Modelling indoor air carbon dioxide concentration using grey-box models

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Abstract

Predictive control is the strategy that has the greatest reported benefits when it is implemented in a building energy management system. Predictive control requires low-order models to assess different scenarios and determine which strategy should be implemented to achieve a good compromise between comfort, energy consumption and energy cost. Usually, a deterministic approach is used to create low-order models to estimate the indoor CO_2 concentration using the differential equation of the tracer-gas mass balance. However, the use of stochastic differential equations based on the tracer-gas mass balance is not common. The objective of this paper is to assess the potential of creating predictive models for a specific room using for the first time a stochastic grey-box modelling approach to estimate future CO_2 concentrations. First of all, a set of stochastic differential equations are defined. Then, the model parameters are estimated using a maximum likelihood method. Different models are defined, and tested using a set of statistical methods. The approach used combines physical knowledge and information embedded in the monitored data to identify a suitable parametrization for a simple model that is more accurate than commonly used deterministic approaches. As a consequence, predictive control can be easily implemented in energy management systems.

Keywords: indoor air quality, ventilation, simulation, stochastic methods, CO_2 prediction, low-order model

1 Introduction

In Europe, buildings consume more energy than the industry and transportation sectors [1]. They are responsible for 40% of energy consumption and 36% of CO_2 emissions [2]. Recent EU directives have focused on reducing operational buildings' energy consumption [3], as 80–90% of energy consumption during their life cycle is produced during the operation stage [4–6].

Half of a building's energy consumption during the operation stage is due to heating, ventilation, and air-conditioning (HVAC) systems [7,8]. Thus, there is a great interest in developing technologies and operational strategies to improve the efficiency of these systems. Building energy management systems (BEMS) play an important role in this sense, because they can be used to apply advanced control strategies in buildings, to optimise HVAC systems.

Recent new approaches to optimise ventilation systems are demand-controlled [9–11]. This means that the ventilation rate varies depending on building occupation. This approach produces more savings in buildings where the occupancy is highly variable, such as institutional buildings or restaurants.

Generally, BEMS are rule-based. This means that the control approach is reactive [12], and future scenarios cannot be evaluated. As a consequence, BEMS cannot decide on the best strategy to ventilate a room or a building according to a set of indoor air quality and energy savings priorities. If predictive control is included in BEMS, the optimal control policy can be determined by minimizing a cost function [13]. In this way, more domains (i.e. cost, energy efficiency or indoor air quality) can be used to calculate the optimal strategy for the HVAC operation.

A considerable amount of research has been carried out to develop models for use in adaptive and predictive control [10,14–18]. However, most of the efforts are focused on the thermal dynamics of the modelled systems and subsystems [10]. Little effort has been made in the field of predicting indoor air CO_2 concentration levels, and there is a lack of simple simulation tools and low-order state space models for predicting room CO_2 concentrations [19].

Usually, a deterministic approach is used to develop simple, low-order state space models for predicting room CO_2 concentrations [10] or calculating ventilation flow rates [20–25]. However, very few studies in the field of indoor air CO_2 concentration address statistical approaches. This research presents the results of using the grey-box modelling method to estimate the indoor air CO_2 concentration in a single test room. There are two main differences between grey-box modelling and the deterministic approach. The deterministic approach only uses knowledge about physics, whilst the grey-box approach combines physics with monitored data. Another difference is that the framework of the first approach is deterministic, and the grey-box framework is stochastic. As a consequence, statistical methods can be used to obtain suitable parametrization [26].

This paper is structured as follows. Section 2 introduces the grey-box modelling concept. Section 3 describes the application of the theoretical method to a case study. Section 4 presents and discusses the results. Finally, Section 5 contains the conclusions.

2 Grey-box modelling

A grey-box model is established using a combination of physical knowledge and information embedded in the monitored data [27]. Grey-box models are comprised of a deterministic function and a stochastic part that represents a continuous-time stochastic differential equation for the physical description of a system [28]. Finally, a discrete-time observation of the underlying physical system is needed to estimate the parameters. The combination of physical and experimental data can be used to identify suitable model parameterization [26].

The first step in grey modelling is to formulate a system of ordinary differential equations that represent well-known physical relationships:

$$dX_t = f(X_t, U_t, \theta, t)dt \qquad \text{(Equation 1)}$$

where X_t is a vector of system states, U_t is a vector containing experimental data, and θ is the vector of parameters that should be identified. To introduce variations that are not described by the deterministic model (i.e. noisy input to the system), a stochastic term is included in Equation 1 to yield the following system of a stochastic differential equation

$$dX_t = f(X_t, U_t, \theta, t)dt + G(\theta, t)dw_t \qquad \text{(Equation 2)}$$

where W_t is a Wiener process, and $G(\theta, t)$ is the diffusion term in the process.

Finally, the monitored output of the system Y_t is used to complete the state-space representation.

$$Y_{t_k} = h(X_t, U_t, \theta, t) + e_t \qquad \text{(Equation 3)}$$

where function $h(X_t, U_t, \theta, t)$ represents the relationship between the state variables and the measurements, and e_t is a vector that describes the noise from the measurements. This noise is assumed to be Gaussian distributed.

In order to estimate θ in the continuous-time model, the maximum likelihood method is generally used in the literature [26–28].

Finally, the system of ordinary differential equations with the estimated parameters is used to carry out the simulation.

Grey-box modelling has been used successfully in the building sector to model the thermal energy demand of a building [26,27,29–32]. Other studies used grey-box modelling for district simulations [33].

Due to the minimal computational effort required by grey-box modelling and its accuracy, it is suitable for implementation in building energy management systems, for predictive control [31].

