/and to conduct an uncertainty analysis. To determine which input parameters mainly affect the indicator uncertainties, a sensitivity analysis is conducted in the following part.

Sensitivity analysis

Rooms CO_2 concentrations

Standardised regression coefficients (SRC) and regression coefficients (R^2) are computed for the average CO_2 concentration for each room (Tables 7, 8, 9, 10, 11). Only the occupied periods are considered in this analysis. The

Table 9 SRCs and R^2 coefficient for the average bathroom CO_2 concentration

CO_2 Weekly average – Occupied room ($\text{CO}_{2,r,occ}$) Bathroom		
Parameter	Mean value	SRC (%)
No_Occ Bathroom	1	40.8
Leakage area Bathroom	$1.72 \times 10^{-3} \text{ m}^2$	– 6.1
Generation of CO_2 by person (day)	0.39 l/min	5.7
No_Occ Bathroom	0	– 4.9
Occupation time Bathroom	6 h	– 3.5
Time, generation of CO_2	6 h	– 3.1
$R^2 = 0.87$		

R^2 coefficients, with values close to or over 0.9, indicate that the regression model provides a good estimation of the output [3].

In all the rooms (Tables 7, 8, 9, 10, 11), we can notice that the number of occupants and the generation of CO_2 per person are more influential than the extracted flow rate. This is mainly due to the nominal and uncertainty values chosen for the flow rates and to the fact that an increase of the extracted flow rate will not necessarily lead to a significant increase of the inlet fresh air in the considered room. In fact, increasing the extracted flow rate can cause, in relation with the airflow pattern (Fig. 3), the transportation of CO_2 from other occupied rooms (for example, in the bathroom, kitchen, and



Table 10 SRCs and R^2 coefficient for the weekly occupied room volume average and occupant CO₂ concentrations

CO ₂ (Weekly occupied room volume average) ($CO_{2,av,occ}$)			CO ₂ by occupant (Weekly average) ($CO_{2,av,occ}$)		
Parameter	Mean value	SRC (%)	Parameter	Mean value	SRC (%)
Generation of CO ₂ by person (night)	0.23 l/min	13.9	Generation of CO ₂ by person (night)	0.23 l/min	17.1
Ambient external CO ₂ concentration	400 ppm	13.6	No_Occ North Bedroom	2	14.8
Generation of CO ₂ by person (day)	0.39 l/min	9.2	Extracted flow rate (Kitchen)	105 m ³ /h	-8.1
No_Occ Liv. Room	2	8.1	No_Occ South Bedroom	2	7.6
Extracted flow rate (Kitchen)	105 m ³ /h	-8.0	No_Occ Kitchen	0	-6.9
No_Occ North Bedroom	2	5.2	Ambient external CO ₂ concentration	400 ppm	6.6
$R^2 = 0.93$			$R^2 = 0.95$		

Table 11 SRCs and R^2 coefficient for the time fraction spent over 1500 ppm and for the cumulative CO₂ concentration over 1500 ppm

Time fraction CO ₂ > 1500 ppm ($f_{t,c>1500}$)			Cumulative CO ₂ concentration over 1500 ppm (ppm.h) ($CO_{2,cum>1500}$)		
Parameter	Mean value	SRC (%)	Parameter	Mean value	SRC (%)
No_Occ South Bedroom	2	17.2	Generation of CO ₂ by person (night)	0.23 l/min	21.2
Generation of CO ₂ by person (night)	0.23 l/min	15.4	No_Occ North Bedroom	2	18.5
No_Occ Kitchen	0	-7.3	Leakage area Liv. Room	6.16.10 ⁻³ m ²	13.9
No_Occ North Bedroom	2	6.3	Extracted flow rate (Kitchen)	105 m ³ /h	-11.0
No_Occ Liv. Room	0	-5.0	Door undercut dimension	0.01 m	-5.7
Extracted flow rate (Kitchen)	105 m ³ /h	4.5	No_Occ South Bedroom	2	3.3
$R^2 = 0.93$			$R^2 = 0.95$		

corridor). This increase can also have a relatively limited impact on a room CO₂ concentration if the leakage and air inlet areas are considerably larger in other rooms.

In bedrooms (Table 7), important parameters are unsurprisingly the number of occupants and the generation of CO₂ per person at night. Bedrooms and living room leakage areas as well as the door undercut dimension are also significant. Higher leakage areas in bedrooms can increase the inlet fresh airflow rate, a reduction of living room leakage area and an increase of the door undercut area can contribute to a better air distribution respecting the expected airflow pattern in the building, as shown in Fig. 3.

