REAL-TIME VENTILATION CONTROL BASED ON A BAYESIAN ESTIMATION OF OCCUPANCY

by Haolia Rahman

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Research Article

Real-time ventilation control based on a Bayesian estimation of occupancy

Haolia Rahman[1], Hwataik Han[2] (✉)

1. Politeknik Negeri Jakarta, Jl. Prof. DR. G.A. Siwabessy, Depok 16425, Jawa Barat, Indonesia
2. Kookmin University, 77 Jeongneung-ro, Seongbuk-gu, Seoul. 02707, R.O. Korea

Abstract

Demand-controlled ventilation (DCV) is commonly implemented to provide variable amounts of outdoor air according to an internal ventilation demand. The objective of the present study is to investigate the applicability and the performance of occupancy-based DCV schemes in comparison with time-based and CO_2-based DCV schemes. To do this, we apply the occupancy estimation method by the Bayes theorem to control the ventilation rate of an office building in real-time. We investigated six cases in total (two cases for each control scheme). Experiments were conducted in a small office room with controllable ventilation equipment and relevant sensors. The observed results indicated that the occupancy-based schemes relying on Bayes theorem could be applied successfully to perform continuous control of ventilation rates without causing recursive problems. Additionally, we discussed the time delays associated with the control procedure, including dispersion time, sensor-response time, and data processing time. Finally, we compared the performance of the proposed approach in six DCV cases in terms of a resultant indoor CO_2 level and the total ventilation-air volume. We concluded that DCV control based on both occupancy and floor area provided the best conformity to the ASHRAE standard among the analyzed schemes.

Keywords

occupancy estimation;
Bayesian MCMC;
carbon dioxide;
ventilation control

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Indoor/Outdoor Airflow and Air Quality

1 Introduction

In recent years, the global awareness of the environmental impact and exhaustion of energy resources has increased due to a considerable augmentation in energy use. In general, heating, ventilation, and air-conditioning (HVAC) systems consume the largest amount of energy in buildings in most developed countries, constituting a sector that exceeds any other in terms of energy consumption (Pérez-Lombard et al. 2008). This issue is unavoidable as most people demand better services in buildings, thereby increasing energy consumption. Accordingly, increasing attention has been devoted on the ways to operate buildings establishing efficient energy use, while simultaneously maintaining a comfortable indoor environment. Demand-controlled ventilation (DCV) has been introduced as one of the energy-efficient operation methods, in which the ventilation rate is adjusted based on occupancy or only when needed (Taylor 2006). Several studies have proved the efficiency of this method (Erickson et al. 2014; Parsons 2014; Schibuola et al. 2018; O'Neill et al. 2020). Three primary control strategies, namely, schedule-based, CO_2 level-based, and occupancy-based ones, are commonly used to implement demand management in DCV systems.

Schedule-based DCV is defined as a straightforward way of regulating the outdoor airflow rate. If daily occupancy patterns can be identified specifically, a programmable schedule can be set automatically to adjust fan or dampers accordingly (Labeodan et al. 2015). Alternatively, the American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) Standard 90.1-2004 (ASHRAE 2004) provides a generic occupancy schedule for different building types. This simple and low-cost controlling method allows significantly saving energy in HVAC facilities, assuming that it is appropriately implemented (Murphy and Maldeis 2009; Duarte 2013). However, schedule-based DCV may be unsuitable in buildings with unpredictable occupancy patterns.

E-mail: hhan@kookmin.ac.kr

List of symbols

A	floor area (m^2)
C	CO_2 concentration (ppm)
C_{max}	maximum set-point indoor CO_2 concentration in Case 4 (ppm)
C_{min}	minimum set-point indoor CO_2 concentration in Case 4 (ppm)
C_R	measured indoor CO_2 concentration in Case 4 (ppm)
C_{SA}	CO_2 supply outdoor concentration (ppm)
$\dot{m}$	CO_2 generation rate per person (g/(min·person))
n	number of data points
N	number of occupants (person)
N_{est}	estimated number of occupants (person)
N_{act}	actual number of occupants (person)
q_A	outdoor airflow rate required per unit area in Case 6 (L/(s·m^2))
q_N	outdoor airflow rate required per person in Case 6 (L/(s·person))
q_n	outdoor airflow rate required per person in Case 5 (L/(s·person))
Q	ventilation rate (L/s)
Q_{max}	maximum set-point ventilation rate in Case 4 (L/s)
Q_{min}	minimum set-point ventilation rate in Case 4 (L/s)
Q_N	people outdoor airflow rate (L/s)
Q_A	area outdoor airflow rate (L/s)
$R^2(T)$	normalized cross-correlation
t	time (min)
T	time delay (min)
X	variable proposal
$\mathcal{N}(\mu_i, \sigma_i^2)$	Gaussian distribution
μ_i	mean of variable prior distribution
$\mu_{\dot{m}}$	mean of CO_2 generation rate per person prior distribution (g/(min·person))
μ_N	mean of number of occupants prior distribution (person)
μ_Q	mean of ventilation rate prior distribution (L/s)
μ_{SA}	mean of CO_2 supply outdoor concentration prior distribution (ppm)
σ_i^2	variant of variable prior distribution
σ_i	standard deviation of variable prior distribution
$\sigma_{\dot{m}}$	standard deviation of CO_2 generation rate per person prior distribution (g/(min·person))
σ_N	standard deviation of number of occupants prior distribution (person)
σ_Q	standard deviation of ventilation rate prior distribution (L/s)
σ_{SA}	standard deviation of CO_2 supply outdoor concentration prior distribution (ppm)

