Smart Ventilation for Energy Conservation in Buildings

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https://doi.org/10.5109/2321005

出版情報：Evergreen. 6 (1), pp.44-51, 2019-03. 九州大学グリーンアジア国際リーダー教育センター
バージョン：

EVERGREEN Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy, Vol. 06, Issue 01, pp.44-51, March 2019

Smart Ventilation for Energy Conservation in Buildings

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(Received November 23, 2018; accepted March 26, 2019).

This paper introduces various smart ventilation methods for energy conservation in buildings, with a focus on occupant-based demand-controlled ventilation. An occupancy estimation algorithm is developed using a Bayesian Markov chain Monte Carlo algorithm based on indoor carbon dioxide concentrations. Experiments are conducted to control the outdoor airflow rate in real time according to the estimated number of occupants. Six different ventilation schemes are tested and compared with the ventilation standard of the American Society of Heating, Refrigerating, and Air-Conditioning Engineers. Our results show that occupant-based demand-controlled ventilation is more effective compared to other control schemes in terms the total ventilation air volume needed. The real-time ventilation control algorithm is applied successfully without any recursive problems. The occupancy estimation algorithm needs to be developed further to improve the estimation accuracy and reduce time delays.

Keywords: smart ventilation, occupancy estimation, Bayesian method, carbon dioxide concentration, demand-controlled ventilation

1. Introduction

Ventilation is essential to providing comfortable and safe indoor environments. Because energy is consumed for ventilation, it is necessary to supply fresh outdoor air in energy-efficient ways. The amount of energy used for heating, ventilation, and air conditioning (HVAC) by commercial buildings in Korea is reported to be approximately 49% of their total energy consumption[1)]. Recently, buildings have become increasingly more airtight and well-insulated to conserve energy used for heating and cooling. The percentage of energy that a building uses for ventilation relative to the total energy it uses becomes greater as the building becomes more energy conservative. For nearly-zero-energy buildings, this percentage becomes significant, as the supply of minimum outdoor fresh air cannot be eliminated in any case to save further energy.

There has been extensive research on efficient ventilation methods (i.e., smart ventilation) that can provide sufficient fresh outdoor air in energy-efficient ways. Smart ventilation is not limited to the smart operation of ventilation systems—it also includes the effective design of room airflows and the development of efficient ventilation systems including, heat-recovery ventilators (HRVs) and fans.

The first step toward smart ventilation is to provide standards for the required ventilation rate for occupants. This rate is defined as the "minimum" ventilation rate for "appropriate" indoor air quality[2)]. The word "appropriate" means neither harmful nor dissatisfactory in terms of health and comfort, respectively. It does not mean that the air is perfectly clean or completely uncontaminated. It expresses an optimal state in terms of energy usage and air quality, which generally refers to indoor air with 80% of occupants statistically satisfied. Standard ventilation rates for various building types can be found in the literature[2, 3)].

In this paper, some of the researches recently conducted at Kookmin University are introduced regarding smart ventilation methods. The focus is mostly on demand-controlled ventilation using occupancy estimation based on carbon dioxide (CO_2) concentrations.

2. Smart ventilation methods

Ventilation energy consists of the heating and cooling load required for exchanging indoor air with outdoor air at different temperatures and the fan power for operating electric fan motors. The heating and cooling load comprises a considerable part of the total ventilation energy, especially during extreme weather conditions. HRVs have been developed with various types of heat exchangers, such as flat plate, rotary wheel, and heat pipe units. Many studies have been conducted to improve the heat-recovery efficiency[4,5]. The air path of the flat plate is subdivided into triangular channels, so as to increase the heat-transfer area between two air streams[5]. The air passage is quite complicated, but the heat-recovery efficiency increases substantially. Han[6] modified the air path by eliminating the horizontal plate to reduce the pressure loss further. The efficiency decreases slightly due to the reduction in the heat-transfer area, but the ratio of heat transfer to pressure drop improves significantly.

