Building and Environment 223 (2022) 109455

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Advances in research and applications of CO_2-based demand-controlled ventilation in commercial buildings: A critical review of control strategies and performance evaluation

Xing Lu, Zhihong Pang, Yangyang Fu, Zheng O'Neill [*]

J. Mike Walker '66 Department of Mechanical Engineering, Texas A&M University, College Station, TX, 77843, United States

ARTICLE INFO

Keywords:
CO_2
Control strategies
Demand-controlled ventilation
Energy efficiency
Performance evaluation
CO_2 sensor

ABSTRACT

The carbon dioxide (CO_2)-based demand-controlled ventilation (DCV) has attracted prompt attention from the Heating, Ventilation, and Air-Conditioning (HVAC) industry since its very first invention. Thereafter it has gone through several revolutions due to the rapid advancement in control and sensing technologies. Although a great variety of CO_2-based DCV control strategies have been developed in the last two decades, there lacks a holistic literature review that systematically analyzes and summarizes advances and applications of CO_2-based DCV in commercial buildings. This paper examines the recent advances in the CO_2-based DCV in commercial buildings and focuses on discussing the control-related issues in the applications of the CO_2-based DCV by collecting and assessing the available case studies in the recent two decades in terms of principles, complexity, and performance. First, principles of the different CO_2-based DCV control strategies are elaborated, and their application scenarios are summarized from the case studies. Second, advancements in sensing technologies and actuating control devices are presented. On top of that, performance evaluation of the CO_2-based DCV is conducted to (1) quantify the benefit achieved from the state-of-the-art CO_2-based DCV; and (2) identify common issues and challenges associated with the design and field implementation of the CO_2-based DCV. Finally, conclusions, limitations, and perspectives for future research are summarized.

1. Introduction

The carbon dioxide (CO_2)-based demand-controlled ventilation (DCV) has attracted significant research and application interests from both heating, ventilation, and air-conditioning (HVAC) academia and industry since decades ago [1], as the indoor CO_2 concentration is an effective bio-proxy for indicating the indoor air quality (IAQ).

The CO_2-based DCV is a control strategy for the building HVAC system that modulates the actual outdoor airflow rate based on the indoor CO_2 concentration to maintain a good IAQ and reduce the building HVAC energy consumption. One of the earliest studies of the CO_2-based DCV took place in an office building in Helsinki, Finland, in 1982 [2]. Since then, we have seen the prompt and widespread deployment of this technology in hundreds of thousands of buildings worldwide. Meanwhile, the technology itself has also gone through many profound changes and evolutions in this process. For instance, the CO_2-based DCV technologies have been explored with various control strategies in different HVAC system configurations, including the single-zone variable air volume (VAV) systems [3], multiple-zone single-path VAV systems [4,5], multiple-zone VAV systems with multiple recirculation paths [6], constant-air-volume systems [7], and split air-conditioning systems [8].

Although a great variety of CO_2-based DCV control strategies have been developed in the last two decades, there lacks a literature review that systematically analyzes and summarizes such applications. Such an issue of a limited understanding of the various CO_2-based control strategies or CO_2 sensing has seriously impeded the development of this technology and raised concerns from researchers and practitioners, e.g., Emmerich et al. [9]. On the other hand, the optimal design of HVAC controls and appropriate field implementation are demonstrated to save up to 30% annual HVAC energy use for conventional VAV systems [10–13]. Likewise, different control strategies could yield different energy savings for implementing CO_2-based DCV. However, few studies conducted a holistic performance evaluation of various CO_2-based DCV control sequences. With the CO_2-based DCV continuing to gain popularity in commercial buildings, there is an urgent and practical need for a holistic performance evaluation of the various CO_2-based DCV control

* Corresponding author.
E-mail address: zoneill@tamu.edu (Z. O'Neill).

https://doi.org/10.1016/j.buildenv.2022.109455
Received 18 February 2022; Received in revised form 22 April 2022; Accepted 25 July 2022
Available online 10 August 2022
0360-1323/

Nomenclature

Symbol

A_z	zone area, m^2
CR_z	zone criticalness
C_{oa}	outdoor CO_2 concentration, ppm.
C_r	return air CO_2 concentration, ppm.
C_s	supply air CO_2 concentration, ppm.
C_{set}	zone CO_2 concentration setpoint, ppm.
C_{ss}	steady-state indoor CO_2 concentration, ppm.
C_z	actual zone CO_2 concentration, ppm.
$C_{z\text{-}design}$	steady-state CO_2 concentration at $^{Vot\text{-}design}$, ppm.
$C_{z\text{-}min}$	CO_2 concentration at $V_{ot\text{-}min}$, ppm.
$C_{z\text{-}ref}$	zone reference CO_2 concentration, ppm.
E_v	system ventilation efficiency
E_z	zone ventilation effectiveness
G	indoor CO_2 generation rate per person, L/(s•p)
P_z	number of people in the zone, p.
r	Reference signal
R_a	area-based component of the ventilation rate
R_p	the people-based component of the ventilation rate
u	Control signal/input
u_{pd}	Control signal/input of predictive controller
u_{fd}	Control signal/input of feedback controller
V	zone volume, L.
V_{bz}	breathing zone required ventilation rate, L/s
$V_{bz\text{-}A}$	area component of the breathing zone outdoor airflow, L/s
$V_{bz\text{-}P}$	population component of the breathing zone outdoor airflow, L/s
V_{dz}	zone discharging air flow rate, L/s
V_{oa}	measured outdoor air flow rate, L/s
V_{ot}	required outdoor air flow rate, L/s
$V_{ot\text{-}design}$	design OA flow rate, L/s
$V_{ot\text{-}min}$	OA flow rate at minimum occupancy, L/s
$V_{ot\text{-}mz}$	required OA flow rate for the multi-zone HVAC system
$V_{ot\text{-}sz}$	required OA flow rate for the single-zone HVAC system
V_{ou}	Uncorrected required OA flow rate, L/s
V_z	zone ventilation rate, L/s
x	State variables
y	Output
y_{dam}	OA damper position
Z_p	system level primary air fraction: largest zone primary air fraction
Z_{pz}	zone primary air fraction: the fraction of the zone outdoor airflow to the zone primary airflow

Abbreviation

ACH	Air Change Rate Per Hour
AFMS	Airflow Measurement Station
AHU	Air Handling Unit
ANSI	ASHRAE and American National Standards Institute
ARPA-E	Advanced Research Projects Agency–Energy
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BAS	Building Automation System
CO_2	Carbon Dioxide.
CIAI	Indoor Air-Quality Index
CFFC	Feedforward-Feedback Control
CRBMs	Commercial Reference Building Models
CVRMSE	Coefficient of Variation of the Root Mean Square Error
DCV	Demand-Controlled Ventilation
DDC	Direct Digital Control
DFDDTU	Dual Fan Dual Duct VAV Terminal Unit
DOE	U.S. Department of Energy
EES	Engineering Equation Solver
ERV	Energy Recovery Ventilator
HVAC	Heating, Ventilating, And Air-Conditioning
IAQ	Indoor Air Quality
IDA	InDoor Air
FPTU	Fan-Powered Terminal Unit
MBE	Mean Bias Error
MD	Measurement Disturbance
MPC	Model Predictive Controller
NDIR	Non-Dispersive Infrared
NIST	National Institute of Standards and Technology
OA	Outdoor Air
OAR	Outdoor Air Ratio
PFPTU	Parallel Fan-Powered Terminal Unit
PI	Proportional–integral
PID	Proportional–integral–derivative.
RL	Reinforcement Learning
RP	Research Project
SFPTU	Series Fan-Powered Terminal Unit
TAB	Test, Adjust, and Balancing
T&R	Trim-And-Respond
TVOC	Total Volatile Organic Compounds
VAV	Variable Air Volume
VOC	Volatile Organic Compounds
VRP	Ventilation Rate Procedure
VSAT	Ventilation Strategy Assessment Tool

sequences to summarize the existing experience and guide future research.

1.1. Scope and objective

Considering all the limitations and gaps, this paper aims to present a comprehensive review of the pros and cons of the CO_2-based DCV control strategies as well as the sensor technologies developed and implemented in the recent two decades. In addition, the performance of the state-of-the-art CO_2-based DCV technology is assessed through a comprehensive review of simulation-based and field-testing-based case studies. In details, the following topics were reviewed:

- Emerging CO_2-based DCV control strategies and case studies with better performances.
- Advancements in CO_2 sensing technologies.
- A holistic performance evaluation of the state-of-the-art CO_2-based DCV technology.

Various stakeholders are expected to benefit from this review, such as the researchers, designers, engineers, control contractors, building facility managers, and policymakers, whose work is involved with the building ventilation system, indoor air quality, and/or CO_2-based DCV controls. It is noted that this review paper is focusing more on the VAV system because the application of DCV in other systems (e.g., CAV) is rather limited.

1.2. Literature pruning

The literature were collected in the following procedure [14]. First, Google Scholar and Scopus by Elsevier were used as the search engine to find the literature published in English. The keywords for the search were {CO_2 or occupan*} and {demand control* ventilat*}. To highlight the latest progress, the literature were restricted to be published after the year of 2000. This yielded a total of 1098 items in the first place. Secondly, the literature in the pool were carefully and manually filtered by removing the irrelevant items falling outside of the working scope. For instance, the applications of DCV in residential buildings were deemed irrelevant and dropped from the list. This pruning procedure yielded 138 publications of interest, which include the journal article, conference paper, project report, thesis, book section, and patent. For those who are interested in research papers before 2000, please refer to the previous review papers [9,15]. A word cloud analysis of the 138 publication titles is presented in Fig. 1. A stemming and lemmatization method [16] was utilized to get rid of the redundant words and stop words. Fig. 1 shows that computational "simulation," "performance" evaluation, system "monitoring", development of "low"-cost sensors, "smart" "HVAC" control strategy, and "optimization" of energy and ventilation performance are most popular publication title words. In addition, "occupancy" has become an emerging point in the CO_2-based DCV, which is aligned with occupant-centric building design and operation in the last decades [17]. Finally, 63 publications were selected manually that focused on the development and evaluation of CO_2-based DCV control strategies.

The paper is organized as follows. Section 2 elaborates on the different types of CO_2-based DCV control strategies and summarizes their application scenarios. Section 3 reviews critical control components typically used in the DCV control (i.e., the CO_2 sensor, outdoor air flow rate sensor, and local terminal controls). The impacts of sensor errors on the performance of the CO_2-based DCV especially discussed. Section 4 assesses the benefits of energy savings for different CO_2-based DCV case studies and presents the practical issues and challenges when the DCV is implemented in real commercial buildings. Section 5 concludes this paper and discusses the perspectives for future research.

2. Review of CO_2-based DCV control strategies

This section reviews existing CO_2-based DCV control strategies based on an analysis of recent case studies. As shown in Table 1, three types of CO_2-based DCV control strategies, as well as their subcategories, are summarized from research papers, thesis, reports, standards, and guidelines. These three types are rule-based controls, model-based controls, and learning-based controls, respectively. Their existing applications in single-zone and/or multi-zone systems are also outlined. The rule-based approach refers to a group of controllers in which control actions are dictated by predefined rules. For example, the outdoor air flow rate can be determined by the ventilation rate requirement from the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standards and/or guidelines. The model-based approach involves an internal control model that adjusts the control signals to achieve the desired behavior of the process. In the learning-based approach, however, the controllers are learned from online data along the trajectories of the control system in question. Three types of CO_2-based DCV control strategies and their subcategories are detailed in the following sections.

Fig. 1. Word cloud analysis of the 138 publication titles.

2.1. Rule-based control

The rule-based controls can be further divided into three major categories: *Direct Outdoor Air (OA) Controls by the CO_2 Setpoint*, *Ventilation Reset*, and *Ventilation & Zone Minimum Reset*, which will be discussed with details in the following subsections.

2.1.1. Direct Outdoor Air (OA) controls by the CO_2 setpoint

In the first type of the rule-based DCV control, the CO_2 setpoint is directly used to alter the outdoor air damper position; thus, this method is also known as the *Direct OA Control by the CO_2 Setpoint*. This method is widely used in both single-zone systems and multi-zone systems. Depending on the number of CO_2 setpoints used for controls, the *Direct OA Control by the CO_2 Setpoint* could be further divided into the single CO_2 setpoint control and dual CO_2 setpoint control [18].

Fig. 2 illustrates the principles of the two varieties of direct OA control. In the single setpoint control, the OA damper is adjusted to maintain the indoor CO_2 concentration at or below the fixed CO_2 setpoint through a proportional–integral–derivative (PID) control. If the OA damper reaches the minimum intake flow but the population in the zone continues to drop, the OA damper remains at the minimum position. Generally speaking, the single CO_2 setpoint was suggested to be set as the steady-state CO_2 concentration at the minimum occupancy of the zone [18]. Lawrence [19] also recommended that the CO_2 setpoint be set as 90% of the steady-state concentration. The calculation of the steady-state CO_2 concentration according to the ventilation requirements in ANSI/ASHRAE Standard 62.1 is shown in Eq. (1). A table of the recommended CO_2 setpoints for different space types is provided in Ref. [19].

$$C_{set} = 0.9\left(C_{oa} + \frac{8400E_z}{R_p + \frac{R_a A_z}{P_z}}\right), \tag{1}$$

where C_{set} is the zone CO_2 concentration setpoint; C_{oa} is the outdoor air CO_2 concentration; E_z is the zone ventilation effectiveness; R_p is the people-based component of the ventilation rate; R_a is the area-based component of the ventilation rate; P_z is the number of occupants in the zone and A_z is the zone area.

Ke et al. [20] introduced a dual CO_2 setpoint control, which is essentially an on-off controller that modulates the OA flow rate so the indoor CO_2 concentration tends to stay between the two CO_2 setpoints. When the indoor CO_2 concentration hits the upper limit, the design ventilation rate will be used; while when the indoor CO_2 concentration decreases to the lower limit, only the area-component of the ventilation rate will be used.

The User's Manual of ASHRAE Standard 62.1 [21] proposed another example of the dual CO_2 setpoint controls. This method adjusts the outdoor airflow rate in proportion to the percentage of the CO_2 signal in the range of the two CO_2 limits, as shown in Eq. (2). It is noted that this control strategy tends to over-ventilate the space at partial occupancy

Table 1
Summary of CO_2-based DCV control strategies.