The indoor CO_2 level can serve as an appropriate indicator of human bioeffluents, and accordingly, of the occupancy level. On this basis, CO_2-level-based DCV has been widely applied to regulate the supply of outdoor air (Taylor 2006; Shriram and Ramamurthy 2019). Two control strategies correspond to this mode, namely, proportional or exponential control (ASHRAE 2007; Nassif 2012) and set-point control (Schibuola et al. 2018). The advantages and limitations of CO_2-level-based DCV have been actively discussed. Specifically, it has been argued that CO_2 is not a principal contaminant to focus on, and that the supply of outdoor air does not address non-occupant generated contaminants.

In most commercial and residential buildings, ventilation demands generally occur due to occupant- and building-related components. The ventilation rate procedure introduced by ASHRAE Standard 62.1 implies that the ventilation rate should be proportional to the number of occupants and floor area (ASHARE 2013). As occupancy can change over time, the ventilation rate should be adjusted accordingly to maximize efficiency.

Various methods have been developed to determine occupancy. Direct-sensing methods rely on the use of passive infrared sensors (Andrews et al. 2020), radio-frequency identification tags (Zhou and Shi 2011; Li et al. 2012), and video cameras (Liu et al. 2013; Dino et al. 2019). Indirect-sensing methods are based on the measurements of CO_2, sound, humidity, and temperature are preferable over direct-sensing methods in spite of privacy concerns. Among the indirect measures of occupancy, CO_2 concentration has the highest correlation with the number of occupants (Zhang et al. 2012). However, translating CO_2 concentration into occupancy levels is challenging, as mismatches exist in response mechanisms associated with changes in CO_2 concentration and occupancy.

A widely used and straightforward methods to determine the occupancy level from CO_2 concentration is based on physical models. However, at present, the research focused on this subject is limited to the detection of occupancy present (Wang and Jin 1998; Calì et al. 2015) and estimating the number of occupants in the order of tens (Wang and Jin, 1998; Sun et al. 2011). The high accuracy of estimation in the case of a low occupancy level is costly and difficult, but not impossible. It can be achieved by overcoming various sensor-reading uncertainties, such as maintaining the accuracy of the CO_2 and airflow measurements, establishing the correct use of CO_2 generation rates, and providing well-mixed indoor air (ASHRAE 2007; ASTM 2012).

In addition to the use of physical models, statistical methods are also typically utilized to estimate the number of occupants based on CO_2 levels, including neural networks (Alam et al. 2017), extreme learning machine (Jiang et al. 2016), and support vector machine (Ebadat et al. 2013). The literature reports that the advantages of statistical models include high estimation accuracy, less computational time, and the absence of restrictions corresponding to the physical characteristics of building space (Zuraimi et al. 2017). However, developing statistical models requires large databases to perform preliminary diagnostics that includes providing a means for occupancy validation (Rahman and Han 2016).

Recently, the Bayesian Markov chain Monte Carlo (MCMC) method has been widely used to solve problems in various engineering fields, specifically, in estimation problem and uncertainty quantification (Bardsley 2012; Wang et al. 2017). Based on a probabilistic technique relying on observed parameters and a prior belief in a physical model, Bayesian MCMC can be used to obtain a characterization of uncertainties (Wang and Zabaras 2004). However, only a limited number of related studies have been introduced in the field of HVAC (Shin and Han 2015; Rahman and Han 2018). They have proposed applying the Bayesian MCMC method to uncertainty issues in occupancy estimation for given or known airflow rates.

The present study is performed as an extension of the previous research works. It is aimed at applying the occupancy estimation method to real-time DCV cases in an office building. Occupancy estimation relies on the indoor CO_2 concentration, and the ventilation rate is controlled according to the estimated occupancy in a real-time manner. The proposed control system can be classified as a feedback-loop that transmits a portion of the output to the next operation. Therefore, when the system has a circular (recursive) logic (Bastin 1999), a failure of system control may occur. The objective of the present study is to investigate the applicability and the control characteristics of the occupancy-based DCV algorithm in comparison with other time-based and direct CO_2-based DCV schemes. Moreover, we compare the performance of the considered ventilation schemes in terms of the outputted indoor CO_2 levels and the total ventilation-air volume.