A breathing HRV using packed-bed thermal storage has been suggested[7]. It is a new concept of HRV in which a single air duct delivers both the supply and exhaust air in an alternative fashion. In this case, heat is recovered from temporally separated air streams, unlike typical flat-plate HRVs, which recover heat from spatially separated air streams. A single air duct would be useful in buildings with limited ceiling spaces for dual ducts. The heat-recovery efficiency of this kind of system is affected by many parameters, such as the time period of the charging and discharging processes, the thermal mass of the packed-bed storage media, and etc. Some of the parameters are optimized in the study.

In hot and humid climates, a desiccant dehumidification system (DDS) can be a substitute for conventional air conditioning systems to achieve indoor thermal comfort[8]. It can provide cooling effect equivalent to the conventional vapor-compression system with less energy consumption by controlling the humidity level. A desiccant (DSC) block is commonly used to absorb excess water moist[9].

Outdoor air cooling and night purging are methods to reduce the operating hours of mechanical air-conditioning systems by introducing cool outdoor air whenever possible. Experimental and simulation studies have been conducted to investigate the effect of these methods on HVAC energy savings[10, 11]. The ventilative cooling potential (VCP) is the number of hours when ventilation cooling is possible out of the total number of cooling hours. A new VCP has been proposed to account not only for climatic conditions but also for thermal characteristics of buildings, such as the insulation and internal heat source. The VCP has been found to be in good correlation with the actual energy-saving outcomes[12].

Fan power consumption can be reduced by utilizing efficient fans and motors and by designing efficient duct systems with low pressure drops. In addition, mechanical fans can be replaced by natural ventilation forces, such as wind pressure and buoyancy forces. Hybrid ventilation is a practical way of combining mechanical and natural ventilation, so as to save fan power and to provide the necessary airflow rate even when natural ventilation forces are not sufficient[13].

A smart design of indoor air flow distribution can reduce the required airflow rate by improving the effectiveness of ventilation in a given space. The age-of-air concept is widely used to quantify the ventilation effectiveness[14]. Ventilation effectiveness refers to how well the supply air can be distributed spatially in the indoor space. It is affected by the indoor airflow pattern according to the space configurations including the layouts of the supply diffusers and exhaust openings. It is known the displacement ventilation results in greater ventilation effectiveness compared to the mixing ventilation. The effective air change rate would be the real air change rate multiplied by the ventilation effectiveness. The ventilation effectiveness for rooms with multiple inlets and outlets has been investigated by Han[15].

DCV is a smart way of controlling ventilation rates according to the instantaneous ventilation demand, as will be explained in detail in the next section. A list of all of the smart ventilation methods described so far is shown in Table 1.

Table 1. Smart ventilation methods for reducing heating and cooling load and fan power

Energy	Smart Ventilation Method	Category
Heating/cooling load	Heat-recovery ventilator	Equipment
	Outdoor air cooling	System operation
	Night purging	System operation
Fan power	Efficient fan and motor	Equipment
	Duct design	System design
	Hybrid ventilation	System operation
Total airflow rate (heating/cooling load and fan power)	Ventilation effectiveness	Spatial design of air distribution
	Demand-controlled ventilation	Temporal control of airflow rate

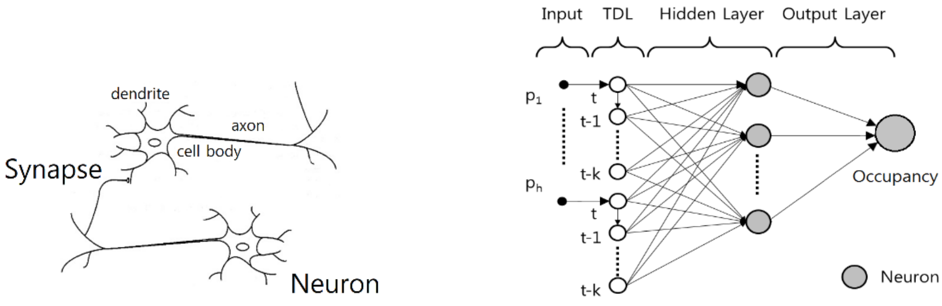


Fig. 1: Biological neural network (left) and artificial neural network (right)