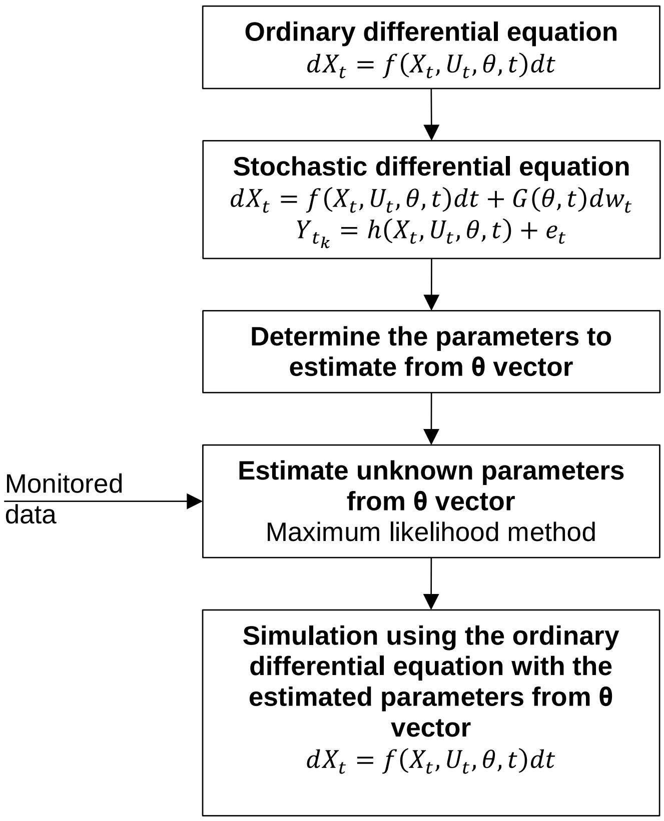

Figure 1. Grey-box modelling approach

3 Methodology

This section presents the methodology used to study the suitability of grey-box modelling to determine the CO_2 concentration in a single room.

3.1 Data collection

The room was an office in TR5, an academic building on the Terrassa Campus of the Universitat Politècnica de Catalunya (UPC). The room's surface area was 31.16 m^2 and its volume was 95 m^3. The maximum occupation of the room was six people, because there were six workstations. However, the maximum occupation reached during the experimentation was three people. The room had one window and one door providing access from the corridor. The window measured 1.40 m long and 1.70 m high, and was positioned 1.25 m above the floor. The room was naturally ventilated via a ventilation grill in the door. The ventilation grill was rectangular and measured 0.40 m long and 0.20 m high, and was positioned 0.10 m above the floor.

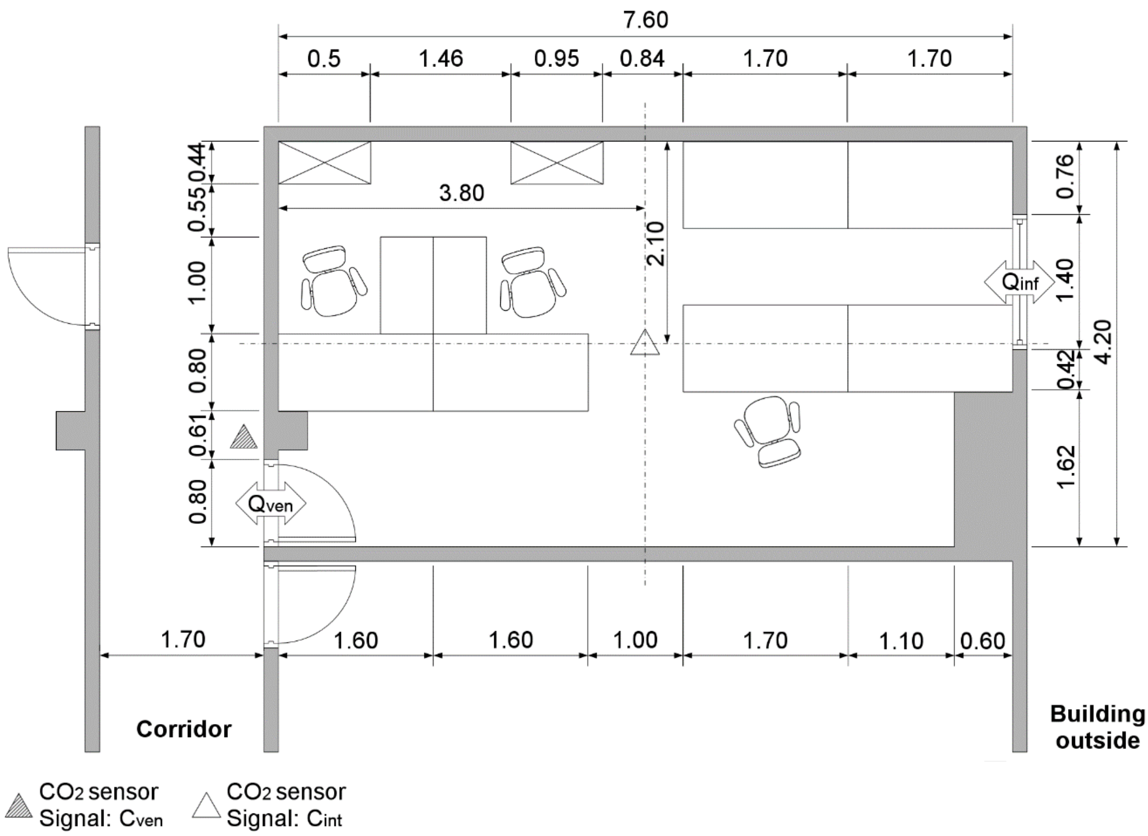

Figure 2. Plan view showing the positioning of sensors and objects inside the room (all measurements are in meters)

The CO_2 concentration in the room and corridor (C_{int} and C_{ven}) was monitored with an Advanticsys IAQM-THCO2 sensor that has a range from 0 to 3,000 ppm, a resolution of 1 ppm, and an accuracy of ±2% of full-scale output. The sensor is calibrated by the manufacturer and is configured by the manufacturer to record an instantaneous value every 15 minutes. Both sensors were located 3.00 m above the floor, under the ceiling.