2 Methodology

2.1 Experimental setup

In the present study, experiments were conducted in an office of a university building with a floor area and a room volume of approximately 37 m^2 and 97 m^3, respectively. Air ducts in the ceiling were connected using supply and return fans. The supply and return diffuser grills were deployed at the opposite corners of the room. Carbon dioxide sensors and velocity meters were installed in the supply and return ducts, as shown in Figure 1. The other CO_2 sensor was installed in the center of the room 2 m above the floor. The CO_2 sensors were calibrated using two standard gases (500 and 2,000 ppm) with the accuracy of ±3% over 0–5,000 ppm. The airflow rates inside the ducts were measured based on the data from the velocity meters (hot-wire anemometers) using the logarithmic Chebyshev method (ISO 2008). We acquired the ventilation rate by averaging the two airflow rates measured in the supply and return ducts. A laser-beam sensor installed at a door frame was utilized to estimate the actual number of occupants in the room to verify the accuracy of the proposed estimation algorithm. Movements were detected whenever a beam between two laser sensors was interrupted by a person walking through. The sensor outputs were stored in the data acquisition storage with one-minute intervals. Figure 2 represents the sensor and control diagram. The data from the indoor-CO_2 concentration sensors were averaged over 10 min for the purpose of smoothing.

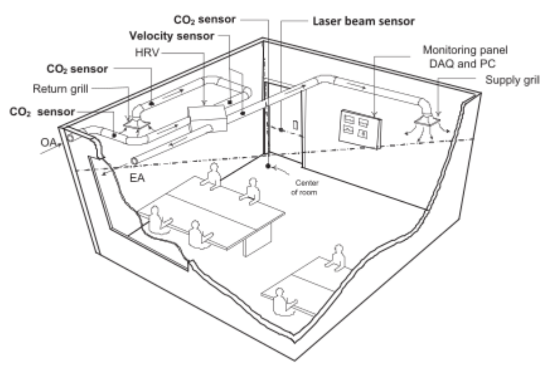


Fig. 1 Experimental setup

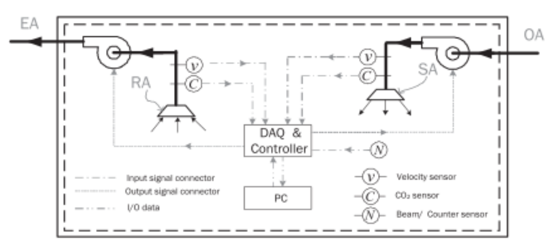


Fig. 2 Sensor and control diagram

2.2 Occupancy estimation

A physical model derived from the CO_2 mass-balance equation was implemented in the proposed occupancy estimation approach, adopting the Bayasian MCMC method introduced by Shin and Han (2015). Several assumptions were specified according to the conditions of the observed room. One assumption corresponded to the distribution function with the assumed Gaussian distribution, formulated as follows:

$$X \sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(X-\mu_i)^2}{2\sigma_i^2}} \tag{1}$$

where X was a proposal value; μ and σ were the mean and standard deviation of specific variables, respectively, concerning the occupant CO_2 generation rate per person ($\dot{m}$), ventilation rate (Q), CO_2 supply outdoor concentration (C_{SA}), and the number of occupants (N). It should be noted that μ and σ were derived based on probable observations and measurements by approximating true values as closely as possible. The mean of $\dot{m}$ ($\mu_{\dot{m}}$) was set according to the present occupant condition, a factor that was equivalent to a typical metabolic level for office work based on the average DuBois surface area of occupants. The standard deviation of $\dot{m}(\sigma_{\dot{m}})$ was assumed to be 30% of the mean or equal to the metabolic difference between sitting quietly and walking slowly (Persily and de Jonge, 2017). The mean of Q (μ_Q) was set according to the measured level of CO_2 in the duct system, and the standard deviation was assumed to be within typical building infiltration values and the measurement accuracy. The prior concentration of outdoor (or background) CO_2 was set to a typical local outdoor concentration according to the standard deviation observed from the recorded data. The mean of N (μ_N) was obtained based on the previous state of posterior N with the assumed standard deviation of 30%. Here, the standard deviation was important in determining the sensitivity of occupancy estimation: a broad range of occupancy required a large standard deviation, and vice versa. An overview of the mean and standard deviation of variables is provided in Table 1.

The Bayesian MCMC algorithm was implemented using the LabView software, and the variables were set accordingly. The timestep of the Bayesian calculation was a three-minute time interval and was repeated during every timestep. During this calculation, 10,000 iterations were executed with a burn-in period set at 5,000 iterations to discard a portion of the initial iterations.