2.1 Demand-controlled ventilation

DCV is a well-known method for controlling the airflow rate in commercial buildings according to the ventilation load. Common measures to determine DCV are time schedules, indoor contaminants, humidity levels, or occupancy rates. If the occupancy pattern throughout the day is known a prior, the time schedule can be programmed to adjust the fan speed or damper openings automatically. ASHRAE Standard 90.1-2004[16) provides a typical occupancy schedule for some building types so that a simple timer can regulate the fresh supply air accordingly.

Secondly, the indoor CO_2 level is a good indicator of human bio-effluent, which can represent the occupancy in spaces where specified dangerous contaminants are not present—for example, in office buildings. For this reason, CO_2-based DCV has been the most applicable method to modulate the supply of outdoor fresh air[17–19)]. However, this method relies on the absolute CO_2 concentration, so the sensors should be periodically calibrated to maintain their proper functioning. Otherwise, the sensor readings tend to drift after a period of time.

Moisture level is also an indicator to control ventilation airflow rate[20)]. As human activities such as showering, washing, cooking and even breathing cause high moisture levels, ventilation is required to control indoor humidity. High moisture level and condensation can cause mould[21)] growth and occupants' health effects.

Fresh outdoor air is required per person. ASHRAE currently recommends ventilation rates based on an occupant component that is proportional to the number of occupants and a building component that is proportional to the building floor area[22)]. Meeting the ventilation rate requires not only occupancy detection to determine whether an occupant is present but also occupancy density, or the number of occupants in the designated area in order to provide a necessary ventilation rate. The building component provides a minimum ventilation rate even when the space is unoccupied.

2.2 Occupancy estimation algorithm

There are various ways of determining the space occupancy, either through direct sensors such as passive infrared (PIR) sensors[23, 24)], radio-frequency identification (RFID) tags[25, 26)], and video cameras, or through indirect measurements of environmental conditions such as CO_2 concentrations, sound levels, humidity, and temperature. Indirect sensing methods are preferred over direct sensors, which hinder privacy. Among the aforementioned indirect methods, CO_2 concentration measurements show the strongest correlation with occupancy rates[27)].

Neural networks and Bayesian inference are common methods to estimate the number of occupants based on the measured CO_2 level. An artificial neural network is a statistical modeling tool for investigating complex nonlinear relationships between input and output variables. It mimics the physiology and functioning of

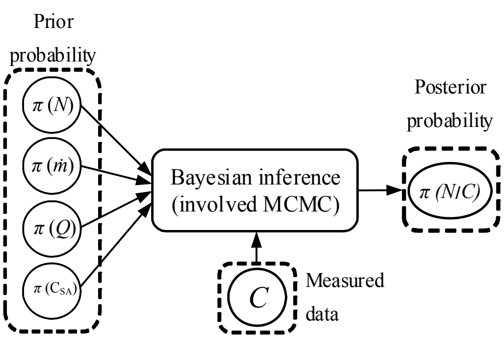


Fig. 2: Concept of a Bayesian inference

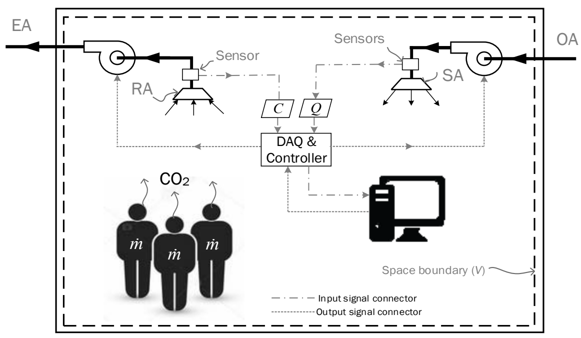
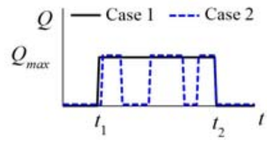
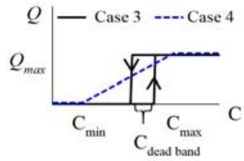
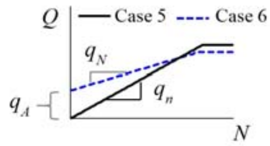