Kitchen extracted flow rate is not an influential factor in the south bedroom. As this room is upwind (Fig. 6), it is likely that wind effects prevail over the mechanical extraction [55]. This effect is amplified by the constant extracted volumetric flow rate considered in the model. In reality, the extracted flow rate can actually increase as a result of an overpressure caused by the wind. The bathroom extracted flow rate, which has a lower nominal value than the kitchen one, is not a major influential factor.

The ambient CO₂ concentration is the second important parameter in the living room (Table 8). This is due to the existence of important air inlet and leakage areas in this room. Increasing the low level (0) of occupancy can lead to a reduction of the average CO₂ concentration. Indeed, this increase can change the state of the room from unoccupied

to occupied and thus add to the average concentration low CO₂ values when few occupants are in the room. Since both the living room and the kitchen are mainly occupied during the daytime, only the number of occupants and the generation of CO₂ per person during this period are relevant. The number of occupants in the living room and the ambient CO₂ concentration increase the kitchen CO₂ concentration. This is due to the airflow pattern that results in a flow from the living room to the kitchen. Moreover, the kitchen air inlet area is considerably lower than the undercut door area. Therefore, the fresh air coming from outside is limited and both the extracted flow rate and the leakage area do not considerably impact the kitchen CO₂ concentration.

In the bathroom (Table 9), the door undercut area is smaller than the kitchen one, so the leakage area has here a larger impact on CO₂ concentration. However, as for the kitchen, the extracted flow rate is not significant, since the major part of the inlet flow rate is coming from other potentially polluted rooms.

This first part of the sensitivity analysis, performed on room CO₂ concentrations, provides some interesting insights to reduce concentrations and uncertainties in the presented model configuration. First, an increase in the kitchen extracted flow rate can improve the air change rate, but would be energy consuming. Moreover, although this increase would reduce the average house CO₂ concentration, it may not be the most effective way to reduce CO₂ exposure



in the bedrooms due to airflows in the building. The CO₂ concentration in bedrooms and its uncertainty would be reduced by the following measures: increasing the door undercuts and reducing the living room inlet and leakage areas (better air distribution respecting the expected airflow pattern) or increasing the inlet air area in the bedrooms. This last solution could also be applied in the bathroom, as it would have a beneficial effect on the bathroom CO₂ concentration. The use of CO₂ or presence detection controlled air inlet vents could reduce both the concentrations and the uncertainties. A numerical study conducted by Laverge et al. [13] concludes that CO₂-controlled inlets can reduce both the exposure to high CO₂ concentration and the building energy demand. The CO₂ concentrations and uncertainties can also be reduced by the use of a balanced ventilation system that would provide an adjusted air inlet flow rate in the different rooms [18]. Furthermore, both balanced ventilation and CO₂ controlled inlet systems are less sensitive to outdoor conditions [13, 14].

Average CO₂ concentration, time fraction, and cumulative CO₂ concentration

Standardised regression coefficients (SRC) and regression coefficients (R^2) are computed for the weekly occupied room volume average and occupant CO₂ concentrations (Table 10) and for the time fraction spent over 1500 ppm and cumulative CO₂ concentration over 1500 ppm (Table 11). The R^2 coefficients, with values over 0.9, indicate that the regression model provides a good estimation of the output [3]. In Table 10, we observe that several influential parameters on the average CO₂ concentration are related to the bedrooms. Some differences between the two average concentrations are observed depending on the calculation of the indicator. In the volume average, the number of occupants in the living room is relatively important due to the large volume of this room. In contrast, the ambient external CO₂ concentration and the diurnal generation of CO₂ per person have a low relative impact on the occupant CO₂ concentration. Actually, the second indicator is more sensitive to the high CO₂ concentrations reached in the most occupied rooms such as the bedrooms at night (Fig. 5). Due to the averaging by occupant, increasing the low level (0) of occupancy in the kitchen can conduct to a reduction of the average CO₂ concentration by adding more occupants and low CO₂ values. The same phenomenon explains the reduction of the time fraction spent over 1500 ppm with the low level (0) of occupancy in the kitchen and in the living room (Table 11).