The error between the estimated number of occupants and the reference could be expressed using the following equation:

$$\text{error} = \sqrt{\frac{\sum\left(N_{\text{est}} - N_{\text{act}}\right)^2}{n}} \Big/ \bar{N} \tag{2}$$

where N_{est} and N_{act} denoted the estimated and the actual numbers of occupants, respectively, while n and $\bar{N}$ was the number of data points and the average of the actual number of occupants during observed periods, respectively.

Table 1 Mean and standard deviation of variables

Variable (i)	μ_i	σ_i (%)
$\dot{m}$	0.554 g/(min·person)	30
Q	Q measurement	30
C_{SA}	420 ppm	5
N	N at the current state	30

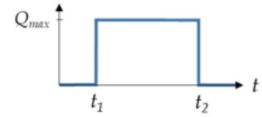
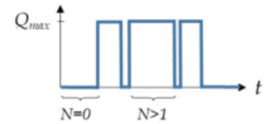
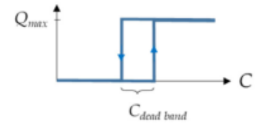
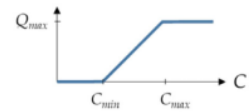
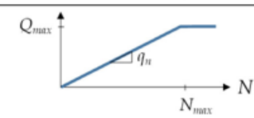
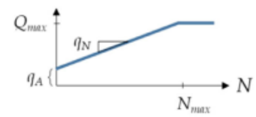
2.3 Ventilation control schemes

Three groups of ventilation schemes were considered in this study. Each group comprised two control cases, as shown in Table 2. Case 1 was defined as a reference case, which, according to the design standard for six occupants in Korea, implied maintaining a constant airflow rate of 41.6 L/s (150 CMH). In this scheme, a fan was controlled according to a schedule: switching on at 9:00 AM and switching off at 9:00 PM. Case 2 was the simplest case among the occupant-based control schemes, it implied using the information about the presence of occupants but not their count. The fan was controlled at a constant rate and was switched on when occupants were present and switched off whenever the space was vacant.

In Cases 3 and 4, the indoor CO_2 level was employed to control the ventilation rate. In Case 3, the fan was set on and off based on the CO_2 level. The fan was on at its maximum design rate when the CO_2 level reached an upper limit of 900 ppm and continued to supply outdoor air until the CO_2 level dropped to the lower limit of 700 ppm. This upper limit was defined to prevent the CO_2 concentration from reaching 1,000 ppm. The difference in the upper and lower limits was called a dead band to avoid short-cycle oscillations in the system. According to (Shell et al. 1998), the ventilation rate in Case 4 was set to be proportional to the CO_2 concentration. As the indoor CO_2 concentration increased, the ventilation rate increased gradually until reaching its maximum at the limit concentration of 1000 ppm.

The last group of the implemented ventilation schemes corresponded to occupant-based control. In Case 5, the ventilation rate was set as proportional to the number of occupants, with 6.96 L/s (25 CMH) per person until it reached the maximum fan capacity. In Case 6, the ventilation rate was set according to the ASHRAE 62.1 standard, which accounted for the occupant ventilation needs (Q_N) and also the ventilation required for building off-gassing (Q_A). The occupancy component of the ventilation rate was designed as follows: the airflow rate required per person (q_N) times the occupancy count (N). The building component was

Table 2 Ventilation schemes

Case	Group of control	Ventilation control	Description	Logic graph
1	Time-based	<Scheduled control> Constant airflow	Scheduled timer from 9 AM to 9 PM	
2		<On/off control> Based on N	Fan ON if $N > 1$ and OFF if $N = 0$	
3	CO_2-based	<On/off control> Based on C	700 ppm < C < 900 ppm	
4		<Proportional control> According to C	$Q = \frac{C_R - C_{\min}}{C_{\max} - C_{\min}}(Q_{\max} - Q_{\min}) + Q_{\min}$	
5	Occupant-based	<Proportional control> According to N	$Q = q_n N$	
6		<Combined control> Based on both N and floor area	$Q = Q_N + Q_A = q_N N + q_A A$	

defined as the airflow rate required per unit area (q_A) times the floor area (A). According to the present experimental conditions, Q_N and Q_A were determined according to Table 6-1 provided in the ASHRAE Standard 62.1 (ASHRAE 2013) at 2.5 L/s per person and 0.3 L/s m^2, respectively. Detailed information about the considered ventilation cases and logic graphs can be found in Table 2.

In the occupant-based schemes, the ventilation rate was regulated by the Bayesian output of the estimated number of occupants. This feedback process relationship is illustrated in Figure 3. The Bayesian MCMC algorithm was developed using LabView, and therefore, the measurement, estimation and control were organized using a unified interface.