Fig. 3: Experimental setup diagram

Table 2. Ventilation control schemes

Case	Group	Ventilation Control	Description	Schematic Graph
1	Time-based	Schedule control	Scheduled timer from 9 AM–9 PM	
2		On/off control based on occupancy	Fan ON if $N>1$ and OFF if $N=0$	
3	Concentration-based	On/off based on CO_2 concentration	700 ppm < C < 900 ppm	
4		Proportional to CO_2	$Q = \frac{C_R - C_{min}}{C_{max} - C_{min}}(Q_{max} - Q_{min}) + Q_{min}$	
5	Occupant-based	Proportional to N	$Q = q_n N$	
6		Proportional to N and A (ASHRAE Std. 62.1)	$Q = Q_N + Q_A = q_N N + q_A A$	

biological neural network shown in Fig. 1 In this case, the output variable is the number of occupants, and the input variables are the CO_2 concentration, airflow rate, and other parameters determining the output variable. Environmental parameters such as humidity, particle concentrations, and door opening frequency can be used as supplementary input variables to improve the correlation accuracy in determining the number of occupants[28]. The more the model is trained, the better the performance is. However, the machine learning process requires that the model be trained on the exact input and output datasets[29].

Unlike an artificial neural network model, a Bayesian model determines the number of occupants by a probabilistic approach[24, 30]. Shin et al.[31] applied a Bayesian method to estimate the number of people in a subway station on the basis of measured CO_2 concentrations. The Bayesian calculation is referred to as a mathematical model, which is derived from a mass balance equation for CO_2. According to the first-order ordinary differential equation, the indoor CO_2 level is determined by the number of occupants (N), CO_2 generation rate per person ($\dot{m}$), supply CO_2 concentration (C_{SA}), and ventilation rate (Q). The number of occupants cannot be obtained from the equation directly because of the fluctuating characteristics of the first order differential equation. The Bayesian method addresses this problem by estimating the posterior probability of the measured indoor CO_2 level. According to Bayes' theorem, the posterior probability $\pi(\theta|x)$ is computed on the basis of the prior probability $\pi(\theta)$ and the likelihood function $f(x|\theta)$ as follows:

$$\pi(\theta|x) = \frac{\pi(\theta)f(x|\theta)}{\int \pi(\theta)f(x|\theta)d\theta} \qquad (1)$$

Here, θ is an occupancy level based on the observed CO_2 concentration x. We input the prior information based on the most likely occurrences in the observed system, and this approach should approximate the actual

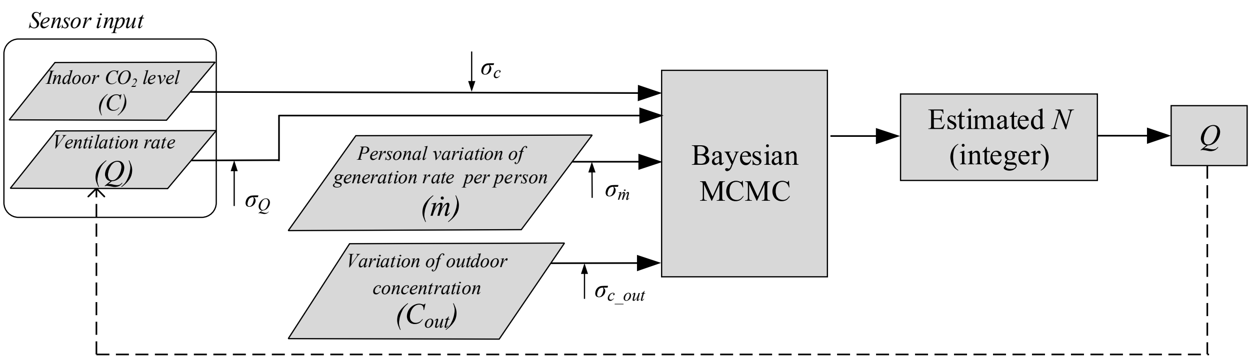


Fig. 4: Block diagram of occupant-based ventilation control

values as closely as possible. Four priors are set according to our system, with N prior determining the probability of the occupancy level and the three remaining priors (ṁ, CSA, Q) determining the CO_2 concentration (Fig. 2).