Since the highest concentrations are reached at night in the bedrooms, both the time fraction spent over 1500 ppm and the cumulative CO₂ concentration over 1500 ppm are affected by the number of occupants in the bedrooms and the generation of CO₂ per person at night (Table 11). The

living room leakage area and the door undercut dimension are also significant for the cumulative CO₂ concentration over 1500 ppm. They both can lead to a better air distribution in the building respecting the expected airflow pattern (Fig. 3) and thus can contribute to an increase of the air change rate in the bedrooms. In a numerical study on the concentration of particulate matter (PM_{2.5}) in a single-storey flat, Das et al. [15] also showed that the infiltration rate, the ambient external concentration, and the internal pollutant generation rate are some of the principal determinants in the contaminant concentration. Interestingly, some predominant parameters affecting the indoor CO₂ concentration can also be predominant in sensitivity studies regarding building energy consumption, such as the air change rate and the occupancy [5] or the number of occupants in the bedroom [10]. The impact of these parameters is, nevertheless, opposite; increasing the air change rate or reducing the occupancy will lead to a positive reduction of the CO₂ concentration but to an increase of the heating demand.

Finally, time variables for CO₂ generation, occupation, windows, and doors have a low influence. This can be due to the fact that their impacts last a shorter period than other variables, to the relatively low standard deviation associated with these values (5 and 30 min) and to the very fast variation of the CO₂ concentration following an opening. However, the combined effect of several time variables can be significant and it might be of interest to investigate it in a further study. Indeed, a numerical study conducted by Hyun et al. [16] found out that the window opening area due to the occupant behaviour is the second dominant parameter in the simulation of a naturally ventilated building.

This second part of the sensitivity analysis, performed on several indicators, highlights the strong influence of the bedroom-related parameters in the presented model configuration. Considering perfect air mixing in the building, a steady-state CO₂ concentration around 800 ppm would be reached in the building at night under average conditions. Therefore, the high concentrations observed are more due to the air distribution than to an insufficient extracted flow rate. In addition, increasing the extracted flow rate would lead to a higher energy consumption. The solutions suggested in the previous section to reduce the bedrooms or the whole building CO₂ concentrations and uncertainties are thus relevant.

Conclusion

With the aim of investigating the variability of indoor CO₂ concentration due to occupant behaviour and physical parameter uncertainties, an uncertainty and sensitivity analysis has been conducted in a mechanically ventilated detached house.



First, the variability of indoor CO₂ concentration is quantified through an uncertainty analysis. Despite acceptable average room CO₂ concentration, large variations, due to input parameter uncertainties, are observed in CO₂ instantaneous concentrations. Moreover, average occupant value is relatively important (higher than 1300 ppm). On the studied period, the time spent by an occupant at a CO₂ concentration over 1500 ppm is around 30%, which is important. We also highlight that large output uncertainties are reached with a standard deviation of 24.4% for the time fraction spent by an occupant over 1500 ppm and 34.9% for the cumulative CO₂ concentration over 1500 ppm. These results highlight the unpredictability of the real world and thus show the importance of the choice of input parameters or/and to conduct an uncertainty analysis. Indeed, the peak concentration may not be adequately represented by averages, and moreover, airflow between rooms can make concentrations in individual rooms much higher than the house average. Second, to determine which input parameters mainly affect the variability, a sensitivity analysis has been performed on room CO₂ concentrations and several indoor CO₂ concentration indicators. It highlights the strong influence of the bedroom-related parameters (number of occupants, generation of CO₂ at night) and of the kitchen extracted flow rate. Therefore, to improve the modelling of indoor CO₂ concentration in a comparable case study, it could be useful to have these parameter values as precise as possible or to include their uncertainties. The sensitivity analysis also shows that the low-level air change rates in the bedrooms are mainly caused by an incorrect air distribution in the building. The CO₂ concentrations and uncertainties could be reduced by increasing the door undercuts, reducing the living room inlet and leakage areas, and increasing the bedroom inlet areas. For this type of ventilation system, it could be of interest to measure the air leakage in each room and calibrate the air inlet area accordingly to reach the expected airflow pattern. The presence of CO₂ controlled air inlets or balanced ventilation systems could be potential solutions to reduce both the concentrations and uncertainties.