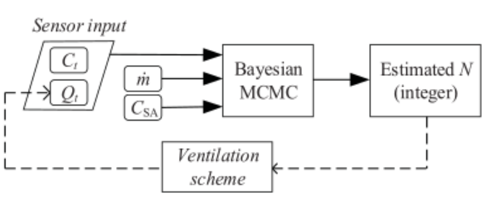


Fig. 3 Block diagram describing the occupant-based ventilation control

3 Results and discussion

3.1 Occupancy estimation

Figure 4 represents the diagnostic plot of posterior N derived at a timestep of the Bayesian MCMC calculation. This plot illustrates the trace plot of the proposed value of N and N accepted after 10,000 iterations. The proposed N could be accepted or rejected according to the Metropolis–Hastings probability.

Typical results of the measured indoor CO_2 concentration and the actual occupancy are represented in Figure 5. They are superimposed with the estimated results by Bayesian posterior with red dots for the constant and varying airflow conditions. The concentration increased and decreased as occupants moved in and out of the room. The estimated results conformed well to the actual occupancy. The error of the varying flow condition (43.5%) was slightly greater than the constant flow condition (33.0%). This was because the airflow rate was neither constant nor unknown but also varied as a result of self-control recurrently driven by airflow rates. The discrepancy between the actual and

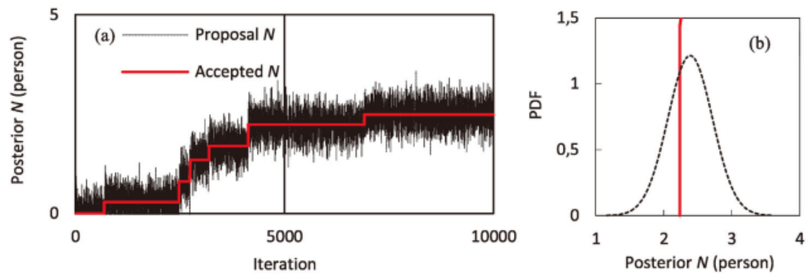
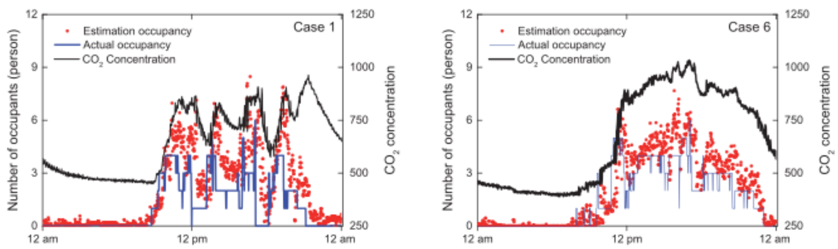


Fig. 4 Diagnostic plot of posterior (a) trace and (b) distribution



(a) Constant airflow rate (b) Varying airflow rate

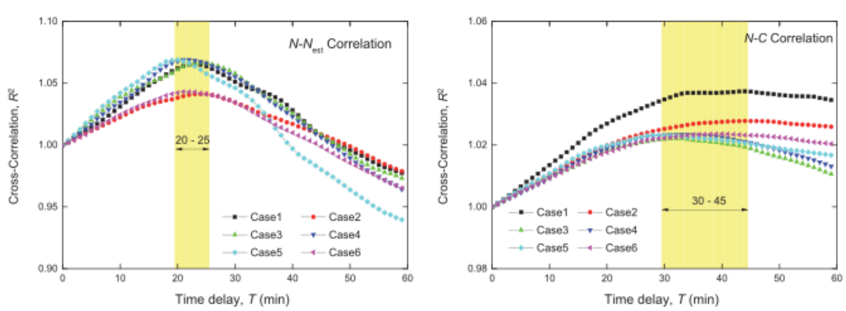
Fig. 5 Occupancy estimation for the constant and varying airflow rate conditions

estimated values of occupancy could be attributed to various uncertainties and the time required to complete the estimation process. In general, it could be observed that the dots representing the estimated occupancy shifted slightly to the right compared with the line graphs representing the actual occupancy.

Quantitative analysis on time delay was conducted to find correlation between two datasets. Autocorrelation was defined as the correlation between a signal and a delayed copy of itself as a function of delay, whereas cross-correlation was a measure of similarity between two different signals as a function of time delay T. Normalized cross-correlations could be obtained between the two datasets representing the estimated and actual occupant numbers according to Eq. (3). Normalized cross-correlation was calculated according to Barnea and Silverman (1972) as follows:

$$R^2(T) = \frac{\int N_{\mathrm{act}}(t) \cdot N_{\mathrm{est}}(t+T)\,\mathrm{d}t}{\int N_{\mathrm{act}}(t) \cdot N_{\mathrm{est}}(t)\,\mathrm{d}t} \tag{3}$$

Figure 6(a) shows the results of measuring cross-correlation between the actual and estimated numbers of occupants corresponding to various airflow conditions, including six cases (each case had a duration of 3 days). The maximum correlations occurred in the narrow range of 20–25 min in all cases. Time lags indicated the total response time in occupancy estimation in the system, comprising three parts: dispersion time, sensor-response time, and data-processing time. The dispersion time was the time required for CO_2 to reach a sensor after a person