The CO2 concentration in a room with people breathing is not homogenous [10,34-36]. However, a representative measurements of CO2 concentration can be effectively done in the centre of the room [36]. For this reason, the room sensor was located in the centre of the room.

An occupancy sheet was used to determine the room occupation. Each occupant noted on the sheet when they entered and left the room. The occupancy sheet was transformed into an occupation signal using the mean occupancy for each quarter of an hour.

Data were collected over four days in May 2016. Figure 3 presents the data set used in this research, and Table 1 presents the indoor and outdoor air parameters during the measurements.

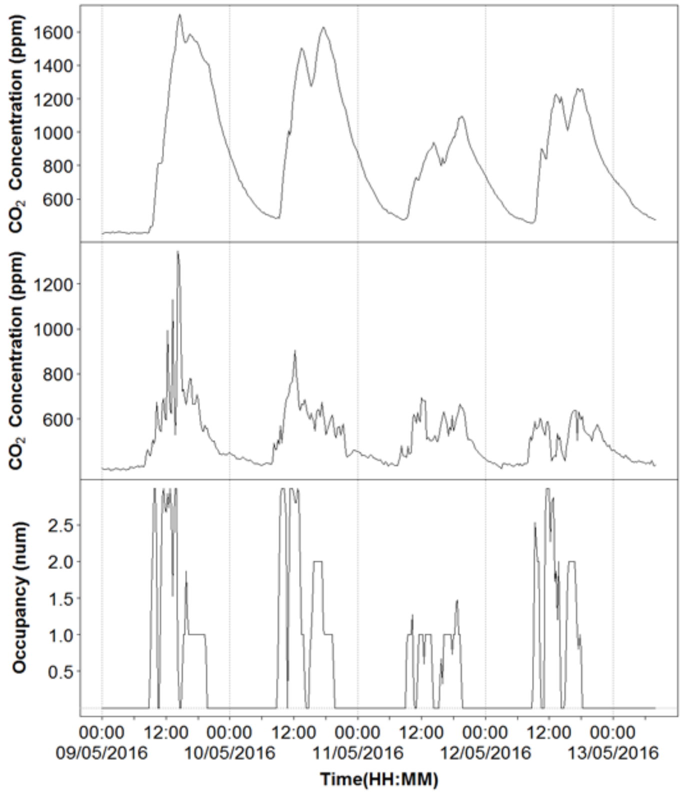

Figure 3. Data set. From the top, the first plot shows the CO_2 concentration observed inside the room, the second shows the CO_2 concentration observed in the corridor, and the last plot presents the occupancy of the room.

Table 1. Measurement conditions

Location	Parameter	Units	Value
Corridor air parameters	Average temperature	ºC	23.5
	Average relative humidity	%	49
Room air parameters	Average temperature	ºC	23.1
	Average relative humidity	%	51
Outdoor air parameters	Average temperature	ºC	14.7
	Average relative humidity	%	82
	Average atmospheric pressure	hPa	1006.8
	Average wind speed	m/s	2.1
	CO_2 concentration	ppm	372

3.2 Modelling process

In this paper, the deterministic function is based on the principal of mass balance in a designated volume (V_r) [20,22,37,38]. The change in CO_2 concentration (C_{int}) in the room is expressed as:

$$\frac{dC_{\text{int}}}{dt}V_r = (C_{\text{ven}} - C_{\text{int}}) \cdot Q_{\text{ven}} + G_{CO_2} \qquad \text{(Equation 4)}$$

where V_r is the volume of air in the assessed room, C_{ven} is the CO_2 concentration of fresh air, C_{int} is the CO_2 concentration in the room, Q_{ven} is the ventilation rate, and G_{CO_2} is the CO_2 generated by the occupants.

In this case, C_{ven} is assumed to be equal to the corridor's CO_2 because the room is ventilated by means of a grill in the door. The G_{CO_2} is calculated using the following equation:

$$G_{CO_2} = K_{\text{occ}} \cdot P \qquad \text{(Equation 5)}$$

where Kocc is the CO_2 emission rate per occupant, and P is the occupancy of the room. To complete the stochastic differential equation a stochastic term is added.

$$dC_{\text{int}} = \frac{Q_{\text{ven}}}{V_{\text{r}}}(C_{\text{ven}} - C_{\text{int}}) \cdot dt + \frac{K_{\text{occ}} \cdot P}{V_{\text{r}}} \cdot dt + \sigma \cdot dw \qquad \text{(Equation 6)}$$

where dw is the Wiener process, and σ is the incremental variance of the Wiener process.

Finally, the monitored output of the system is defined in this paper by the following discrete time equation:

$$Y_{t_k} = C_{int,\,t_k} + e_k \qquad \text{(Equation 7)}$$

where $C_{int,\,t_k}$ is the measured interior CO_2 concentration of the room at time t_k, and e_k is the white noise process describing the measurements' noise.

Equation 6 assumes four hypotheses: i) CO_2 is chemically stable and inert, and there is no absorption process that can reduce the CO_2 concentration; ii) walls, ceilings and furniture do not absorb CO_2; iii) the room has a perfectly mixed condition; iv) the room has a constant ventilation air flow.