Categories	Control Strategies	Reported System (Single-Zone/Multi-zone)	Pros	Cons
Rule-based	Direct OA control by the CO_2 setpoint (single CO_2 setpoint control and dual CO_2 setpoint control) Ventilation reset Ventilation reset & Zone minimum reset	Single-zone & Multi-zone Single-zone & Multi-zone Multi-zone	• Easy implementation • Widely applied in the field • Demonstrated energy savings and ventilation compliance • Comparatively easy implementation	• Potential IAQ problems • Lack of large-scale field tests
Model-based	Predictive control State Feedback Control	Single-zone & Multi-zone Single-zone	• Better performance if fine-tuned	• Complicated implementation • Lack of field demonstration
Learning-based	Reinforcement learning-based control	Single-zone	• Better performance after a long training	• Long training • Complicated implementation • Lack of field demonstration

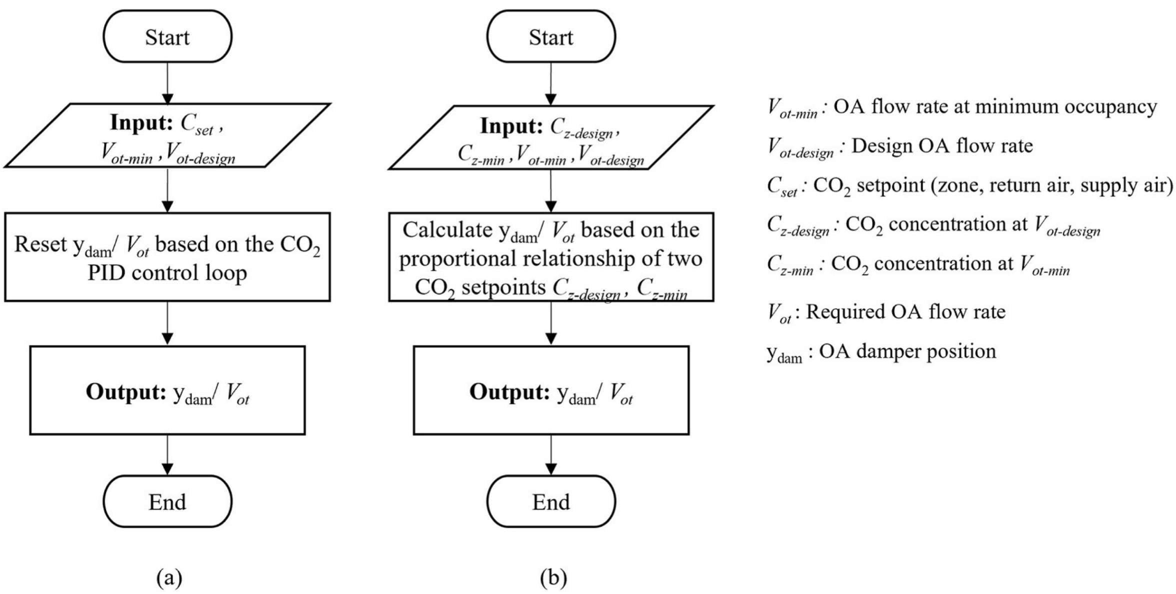

Fig. 2. Flowchart of (a) single setpoint control (b) dual setpoint control.

compared to the ventilation requirement from the ASHRAE 62.1 [18]. Therefore, it is less aggressive in the standpoint of energy savings compared with the single setpoint control.

$$V_{ot} = \frac{C_z - C_{z-min}}{C_{z-design} - C_{z-min}} \left(V_{ot-design} - V_{ot-\min}\right) + V_{ot-\min} \ , \tag{2}$$

where V_{ot} is the required outdoor airflow rate; $V_{ot-design}$ is the design OA flow rate; $V_{ot-\min}$ is the OA flow rate at minimum occupancy; C_z is the actual indoor CO_2 concentration; C_{z-min} is the CO_2 concentration at $V_{ot-\min}$; $C_{z-design}$ is the steady-state CO_2 concentration at $V_{ot-design}$.

The *Direct OA Controls by the CO_2 Setpoint* are not limited to single-zone systems. When it comes to the multi-zone systems, the control could be based on the CO_2 sensor in the common return duct, a representative zone-level CO_2 sensor, or even the CO_2 sensor in the AHU supply air main duct [22]. Due to the easy implementation, the direct CO_2 setpoint controls are widely used in multi-zone systems in field tests [23]. For instance, in a 2015 field survey [23], 67% of the 98 buildings in Minnesota that employed the CO_2-based DCV were found to adopt these controls, while 19% of them installed CO_2 sensors in the common return duct.

The setting of the lower limit for the OA flow (i.e., $V_{ot\text{-}min}$) could pose a direct impact on the energy and ventilation performances of the direct OA controls [23]. Currently, there lacks a consensus on the best practice, but many researchers tend to set this value to be the area-weighted ventilation portion as specified by the Ventilation Rate Procedure (VRP) of ASHRAE Standard 62.1 [23].

Despite the significant energy-saving potential, the *Direct OA Controls by the CO_2 Setpoint* is also known to result in potential IAQ problems for some zones due to the inconsideration of the system ventilation efficiency. Out of the concerns for the overventilation issue in some zones and the underventilation issue in other zones, some studies [9,24,25] discouraged the use of such control strategies for the multi-zone systems.

2.1.2. Ventilation reset

Fig. 3 depicts the flow chart of the *Ventilation Reset* algorithm for the single-zone system and multi-zone system. Under the control sequence for the single-zone systems, the system-level OA requirement is dynamically reset following the minimum ventilation rule in the VRP of ASHRAE Standard 62.1–2019, as shown in Eq. (3).

$$V_{bz} = V_{bz-P} + V_{bz-A} = R_p P_z + R_a A_z \ , \tag{3}$$

where V_{bz} is the breathing zone required ventilation rate; V_{bz-P} and V_{bz-A} are occupant- and area-related components. R_p is the people-based component of the ventilation rate; R_a is the area-based component of the ventilation rate; P_z is the number of occupants in the zone and A_z is the zone area.

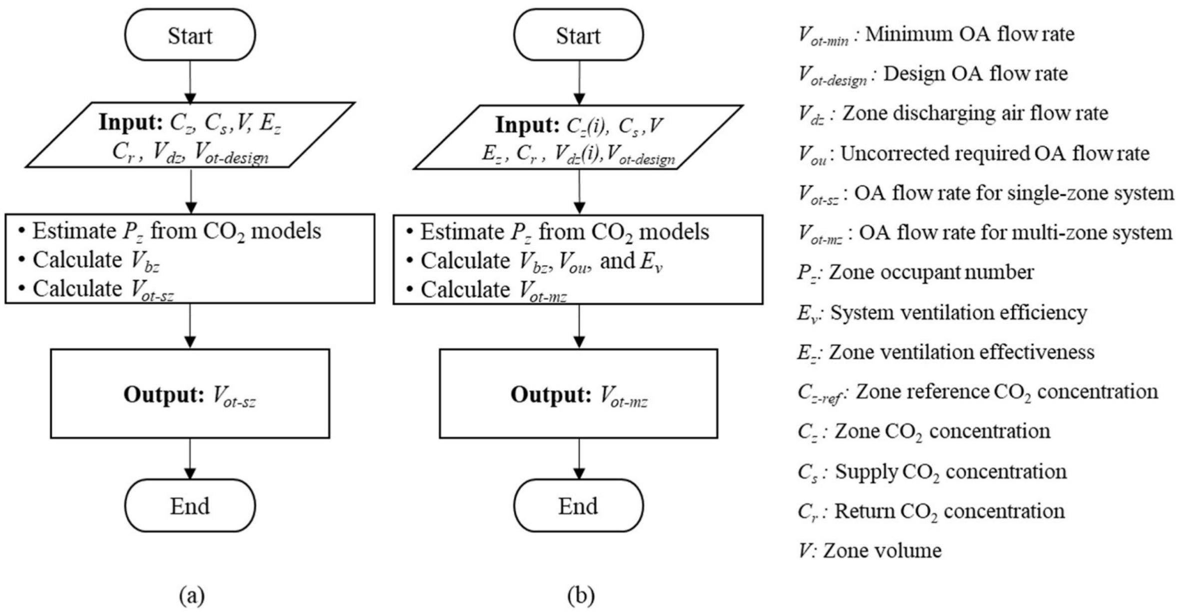

Fig. 3. Flowchart of ventilation reset control for (a) single-zone system (b) multi-zone system.

The dynamic occupant number can be estimated from the indoor CO_2 concentration using multiple approaches (e.g., physical-based and data-driven-based) [26]. Nevertheless, the steady-state physical-based model is often used in most case studies [21]. This is because although the actual system is usually not operated at steady-state and the CO_2 concentration generally lags behind the change in actual occupant number, the steady-state model is effective to calculate the required OA flow rate to maintain an acceptable level of bioeffluent concentration. While the required air flow based on the steady-state equations does not exactly track the source strength of bioeffluents due to transient effects, it generally guarantees an acceptable bioeffluent concentration [27,28]. Eq. (4) shows the steady-state equation to reset the ventilation rate for a single-zone HVAC system. Afroz [29] verified the effectiveness of using the steady-state CO_2 mass balance and proposed the involvement of these equations into the Australian ventilation standard AS 1668.2 [30].

$$V_{ot-sz} = \frac{R_a A_z}{E_z - \frac{C_r - C_{oa}}{8400m}} , \tag{4}$$

where V_{ot-sz} is the required OA flow rate for the single-zone HVAC system; C_r is the return air CO_2 concentration; E_z is the zone air effectiveness.

Instead of using the steady-state equation, Ng. et al. [31] adopted the transient equation (as presented in Eq. (5)) that was discretized from the governing differential equation in Eq. (6) by the forward Euler method. The transient equation has a shorter response time and a higher occupancy estimation accuracy for the highly dynamic occupancy. The results from an Engineering Equation Solver (EES) simulation indicated that the transient equation could maintain an acceptable level of the indoor CO_2 concentration over the whole testing day for a single-zone gymnasium. However, it also exhibited a random oscillatory behavior though the actual occupancy was remained constant, possibly due to the discretization of the derivative term used by the forward Euler method as shown in transient Eq. (5), which increases the error propagation compared with the case using the steady-state equation.

$$N^i = V\frac{C_z^{i+1} - C_z^i}{\Delta t} + \frac{V_z^i\left(C_z^i - C_{oa}^i\right)}{G}, \tag{5}$$

$$V\frac{dC_z(t)}{dt} = N \cdot G + V_z \cdot C_{oa} - V_z \cdot C_z(t), \tag{6}$$

where Δt is time step and i is the current step. C_z, C_{oa}, N, G, V_z, and V represent the indoor CO_2 concentration (ppm), outdoor CO_2 concentration (ppm), number of people, indoor CO_2 generation rate per person (L/(s·person)), ventilation rate (L/s), and zone volume (L) respectively.

For the data-driven ventilation reset algorithms, Rahman et al. [32] investigated the Bayes theorem to estimate the occupancy based on the indoor CO_2 concentration and ventilation rate. Momeni et al. [33] used a two-layer feed-forward neural network to predict the real-time occupancy and the experiment was carried out to validate the proposed control strategy. They compared the data-driven ventilation reset algorithms with the steady-state and transient approach and concluded limited improvements in terms of energy savings were observed [33].

For the multi-zone systems, the *Ventilation Reset* control could be much more complicated since the zone-level OA requirement is different while the OA fraction of the supply air is the same for all the zones. To ensure a proper ventilation that satisfies the requirement of ASHRAE Standard 62.1, the system OA intake should be modulated to guarantee that the critical zone be supplied with an OA flow rate no less than the standard requirement. This leads to a penalty that nearly all the other rooms are over-ventilated in practice, and the unused OA from the non-critical zones is accounted for during recirculation.

The real-time system ventilation efficiency, which is defined as the efficiency with which the system distributes the OA to the ventilation-critical zone, is thus calculated to correct the ventilation rate. Lin et al. [34] evaluated the ventilation reset control in a classroom building. The results showed that 0.3%–11.0% of annual energy costs could be saved depending on the climate zone. In the 2015 field survey of 98 buildings that employed the CO_2-based DCV in Minnesota [23], 15% of the buildings used the *Ventilation Reset* control. The authors concluded that such a strategy provided an excellent control over the indoor CO_2 concentration and delivered good energy savings.

Despite the merits, there is a potential for further energy savings for this control since some non-critical zones tend to be overventilated in operation. A better practice is increasing the VAV box airflow rate of the critical zone prior to increasing the system level OA because the consequent increase in zone-level reheat energy usually consumes less energy than the latter does for conditioning the excess outdoor air [35]. The relevant control sequence is called *Ventilation & Zone Minimum Reset*, which is discussed in Section 2.1.3.

2.1.3. Ventilation & zone minimum reset

The *Ventilation & Zone Minimum Reset* control carries forward the sequences in Section 2.1.2 and further develops the zone-level ventilation reset rules that interact with the system-level control.

Lin et al. [36] proposed two options to dynamically reset the zone minimum primary airflow rate. The control logic is referred to as the ASHRAE RP-1547 Logic [5]. Such control strategies could be broken down into two levels: system level and zone level. The system-level control is the same as that has been described in Section 2.1.2. On the zone level, the minimum primary airflow rate of the critical zone is dynamically reset to maintain the system operation at either a target lower OA rate or a target higher system ventilation efficiency. Simulation and field-testing results have shown that this type of control strategies could achieve significant energy savings in the climate zone that is favorable for economizer operation (e.g., Oakland, CA) since the zone minimum primary airflow setpoint could be lowered during operations with the economizer mode. The simulation results for the same classroom building as mentioned in Section 2.1.2 [36] showed that the annual monetary saving ratios were 24.1% for Fairbanks, AK, and 46.2% for San Francisco, CA.

Despite the advantages, the ASHRAE RP-1547 Logic also suffers from some limitations, e.g., the control is too complex to comprehend, the iterations used in the algorithm cannot be implemented in real control systems, etc. To address such limitation, O'Neill et al. [4] developed a new control sequence on basis of the ASHRAE RP-1547 Logic. This new control sequence is practical and implementable in typical single-duct VAV systems with direct digital control (DDC) systems. Their logic is referred to as the ASHRAE RP-1747 Logic [37]. As depicted in Fig. 4, the ASHRAE RP-1747 Logic uses a trim-and-respond (T&R) control to reset the zone minimum primary airflow based on the system outdoor air status and the zone criticalness. The rationale behind it is that that when the system is supplying a high fraction of outdoor air (e.g., when the economizer is active and the primary air is OA Rich), no zone minimum reset request is generated so all the zone minimum setpoints will fall towards the ventilation minimum. When the system is not supplying 100% outdoor air, at some point the required outdoor air rate at the air handler level will exceed the actual outdoor air rate (i.e., the primary air is not OA Rich). At this point, requests will be generated in the critical zone and the zone minimum airflow setpoint will rise all the way up to zone maximum airflow setpoint, if necessary. O'Neill et al. [37] tested the proposed logic in realistic simulations that accounted for dynamic occupant behaviors and concurrent cooling loads. In addition, they also implemented and assessed the stability of the proposed sequence in a well-instrumented test facility in Iowa, U.S.