(a) N_{act}-N_{est} (b) N_{act}-CO_2 concentration

Fig. 6 Cross correlations between (a) the actual and estimated occupancies and (b) occupancy and CO_2 concentration in six cases entering the room. This depended on the time constant of the room, which was related to the volume of the room, airflow characteristics, and the relative distance of a sensor from the source. The sensor-response time could be found in sensor specifications. It depended on the type of a sensor and its characteristics. In the conducted experiments, the response time was within a few minutes. Finally, the data-processing time was defined as the time required for dynamic measurement and the computation time for Bayesian iterations. Dynamic measurements were required to monitor the trends in CO_2 changes. In the present study, the measurement interval was equal to 1 min, and three timesteps were executed to perform the dynamic measurements of CO_2 variations. The value at each timestep was averaged over 10 minute intervals in order to smooth out the concentration fluctuations. Compared with the time for dynamic measurements, the computation time for data smoothing and Bayesian iterations was deemed negligible.

The time required for the physical dispersion of CO_2 was the main reason of time lag in ventilation control. Figure 6(b) shows the correlation between the actual occupancy and CO_2 concentration. We noted that the time delay of a room concentration response of 30–45 minutes was even greater than that of occupancy estimation. This was confirmed by the correlation observed between the estimated occupancy and CO_2 concentration, as shown in Figure 7. Maximum delays occurred in the range of 8–20 min, meaning that the estimated N advanced CO_2 response by that amount of time. This is explained in the schematic shown in Figure 8. The Bayesian estimation method uses the initial changes in concentration before CO_2 builds up in the room. We concluded that there was a time delay in occupant-based control; however, it was shorter than that of concentration-base control.

Earlier studies have reported the time delays of 10–20 min in CO_2 detection (Meyn et al. 2009), those of 30 min

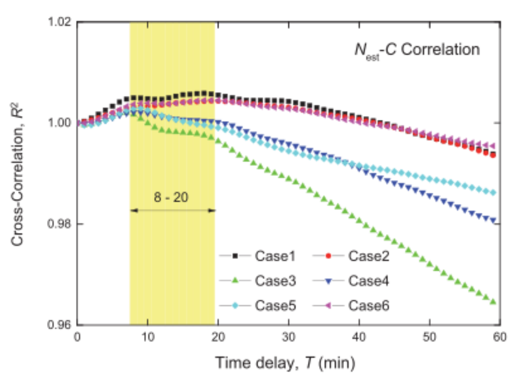


Fig. 7 Cross correlations between the estimated occupancy and CO_2 concentration

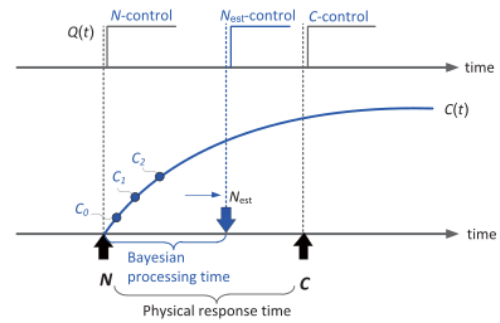


Fig. 8 Schematic graph illustrating the time required for Bayesian processing and obtaining a physical response of concentration dispersion

in CO_2 dispersion (Labeodan et al. 2015), and the delays of 20 and 45 min reaching the steady state in CO_2 detection (Dedesko et al. 2015; Zuraimi et al. 2017). It was demonstrated that airflow control based on CO_2-based occupancy detection exhibited significant delays (Wang and Jin 1998; Wang et al. 2003; Lu et al. 2011).

3.2 Effect of ventilation schemes

Figure 9 represents the real-time ventilation rates along with the actual number of occupants and CO_2 concentrations for all analyzed ventilation control schemes. Case 1 provided a constant airflow rate that was adequate for six people; this rate was excessive when the room was not fully occupied. This control scheme could lead to over-ventilation when the number of occupants was less than design capacity. The ventilation rate pattern of Case 2 was nearly the same as in Case 1, except for the fact that the ventilation was occasionally shut off when the room was unoccupied.

CO_2 concentration did not reach 1000 ppm except for a short period on day 3 in Case 3. These spikes could have occurred as occupants entered the room at almost the same time, and therefore, the level of CO_2 augmented faster than its dilution by ventilation. The advantage of Case 4 over Case 3 was that the fan rate was proportional to CO_2 concentration, and therefore, the fan did not wait for a considerable increase in CO_2 concentration to build up. The ventilation pattern of Case 4 matches the CO_2 concentration profile. However, this control scheme implied keeping the fan on until CO_2 concentration declined after the room was vacated completely.