This paper presents 4 different models to simulate the CO_2 concentration inside a room. The characteristics of these models are summarized in Table 2.

Table 2. Grey-box models used

Model	State space representation	Observation	Input	Estimated parameters
M1	$dC_{\text{int}} = \frac{Q_{\text{ven}}}{95}(372 - C_{\text{int}}) \cdot dt + \frac{33{,}800 \cdot P}{95} \cdot dt + \sigma \cdot dw$ $Y_{t_k} = C_{\text{int},\, t_k} + e_k$	C_{int}	P	C_{int}, Q_{ven}, σ, e_k
M2	$dC_{\text{int}} = \frac{Q_{\text{ven}}}{95}(372 - C_{\text{int}}) \cdot dt + \frac{K_{\text{occ}} \cdot P}{95} \cdot dt + \sigma \cdot dw$ $Y_{t_k} = C_{int,\, t_k} + e_k$	C_{int}	P	C_{int}, Q_{ven}, K_{occ}, σ, e_k
M3	$dC_{\text{int}} = \frac{Q_{\text{ven}}}{95}(C_{\text{ven}} - C_{\text{int}}) \cdot dt + \frac{K_{\text{occ}} \cdot P}{95} \cdot dt + \sigma \cdot dw$ $Y_{t_k} = C_{\text{int},\, t_k} + e_k$	C_{int}	P, C_{ven}	C_{int}, Q_{ven}, K_{occ}, σ, e_k
M4	$dC_{\text{int}} = \frac{Q_{\text{ven}}}{95}(C_{\text{ven}} - C_{\text{int}}) \cdot dt + \frac{Q_{\text{inf}}}{95}(372 - C_{\text{int}}) \cdot dt + \frac{K_{\text{occ}} \cdot P}{95} \cdot dt + \sigma \cdot dw$ $Y_{t_k} = C_{\text{int},\, t_k} + e_k$	C_{int}	P, C_{ven}	C_{int}, Q_{ven}, $Q_{inf,}$ K_{occ}, σ, e_k

The first model (M1) is used to estimate the existing ventilation in the room. The only input in the model is occupancy. The rest of the parameters are constant values. The CO_2 concentration of the supply air (C_{ven}) used is 372 ppm. This value is the average reading of an external CO_2 sensor located outside the building. It is similar to other values obtained in other studies [39]. The human emission rate of CO_2 for an adult seated, reading or writing is 32,500 mg/h (16.5 L/h) for a woman and 36,600 mg/h (18.6 L/h) for a man [22]. Usually, the room used to carry out the experiments is occupied by two women and one man. The value used in this research for the human emission rate of CO_2 is 33,900 mg/h (17.3 L/h), which is the weighted average of the aforementioned values.

The difference between M1 and the second model (M2) is that the human emission rate of CO_2 is estimated instead of a fixed rate. Model 3 (M3) added the measured CO_2 concentration of the supply air, the rest of the parameters remained as in M2.

Finally, model 4 (M4) incorporates the ventilation due to window infiltrations (Q_{inf}). Equation 6 should be modified to consider this change.

$$dC_{\text{int}} = \frac{Q_{\text{ven}}}{V_{\text{r}}}(C_{\text{ven}} - C_{\text{int}}) \cdot dt + \frac{Q_{\text{inf}}}{V_{\text{r}}}(C_{\text{inf}} - C_{\text{int}}) \cdot dt + \frac{K_{\text{occ}} \cdot P}{V_{\text{r}}} \cdot dt + \sigma \cdot dw \qquad \text{(Equation 8)}$$

The parameters of the assessed grey-box models are estimated using the CTSM-R Version 1.0.0 package for an R environment. This package uses the maximum likelihood and Kalman filtering for the estimations [40]. A 2.50-GHz Intel Core i7 personal computer was used to carry out the estimations.

3.3 Model validation

This paper proposes a set of models to estimate CO_2 concentrations in indoor spaces, based partially on the physical characteristics of the system. Consequently, the first step in the model validation process is to check whether the estimated parameters are feasible in terms of the physics of the system [27–30]. The estimated parameters are compared with the literature and the ASHRAE standard.

Then, using all the data set, a set of statistical tests are used to determine whether the estimated parameter values describe the dynamics of the system. The statistical tests and the model validation process are based on previous studies [27–29].

The first statistical test is the assessment of parameter significance. The probability value of the parameters should be less than 0.05, otherwise the parameter is insignificant [40]. Then, the derivative of the objective function compared to the particular initial state or parameter is assessed. If the values that are obtained are not close to zero, the solution may be a local optimum, but not the true optimum [41]. Subsequently, the derivative of the penalty function with respect to the particular initial state or parameters is assessed. If this value is significant compared to the derivative of the objective function with respect to the particular initial state or parameter, the particular initial state or parameter may be close to one of its limits. Then, the estimation should be repeated with new limits [40]. The correlation matrix of the parameter estimates is also calculated to ensure that off-diagonal values are far from 1 or -1. Values on the off-diagonal that are near to 1 or -1 indicate that the model is over-parametrized. Then, the elimination of some model parameters should be taken into consideration [40].

The assumption of white noise residuals is assessed with the autocorrelation function and the cumulated periodogram [27,28]. Finally, the root mean square error deviation is used to assess whether the calculated model can predict the system with reasonable accuracy. All the aforementioned statistical tests are provided by the CTSM-R package.

4 Results and discussion

All the estimated parameters of all the models reported reasonable values. The estimated ventilation flows ranged between 20.13 m^3/h and 92.16 m^3/h. These values are lower than established by the standards. This is an expected result, because the room only has natural ventilation through the corridor. In addition, the CO_2 concentration reaches and surpasses

1000 ppm during working hours. The RMSE of the assessed models ranges between 41.09 and 370.67 ppm. However, only one model can be considered statistically relevant.