It would be of interest to extend such study on different buildings, over a longer period of time and considering several base case scenarios (for example, with the indoor doors always open or closed, or with the outdoor windows always closed, or with other time and level variables). It would also be of interest to consider temperature differences and leakage in the attic and cellar or other probability distributions. Furthermore, the approach developed in this study is not intended to provide definitive conclusions on the uncertainties related to the indoor CO₂ concentration but rather to target the most influential parameters on which it will be necessary to improve the knowledge (limiting the uncertainties). This study particularly points out the need for a more precise characterisation of the occupant behaviour. This characterisation could be inspired

by methods developed in studies on the determinants of energy consumptions of the household sector [56–59]. Moreover, future buildings will be built with some connected objects, such as thermostats or CO₂ sensors. These are potential solutions to develop the knowledge of occupant behaviour. But also, improving the knowledge of CO₂ in dwelling is a relevant subject for occupants to be able to interpret the importance of their measurements. Furthermore, other contaminants and indicators could be implemented to improve the characterisation of the IAQ. This way, more information would be provided on uncertainties related to the IAQ and other solutions to improve indoor air quality would be identified. Finally, the approach developed in this paper could be generalized at the building design phase, by focusing on reducing most influential parameters uncertainties.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Appendix

Figures 10, 11, 12, and 13.

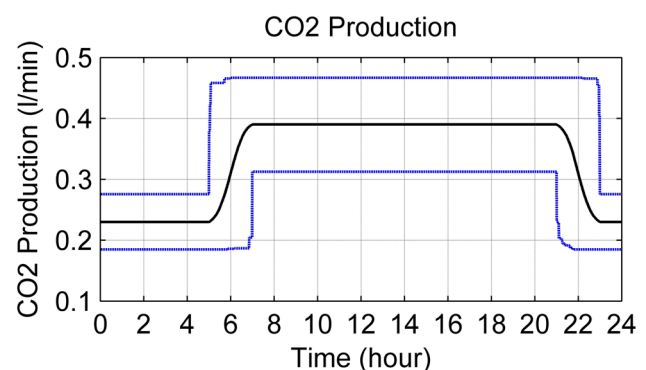


Fig. 10 CO₂ production per person schedule [mean (solid line), minimum and maximum (dotted line)] for the 500 simulations