In the 2015 field survey of 98 Minnesota buildings that employed the CO_2-based DCV [23], 19% of the observed system adopted the

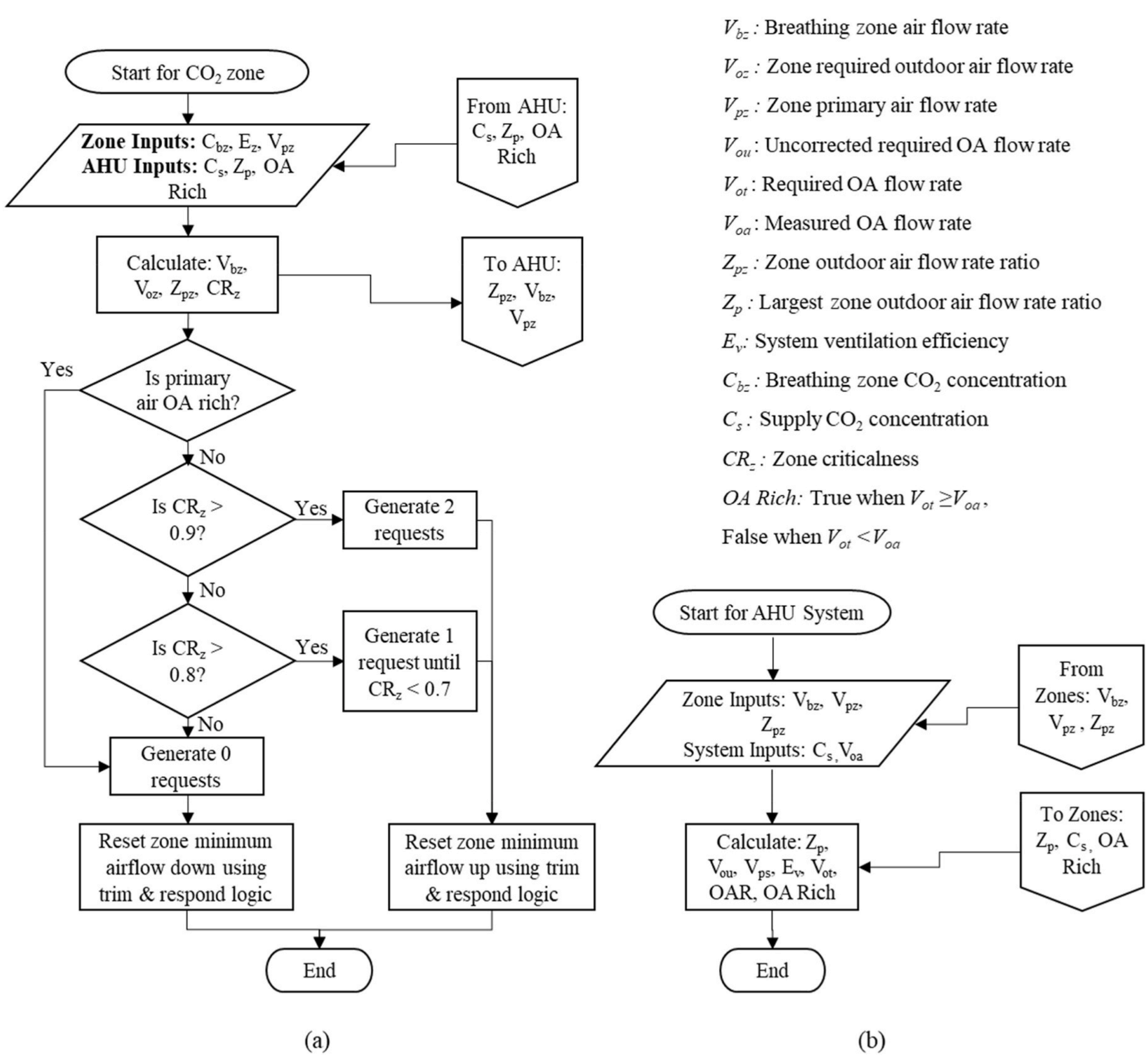

Fig. 4. Flowchart of control logics in the ASHRAE RP-1747 for ventilation & zone minimum reset control (a) Zone level - zone with CO_2 sensors (b) System - AHU level.

Ventilation & Zone Minimum Reset control. Their analysis showed that this sequence performed the best in terms of energy savings compared to the other investigated sequences. However, it is noted that this control strategy may still lead to a small risk of under-ventilation when the system operates at the economizer mode under cold weather, possibly due to the fact that a small amount of outdoor air may be sufficient to meet the building cooling load. In addition, as DCV reduces outdoor air intake airflows for ventilation to the building, the minimum limits may need to be applied in this control strategy to ensure that an adequate makeup is provided for building exhausts to facilitate the building pressure control.

Recently, the ASHRAE RP-1747 Logic had been further expanded to the multi-zone VAV systems with multiple recirculation paths [6,38]. Although the DCV control sequences for these systems have not yet been finished partly due to the mathematical complexity of CO_2 mass balance equations and the ASHRAE Standard 62.1 requirements for these systems, the similar DCV control sequences of the following systems have been developed and evaluated using the virtual testbed of the Iowa Energy Center's Energy Resource Station: parallel fan-powered terminal unit (PFPTU) with a constant volume fan; series fan-powered terminal unit (SFPTU) with a constant volume fan; and dual fan dual duct VAV terminal unit (DFDDTU) – snap acting control [39]. ASHRAE RP-1819 report [6] provides the details of this simulation-based CO_2-based DCV study of VAV systems with multiple recirculation paths.

2.2. Model-based control

The model-based controls can be further divided into two major categories: *Predictive Control*, and *State Feedback Control*, which will be discussed with details in the following subsections. Fig. 5(a) depicts the flow chart of the model-based control strategies and Fig. 5(b)–5(d) show the commonly used formulation of the model-based controllers. Fig. 5(b) and (c) are the predictive controllers which are discussed in Section 2.2.1 and Fig. 5(d) is a generalized structure of the state feedback controller which is discussed in Section 2.2.2.

2.2.1. Predictive control

In *Predictive Control* strategies, the required OA flow rate is determined by an internal control model which predicts the impact of the disturbances (e.g., varied occupancy) on the controlled variables (e.g., CO_2 concentration) and adjusts the control signals (e.g., zone air flow rate) to achieve the desired behavior.

Lu et al. [40,41] used a simple open-loop predictive model from Eq. (7) to determine the ventilation rate in a single-zone sports training arena. The occupant number was estimated from the CO_2 sensor measurements. The control strategy was verified to have a similar energy and ventilation performance to that of the PID controller.

$$C_z(t) = C_{ss} + (C_z(0) - C_{ss})\, e^{-\frac{V_z}{V}t}, \tag{7}$$

where C_{ss} is the steady-state indoor CO_2 concentration (ppm).

Gruber et al. [42] proposed a combined feedforward-feedback control (CFFC) for the ventilation control in an office room. Apart from the predictive loop, a parallel feedback loop was added. As shown in Fig. 5 (b), the predictive controller first computed the control signal (i.e., zone air flow rate) required to maintain the CO_2 setpoint, and eventually, the entire control was managed by the parallel feedback controller.

Gruber et al. [42] also implemented a closed-loop model predictive controller (MPC), which was more complex than the CFFC. As illustrated in Fig. 5(c), a sequence of future optimal control signals (i.e., zone air flow rate) was determined by the optimizer over a control horizon with considerations of cost function and constraints, but at the current time step, only the first control signal was implemented. The horizon was then moved forward, and the procedure was repeated. When designing the MPC in this case, the parameters such as the volume of the room as well as the time constant of the HVAC system components in their predictive model need to be carefully estimated. In addition, tuning the weights in the objective function can also be extensive and

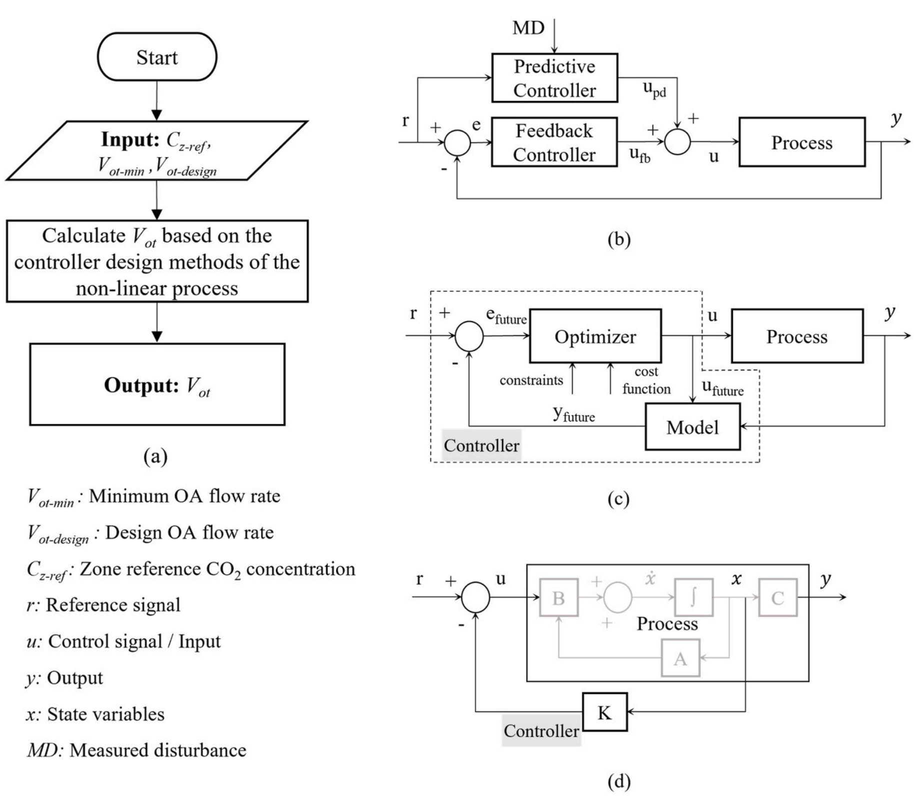

Fig. 5. (A) Flowchart of model-based control; and exemplary control block diagrams of b) combined feedforward-feedback control (c) receding horizon model predictive control (d) state feedback control.

time-consuming. The results from Gruber et al. [42] showed the performances of the CFFC and the MPC were very similar with small errors and time delays of the estimated occupancy. But for the large estimation errors and delays, CFFC has a large CO_2 concentration deviation over the setpoint especially when the occupancy is underestimated. However, the closed-loop MPC could still reside close to the setpoint.

Liu et al. [43] implemented a multivariate MPC in a server room for energy efficiency and an acceptable indoor CO_2 concentration. The multi-objective genetic algorithm was developed to find the optimal ventilation setpoints. The results showed that the proposed MPC controller outperformed the baseline Proportional–integral (PI) controller with an energy-saving ratio of 5.22% and 13.39% less CO_2 content over the setpoint.

Rackes et al. [44] proposed a multi-objective optimization strategy to determine the OA flow rate and zone temperature setpoints in a multi-zone medium office. The medium office in the Commercial Reference Building Models (CRBMs) developed by the U.S. Department of Energy (DOE) was used as the virtual testbed. The objective function was to minimize the HVAC energy consumption, indoor CO_2 concentration, and total volatile organic compounds (TVOC) concentration. The control strategies were tested in different typical days. The simulation results showed that the control strategy could save 20–30% energy consumption in winter with the IAQ being unchanged or improved. Besides, some cases in summer and mild seasons also showed significant IAQ improvements with a low energy cost.

Instead of using a centralized approach, Wang et al. [45] proposed a distributed model-based optimization strategy for the multi-zone ventilation system. In this control strategy, the system- and zone-level airflow rates were optimized in a distributed manner and coordinated by a central agent. The proposed distributed approach was reported to have a similar control performance with that of the centralized approach but provides better scalability and reconfigurability.

2.2.2. State feedback control

The differential equation Eq. (6) has nonlinear dynamics due to a multiplication of the ventilation rate and indoor CO_2 concentration [46]. In *State Feedback Control* strategies, different feedback linearization methods have been investigated to design a linear controller in the existing case studies.

The direct feedback linearization technique was employed by Ref. [47] to compensate for the nonlinearity in dynamics and the proposed control strategy performed better than the PID controller. Kang et al. [111] linearized a multi-input multi-output HVAC system including the CO_2 concentration using the feedback linearization technique [48]. On top of that, two linear controllers, i.e., a pole placement and a linear-quadratic regulator, were designed to regulate the linearized system at the desired CO_2 concentration and temperature setpoints. Lachhab et al. [49] linearized the bilinear differential equation of the single-zone ventilation system and formulated a state-feedback controller as shown in Fig. 5(d). The experiment results showed that the state-feedback controller outperformed the PID and ON/OFF controllers in terms of fan energy consumption and indoor CO_2 level [49], but was inferior to the MPC in terms of these two metrics as well as the control metrics such as the settling and rise times [50]. Škrjanc et al. et al. [51] designed an internal model control system with an inner loop after the linearization, which constantly checked the indoor CO_2 concentration, and adjusted the OA flow rate accordingly to achieve a desired CO_2 concentration. The results showed the proposed internal model control improved the indoor CO_2 concentration significantly compared to what the PI controller achieved.

It can be concluded that for the model-based control strategies, most studies are targeted at demonstrating the efficacy of the controller design. The model-based controller designs are generally complicated due to the system's nonlinearity. The parameters in the control model as well as the exogenous inputs need to be accurately estimated. These limitations prevent the practical application of the model-based control strategies to be used in field testing. In addition, the majority of the studies only considered the ventilation control, with only two studies [44,48] accounting for the collaborative control of both zone CO_2 concentration and zone air temperature.