The Markov chain Monte Carlo (MCMC) approach generates random sampling from some probability distribution so that Bayes' process can be applied repeatedly. Finally, we use the Metropolis–Hastings (MH) algorithm, which rejects or accepts the sample trials of some proposed moves. A detailed description of the Bayesian MH-MCMC algorithm is provided by Rahman and Han[32)].

2.3 Ventilation schemes

Various ventilation schemes have been tested in an office room at Kookmin University. The room is equipped with various sensors and facilities for environmental control that enable various ventilation experiments as in Fig. 3.

Ventilation schemes can be categorized into three groups: time-based, concentration-based, and occupant-based. Each group possesses two control cases. Case 1 is a time schedule control in which ventilation is "ON" during the daytime (9 AM–9 PM) and "OFF" afterward. Case 2 is an occupancy detection control in which ventilation is "ON" when the space is occupied and "OFF" when the space is vacant. The airflow rate is set at a constant value of 41.6 L/s for six people.

Case 3 and Case 4 belong to the concentration-based group, which is based on the indoor CO_2 level. In Case 3, ventilation is "ON" and "OFF" based on the CO_2 concentration, with the upper limit at 900 ppm and the lower limit at 700 ppm. Case 4 is the CO_2 proportional control. The ventilation rate is increased gradually up to the maximum limit concentration of 1000 ppm.

The last group of ventilation schemes is occupant-based ventilation control. We assume this group is catagorized as smart ventilation control since ventilation rate is regulated according to estimated occupant. Case 5 sets the ventilation rate proportional to the number of occupants, i.e. 6.96 L/s per person. The rate is zero when there is no one inside. For Case 6, the ventilation rate refers to ASHRAE Standard 62.1-2004[22)], in which ventilation accounts not only for an occupant component but also for a building component. The occupant component consists of the airflow rate proportional to the zone population, and the building component consists of the airflow rate proportional to the zone floor area. The proportional constants, q_N and q_A, are given as 3.5 L/s per person and 0.3 L/s per square meter, respectively. A summary of the ventilation control schemes is shown in Table 2.

The indoor CO_2 level and ventilation rate per person are the parameters used to quantify the effectiveness of proposed ventilation scheme. The indoor CO_2 threshold is referring to ASHRAE 62-1989[33)] where an acceptable level is defined not to exceed 1000 ppm. Meanwhile, ASHRAE 62.1-2004 is a reference for the ventilation rate per person based on the actual occupant.but for verification of the proposed estimation algorithm.

Figure sensor is installed at the door to count the number of people entering and exiting the room. Two infrared beams are emitted from the counter, and these beams are positioned apart horizontally

.

3. Results and discussion

The procedure for occupant-based ventilation control is shown in Fig. 4. Concentrations of CO_2 are measured using a non-dispersive infrared (NDIR)-type sensor, and airflow rates are measured using hot-wire anemometers in supply and exhaust ducts. Outdoor CO_2 levels, humidity, temperature, and wind speed are also acquired continuously. The time interval of data acquisition is one minute. A motion sensor is installed at the door to count the number of people entering and exiting the room. Two infrared beams are emitted from the counter, and these beams are positioned apart horizontally to detect the direction of movement by the sequential cutoffs. The actual number of occupants was not used for ventilation control but for verification of the proposed estimation algorithm.