The estimation of the ventilation flow rate obtained with M1 is reasonable (24.40 m^3/h). The p-value of the t-test is below 0.05 in all estimated parameters, except e. However, this parameter is not important for the resultant model and this value can be accepted. The derivative of the objective function with respect to each parameter is close to 0 and the derivative function with respect to each parameter is not significant compared to dF/dPar (Table 3 and Table 4). The autocorrelation plot shows that the residues are not random, because most of the autocorrelations are outside of the 95% confidence bands. The values of the cumulated periodogram are outside of the 95% confidence bands (Figure 4). As a consequence, is not possible to affirm that the residuals obtained can be regarded as white noise. The model follows the trend, however it overestimates the peaks and underestimates the lower values. The RMSE is 370.67 ppm, the highest of the four models. According to the results, this model cannot be considered useful to simulate the CO_2 inside the room.

Table 3. Statistical tests for M1

<table>
<tr><th>Parameter</th><th>Estimation</th><th>Standard error</th><th>Pr(>|t|)</th><th>dF/dPar</th><th>dPen/dPar</th></tr>
<tr><td>C_{int}</td><td>393</td><td>45</td><td>0.000</td><td>1.9346E-05</td><td>1.9346E-05</td></tr>
<tr><td>Q_{vent}</td><td>24.40</td><td>0.18</td><td>0.000</td><td>5.5770E-03</td><td>5.5770E-03</td></tr>
<tr><td>σ</td><td>96.54</td><td>0.03</td><td>0.000</td><td>-4.9756E-06</td><td>1.1645E-03</td></tr>
<tr><td>e</td><td>0.00</td><td>49.23</td><td>8.200</td><td>1.1645E-03</td><td>-4.9756E-06</td></tr>
</table>

Table 4. Correlation coefficients for M1

	C_{int}	Qvent	E
Q_{vent}	0.01		
e	-0.02	-0.71	
σ	-0.04	-0.06	0.17

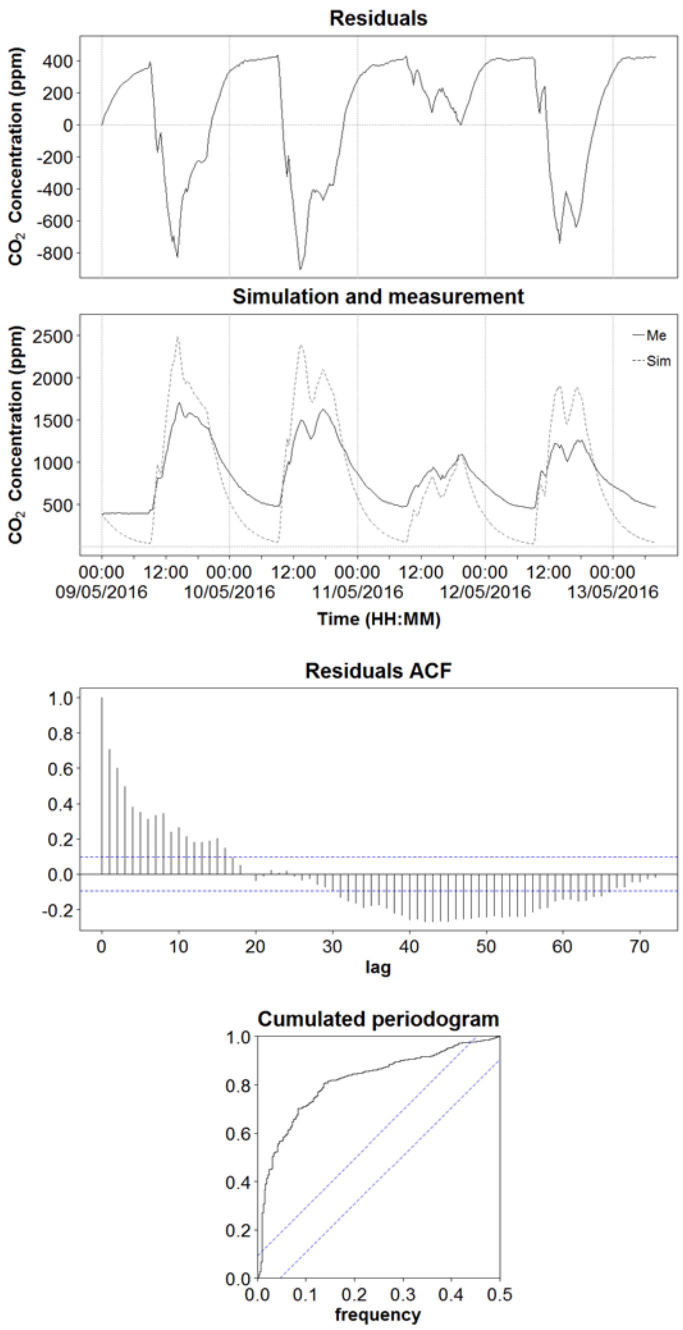

Figure 4. On the upper left, the residuals plot for M1 is presented; on the bottom left, the measured data compared to the simulated data for M1 is plotted. On the top right, the autocorrelation function (ACF) for the residuals of M1 is plotted, and on the bottom right the cumulated periodogram for M1 is presented.

M2 reported similar results to M1. The statistical parameters were all inside the acceptable range (Table 5 and Table 6), but the autocorrelation function and the cumulated periodogram were out of the 95% confidence bands (Figure 5). The root mean square error of this model was 156.34 ppm. The human emission rate of CO_2 estimated by the model is 62% lower than that established in the literature. However, this result cannot be taken into account, because the results of statistical tests recommend discarding this model.