2.3. Learning-based control

Reinforcement learning (RL) was used to control the single-zone ventilation system to keep the indoor CO_2 concentration at or below the setpoint while reducing energy consumption [52]. The experimental results revealed that Q-Learning, a model-free online RL technique, could save 78.08% more energy consumption compared to the ON/OFF controller. Compared with the PI controller, the RL controller consumed 1.74% more energy, but achieved a slightly better CO_2 concentration level. Heo et al. [53] developed a deep reinforcement learning (Deep Q Network) controller to optimize the energy and IAQ (evaluated in terms of the indoor PM10 level) in a subway station. After 50,000 episodes of training, the controller could save 14.4% energy and still control the PM10 concentration to an acceptable level. It is noted that although the same methodology could be theoretically applied to the RL-based CO_2-based DCV, the particularly long training time of the RL agent is a major hurdle for the RL controller to be used in real applications.

3. Control components

This section reviews the issues of critical control components on the DCV system performance. The CO_2 sensor and OA flow sensor are two critical sensor types in the CO_2-based DCV control strategies. Section 3.1 reviews the performance of the CO_2 sensors and summarizes the best practice of the CO_2 sensor placement due to the uneven CO_2 concentration spatial distribution. Section 3.2 discusses the issues with the OA flow measurement. Section 3.3 reviews how the sensor error impacts the performance of the CO_2-based DCV control strategies. Section 3.4 reviews the issues of the local controls of actuating control devices on the DCV system performance.

3.1. CO_2 sensor

With rapid developments in sensing technologies, the price of the commercial CO_2 sensor for DCV systems has reduced from \$400–500 per sensor in 1998 [54] to as low as \$20 per sensor today [55]. Although the new CO_2 sensing technologies keep emerging [56–58], the commercial CO_2 sensors used in DCV systems today are still mainly based on non-dispersive infrared (NDIR) detection. This technique has been long subject to the sensor drift issue due to the aging of the light source and the accumulated dust or particles [9]. As another prevalent type, the electrochemical CO_2 sensors are also used in some DCV control products but they do not last as long as NDIR sensors [15]. In the last 20 years, the performance of CO_2 sensors for DCV systems has been evaluated for multiple times through either laboratory testing or field tests.

3.1.1. Sensor performance

Fisk et al. [59] first evaluated the accuracy of 44 NDIR-based CO_2 sensors located in nine commercial buildings in 2006. The tested CO_2 sensors were frequently found to have more than 20% error for the measurement of the peak indoor-outdoor CO_2 concentration differences. In addition, no clear relationship was found between the sensor accuracy and sensor age. A follow-up larger-scale field testing was conducted in 2010 [60]. The accuracy of 208 single-location CO_2 sensors in 34 commercial buildings was evaluated. The results showed that the accuracy level of the investigated single-location CO_2 sensors was frequently lower than the required accuracy level in the by-then latest California Title 24 Standard, i.e. ±75 ppm [61]. The average absolute value of error was as high as 154 ppm. In addition, significant differences were found between the average sensor accuracies from different manufacturers. The multi-location CO_2 measurement system with more expensive sensors demonstrated a higher accuracy level according to the field testing results.

In 2009, Maripuu [62] conducted a functional testing of the different types of commercial CO_2 sensors in the laboratory including the NDIR sensors and the electrochemical sensors. A total of 12 different models of CO_2 sensors were tested. The functional testing results showed that the majority of CO_2 sensors fulfilled the manufacturer-specified accuracy. The tested NDIR sensors had a higher accuracy level over the electrochemical sensors, while the latter showed a somewhat shorter response time. In addition, the long-term stability of the NDIR CO_2 sensors was assessed in one existing DCV system with the sensors having a history of five years. The results showed that the majority of the tested CO_2 sensors had reasonable long-term stability. The absolute drift was less than 30 ppm for most of the time, while the average drift was about 18 ppm.

A similar functional testing was conducted in the same year for 15 models of NDIR wall-mounted CO_2 sensors in the Iowa Energy Center [63]. A total of 45 sensors were evaluated, with three sensors being selected for each model. The performance evaluation included the accuracy, linearity, repeatability, hysteresis, humidity sensitivity, temperature sensitivity, pressure sensitivity, and long-term aging effects. The testing results showed a wide variation in sensor performance among the various models. In some cases, a wide variation occurred among the sensors of the same model. To be specific, none of the sensor models or individual sensors met the manufacturer-specified accuracy level. The error of many new CO_2 sensors could reach 75 ppm during the testing, and higher than 200 ppm on some occasions. Most of the sensors performed moderately in terms of nonlinearity, repeatability, and hysteresis. The humidity level did not have a significant impact on the accuracy level, while the temperature and pressure variations did. In the one-year consecutive testing, a wide variation in aging effects occurred among the different sensor models. Some models showed an aging effect of less than 30 ppm deviation in one year, while some showed a large deviation up to 300 ppm.

In 2014, three models of inexpensive commercial NDIR sensors were evaluated in an experimental chamber to determine their steady-state and transient responses to CO_2 concentration [64]. It turned out that all the three sensors responded linearly and accurately within a 5% error range when being tested at CO_2 concentrations from 400 to 1900 ppm. In addition, the three models were not significantly affected by temperature due to the feature of the built-in temperature compensation.

Recently, Berquist et al. [55,65] tested three models of low-cost NDIR CO_2 sensors in the laboratory chamber. It was noted that for one model, 19% of the measurement errors fell outside of the range specified by the manufacturer, while the other two models achieved reasonable results in terms of accuracy, linearity, repeatability, and hysteresis. The authors concluded from the testing results that the low-cost CO_2 sensors ($20 each) may not be suitable for the DCV application, but the sensors which cost around $60 per m^2 are good enough for such a purpose.

Table 2
Comparison of the requirements for CO_2 sensor performance.

Building energy codes		DOE ARPA-E – SENSOR program [67]
Building Energy Efficiency Standards Title24 [61]	• Sensor Precision: 75 ppm at a 600 and 1000 ppm concentration • Sensor Calibration Frequency: < once every 5 years	• Commercial price (including the sensor installation and commissioning): $\leq$0.08 $/ft^2 • Sensor Precision: $\pm$30 ppm, 400–2000 ppm • Sensor Drift: <10 ppm/year • Lifetime:> 3 years • Selectivity: < 5 ppm change for common gases such as water vapor and volatile organic compounds (VOCs) commonly found in building applications. • Time response: <1 min
ASHRAE Standard 189.1 [66]	• Sensor Precision: 50 ppm at 1000 ppm concentration•	

Table 2 lists the requirements for CO_2 sensor performance in the existing building energy standards [61,66] as well as the SENSOR (i.e., Saving Energy Nationwide in Structures with Occupancy Recognition) program [67] of the U.S. Department of Energy (DOE) Advanced Research Projects Agency – Energy (ARPA-E). The left column shows the required CO_2 sensor performance in the present building applications while the right column shows the minimum requirement for the research and development, which reflects the anticipated CO_2 sensor performance for the future applications: low cost, high accuracy, more robustness, and long lifespan.

As can be summarized from the above trend reviews of the CO_2 sensor performance, although some studies have proved that the inexpensive NDIR CO_2 sensors might be accurate enough for the DCV application [55,62,64,65], a high level of uncertainties and errors still exist for the CO_2 concentration measurement in many case studies. For instance, some testing results showed that many CO_2 sensors could not meet the accuracy level required by the building codes [59,60,68] or stated in the manufacturer's specifications [65]; besides, the testing also showed a wide variation in the measurement even for the same sensor model [63]. Therefore, alternatives to low-cost NDIR sensors are still needed. In addition, the sensor calibrations during the deployment and maintenance thereafter are periodically required to ensure the functionality of the DCV systems.

3.1.2. Sensor placement

Although many existing multi-zone DCV systems use the single CO_2 sensor in the common return duct since it is the least expensive approach, it is not recommended, as mentioned in Section 2.1.1. If the common return duct approach was adopted, the local code officials should be consulted and a more conservative CO_2 setpoint may need to be considered [23]. For the CO_2 sensor placement in the zone, several standards and DCV guidance documents all suggest that the sensors should be installed between 3 ft and 6 ft above the floor or at the anticipated height of the occupants' heads [61,66,69].

Some studies also provided recommendations for sensor placement based on their investigations of the CO_2 concentration spatial distribution. For instance, Mui et al. [70] suggested placing the sensor near the return duct with a more conservative setpoint (20 ppm down) in order to achieve an acceptable IAQ considering the uneven CO_2 concentration distribution. Based on the field measurements, Fisk et al. [60] suggested that the measurements collected near the return-air grilles may be preferrable to the measurements collected at wall-mounted locations since the CO_2 concentrations at return grilles did not vary much. Using CFD simulations, Pei et al. [71,72] also showed that the sensors placed near the room exhaust had discrepancies less than 55 ppm for the mixed ventilation mode. However, it is noted that the higher ventilation rates are used in this study which represented variable air volume systems with an economizer mode or dedicated outdoor air system. In the field tests of DCV systems in schools and classrooms [73], the measured CO_2 concentration near the return air grill showed good correspondence to the CO_2 concentration measured in the zone near the occupants. For the displacement ventilation, the wall-mounted CO_2 sensors at breathing height may be more suitable and yielded relatively smaller errors than the sensors placed near the room exhaust due to the thermal stratification [74,75]. Apart from that, a couple of studies verified that the sensors placed on the desk were unstable, and the readings would vary significantly mainly due to the impact of the occupant's thermal plume [76–78].

From the above reviews, it could be concluded that there is no one-for-all best location for the CO_2 sensor placement, since the CO_2 concentration distribution varies zone by zone. Overall, the CO_2 sensors should not be placed in proximity to the occupants, or near the doors and windows. For the mixed ventilation, the placement near the return-air grilles might be more suitable, while for the displacement ventilation, the wall-mounted sensor placement might be more suitable.

3.2. Outdoor airflow sensor

DCV operation does not only depend only on the input of CO_2 sensors but also involves the measurement of OA flow rate for some control strategies (e.g., ASHRAE RP-1747 Logic). An airflow measurement station (AFMS) with the thermal dispersion air velocity sensor is proved to have a measurement error generally less than 10% [79]. Hacker [23] tested the accuracy of AFMS in five DCV systems and the results indicated that these sensors performed accurately for most of the time and over a range of airflows. The accuracy level of the AFMS usually degrades at a low outdoor air intake flow rate. This is because the OA intake is generally sized for the economizer mode; hence the AFMS would become less accurate when the DCV is activated if the OA ductworks for economizer mode and DCV operation are not separated in the design.

3.3. Sensor error impact

The impact of the sensor error on DCV systems has been analyzed qualitatively and quantitively by many studies. Berquist [55] qualitatively analyzed the impact of the sensor performance degradation on the DCV systems. For example, if the CO_2 sensor has a negative error, it would cause the DCV system to activate later and deactivate earlier than desired and would likely reduce the IAQ and building energy consumption. Limited resemblance to a linear line would make the activation or deactivation of the DCV system's operational modes more uneven.

Lu et al. [80] quantified the sensor error impact of the CO_2 sensors and OA flow sensors in a multi-zone single-path DCV system which implemented the control strategy introduced in Section 2.1.3. The results showed that the sensor errors had a larger impact on the ventilation performance than the energy performance. In addition, to reveal the sensor importance in this DCV control strategy, a stochastic approach was conducted using a sensitivity analysis. The results show that energy savings potential and ventilation performance were influenced mostly by the accuracy of system-level sensors (i.e., the CO_2 sensors at the supply duct and OA duct). The accuracy of zone-level airflow sensors had a negligible impact on both energy savings and ventilation performance. The accuracy of the zone-level CO_2 sensors, however, had a more significant influence on the ventilation performance compared with the zone-level airflow sensors. The accuracy from the CO_2 sensor in the zone with relatively large loads (i.e., critical zones) moderately affects the energy savings and ventilation performance. This information is critical and valuable for the practitioners during their maintenance and commissioning process. A similar methodology was applied to the zone VAV systems with multiple recirculation paths to rank the sensors with the largest error impacts [6].

3.4. Local controls

Apart from sensor non-idealities, local controls in actuating control devices such as VAV terminal units, would also impact the performance of the DCV control.

VAV terminal units might fail to perform as expected when a very low airflow setpoint is commanded based on the DCV strategies. Liu et al. [81,82] identified the major factors (i.e., inlet conditions, low variable air volume damper positions, and low airflow rates) that caused the inaccuracy and instability of VAV terminal unit performance. Through a massive VAV box laboratory testing [83], it is reported that most VAV terminal units are highly accurate down to about 0.003 inch velocity pressure (VP) and controllable minimum setpoints are approximately 8%–12% of the maximum airflow. This low achievable controllable minimum setpoints could benefit the implementation of DCV controls and bring more energy savings.

In addition, potential air balancing issues between the zone terminals (e.g., incorrect zone terminal damper control) could also cause overventilation or underventilation. Zhao [84] compared several different outdoor airflow control sequences of a multi-zone VAV system in the laboratory setting. The results suggested that although some of the control sequences could meet the outdoor airflow rate requirement at the system level, the problem of overventilation and underventilation happened frequently at the zone level regardless of the control strategies for the system-level outdoor airflow. Different model-based air--balancing methods were thus studied to realize more accurate airflow controls. Jing et al. [85] developed a physical model for the airflow network using a Bayesian linear regression. This model was used to control the VAV damper position without causing an uneven distribution of the outdoor air. Cui et al. [86] built a data-driven model for the duct branch system to control the damper's angle based on the desired airflow rate. The proposed data-driven black model did not require the detailed duct fitting information as its input. An experiment was conducted in a DCV system to verify the simulation results. The results showed that the proposed method could effectively alleviate the overventilation problem.

4. Performance evaluation of the CO_2-based DCV

Two research questions arise while evaluating the performance of the CO_2-based DCV: (1) How much benefit could be achieved from the DCV control strategy? (2) What are the practical issues when the DCV is implemented in real buildings? The following section discusses these two questions from the perspective of practical implementation. Section 4.1 introduces the common baseline for the performance evaluation and Section 4.2 presents the overview of the performance metrics that are commonly used. Simulation-based, experimental, field-testing approaches to conducting the performance evaluation were reviewed and described in Section 4.3. A detailed discussion is presented in Section 4.4. Section 4.5 summarizes the rising issues during the deployment and operation in real buildings.

4.1. Baseline

The selection of the baseline for quantifying the impact of a DCV control varies based on use cases. The most commonly-used baseline is the same HVAC system with a fixed outdoor airflow rate which is calculated based on ASHRAE Standard 62/62.1 Section 6.2 (e.g. Refs. [34,36,37]), California Title 24 [87] (e.g. Refs. [4,38]), or InDoor Air (IDA3) Class 3 in EN 13779 [88]. There are also studies that compared the proposed DCV strategies with the existing ones. Therefore, the baseline in these cases would be the system in which the existing DCV strategies were implemented.