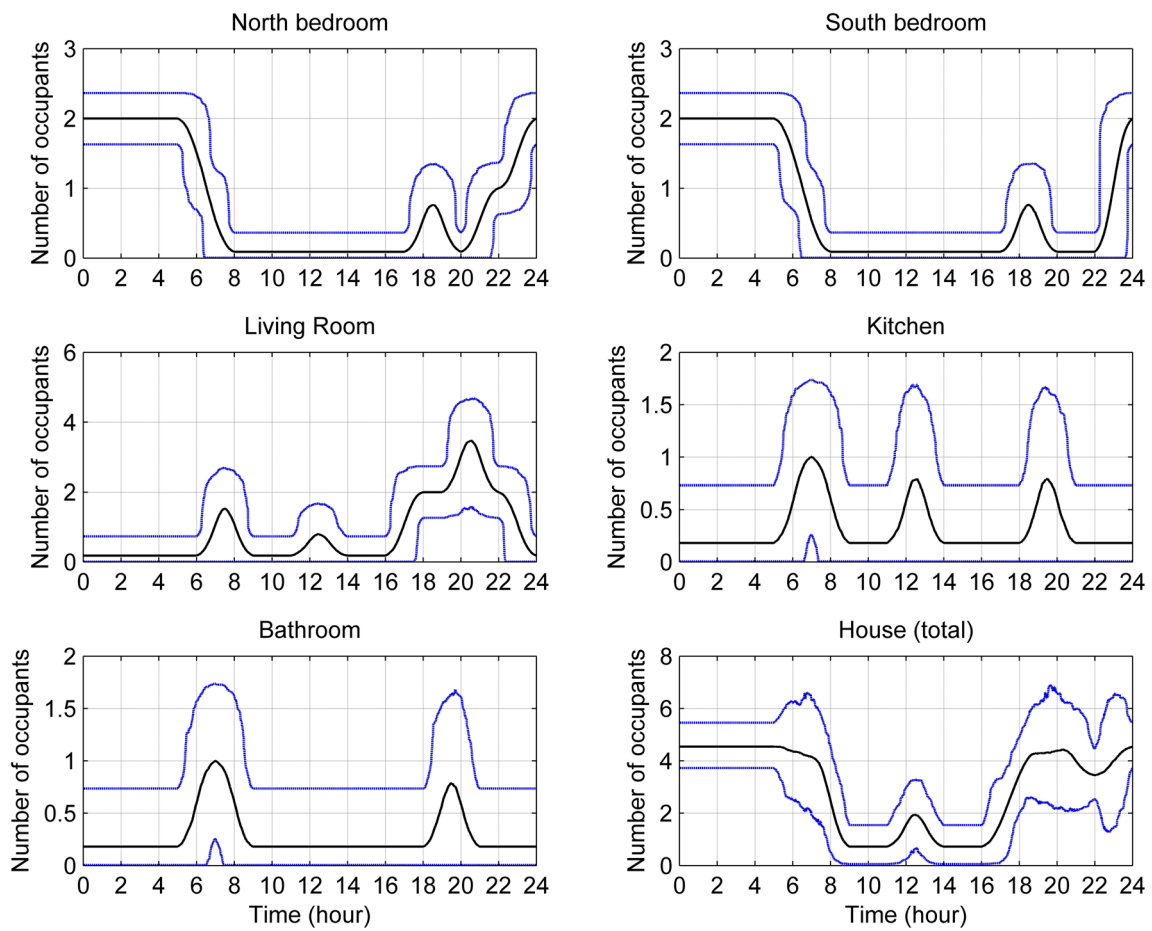


Fig. 11 Occupancy schedule [mean (solid line), 5th and 95th percentiles (dotted line)] for the 500 simulations