Figure 5 shows the measured CO_2 concentrations and the occupancy estimations. It can be seen from the graphs in Fig. 5 that the CO_2 concentration increases and decreases as occupants move in and out of the room. The blue scatters show the estimated occupancy in real time. The estimated occupancy is in good agreement with the

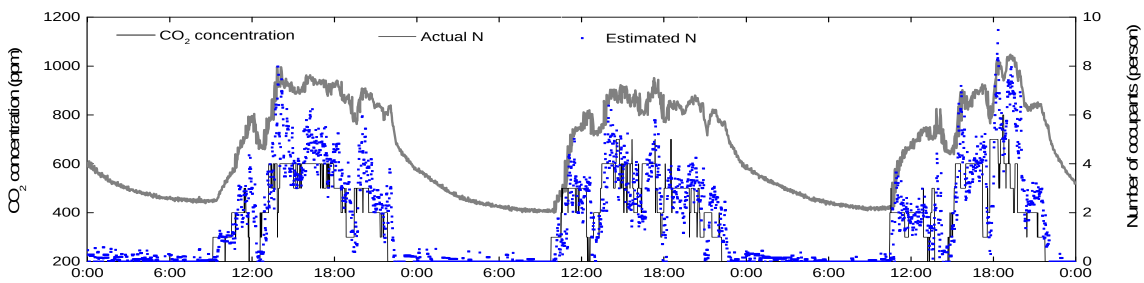


Fig. 5: Occupancy estimations

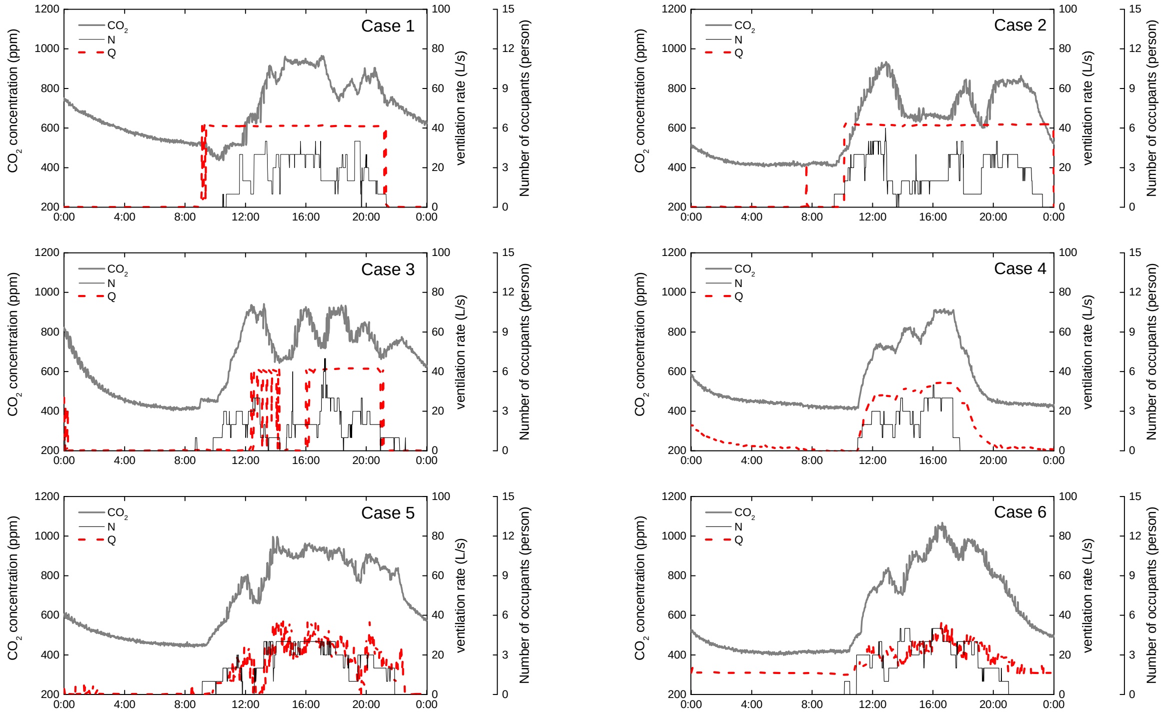


Fig. 6: Measured CO_2 concentrations and ventilation rates for six ventilation control cases

exact occupancy. The coefficient of variation is 43 ± 5%. Note that the airflow rate is not constant but varies according to the estimated occupancy. There are previous studies focused on the estimated occupancy based on variations in CO_2 concentration while the airflow rate remained constant[32].