4.2. Evaluation metrics

4.2.1. Energy and economics

The source and site energy savings of the HVAC system are often used to evaluate the performance of a DCV from the energy perspective [4,38]. The breakdowns of HVAC energy savings such as cooling, or heating are also used by some special cases.

From the economics perspective, total cost savings [34,36], cost savings per area and cost savings per design outdoor airflow rate [23], and life cycle cost savings per area [87] are used. To demonstrate the cost-effectiveness of the DCV system, the simple payback period is calculated in some studies [23,89,90], as shown in Eq. (8).

$$N_{pb} = \frac{S_{DCV}}{C_{DCV}}, \tag{8}$$

where S_{DCV} is the annual utility savings coming from the CO_2-based DCV strategy as compared with the baseline case and C_{DCV} is the installed cost associated with the implementation of CO_2-based DCV.

4.2.2. Ventilation

Most existing studies quantify the ventilation performance of a DCV by analyzing the indoor CO_2 concentration level. For instance, the excessive indoor CO_2 content, which is defined as the integration of the indoor CO_2 concentration over a recommended limit, could be calculated to serve this purpose [43,45]. Some studies used the peak and average indoor CO_2 concentration as the ventilation metric [3,32,44]. The IDA classes [73] and indoor air-quality index (CIAI) [53] for indoor CO_2 concentration were also used to represent the CO_2 level. In addition, the outdoor air ratio (OAR), as shown in Eq. (9) was used as a system-level ventilation metric in some studies for multi-zone VAV systems [4,37,38]. The system OAR smaller than 1 denotes the system outdoor air is insufficient.

$$OAR = \frac{V_{oa}}{V_{ot}}, \tag{9}$$

where V_{oa} is the actual outdoor air induced into the AHU and V_{ot} is the required outdoor air by the building codes or standards, where the value of V_{ot} is limited to the design value.

4.3. Evaluation approaches

4.3.1. Simulation

Building energy and IAQ simulations were typical tools in terms of assessing the benefits of implementing the CO_2-based DCV. Fig. 6 depicts the general framework of a simulation engine and its components, including the building zone thermal load module, zone CO_2/contaminant module, HVAC system and component module, and the system controller that implements the DCV control strategies. The major inputs related to the operation of a DCV include the occupancy profile data, which influences the zone CO_2 concentration, and the configuration of the building HVAC system. It is noted that although there have been different simulation tools to implement such a framework; however, different tools may have their own assumptions and limitations. It is recommended to choose the simulation engine based on the actual needs and the HVAC system so that the characteristics could be captured via simulation [91]. Table 3 summarized pros and cons of mainstream simulation tools for modeling CO_2-based DCV systems.

The early design brief of CO_2-based DCV systems [69] introduced the use of several building energy simulation tools to enable the proper modeling of the CO_2-based DCV system. The early tools include DOE-2 [95], eQuest [96], and Virtual Environment [97]. The DCV strategies in these tools are simulated by controlling the outside air volume on the system level with a sensor in the return air duct of a single-zone system or with multiple sensors in the indoor spaces served by a multi-zone system. On the zone level, a zone minimum flow fraction is specified

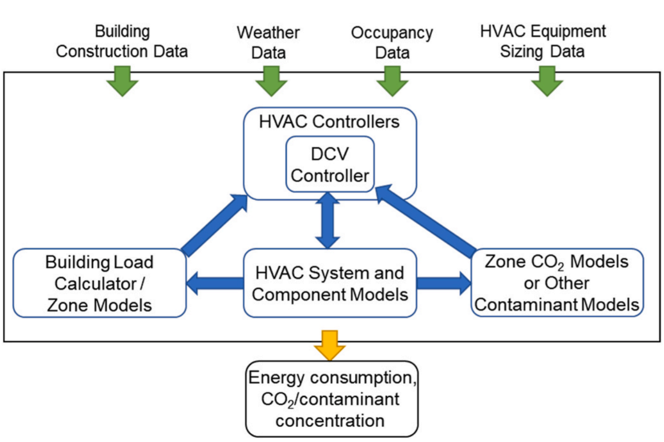

Fig. 6. The general framework of the simulation engines to perform the evaluation of CO_2-based DCV.

Table 3
Summary of pros and cons of mainstream simulation tools for modeling CO_2-based DCV systems.

Building Simulation Software	Pros	Cons
CONTAM [92]	• Built-in simple DCV controllers • Multi-zone IAQ and ventilation analysis program	• Not capable of modeling complex control strategies • Not for building energy analysis
VSAT [90]	• Could simulate specific ventilation strategies for several common building types • A user-friendly and self-explanatory interface	• Not capable of modeling complex control strategies • Limited HVAC system types and DCV control strategies
EnergyPlus [93]	• Built-in modules to model the code-compliant CO_2-based DCV for common HVAC systems • Accurate load and infiltration calculation	• Hard to simulate the dynamic behavior of DCV controls and local controls • Hard to reflect realistic airflow distribution
Modelica [94]	• Could support dynamic behavior of DCV systems • Could support pressure-related calculation and reflect realistic airflow distribution	• Significant modeling efforts and expertise • Large computational time for the annual performance evaluation

to reset the zone minimum airflow rate upward or downward based on the determined zone OA flow rate requirements. Although these simulation tools provide a quick prediction of the energy impacts of DCV, they are not capable of modeling complex control strategies and HVAC air loop systems. In addition, these tools provide less realistic simulation results due to the simplified algorithms such as the simulation of the radiant effects and the infiltration effects.

In an early study, Persily et al. [98] used the multi-zone IAQ and ventilation analysis program CONTAM [92] to simulate the IAQ impacts of the DCV since some simple DCV control strategies, such as the dual CO_2 setpoint control, were incorporated into the CONTAM program as a built-in feature. However, the CONTAM energy analysis feature is usually not as accurate as that obtained from the other building energy performance simulation tools [99].

Braun et al. [90] developed the Ventilation Strategy Assessment Tool (VSAT) that could simulate specific ventilation strategies for several common building types. The tool has a user-friendly and self-explanatory interface and can calculate the energy and economics results easily with customized inputs. One limitation of VSAT is that it only incorporated limited HVAC system types and DCV control strategies into the program; thus, the application is limited.

Considering the limitations of the above simulators, EnergyPlus [93] and Modelica [94] stand out as the two mainstream simulation platforms to be used for modeling the CO_2-based DCV systems. EnergyPlus has built-in modules to model the CO_2-based DCV as specified by the VRP defined in ASHRAE Standard 62.1–2019 for single and multiple path systems, and the indoor air quality procedure [100]. It also supports the easy modeling of the dual CO_2 setpoint control as discussed in Section 2.1.1 above. For the complex rule-based CO_2-based DCV, the control sequence can be coded with the built-in Energy Management System (EMS) module, which provides a high-level and supervisory control to override selected aspects of EnergyPlus modeling (i.e., zone minimum air flow rate, system minimum OA flow rate). Since the infiltration and inter-zonal air flow rate pose an influence on the indoor CO_2 concentration, the built-in airflow network module could be used to realistically model these effects. Another workaround is to couple CONTAM with EnergyPlus to run a co-simulation. For instance, the co-simulation platform combining EnergyPlus CONTAM [92] has been successfully adopted for evaluating the control strategy as discussed in Section 2.1.3 [4]. In such a co-simulation framework, the zone infiltration flow rate and zone mixing air flow rate are passed from CONTAM to EnergyPlus, and EnergyPlus takes care of zone contaminant calculation and DCV. Although the EnergyPlus-based simulation provides a far better fidelity than the earlier simulators do, it still has the limitations for simulating the dynamic behavior of the DCV controls and local controls. Furthermore, it is hard to reflect the realistic airflow distribution in EnergyPlus if the airflow network module is not used, which may influence the modeling results.

These limitations related to controls could be properly addressed using Modelica [94]. Modelica is an equation-based, object-oriented language to model complex engineered systems that are described by coupled systems of differential, algebraic and discrete equations. Jorissen [101] developed a validated Modelica-based airflow model using existing sensors from a real office building with 23 zones being tested. Validation results showed that the Modelica model could accurately compute the total mass flow rates in the airflow system, proving the validity of the model and demonstrating the use of Modelica to perform detailed building airflow calculations. Merema et al. [102] modeled the CO_2-based DCV system of a lecture room using the Modelica models from the IDEAS library [103]. The simulated results were compared and calibrated based on the monitoring data of room temperatures and CO_2 concentrations. The simulated energy consumption was evaluated against the measured energy consumption using the mean bias error (MBE) and the coefficient of variation of the root mean square error (CVRMSE) to ensure that the predictions were reliable. The following parameters were adjusted during the calibration: thermostat convective fraction of the zone air temperature sensor, the air infiltration rate, the capacity of zone air, the PI setting of the VAV local controllers, and the CO_2 generation rate. The results demonstrated that the convective fraction, the air capacity, and the airtightness were the key calibrated parameters. After the calibration, both the heating and fan energy consumption fell in good agreement with the measured data with an MBE of 4.8% and −1.8%, respectively. Apart from using the available models in the IDEAS library, the system OA controller and zone-level local controllers in the Modelica Buildings Library [104] are also readily available for implementing the DCV control following the VRP framework defined in ASHRAE Standard 62.1–2019. Despite the great flexibility of modeling the dynamics of the DCV systems using Modelica, it is worth mentioning that modeling with Modelica usually takes great modeling efforts and computational time, especially for the annual performance evaluation.

4.3.2. Experiment/field-testing

The performance evaluation of DCV through field tests often involves data collection at different locations at both the system level and zone level. The data could be usually obtained from the building automation system (BAS). However, when the data is not available from the BAS, or when the BAS data is not reliant, installing data loggers is usually the only solution. The collected data should be processed for calculating the relevant performance metrics (e.g., energy savings).

It is extremely difficult to conduct comparative experiments for the DCV case and baseline case, which needs to have identical weather conditions, internal gains, and occupancy profiles. Therefore, the separate experimental data for the DCV case and baseline case are usually collected in practice. The performance metrics are then normalized based on varying factors such as the weather condition, occupancy profile, etc. Lawrence et al. [3] used this approach to estimate the daily and hourly cooling and heating energy savings from a real building that deployed the DCV.

In some other field studies, the energy-saving potential was estimated from the measured outdoor air flow rate and fixed design outdoor airflow rate; hence the saved energy was actually the energy used to condition the extra intake of OA. Hackel et al. [23] used this approach to estimate the cost savings of six multi-zone VAV systems in Minnesota. Obviously, this method did not consider the zone terminal reheat energy; thus, the energy savings were usually underestimated.

4.4. Discussion

Table 4 summarizes the performance evaluation of different DCV control strategies in the last two decades. The compared baseline, performance metrics, evaluation approach, and testing conditions are presented to guide the practitioners. In particular, different influencing factors are discussed in the following sections, including building types, system configurations (i.e., single-zone or multi-zone), climate zones, testing periods, etc. Section 4.4.5 presents of a high-level summary.

4.4.1. Building types

Most studies were conducted on a single building type, and most of the object buildings are office buildings. From the studies that included various building types, a general takeaway is that the greatest cost savings occur in buildings that have dynamic and unpredictable occupancy levels, such as auditoriums, gyms, and retail stores [3,89,98]. In other words, the building spaces with constant occupancy patterns or low occupant densities are generally not ideal candidates for implementing CO_2-based DCV considering the energy-saving potential. Although most of such studies are targeted at the single-zone systems, the conclusion could be safely extended to the multi-zone systems [23].

4.4.2. System configurations

Early studies of the rule-based DCV control strategies usually focused on the single-zone system, while the recent studies tend to extend the focus to the multi-zone system. Instead of using the CO_2 mass balance equation to derive the relationship between the ventilation rate and CO_2 concentration, the data-driven approaches are gaining popularity to estimate the occupancy from CO_2 sensing for the control implementation [32,33,105]. However, such data-driven occupancy estimation approaches do not significantly improve accuracy but become rather complicated for implementations in real applications. Unlike the rule-based DCV control strategies, most model-based DCV control strategies are for the single-zone system and are often only demonstrated in the zone-level ventilation control.

4.4.3. Climate zones

In terms of the impact of climate zones, various studies conclude that the greatest cost savings are likely to be achieved in the climate zone with a hot summer and/or cold winter [34,36–38,89,98] regardless of the DCV control strategies and system types. It is also noted that the *ventilation & zone minimum reset* control strategy, as discussed in Section 2.1.3, has a high energy saving ratio even for the mild weather condition with the air-side economizer operation because the zone minimum airflow setpoint could be lowered during the economizer mode. However, due to the mild thermal loads, the simple payback periods still might be high.

4.4.4. Other aspects

For the testing periods, some rule-based DCV studies investigated the annual performance while all the model-based DCV control strategies only covered a limited testing period. For the evaluation approaches, most studies conducted either simulation or field testing, while only one study evaluated the proposed DCV strategies through both simulation and field testing [4]. The majority of the rule-based DCV strategies have been evaluated through the high-fidelity virtual testbed or field tests; however, most of the model-based DCV strategies were evaluated in the simulation environment. For the baseline, most studies used the constant outdoor airflow rate calculated from ASHRAE Standard 62.1 VRP. In contrast, some other studies compared the newly-proposed DCV control strategy with the existing one [32,33,40,44,49].

Table 4
Summary of performance evaluation of different CO_2-based DCV control strategies.