The ventilation pattern considered in Case 5 was represented by demand, meaning that the Bayesian method estimated the number of occupants and controlled the ventilation rate accordingly. Recursive problems did not arise in the feedback loop control. Although the algorithm

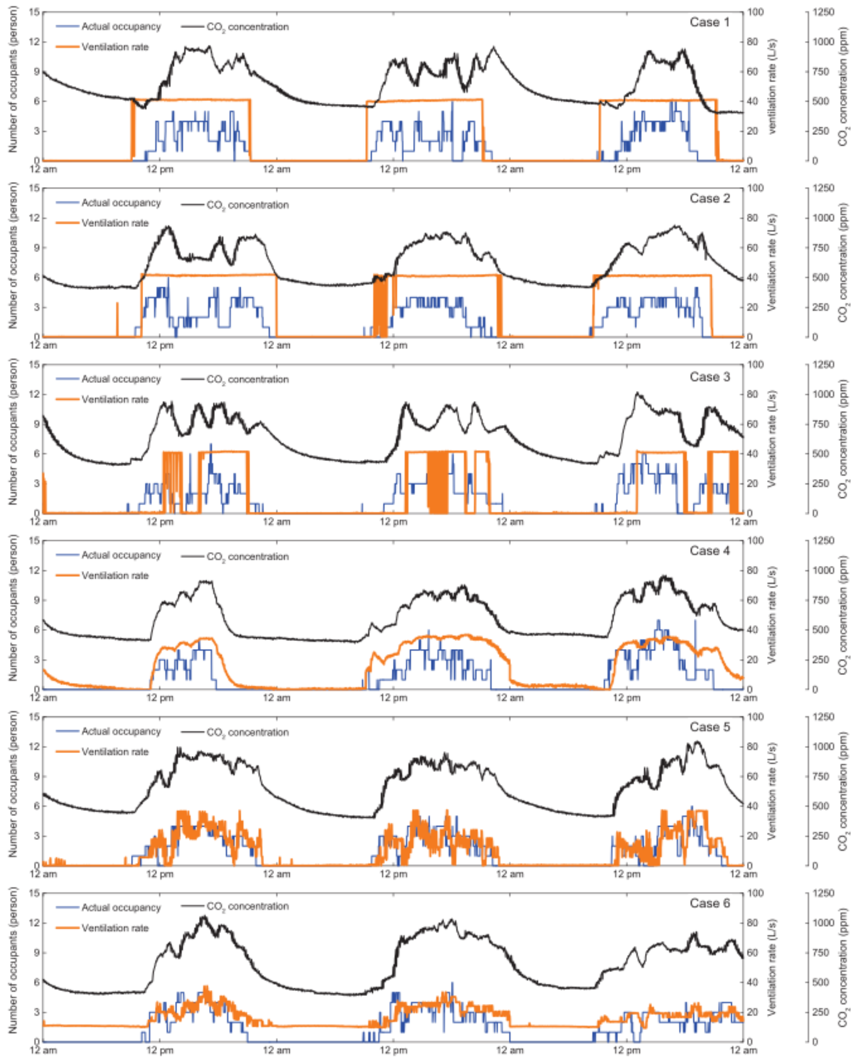


Fig. 9 CO_2 concentration and ventilation rate measurement in the six analyzed ventilation control cases

required informative priors, an incorrect estimation at one step did not significantly affect the calculation of the next step. Similarly as in Case 5, ventilation control based on the estimated number of occupants was successfully realized in Case 6. Moreover, in Case 6, the supply of outdoor air was modulated according to the requirements of occupants and the building area. In addition, the minimum airflow rate was supplied at night when occupants were absent so that the possible augmentation of the concentration of contaminants from building materials could be prevented. This scheme implied that the airflow rate at the maximum capacity was maintained at a value slightly smaller than that in Case 5.

The performance estimates of the considered ventilation schemes are summarized in Table 3. The average values and standard deviations are shown in the table corresponding to occupied periods. Over three days, the average occupancy density was similar among all cases. Furthermore, the average concentrations were comparable in all cases, being maintained well below 1,000 ppm. With respect to maximum concentration, Case 3 and Case 6 exhibited the values slightly greater than 1,000 ppm for a short period of time. The average ventilation rates in Case 1 and Case 2 were almost twice greater that those observed in Cases 5 and 6 during an occupied period. The ventilation rate and the total ventilation-air volume indicated the power consumption