Table 5. Statistical tests for M2

Parameter	Estimation	Standard error	Pr(>|t|)	dF/dPar	dPen/dPar
C_{int}	393	16	0.000	-5.9627E-06	0.0000E+00
Q_{vent}	92.16	0.45	0.000	-5.8693E-06	0.0000E+00
K_{occ}	12,862	370	0.000	2.6688E-05	0.0000E+00
σ	33.45	0.04	0.000	-9.2872E-06	0.0000E+00
e	0.00	262.39	0.971	-5.3579E-06	1.0000E-04

Table 6. Correlation coefficients for M2

	C_{int}	Q_{vent}	K_{occ}	σ
Q_{vent}	0.01			
K_{occ}	0.03	0.62		
σ	-0.01	0.03	0.06	
e	0.00	0.00	0.00	0.00

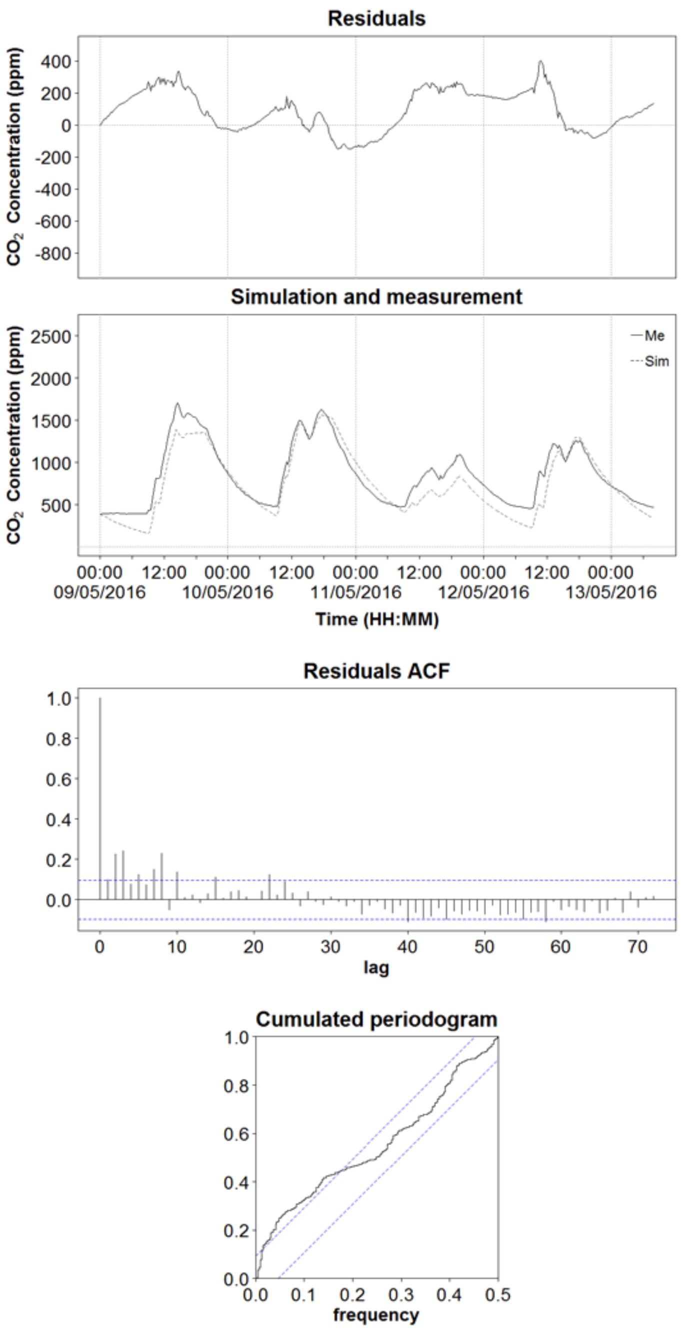

Figure 5. On the upper left, the residuals plot for M2 is presented; on the bottom left, the measured data compared to the simulated data for M2 is plotted. On the top right, the ACF for the residuals for M2 is plotted, and on the bottom right the cumulated periodogram for M2 is presented.

The best results are those of M3. The estimated values are reasonable (Table 7). The estimated ventilation flow rate is 20.13 m^3/h ($0.21\ h^{-1}$). This value is similar to the results of similar research. For example, a study of the natural ventilation in college student dormitories reported an air change rate above $0.5\ h^{-1}$ [20]. Another study related with ventilation in a commercial building reported an air change rate of $0.1\ h^{-1}$ [21]. According to the ASHRAE handbook, the required minimum ventilation for the assessed room should be 121.31 m^3/h, taking into account that no more than six people are expected to occupy the area for its normal use. The human emission rate of CO_2 estimated by the model is 12,793 mg/h (6.5 L/h). According to the literature [22], the human emission rate of CO_2 for an adult who is seated or reading or writing is 32,500 mg/h (16.5 L/h) for a female and 36,600 mg/h (18.6 L/h) for a male. The value of the human emission rate of CO_2 is 62% lower than the reference. As reported by other studies in the field [22], the reference value is calculated using a hypothesis that cannot be true for this case. However, the estimated value has the same order of magnitude.

All the statistical tests calculated for M3 are inside the boundaries (Table 7 and Table 8). In addition, values of the autocorrelation plot and the cumulated periodogram are inside of the 95% confidence bands (Figure 6). As a consequence, the residuals obtained can be regarded as white noise. The root mean square error for the third model was 41.10 ppm. This value is lower than that found in other studies presented in the literature that used deterministic approaches, such as Pantazaras study [10] who reported a RMSE ranging from 50 to 60 ppm. The accuracy of the reported model in this research is sufficient, because it is close to the accuracy of most commercial CO2 sensors. In this case, taking into account that the accuracy of the sensors is ±2% of full scale, the accuracy of the sensor is ±60 ppm.