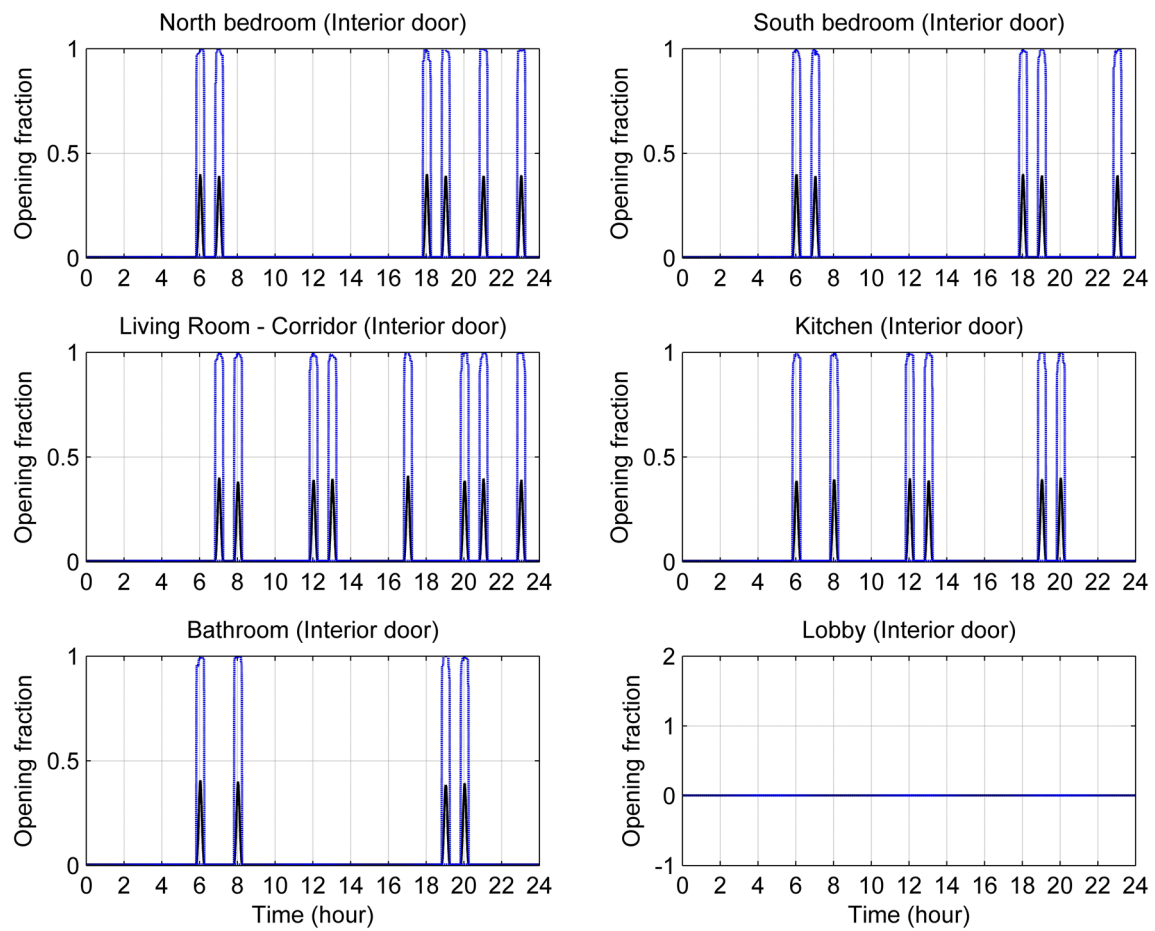


Fig. 12 Interior doors opening schedule [mean (solid line), minimum and maximum (dotted line)] for the 500 simulations



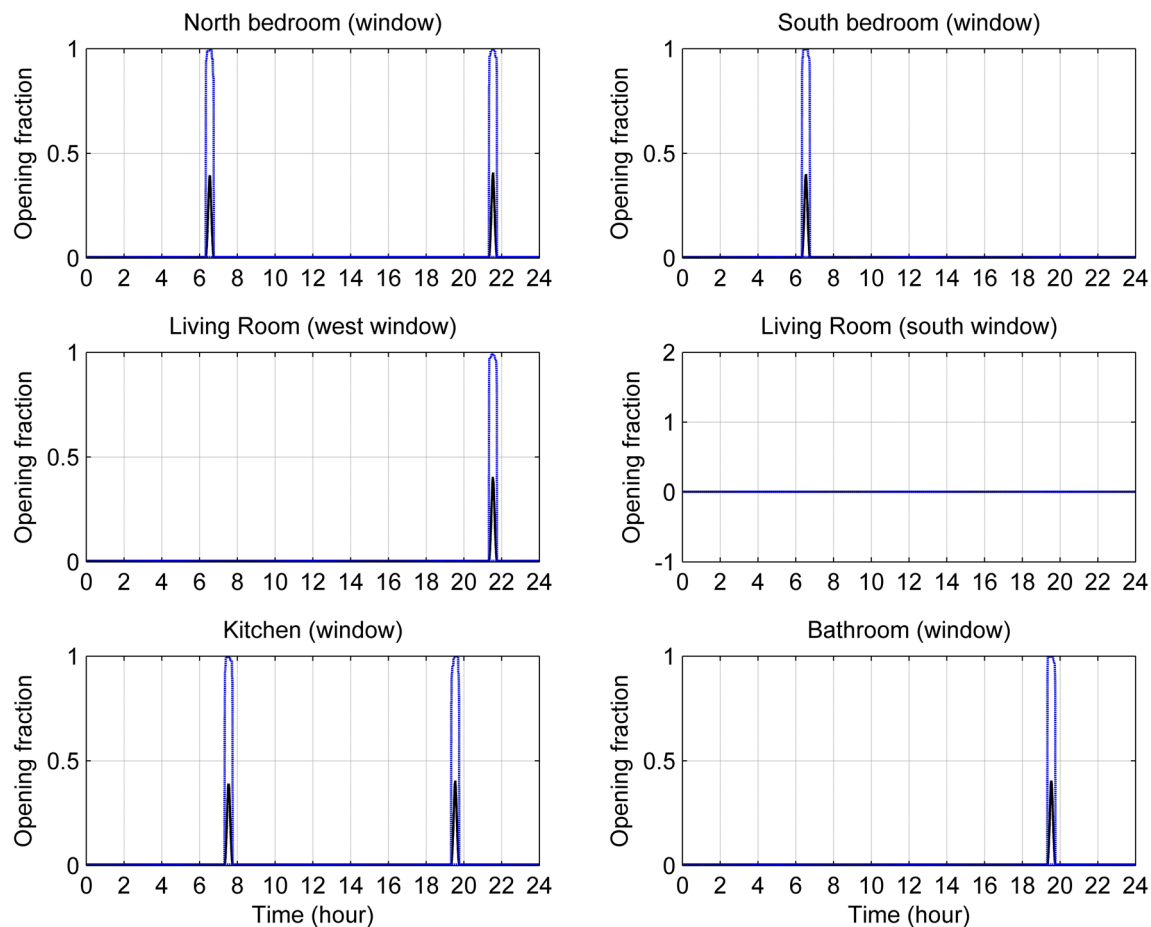


Fig. 13 Exterior windows opening schedule [mean (solid line), minimum and maximum (dotted line)] for the 500 simulations

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