Table 3 Summary of results for the analyzed ventilation schemes during occupied period

	t-control		*C*-control		*N*-control	
Variable	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Average occupancy (person)	2.7±1.3	2.6±1.3	2.5±1.2	2.8±1.4	2.7±1.2	2.6±1.2
Average indoor CO_2 conc. (ppm)	762±131	722±114	767±125	750±113	778±122	800±138
Maximum indoor CO_2 conc. (ppm)	966	973	1057	961	997	1068
Daily average ventilation rate (L/s)	39.5±7.2	39.4±8.8	22.7±20.1	29.5±7.3	17.3±10.1	20.2±5.2
Ave. ventilation rate per person (L/s per person)	14.4	15.0	9.0	10.4	6.5	7.7
Total ventilation air volume (m^3/day)	1440	1716	958	1053	718	939

of the fan and the heating/cooling loads according to air changes. In this table, the average ventilation rate per person is defined as the average ventilation rate divided by the average occupancy, which is equivalent to the amount of outdoor air received per person. Case 5 exhibited the lowest average ventilation rate per person, followed by Case 6 and Case 3. Although Case 3 returned a fairly low ventilation rate, it was associated with two major drawbacks. The ventilation performance would decrease with the degradation of sensors, as the ventilation rate is directly related to the absolute CO_2 level. The estimation of occupancy by the Bayes method is relatively insensitive to the degradation of sensors, since it monitors the relative trends in CO_2 changes. Moreover, indoor pollutants other than CO_2 are also relevant to indoor air quality and may not be vented out by a system that considers only CO_2 concentration as input.

Figure 10 shows the ventilation rates derived from the reference ventilation rate of the ASHRAE 62.1 standard. The shaded area in the figure illustrates the supply-air

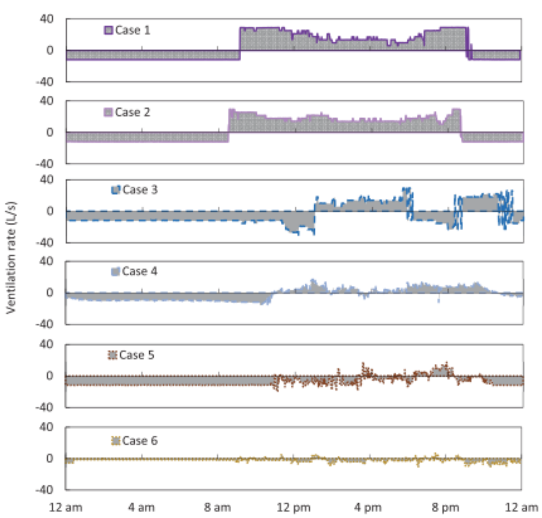


Fig. 10 Ventilation rates in the analyzed schemes subtracted from the ventilation rate of the ASHRAE 62.1 Standard

volume, while the areas below and above the *x*-axis indicate whether the room is under- or over-ventilated, respectively. It was noted that the occupant-based control schemes (Cases 5 and 6) produced the smallest shaded area, specifically, in Case 6, which almost fully complied with the standard. However, there was a considerable shaded area below the *x*-axis in Case 5, as the ventilation was zero when the building was vacant, which would degrade IAQ overnight. Case 1 represented the widest shaded area among the considered schemes. In addition, even though Case 2 was occupant-based, it relied only on the occupancy but not on the number of occupants, so it often resulted in the over-ventilation of the space.

Although Cases 3 and 4 were both based on CO_2 concentration measurements, they were rather different in terms of performance. As Case 3 did not account for a gradual increase in CO_2 levels that followed gradual augmentation in occupancy, the profile did not comply with that of the standard. However, Cases 4 and 5 exhibited similar patterns with respect to each other, as the ventilation rate was defined proportionally to their indoor variables.

4 Conclusions and futher work

In the present paper, we realized ventilation control based on real-time occupancy estimation in a small-scale office building. The Bayesian MCMC algorithm was employed to estimate the number of occupants based on the measured CO_2 concentration and a current ventilation rate. The DCV characteristics were compared among several alternative control schemes, including the time-based and concentration-based ones. From the obtained results, we outlined the following conclusions:

1) Real-time ventilation control based on the estimated occupancy could be successfully applied to an office without causing any recursive problems. The estimated occupancy conformed well to the actual occupancy within a reasonable range (43.5%). Estimation errors were caused by fluctuations and uncertainty in CO_2 measurements and time delays in the dynamic Bayesian process.

Time delays in occupancy estimation were found to be approximately 20–25 min, including the physical response time and the data-processing time in the considered experimental setup. Therefore, further efforts are required to reduce the uncertainty in the estimated occupancy by investigating the time delays associated with the Bayesian algorithm.

2) The occupancy-based ventilation control schemes were compared with the time-based and concentration-based ones. The occupancy-based schemes were found to be effective in terms of the total ventilation-air volume compared with the analyzed alternative schemes. Moreover, they exhibited less time delay compared with the concentration-based schemes. The occupancy-proportional scheme (Case 5) required a slightly lower ventilation rate in terms of controlling indoor CO_2 concentration; however, the ASHRAE scheme (Case 6) was preferable with respect to controlling unknown indoor contaminants by supplying the minimum ventilation rate.

Further research work is required to improve the Bayesian estimation method and the ventilation control algorithm to reduce the estimation errors and control time delays aiming to establish more robust and durable demand control ventilation system that would be applicable to a majority of building applications.

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