Table 7. Statistical tests for M3

Parameter	Estimation	Standard error	Pr(>|t|)	dF/dPar	dPen/dPar
C_{int}	393	14	0.000	0.0000E+00	0.0000E+00
Q_{vent}	20.13	0.71	0.000	-3.6668E-06	0.0000E+00
K_{occ}	12,793	306	0.000	0.0000E+00	0.0000E+00
σ	27.66	0.06	0.000	-9.2670E-06	0.0000E+00
e	13.33	0.75	0.001	6.8335E-06	0.0000E+00

Table 8. Correlation coefficients for M3

	C_{int}	Q_{vent}	K_{occ}	σ
Q_{vent}	-0.04			
K_{occ}	-0.03	0.57		
σ	-0.02	-0.02	-0.10	
e	0.02	0.05	0.13	-0.73

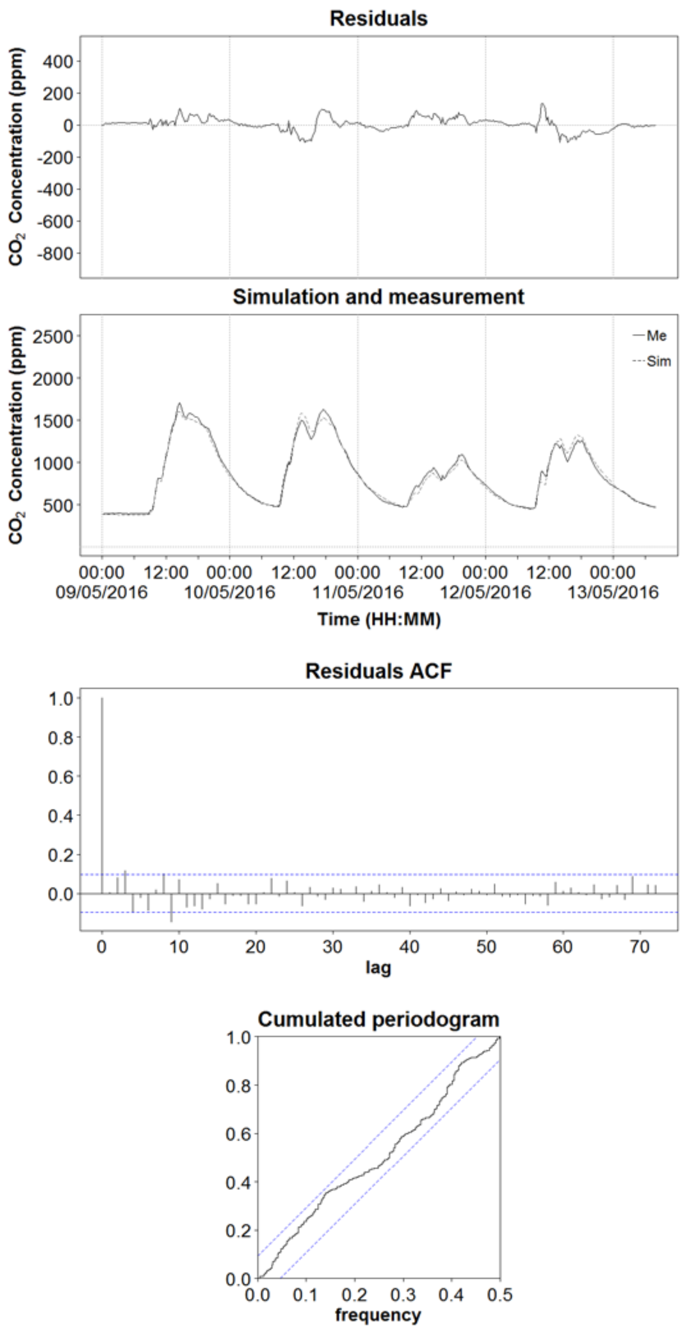

Figure 6. On the upper left, the residuals plot for M3 is presented; on the bottom left, the measured data compared to the simulated data for M3 is plotted. On the top right, the ACF for residuals for M3 is plotted, and on the bottom right the cumulated periodogram for M3 is presented.

The last model (M4) reported a similar value of the root mean square error to M3 (41.18 ppm). However, statistical tests showed that the parameter window infiltrations are not relevant for the model (Table 9 and Table 10). Therefore, the fourth model is discarded.

Generally, in the literature, infiltrations are unified with the supply air [10]. The results of this research enable us to affirm that the approximation generally used in the literature is acceptable. Further research considering measured external CO_2 should be carried out to affirm that infiltrations are not relevant to model the internal CO_2 concentration in buildings with good air tightness.