Control Category	Year/ Ref.	DCV Control Strategies	Simulation/ Field Test	System Type	Room/ Building Type	Climate	Evaluation Period	Baseline	Energy Saving	Ventilation
Rule-based	2003 [3]	Direct OA control (PI)	Field Test	Packaged rooftop unit & heat pump; Single zone	Schools, fast food restaurants, drug stores	2 different climate zones in California	Summer and winter weeks	Constant rate (ASHRAE 62 VRP)	Cost saving: 4–23% for cooling; small for heating	No change or improved CO_2 level
	2003 [89]	Direct OA control (PI)	Simulation (VSAT)	Packaged rooftop unit & heat pump; Single zone	Classroom, auditorium, gym, office, restaurants, retail store	16 different climate zones in California	Whole year	Constant rate (ASHRAE 62 VRP)	Cost saving: 2.7–51%; Payback year: 0.4–39 with an average of 2 years	Not mentioned
	2003 [98]	Direct OA control (dual CO_2 setpoint control)	Simulation (CONTAM)	Single zone	Office, conference room, lecture hall, classroom, fast food restaurant	6 cities in the U.S.	Whole year	Constant rate (ASHRAE 62 VRP)	10–80%	Average CO_2 level 100 ppm higher; VOC level 2–3 times higher
	2012 [22]	Direct OA control (supply air, PI)	Simulation (eQuest)	Multi-Zone	Office building	7 cities in U.S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	15–23%	Not mentioned
	2014 [106, 107]	Direct OA control (PI)	Field Test	Package air conditioner with energy recovery ventilator	Office building	Gifu, Japan	One summer day, one winter day	Without DCV and energy recovery ventilator (ERV)	20–30%	Not mentioned
	2014 [108]	Direct OA control (PI)	Field Test	Multi-Zone	Classroom building	Venice, Italy	Cover whole summer and winter	Constant ventilation airflow rate	31% heating energy in winter and 40% fan energy	Not mentioned
	2012 [109]	Ventilation reset with limited sensors	Field Test	Multi-Zone	Office building one floor	Hongkong, China	Cool spring day, Summer day, Cold Winter day	Two-stage direct OA control	45–52%	No change or improved CO_2 level
	2014 [34]	Ventilation reset (steady-state CO_2 balance)	Simulation (Energyplus)	Multi-Zone	Office building	16 climate zones in U.S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	Cost saving: 0.3–11%	Not mentioned
	2020 [110]	Ventilation reset (ANN)	Simulation (MATLAB)	Single Zone	University auditorium	West Lafayette, U. S.	One day (March 10, 2019)	Constant rate (ASHRAE 62.1 VRP); Ventilation reset (steady-state & transient CO_2 balance)	5–9% compared to mass balance method	Maintain similar CO_2 level
	2020 [32, 105]	Ventilation reset (Bayesian MCMC)	Field Test	Single Zone	Office building	Seoul, Korea	Three days	Dual CO_2 setpoint control	10% less ventilation rate to dual CO_2 setpoint control	6% higher average CO_2 level
	2015 [36]	Ventilation reset + zone minimum reset	Simulation (Energyplus)	Multi-Zone	Office building	16 Climate zones in U.S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	Cost saving: 24.1–46.2%; \$0.36–0.98/ cfm	Not mentioned
	2019 [37]	Ventilation reset + zone minimum reset	Simulation (Energyplus + CONTAM) & Field Test	Multi-Zone	Office building	4 climate zones in U.S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	9%–32%	Outdoor air ratio
	2020 [38]	Ventilation reset + zone minimum reset	Simulation (Energyplus + CONTAM)	Multi-Zone	Office building	4 climate zones in U.S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	7%–21%; \$0.2–0.42/cfm	Outdoor air ratio
	2015 [23]	Direct OA control; Ventilation reset; Ventilation	Field Test	Multi-Zone	Office; library; gallery	Minnesota, U. S.	Whole year	Constant rate (ASHRAE 62.1 VRP)	Maximum 34% of AHU energy consumption; \$0.05–0.43/ft^2; \$0.39–1.14/	Poor CO_2 level for direct OA control by return duct CO_2 sensor

(continued on next page)

Table 4 (*continued*)

Control Category	Year/ Ref.	DCV Control Strategies	Simulation/ Field Test	System Type	Room/ Building Type	Climate	Evaluation Period	Baseline	Energy Saving	Ventilation
		reset + zone minimum reset							cfm, Payback year:4-8	
	2020 [111]	Discrete outdoor air flow rate determination	Field Test	Multi-Zone	Lab room	Dalian, China	Two hours	Constant ventilation airflow rate (55% of the maximum OA)	6.1%	Not mentioned
Model-based	2013 [41]	Open-loop predictive	Simulation (Matlab/ Simulink)	Single Zone	A sports training arena	Finland	Two weeks	Dual CO_2 setpoint control	NA (ventilation rate: 34–38%)	Slightly higher average CO_2 level
	2014 [43]	Model predictive control	Simulation (Matlab/ Simulink)	Single Zone	A server room	East Netherland	Two weeks	Direct OA control with PI controller	5.2%	CO_2 content reduced by 13.39%
	2014 [44]	Multi-objective optimization	Simulation (EnergyPlus + GenOpt)	Multi Zone	Office building	Philadelphia, U.S.	Cold winter day, hot summer day, and mild fall day	Constant rate (ASHRAE 62.1 VRP); Ventilation reset DCV	20%–45% of HVAC site energy in Jan.	Nearly unchanged or improved CO_2 level and TVOC level
	2020 [45]	Multi-agent based distributed optimization	Simulation (Matlab + TRNSYS)	Multi-Zone	Medium office with six rooms	Hong Kong, China	Hot and humid day; cool and dry day	Constant rate (ASHRAE 62.1 VRP)	11%–19%	Lower CO_2 content by 59%–100%
	2014 [48]	Linearization and controller design (LQR and pole placement)	Simulation	Single zone	Single room	Not mentioned	Five hours	NA	NA	NA
	2018 [49]	Linearization and controller design (state feedback control)	Field Test	Single zone ventilation system	Lab room	Rabat, Morocco	Three days	On/off, PID controller	47% compared to off/on the controller; 21% compared to PID controller	Fewer fluctuations of CO_2 level to the varied occupancy
	2014 [51]	Linearization and controller design (Internal model control)	Simulation	Single zone ventilation system	Gallery	Not mentioned	Sixteen hours	PI controller	3%	Fewer fluctuations of CO_2 level to the varied occupancy
Learning-based	2014 [52]	Reinforcement learning	Simulation	Single zone ventilation system	Single room	Not mentioned	One day	PI controller	1.74%	Nearly unchanged or improved CO_2 level

4.4.5. *Summary*

From Table 4 and the above analysis, we can see that the performance of DCV systems varies significantly with the factors such as the control sequence, building and system configuration, occupancy schedule, climate zone, and baseline determination. Therefore, it is difficult to provide an overall conclusion on the maximum benefits from the state-of-art DCV control strategies. To give a high-level summary, we choose the office building as the benchmark building type and the constant OA flow rate calculated from the ASHRAE 62.1 VRP as the baseline. The following conclusions could be reached from this review study:

- For the single-zone office building, under the premise that the ventilation requirement is maintained, the cost savings of DCV usually range from 2.7 to 12.5%, depending on the control sequence and climate zone. In most cases, the simple payback period is less than two years.
- For the multi-zone office building, under the premise that the ventilation requirement is maintained, the cost savings usually range from 0.3 to 46.2% depending on the control sequence and climate zone. The ventilation reset with the zone minimum reset control logic achieves the best performance regarding cost savings among all the DCV control strategies in field testing. In most cases, the simple payback period is estimated to be between four to eight years.

4.5. *Prevailing issues in design and operation*

While the impacts of the CO_2-based DCV in terms of energy savings and ventilation have been well investigated and demonstrated, little is known about the rising issues during its deployment and operation in real buildings. This section reviews the existing field evaluations to fill this knowledge gap. Table 5 summarizes all the emerging issues identified from the cases studies of field testing, with the topics ranging from design, deployment, and commissioning, to system operation.

Acker et al. [25] conducted a field testing in six commercial buildings where the CO_2-based DCV was implemented between 2006 and 2008. One of the six buildings failed the control loop testing when the physical output of the CO_2 sensor did not signal the damper movement. All the buildings failed the outdoor supply air balancing test. The authors ascribed the incorrect OA rate to the inappropriate test, adjust and balancing (TAB) process with limited design specification schedules of DCV system information. The authors also pointed out that the multi-zone systems that only use CO_2 sensors at the common return duct cannot guarantee the indoor air quality for the critical zone due to this zonal averaging CO_2 sensor location. The CO_2-based DCV systems in this case did not operate as expected due to the control loop error, poor sensor placement, and improper TAB with the information provided in design documents.

Schibuola et al. conducted a long-term performance monitoring of

Table 5
Summary of the issues during the DCV design and operation.

Year/ Ref.	DCV Control Strategies	Building/System	Issues/Problems
2011 [25]	Direct OA control	Four office buildings, two schools	• Broken control link between CO_2 sensors and outside air damper positioning. • Poor sensor placement at the return main duct. • Improper TAB with the information provided in design documents.
2014 [108]	Direct OA control	Classroom building; A rooftop unit with two internal AHUs (not a typical HVAC design)	• Untuned PID controller.
2018 [73]	Direct OA control	Four lecture rooms and landscaped offices	• Inappropriate design minimum and maximum air flow rate according to the realistic occupancy. • Wrong CO_2 sensor placement.
2019 [114]	Direct OA control	New schools	• Wrong CO_2 sensor placement.
2017 [4]	Ventilation & zone minimum reset	Medium office buildings; Single path multi-zone VAV systems	• The limits set in the complex rule-based control strategies caused a small risk of underventilation. • The inappropriate setting of control parameter some control parameter settings such as the dead band and time delay. • Required zone minimum lower than the VAV box controllable minimum in some cases. • The potential risk of under-ventilation when determining the design outdoor air flow rate. • The potential of the building pressurization issues.

the CO_2-based DCV system in a classroom building [108] and a library [112,113] using the direct OA control based on the return duct CO_2 sensor. The results showed that the PI controller caused significant oscillations around the CO_2 concentration setpoint due to the impacts of the dynamic occupancy and inertia of the system. After the manual tuning of the proportional gain, a considerable OA flow rate reduction with a better control of the indoor CO_2 concentration level was realized, which indicated that the CO_2 control loop tuning in an individual building is critical for the control strategy implementation.

Merema et al. carried out two half-month monitoring studies of the CO_2-based DCV systems in school and office buildings [73]. Although the tested control strategies ensured a good IAQ and energy savings for all the cases, there still emerged some issues related to the control design of the minimum and maximum OA flow rate as well as the CO_2 sensor position. The first issue was found in an office building where the OA was at the minimum airflow rate for 67% of the time which indicated that the minimal airflow rate setpoint could not meet the requirement of the actual occupancy. The second issue was noticed in the lecture room where the CO_2 sensor installed above the return air grille with a higher value compared to the values measured in the occupied zone.

Simanic et al. [114] conducted a long-term indoor air quality monitoring of the newly built low-energy schools in Sweden. They found that the schools with CO_2-based DCV provided satisfactory indoor climates in terms of CO_2 concentration levels. However, they identified one issue regarding the sensor placement. The short circuit between the supply air and the exhaust air devices due to high supply air temperatures would underestimate the CO_2 levels in the occupied spaces.

In the ASHRAE Project 1747 [4], the developed DCV logic was tested through a series of full-scale operational tests at the Iowa Energy Center's Energy Resource Station facility from November to December 2016. The field testing demonstrated the successful implementation of the proposed DCV logic in a real HVAC control system with close compliance with the ventilation requirements of Standard 62.1 under varying occupancy and operating conditions. The tested control sequences were generally stable for most operation scenarios, though several issues were identified in the testing period. First, the complex rule-based control suffered from a stability issue due to the incorrect setting regarding the hysteresis and therefore, some limits were added to ensure the stability of the control. However, this may result in a small risk of underventilation in circumstances where transients lead to the fluctuating ventilation requirement. Second, some control parameter settings such as the dead band and time delay are critical and sensitive to the tuning of the OA control. In addition, the trim and response rate for the zone minimum rest may need to be tuned for a stable operation. Thirdly, the zone required OA in some cases was found to be lower than the VAV box controllable minimums. This may slightly limit the airflow reductions and energy savings associated with DCV operation in economizer modes. Fourthly, the assumption of the design system ventilation efficiency equal to 1 might be conservative to ensure compliance with Standard 62.1 at all times. Therefore, the designer for this control strategy should determine the design outdoor air intake flow with care. Fifth, the control strategy does not account for the building pressure control.

5. Conclusions and future directions

5.1. Concluding remarks

This review paper focuses on the DCV control-related topics, along with the performance assessment through available case studies. We reviewed the publications regarding the "control" system, including the available CO_2-based DCV control strategies and sensors for the CO_2-based DCV controls. The conclusions are summarized as follows:

- *Direct OA Controls by CO_2 Setpoint* are mostly widely used in earlier DCV applications and could be adopted in both single-zone and multi-zone systems. However, some practitioners have specific concerns about implementing control strategies for the multi-zone systems due to the potential adverse impacts on IAQ.
- *Ventilation Reset* control dynamically resets the OA flow rate, which derives the real-time occupancy from the steady-state mass balance. Transient equations and other data-driven methods could also replace the steady-state equations. However, the merits of these approaches need to be further demonstrated.
- *Ventilation & Zone Minimum Reset* is the most promising control strategy for multi-zone systems due to the dynamic interaction between the system and zone level OA control. This type of control strategy can save significant energy costs in climates that are favorable for economizing because the zone primary airflow minimum setpoint could be lowered during the economizer mode at the system level.
- For the model-based control strategies, most studies are targeted at demonstrating the efficacy of the controller design. The model-based controller designs are generally complicated due to the system's nonlinearity. In addition, the parameters in the control model and the exogenous inputs need to be accurately estimated. This prevents the implementation of the model-based control strategies at a large scale in the field.

- The application of learning-based controller in DCV systems is still premature. The particularly long training time of the RL agent is a significant hurdle for the real-world applications of learning-based controllers, which is a well-known problem for applications in many other domains as well [115].
- Many model-based and learning-based control strategies only consider the ventilation control of the indoor CO_2 concentration. To our best knowledge, only two studies accounted for the collective control of both zone CO_2 concentration and zone air temperature.
- Commercial CO_2 sensors mainly used in DCV systems today are still NDIR sensors, although the price per sensor could be reduced to \$20.
- Although a few studies prove some inexpensive NDIR CO_2 sensors (~ \$60 per sensor) would perform sufficiently accurately for the DCV [55,62,64,65], significant uncertainties of the measurement errors still exist in many cases.
- The accuracy of the AFMS will degrade at the low outdoor air intake flow rate, and a separate OA ductwork for the economizer is suggested.
- Local controls in actuating control devices such as VAV terminal units would impact the performance of the DCV control. VAV terminal units might fail to perform as expected at very low airflow rates but the minimum controllable setpoints could be approximately 8%–12% of the maximum airflow. In addition, potential air balancing issues between the zone terminals could cause overventilation or underventilation. Different model-based air-balancing methods were studied to realize more accurate airflow controls.