Errors were generated as a result of severe concentration fluctuations due to frequent in-and-outs and unavoidable delays such as CO_2 sensor response time, air mixing and dispersion delays, and data processing time. However, these delays can be reduced by improving sensor accuracy and sensitivity, optimizing indoor air mixing, and reducing the time of data processing.

Figure 6 shows the real-time ventilation rates along with the actual number of occupants and CO_2 concentration for the six ventilation schemes. Case 1 provides a constant airflow rate adequate for six people; this rate is more than sufficient when the room is not fully occupied. The ventilation rate pattern of Case 2 is nearly the same as Case 1, except for the fact that the ventilation is off shortly from time to time.

The ventilation is on and off depending on the CO_2 level for Case 3. The concentration does not exceed 1000 ppm. The advantage of Case 4 over Case 3 is that the continuous fan operation is proportional to the CO_2 concentration; thus, it does not have to wait for the concentration to build up to a certain level. It shows the ventilation pattern of Case 4 matching the CO_2 profile. However, this control scheme lets the fan remain on until the room concentration decays after the room is vacated completely.

The ventilation rate patterns of Cases 5 and 6 mostly follow the actual occupancy pattern. This result means that the Bayesian method is applicable not only to occupancy estimation but also to control the ventilation rate based on the estimated number of occupants. It does not cause any recursive problems in feedback control. Even though the algorithm adopts informative priors, with the proposed method, a false estimation at the current step would not significantly affect the calculation of the next step.

Table 3. Effect of ventilation schemes when the building is in occupied period.

Description	Case						Reference
	1	2	3	4	5	6	
Average indoor CO_2 (ppm)	800	766	691	722	809	829	<1000 ppm
Average ventilation rate per person (L/s per person)	14,7	10,4	11,5	15,0	6,8	7,3	7.6

The effect of the ventilation scheme is summarized in Table 3. The table shows that the average CO_2 concentrations of all cases are below 1000 ppm. Meanwhile, the average ventilation rates per person are relatively low in Case 5 and Case 6 compared to other cases, which are close to the reference. Thus, occupant-based ventilation control saves energy by reducing total ventilation air volume.

3 Conclusions

In this paper, smart ventilation is investigated for energy conservation in buildings. Various smart ventilation methods are categorized, and some of the current research topics are introduced with the focus on DCV, particularly occupant-based control methods. Following conclusions can be drawn from the study:

1. Smart ventilation can be achieved by reducing the heating and cooling load by applying HRVs and using outdoor air cooling or purging at night. Fan power can be saved by using efficient fans and designing low-pressure-drop duct systems. Hybrid ventilation is another way of saving mechanical fan power consumption by utilizing natural ventilation forces. Ventilation effectiveness can be improved by designing efficient spatial airflow distribution.
2. DCV is a smart way of controlling ventilation rates according to the instantaneous ventilation demand, which can be categorized into time-based, concentration-based, and occupant-based control schemes. Experimental results of six different cases of ventilation schemes show that occupant-based DCV is more effective compared to other control schemes in terms of indoor environmental quality and the total ventilation air volume.
3. The number of occupants is estimated using a Bayesian MCMC method with a reasonable error range. The real-time ventilation control based on the estimated occupancy is applied successfully without any recursive problems. The algorithm can be further improved by reducing estimation errors and time delays, and it should be further developed to become more robust and durable.

Because the Bayesian inference relies on a mathematical model, the parameters in the model should be adjusted periodically because of sensor degradation and system changes. A self-adjusting algorithm can be developed further based on the data accumulated by adopting an automatic machine learning process.

Acknowledgements

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2016R1D1A1B01009625), and by Global scholarship of Kookmin University.

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