Table 9. Statistical tests for M4

Parameter	Estimation	Standard error	Pr(>|t|)	dF/dPar	dPen/dPar
C_{int}	393	13	0.000	-2.9813E-06	0.0000E+00
Q_{vent}	20.10	0.78	0.000	-4.1809E-05	0.0000E+00
Q_{inf}	0.00	0.01	0.996	4.0135E-05	0.0000E+00
K_{occ}	12,748	330	0.0000E+00	6.1870E-05	0.0000E+00
σ	29.67	0.04	0.0000E+00	-1.8548E-04	0.0000E+00
e	0.00	126.39	0.910	8.2055E-04	8.0000E-04

Table 10. Correlation coefficients for M4

	C_{int}	Q_{vent}	Q_{inf}	K_{occ}	σ
Q_{vent}	0.00				
Q_{inf}	0.00	-0.02			
K_{occ}	0.00	-0.55	0.00		
σ	-0.02	0.07	0.00	0.10	
e	0.00	-0.02	1	0.00	0.00

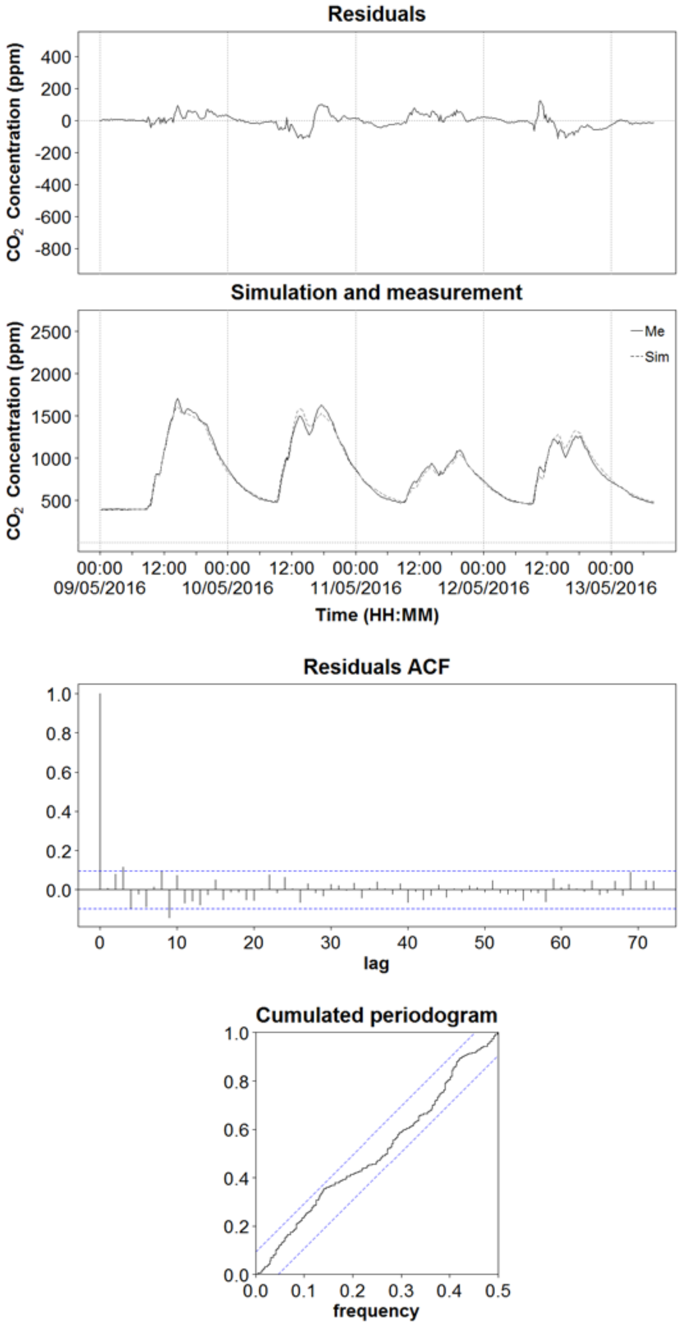

Figure 7. On the upper left, the residuals plot for M4 is presented; on the bottom left the measured data in front of simulated data for M4 is plotted. On the top right, the ACF for the residuals for M4 is plotted, and on the bottom right the cumulated periodogram for M4 is presented.

The average computation time needed to carry out the estimation of the parameters, the statistical tests and the simulations for the current dataset was less than 3 seconds for each model.

5 Conclusions

This study investigated the possibility of using grey-box modelling for the CO_2 concentration in a room. The procedure proposed in this paper for modelling indoor air CO_2 concentration is formulated as a system of stochastic differential equations. To identify the parameters of each model, the maximum likelihood method is used. The models are validated using a set of statistical methods and physical interpretation of the estimated parameters. With these arguments, the best model is identified.

The main contribution of this paper is a new approach to model the indoor CO_2 concentration in a specific room, which could be broadened to entire buildings in the future. The proposed approach enables to obtain more accurate and simplistic models to simulate indoor CO_2 than currently applied deterministic approaches.

The results of this research demonstrated that once a model has been identified for a specific room, the CO_2 concentration can be modelled inside the room using the occupancy, the ventilation rate, and the CO_2 concentration of the ventilation air flow.

The results of this research can be used to implement a tool in a BEMS to analyse the existing levels of ventilation in a building. In this way, we can detect which rooms are under-ventilated or over-ventilated, and the building maintenance team can then investigate any potential problems. When the system is parametrized, a predictive control strategy can be implemented in a BEMS to optimize the building ventilation system. However, before implementing predictive control, the accuracy of different prediction horizons should be assessed.

Further research is required to investigate whether the proposed approach can be used to configure a model and determine the occupancy of a room when we know the CO_2 concentration in the room, the ventilation rate, and the CO_2 concentration of the ventilation air flow. As a result, a service could be implemented in a BEMS to estimate the occupancy of a room.

The approach used one CO_2 sensor to estimate the model parameters. In this case, a perfect, mixed condition in the room is assumed. Extreme care should be taken when the location of a CO_2 sensor is selected, due to the highly localised nature of indoor CO_2 concentrations. For this reason, further research is required to determine how many sensors are needed to estimate ventilation parameters with an acceptable level of accuracy. In addition, the optimal position of sensors should be studied.

Another aspect that should be studied in the future is the difference between the value of the human emission rate of CO2 obtained using grey-box modelling, and the value generally used in the literature.

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