Finally, a performance evaluation of the CO_2-based DCV is conducted. Two research questions are being answered: (1) How much benefit could be achieved? (2) What are the common issues during the design and operation? The summarized answers are listed as follows:

- The associated benefits would be varied with different control sequences, building and system types, occupancy schedules, climate zones, and the compared baselines.
- The most considerable cost savings from CO_2-based DCV occur for buildings with variable and unpredictable occupancy levels, such as auditoriums, gyms, and retail stores. However, the most studied building type is the office building. For the single-zone and multi-zone office buildings, the cost savings range from 2.7 to 12.5% and 0.3–46.2%, respectively, which depends on the implemented sequences and climate zones. In most cases, the payback period was less than two years for single-zone systems, and the payback period was estimated between four and eight years for multi-zone systems. The ventilation reset strategy with the zone minimum reset performs better than all other field implemented DCV control strategies.
- The common issues for the field implementation include the incomplete information regarding the CO_2-based DCV in the design document, inappropriate TAB procedure during the deployment and commissioning, inappropriate sensor placement, wrong settings of the critical control limits and parameters, and untuned local controller. It can be seen that the commissioning is a crucial step for the CO_2-based DCV to achieve the expected performance.

5.2. Future research questions and directions

This review covers important and urgent topics regarding the control-related issues for CO_2-based DCV in commercial buildings, but also identifies gaps with potential improvement suggestions for further research, which are summarized as follows:

- The low-cost commercial NDIR CO_2 sensors still have reliability issues. Therefore, alternatives to low-cost NDIR sensors are desperately needed.
- There is limited guidance on recommissioning of the CO_2-based DCV system, and the best practices of the sensor calibration and system maintenance of the DCV systems are largely unknown. The automated fault detection and diagnostic for the DCV systems are lacking.
- Our review indicates the importance of setting the design and control parameters in the rule-based DCV control strategies, such as the design OA higher and lower limits and the hysteresis parameters in the control sequences. Future investigations are needed to provide insights on the optimal parameter settings.
- Our review identifies the lack of field tests of advanced rule-based CO_2-based DCV strategies, as listed in Section 2.1.2 – Section 2.3, especially for the multi-zone system. Although the ventilation & zone minimum reset control has demonstrated its efficacy in the ASHRAE RP 1747 functional test, there are limited field tests for this relatively new strategy in the real building operation. The vast of majorities of new sequences are only tested through simulation-based studies. All the model-based sequences were only tested in the simulation environment. However, the simulation has inevitable shortcomings and artifacts such as the assumption of the well-mixed air, the simplifications of the local controls, etc. ASHRAE 1747 project functional tests did show rare cases where CO_2 concentration exceeds 2000 ppm. However, this is never shown in its simulation.
- Although the model-based controllers are hardly implemented in the field, the results from the model-based optimization have the potential to be extracted into the expert knowledge and used in the rule-based control strategies [116]. The future work of the model-based controllers should be compared to the high-performance rule-based control strategies identified in this paper.
- There exist limited comparative studies between the CO_2-based DCV strategies and the DCV strategies from occupancy detection using other sources [117]. The comparisons need to include the sensor performance, the performance evaluation from the energy and ventilation perspectives, the implementation complexity, the costs of the installation and maintenance, etc.
- There exist no comprehensive studies that compare the performance of different CO_2-based DCV strategies in a standardized setting. For future performance evaluation, different CO_2-based DCV strategies should be tested in the same test conditions such as the building and system type, the climate condition, the occupancy schedule, etc. A general performance index that considers the trade-off between energy and ventilation performance should be developed.

5.3. Limitations of this review paper

The limitations of this review paper are also outlined as follows:

- An exhaustive literature search described in Section 1.2 has been implemented to collect all the recent publications and reports related to CO_2-based DCV applications. However, the findings and conclusions of this review paper might still be restrained since the methodologies and control methods analyzed herein are inevitably limited to the literature available. For example, the application of CO_2-based DCV in VAV systems is discussed in detail, while the other system configurations, such as the CAV system, are only briefly mentioned in this paper since the majority of the returned case studies from literature research are focused on the VAV system. Furthermore, the application of learning-based controls in CO_2-based DCV systems is somewhat limited in the existing literature; hence this paper does not present a deep analysis of it.
- Advanced control algorithms (e.g., model-based/learning-based controls) and sensing technologies are rapidly evolving but have yet to be applied on a large scale in CO_2-based DCV applications. This will provide an unprecedented opportunity for stakeholders to levitate the energy efficiency and penetration rate of CO_2-based DCV to the next level. This review paper didn't discuss this topic in-depth since researchers are still trying to figure out how these technologies can be better incorporated into building systems. However, it is

believed that the basic control algorithms of DCV elaborated in this paper should be able to provide practical guidance on the development of learning- and sensing-driven DCV control strategies in the future.

CRediT authorship contribution statement

Xing Lu: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Zhihong Pang:** Writing – review & editing, Methodology. **Yangyang Fu:** Writing – review & editing, Methodology. **Zheng O'Neill:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study is supported by the U.S. National Science Foundation (NSF) project # 2050509 "PFI-RP: Data-Driven Services for High Performance and Sustainable Buildings."

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2022.109455.

References

[1] A. Persily, W.S. Dols, S.J. Emmerich, L.C. Ng, The role of carbon dioxide in ventilation and IAQ evaluation: 40 years of AIVC, in: 40th Air Infiltration and Ventilation Centre Conference, 2019. Ghent.
[2] D. Södergren, A CO_2-controlled ventilation system, Environ. Int. 8 (1–6) (1982) 483–486.
[3] J.E.B. Tom Lawrence, Initial cooling and heating season field evaluations for demand-controlled-ventilation, Submitted to California Energy Commission As Deliverables (2003), 3.1.3a and 3.1.4a.
[4] Z.D. O'Neill, Y. Li, H.C. Cheng, X. Zhou, S.T. Taylor, ASHRAE 1747-RP. Implementation of RP-1547 CO_2-based Demand Controlled Ventilation for Multiple Zone HVAC Systems in Direct Digital Control Systems, 2017.
[5] X. Lin, J. Lau, G. Yuill, ASHRAE 1547-RP. CO_2-Based Demand Controlled Ventilation for Multiple Zone HVAC Systems, 2013.
[6] Z.D. O'Neill, X. Lu, T. Yang, X. Zhou, ASHRAE 1819-RP: CO_2 Demand Controlled Ventilation in Multiple Zone VAV Systems with Multiple Recirculation Paths, 2020.
[7] S. Zhang, Z. Ai, Z. Lin, Novel demand-controlled optimization of constant-air-volume mechanical ventilation for indoor air quality, durability and energy saving, Appl. Energy 293 (2021), 116954.
[8] S. Shriram, K. Ramamurthy, Assessment of CO_2-based demand controlled ventilation requirement for a flexible work environment with ductless split air conditioners, Sci. Technol. Built Environ. 25 (7) (2019) 805–818.
[9] S.J. Emmerich, A.K. Persily, State-of-the-art Review of CO_2 Demand Controlled Ventilation Technology and Application, 2001.
[10] G. Paliaga, R. Singla, C. Snaith, S. Lipp, D. Mangalekar, H. Cheng, M. Pritoni, Re-Envisioning RCx: Achieving Max Potential HVAC Controls Retrofits through Modernized BAS Hardware and Software, 2020.
[11] M. Wetter, J. Hu, M. Grahovac, B. Eubanks, P. Haves, OpenBuildingControl: Modeling Feedback Control as a Step towards Formal Design, Specification, Deployment and Verification of Building Control Sequences, Building Performance Modeling Conference and SimBuild, 2018.
[12] K. Zhang, D.H. Blum, M. Grahovac, J. Hu, J. Granderson, M. Wetter, Development and Verification of Control Sequences for Single-Zone Variable Air Volume System Based on ASHRAEGuideline 36, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), 2020.
[13] R. Kiriu, J. Stein, Medical office building thrives with advanced control sequences, ASHRAE J. 63 (2021) 62–67.
[14] X. Lu, Z. Pang, Y. Fu, Z. O'Neill, The nexus of the indoor CO_2 concentration and ventilation demands underlying CO_2-based demand-controlled ventilation in commercial buildings: a critical review, Build. Environ. 218 (2022) 109–116, https://doi.org/10.1016/j.buildenv.2022.109116.
[15] M.G. Apte, A Review of Demand Control Ventilation, LBNL-60170 Report, Lawrence Berkeley National Laboratory, Berkeley, CA, USA, 2006.
[16] H. Jabeen, Stemming and lemmatization in Python. https://www.datacamp.com/community/tutorials/stemming-lemmatization-python, 2021.
[17] T. Yang, A. Bandyopadhyay, Z. O'Neill, J. Wen, B. Dong, From occupants to occupants: a review of the occupant information understanding for building HVAC occupant-centric control, Build. Simulat. (2021) 1–20.
[18] J. Murphy, CO_2-Based Demand-Controlled Ventilation with ASHRAE Standard 62.1-2004, Trane Engineers Newsletter, 2005.
[19] T.M. Lawrence, Selecting CO_2: criteria for outdoor air monitoring, ASHRAE J. 50 (12) (2008).
[20] K. Yu-Pei, S. Mumma, Using carbon dioxide measurements to determine occupancy for ventilation controls, Build. Eng. 103 (1997) 365.
[21] ASHRAE, 62.1 User's Manual, 2016.
[22] N. Nassif, A robust CO_2-based demand-controlled ventilation control strategy for multi-zone HVAC systems, Energy Build. 45 (2012) 72–81.
[23] Seventhwave, Energy Savings from Implementing and Commissioning Demand Control Ventilation Lessons Learned from Observed Practical Approaches, Minnesota Department of Commerce, Division of Energy Resources, 2015.
[24] W.J. Fisk, Recommended Changes to Specifications for Demand Controlled Ventilation in California's Title 24 Building Energy Efficiency Standards, Lawrence Berkeley National Laboratory, Environmental Energy Techologies Division Indoor Environment Department, 2010.
[25] B. Acker, K. Van Den Wymelenberg, Demand control ventilation: lessons from the field-how to avoid common problems, Build. Eng. 117 (2011) 502.
[26] X. Lu, Z. Pang, Y. Fu, Z. O'Neill, The Nexus of the Indoor CO_2 Concentration and Ventilation Demands Underlying CO_2-based Demand-Controlled Ventilation: A Critical Review, 2021.
[27] S.T. Taylor, CO_2-based DCV using 62.1-2004, ASHRAE J. 48 (5) (2006) 67–75.
[28] T.M. Lawrence, J.E. Braun, Evaluation of simplified models for predicting CO_2 concentrations in small commercial buildings, Build. Environ. 41 (2) (2006) 184–194.
[29] Z. Afroz, G. Higgins, G.M. Shafiullah, T. Urmee, Evaluation of real-life demand-controlled ventilation from the perception of indoor air quality with probable implications, Energy Build. 219 (2020) 21.
[30] S. Australia, The Use of Ventilation and Airconditioning in Buildings Mechanical Ventilation in Buildings, 2012. AS 1668.2-2012.
[31] M.O. Ng, M. Qu, P.X. Zheng, Z.Y. Li, Y. Hang, CO_2-based demand controlled ventilation under new ASHRAE Standard 62.1-2010: a case study for a gymnasium of an elementary school at West Lafayette, Indiana, Energy Build. 43 (11) (2011) 3216–3225.
[32] H. Rahman, H. Han, Real-time ventilation control based on a Bayesian estimation of occupancy, Build. Simulat. (2021) 11.
[33] M. Momenia, D.-C. Wub, A. Razbanc, J. Chend, Data-driven demand control ventilation using machine learning CO_2 occupancy detection method, in: Proceedings of ECOS 2020 - the 33rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, 2020. Osaka, Japan.
[34] X.B. Lin, J. Lau, Demand controlled ventilation for multiple zone HVAC systems: CO_2-based dynamic reset (RP 1547), HVAC R Res. 20 (8) (2014) 875–888.
[35] X.L. Lin, Josephine, Applying demand-controlled ventilation multiple-zone VAV systems in buildings, ASHRAE J. (2016 January) 30–37.
[36] X.B. Lin, J. Lau, Demand-controlled ventilation for multiple-zone HVAC systems-Part 2: CO_2-based dynamic reset with zone primary airflow minimum set-point reset (RP-1547), Sci. Technol. Built Environ. 21 (8) (2015) 1100–1108.
[37] Z.D. O'Neill, Y.F. Le, H.C. Cheng, X.H. Zhou, S.T. Taylor, Energy savings and ventilation performance from CO_2-based demand controlled ventilation: simulation results from ASHRAE RP-1747 (ASHRAE RP-1747), Sci. Technol. Built Environ. 26 (2) (2020) 257–281.
[38] X. Lu, T. Yang, Z. O'Neill, X. Zhou, Z. Pang, Energy and ventilation performance analysis for CO_2-based demand-controlled ventilation in multiple-zone VAV systems with fan-powered terminal units (ASHRAE RP-1819), Science Technology for the Built Environment 27 (2) (2020) 139–157.
[39] X. Lu, T. Yang, Z. O'Neill, X. Zhou, Energy and ventilation performance analysis for CO_2-based demand-controlled ventilation in multiple zone VAV systems with multiple recirculation paths, in: 2020 Building Performance Analysis Conference and SimBuild Co-organized by ASHRAE and IBPSA-USA ASHRAE, 2020, pp. 308–316.
[40] T. Lu, X.S. Lu, M. Viljanen, A novel and dynamic demand-controlled ventilation strategy for CO_2 control and energy saving in buildings, Energy Build. 43 (9) (2011) 2499–2508.
[41] X.S. Lu, T. Lu, M. Viljanen, C.J. Kibert, A new method for controlling CO_2 in buildings with unscheduled opening hours, Energy Build. 59 (2013) 161–170.
[42] M. Gruber, A. Truschel, J.O. Dalenback, CO_2 sensors for occupancy estimations: potential in building automation applications, Energy Build. 84 (2014) 548–556.
[43] H. Liu, S. Lee, M. Kim, H. Shi, J.T. Kim, C. Yoo, Finding the optimal set points of a thermal and ventilation control system under changing outdoor weather conditions, Indoor Built Environ. 23 (1) (2014) 118–132.
[44] A. Rackes, M.S. Waring, Using multiobjective optimizations to discover dynamic building ventilation strategies that can improve indoor air quality and reduce energy use, Energy Build. 75 (2014) 272–280.
[45] W.Z. Li, S.W. Wang, A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering indoor air quality and energy use, Appl. Energy 275 (2020) 13.
[46] F. Lachhab, M. Essaaidi, M. Bakhouya, R. Ouladsine, A state-feedback approach for controlling ventilation systems in energy efficient buildings, in: M. Essaaidi, Y. Zaz (Eds.), Proceedings of 2015 3rd Ieee International Renewable and Sustainable Energy Conference, Ieee, New York, 2015, pp. 665–670.

[47] Z. Shi, X. Li, S. Hu, Direct feedback linearization based control of CO_2 demand controlled ventilation, in: 2010 2nd International Conference on Computer Engineering and Technology, IEEE, 2010. V2-571-V2-574.

[48] C.S. Kang, J.I. Park, M. Park, J. Baek, Novel modeling and control strategies for a HVAC system including carbon dioxide control, Energies 7 (6) (2014) 3599–3617.

[49] F. Lachhab, M. Bakhouya, R. Ouladsine, M. Essaaidi, Context-driven monitoring and control of buildings ventilation systems using big data and Internet of Things-based technologies, Journal of Systems and Control Engineering 233 (3) (2019) 276–288.

[50] A. Berouine, R. Ouladsine, M. Bakhouya, F. Lachhab, M. Essaaidi, A Model Predictive Approach for Ventilation System Control in Energy Efficient Buildings, Ieee, New York, 2019.

[51] I. Skrjanc, B. Subic, Control of indoor CO_2 concentration based on a process model, Autom. ConStruct. 42 (2014) 122–126.

[52] J. Zhu, F. Lauri, A. Koukam, V. Hilaire, Managing ventilation systems for improving user comfort in smart buildings using reinforcement learning agents, in: Proceedings of European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECML/PKDD 2014), 2014, pp. 149–155.

[53] S. Heo, K. Nam, J. Loy-Benitez, Q. Li, S. Lee, C. Yoo, A deep reinforcement learning-based autonomous ventilation control system for smart indoor air quality management in a subway station, Energy Build. 202 (2019) 16.

[54] M. Schell, D. Int-Hout, Demand control ventilation using CO_2, ASHRAE J. 43 (2) (2001) 18–29.

[55] J. Berquist, C. Banister, Feasibility of low-cost CO_2 sensors for demand-controlled ventilation—Part 1. Laboratory testing (VC-20-004), in: 2020 ASHRAE Virtual Conference, ASHRAE, 2020.

[56] D. Schwartz, Ultra-Low SWaP CO_2 Sensing for Demand Control Ventilation Final Report, PARC, 2020.

[57] J.O. Hallstrom, Z.R. Ni, STTR Phase I: Low-Cost, High-Accuracy, Whole-Building Carbon Dioxide Monitoring for Demand Control Ventilation, Dioxide Materials, Inc., Boca Raton, FL (United States), 2018.

[58] J. Boudaden, A. Klumpp, H.-E. Endres, I. Eisele, Towards low cost and low temperature capacitive CO_2 sensors based on amine functionalized silica nanoparticles, Nanomaterials 9 (8) (2019) 1097.

[59] W.J. Fisk, D. Faulkner, D.P. Sullivan, Accuracy of CO_2 Sensors in Commercial Buildings: a Pilot Study, Ernest Orlando Lawrence Berkeley NationalLaboratory, Berkeley, CA (US), 2006.

[60] W.J. Fisk, CO_2 Monitoring for Demand Controlled Ventilation in Commercial Buildings, 2010.

[61] CaliforniaEnergyCommission, Building Energy Efficiency Standards for Residential and Nonresidential Buildings., Title 24, Part 6, California Code of Regulations, 2019. Title 24.

[62] M.-L. Maripuu, Demand Controlled Ventilation (DCV) Systems in Commercial Buildings Functional Requirements on Systems Components, Department of Energy and Environmen, Chalmers University of Technology, Gothenburg, Sweden, 2009.

[63] S.S. Shrestha, Performance Evaluation of Carbon-Dioxide Sensors Used in Building HVAC Applications, Mechanical Engineering, Iowa State University, 2009.

[64] M. Roberts, Steady State and Transient Response Characteristics of Commercial Non-dispersive Infrared Carbon Dioxide Sensors, Auburn University, 2014. Mechanical Engineering.

[65] J. Berquist, C. Banister, Feasibility of low-cost CO_2 sensors for demand-controlled ventilation—laboratory chamber testing, Build. Eng. 126 (2) (2020).

[66] ASHRAE, ANSI/ASHRAE/ICC/USGBC/IES 189.1-2020, Standard for the Design of High-Performance Green Buildings, ASHRAE, Inc, Atlanta, GA, USA, 2020.

[67] A.R.P.A. Energy, in: D.o. Energy (Ed.), Saving Energy Nationwide in Structures with Occupancy Recognition (Sensor), 2017.

[68] A. Mylonas, O.B. Kazanci, R.K. Andersen, B.W. Olesen, Capabilities and limitations of wireless CO_2, temperature and relative humidity sensors, Build. Environ. 154 (2019) 362–374.

[69] EnergyDesignResources, Design Brief of Demand-Controlled Ventilation, 2007.

[70] K.W. Mui, W.T. Chan, Pilot study for the performance of a new demand control ventilation system in Hong Kong, J. Architect. Eng. 11 (3) (2005) 110–115.

[71] G. Pei, D. Rim, S. Schiavon, M. Vannucci, Effect of sensor position on the performance of CO_2-based demand controlled ventilation, Energy Build. 202 (2019) 11.

[72] G. Pei, D. Rim, Experimentally validated CFD analysis on the optimal sensor location for the CO_2-based demand-controlled ventilation, Build. Eng. 126 (1) (2020).

[73] B. Merema, M. Delwati, M. Sourbron, H. Breesch, Demand controlled ventilation (DCV) in school and office buildings: lessons learnt from case studies, Energy Build. 172 (2018) 349–360.

[74] M. Schafer, R. Detzer, J. Hesselbach, S. Bohm, P. Shinde, C.X. Lin, CO_2 and thermal gradient based demand-driven stratified ventilation - experimental and simulation study, HVAC R Res. 19 (6) (2013) 676–692.

[75] N. Mahyuddin, H. Awbi, The spatial distribution of carbon dioxide in an environmental test chamber, Build, Environ. Times 45 (9) (2010) 1993–2001.

[76] J. Pantelic, S.H. Liu, L. Pistore, D. Licina, M. Vannucci, S. Sadrizadeh, A. Ghahramani, B. Gilligan, E. Sternberg, K. Kampschroer, S. Schiavon, T. Wellbuilt Wellbeing Project, Personal CO_2 cloud: laboratory measurements of metabolic CO_2 inhalation zone concentration and dispersion in a typical office desk setting, J. Expo. Sci. Environ. Epidemiol. 30 (2) (2020) 328–337.

[77] R.K. Bhagat, M.S.D. Wykes, S.B. Dalziel, P.F. Linden, Effects of ventilation on the indoor spread of COVID-19, J. Fluid Mech. 903 (2020) 18.

[78] A.K. Melikov, D.G. Markov, Validity of CO_2 based ventilation design, in: E3S Web of Conferences, 2019, 05007. EDP Sciences.

[79] W. Fisk, D. Sullivan, S. Cohen, H. Han, Measuring Outdoor Air Intake Rates into Existing Building, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), 2009.

[80] X. Lu, Z. O'Neill, Y. Li, F. Niu, A novel simulation-based framework for sensor error impact analysis in smart building systems: a case study for a demand-controlled ventilation system, Appl. Energy 263 (2020), 114638.

[81] R. Liu, J. Wen, X. Zhou, C. Klaassen, Stability and accuracy of variable air volume box control at low flows. Part 1: laboratory test setup and variable air volume sensor test, HVAC R Res. 20 (1) (2014) 3–18.

[82] R. Liu, J. Wen, X. Zhou, C. Klaassen, A. Regnier, Stability and accuracy of variable air volume box control at low flows. Part 2: controller test, system test, and field test, HVAC R Res. 20 (1) (2014) 19–35.

[83] S. Taylor, ASHRAE Guideline 36 - High Performance Sequences of Operation for HVAC Systems (With Lab Demonstration), BEST Center's 2020 Annual Institute, 2020.

[84] T.Y. Zhao, J.M. Wang, C. Liu, P.M. Hua, Y. Zhou, Y. Zhao, Comparative study of outdoor airflow requirement and distribution in multi-zone VAV system with different control strategies, Sci. Technol. Built Environ (2020) 20.

[85] G. Jing, W.J. Cai, X. Zhang, C. Cui, X.H. Yin, H.C. Xian, Modeling, air balancing and optimal pressure set-point selection for the ventilation system with minimized energy consumption, Appl. Energy 236 (2019) 574–589.

[86] C. Cui, X. Zhang, W.J. Cai, An energy-saving oriented air balancing method for demand controlled ventilation systems with branch and black-box model, Appl. Energy 264 (2020) 15.

[87] T.Z. Hong, W.J. Fisk, Assessment of energy savings potential from the use of demand controlled ventilation in general office spaces in California, Build. Simulat. 3 (2) (2010) 117–124.

[88] EN13779, Ventilation for Non-residential Buildings. Performance Requirements for Ventilation and Room-Conditioning Systems, 2007.

[89] J.E. Braun, K. Mercer, T. Lawrence, Evaluation of Demand Controlled Ventilation, Heat Pump Heat Recovery, and Enthalpy Exchangers, California Energy Commission, 2003. Submitted to California Energy Commission as a final report for Deliverables 3.1.6b and 4.2.6a.

[90] J.E. Braun, K. Mercer, VSAT-ventilation Strategy Assessment Tool, Submitted to California Energy Commission, 2003, 3.2.

[91] G. Augenbroe, Trends in Building Simulation, Advanced Building Simulation, Routledge 2004, pp. 18-38.

[92] W.S. Dols, B.J. Polidoro, Contam User Guide and Program Documentation Version 3.2, 2015.

[93] D.B. Crawley, L.K. Lawrie, C.O. Pedersen, F.C. Winkelmann, Energy plus: energy simulation program, ASHRAE J. 42 (4) (2000) 49–56.

[94] S.E. Mattsson, H. Elmqvist, M. Otter, Physical system modeling with Modelica, Control Eng. Pract. 6 (4) (1998) 501–510.

[95] B. Birdsall, W. Buhl, K. Ellington, A. Erdem, F. Winkelmann, Overview of the DOE-2 Building Energy Analysis Program, Report LBL-19735m Rev. W, Lawrence Berkeley Laboratory, Berkeley, CA, 1990.

[96] eQUEST, The QUick energy simulation tool. https://www.doe2.com/equest/, 2018, 05/04/21.

[97] VirtualEnvironment, Leading integrated suite for accurate whole building performance simulation. https://www.iesve.com/software/virtual-environment, 2021, 05/04/21.

[98] A. Persily, S. Emmerich, M. Taylor, Simulations of Indoor Air Quality and Ventilation Impacts of Demand Controlled Ventilation in Commercial and Institutional Buildings, US Department of Commerce, National Institute of Standards and Technology, 2003.

[99] W.S. Dols, S.J. Emmerich, B.J. Polidoro, Coupling the multizone airflow and contaminant transport software CONTAM with EnergyPlus using co-simulation, Build. Simulat. 9 (4) (2016) 469–479.

[100] B. Chenari, F.B. Lamas, A.R. Gaspar, G.d.S. Manuel Carlos, Development of a new CO_2-based demand-controlled ventilation strategy using EnergyPlus, energy for sustainability international conference: designing cities communities for the future, Funchal (2017), 8–10 February.

[101] F. Jorissen, W. Boydens, L. Helsen, Simulation-based occupancy estimation in office buildings using CO_2 sensors, in: 15th IBPSA Conference, IBPSA, 2017, pp. 1073–1082.

[102] B. Merema, D. Saelens, H. Breesch, Analysing modelling challenges of smart controlled ventilation systems in educational buildings, J. Build. Perf. Simul. 14 (2) (2021) 116–131.

[103] F. Jorissen, G. Reynders, R. Baetens, D. Picard, D. Saelens, L. Helsen, Implementation and verification of the IDEAS building energy simulation library, J. Build. Perform Simulat. 11 (6) (2018) 669–688.

[104] M. Wetter, W. Zuo, T.S. Nouidui, X. Pang, Modelica buildings library, J. Build. Perform Simulat. 7 (4) (2014) 253–270.

[105] H. Han, M. Hatta, H. Rahman, Smart ventilation for energy conservation in buildings, Evergreen Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy 6 (1) (2019) 44–51.

[106] Y.Q. Fan, K. Ito, Integrated building energy computational fluid dynamics simulation for estimating the energy-saving effect of energy recovery ventilator with CO_2 demand-controlled ventilation system in office space, Indoor Built Environ. 23 (6) (2014) 785–803.

[107] Y. Fan, K. Kameishi, S. Onishi, K. Ito, Field-based study on the energy-saving effects of CO_2 demand controlled ventilation in an office with application of energy recovery ventilators, Energy Build. 68 (2014) 412–422.

[108] L. Schibuola, M. Scarpa, C. Tambani, Performance optimization of a demand controlled ventilation system by long term monitoring, Energy Build. 169 (2018) 48–57.

[109] K. Shan, Y.J. Sun, S.W. Wang, C.C. Yan, Development and In-situ validation of a multi-zone demand-controlled ventilation strategy using a limited number of sensors, Build. Environ. 57 (2012) 28–37.

[110] A.G. Alam, H. Rahman, J.K. Kim, H. Han, Uncertainties in neural network model based on carbon dioxide concentration for occupancy estimation, J. Mech. Sci. Technol. 31 (5) (2017) 2573–2580.

[111] T.Y. Zhao, P.M. Hua, W.H. Dai, J.L. Zhang, L.D. Ma, An optimal control method for discrete variable outdoor air volume setpoint determination in variable air volume systems, Build. Environ. 167 (2020) 16.

[112] L. Schibuola, M. Scarpa, C. Tambani, CO_2 based ventilation control in energy retrofit: an experimental assessment, Energy 143 (2018) 606–614.

[113] L. Schibuola, M. Scarpa, C. Tambani, Annual performance monitoring of a demand controlled ventilation system in a university library, in: M.C. Masoero, I. Arsie (Eds.), 71st Conference of the Italian Thermal Machines Engineering Association, Elsevier Science Bv, Amsterdam, 2016, pp. 313–320.

[114] B. Simanic, B. Nordquist, H. Bagge, D. Johansson, Indoor air temperatures, CO_2 concentrations and ventilation rates: long-term measurements in newly built low-energy schools in Sweden, J. Build. Eng. 25 (2019) 12.

[115] Z. Wang, T. Hong, Reinforcement learning for building controls: the opportunities and challenges, Appl. Energy 269 (2020), 115036.

[116] A. Franco, E. Schito, Definition of optimal ventilation rates for balancing comfort and energy use in indoor spaces using CO_2 concentration data, Buildings-Basel 10 (8) (2020) 19.

[117] B.W. Hobson, H.B. Gunay, A. Ashouri, G.R. Newsham, Occupancy-based predictive control of an outdoor air intake damper: a case study, Computer (2020) 630.