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The nexus of the indoor CO_2 concentration and ventilation demands underlying CO_2-based demand-controlled ventilation in commercial buildings: A critical review

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

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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. Since then, it has been penetrating from simple single-zone systems to complex system configurations in commercial buildings. While there has accumulated a large number of research on DCV applications, the most recent review paper on this topic was dated back to 2001 and inevitably missed a lot of recent revolutionary technologies. Therefore, to understand the opportunities and challenges associated with the CO_2-based DCV, this study presents a timely review on the revolutions of the CO_2-based DCV in commercial buildings, with a focus on the literature published in the last two decades. This paper is mainly centered on the trends and fundamental updates of the CO_2-based DCV, with a particular focus on the nexus of the indoor CO_2 concentration and ventilation "demands". First, the changes in building energy codes and standards related to the CO_2-based DCV are reviewed. Second, the trends of paper distribution and the topic keywords are identified through the bibliographic analysis. Third, the fundamental updates regarding the indoor CO_2 concentration are presented. The correlations between the CO_2 and its influencing factors are discussed, and the CO_2 concentration spatial distribution in different scenarios is summarized. Fourth, the role of CO_2 in ventilation control is clarified. The correlation studies of the CO_2 concentration and various ventilation "demands" are reviewed, and the impacts of the CO_2-based DCV on indoor air quality are presented.

1. Introduction

The carbon dioxide (CO_2)-based demand-controlled ventilation (DCV), which is defined as a smart energy-efficiency measure [1] that varies the rate at which the outdoor air is delivered to the zone to respond to the actual ventilation "demands" (needs), has received increasing attention from the heating, ventilation, and air-conditioning (HVAC) industry since decades ago. In the CO_2-based DCV, the CO_2 concentration is used as a proxy to indicate the indoor air quality (IAQ) [2], based on which the ventilation rate is dynamically reset; hence the building energy consumption for heating and cooling could be saved while an acceptable IAQ is also maintained. One of the earliest studies of the CO_2-based DCV took place in an office building in Helsinki, Finland, in 1982 [3]; since then, we have seen the deployment of this technology in hundreds of thousands of buildings across the world. Meanwhile, the technology itself has also gone through a lot of profound changes and evolutions [4].

There have been several comprehensive literature reviews [4,5] and guidelines [6,7] on the topic of CO_2-based DCV between 2001 and 2007. While these publications provided helpful guidance on the technology and application, they suffered from some limitations and have not incorporated the latest development and application of CO_2-based DCV since then.

1.1. Previous related literature reviews and guidelines

Table 1 presents the summary of the previous related literature reviews and guidelines. A National Institute of Standards and Technology (NIST) report prepared by Emmerich and Persily [4] in 2001 was the first of its kind review paper to elaborate on the application of the CO_2-based DCV technology. Several aspects were covered in this report, e.g., the rationale of using the CO_2 concentration as a metric for building ventilation, an analysis of several simulation-based and field-testing

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

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Nomenclature

Symbol

A_D	DuBois surface area, m^2
A_z	zone area, m^2
C_{oa}	outdoor CO_2 concentration, ppm.
C_{ss}	steady-state indoor CO_2 concentration, ppm.
C_z	indoor CO_2 concentration, ppm.
G	indoor CO_2 generation rate per person, L/(s•p)
M	physical activity level, met.
P_z	number of people in the zone, p.
R_a	area-based component of the ventilation rate
R_p	the people-based component of the ventilation rate
V	zone volume, L.
V_{bz}	breathing zone required ventilation rate, L/s
$V_{bz\text{-}P}$	population component of the breathing zone outdoor airflow, L/s
$V_{bz\text{-}A}$	area component of the breathing zone outdoor airflow, L/s
Vz	zone ventilation rate, L/s

Abbreviation

ACH	Air Change Rate Per Hour
AHU	Air Handling Unit
ANSI	American National Standards Institute
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BAS	Building Automation System
BMR	Basal Metabolic Rate
CO_2	Carbon Dioxide.
DCV	Demand-Controlled Ventilation
HVAC	Heating, Ventilating, And Air-Conditioning
IAQ	Indoor Air Quality
IAQP	Indoor Air Quality Procedure
ICC	International Code Council
IES	Illuminating Engineering Society
IMC	International Mechanical Code
NIST	National Institute of Standards and Technology
NO_2	Nitrogen Dioxide.
RQ	Respiratory Quotient
RV	Room Volume
tTHM	trihalomethanes
TVOC	Total Volatile Organic Compounds
USGBC	U.S. Green Building Council
VAV	Variable Air Volume
VOC	Volatile Organic Compounds
VRP	Ventilation Rate Procedure

Table 1
Summary of covered topics in previous related literature reviews and guidelines.

Reference	Year	Covered Topics
[4]	2001	• Standard evolution related to DCV • DCV considering the non-occupant pollutants • Summary of control strategies • DCV best application conditions • DCV and indoor humidity condition
[5]	2005	• Standard evolution related to DCV • Control strategy issues • Sensor related topic
[6]	2005	• DCV best application conditions • Summary of control strategies
[7]	2007	• Standard evolution related to DCV • DCV implementation and commissioning • Energy modeling of DCV systems • Energy savings from DCV

case studies of DCV, and the updated technologies for CO_2 concentration sensing. Besides, the authors also proposed a preliminary guideline for the CO_2-based DCV application, in which the best practice and remaining issues of DCV were pointed out. In spite of the unique technical merits and contributions offered by this 2001 report, there is a need to have fresh reviews of the CO_2-based DCV because many technological breakthroughs and innovations achieved in the recent two decades were not included (e.g., better understanding of CO_2 and ventilation demands, novel control strategies, and sensor technologies). Considering that several significant changes regarding the minimum ventilation rate were adopted by building energy codes and standards after 2001 (as noted in Section 2), the energy savings potential reported in Ref. [4] may be outdated and needs to be refreshed.

Apte [5] conducted a review on the background and progress of the DCV technology in 2005. The market penetration and acceptance of the DCV technology were analyzed in the context of its benefits and limitations. However, the various types of DCV strategies were not discussed. Besides, the energy savings benefitting from DCV applications were not quantified.

Murphy [6] summarized the best practice of implementing the CO_2-based DCV in a 2005 report. The code-compliant requirements for dynamic reset of outdoor air were discussed in detail within the context of The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 62.1–2004. Several practical tips on the appropriate usage of various sensors (including both occupancy and CO_2 sensors) for the implementation of DCV control were recommended.

In a design brief published in 2007 [7], several issues concerning the DCV control were discussed from the perspective of engineering implementation. An overview of the ventilation requirements for different building types in various codes and standards (e.g., ASHRAE Standard 62.1, California Title 24, etc.) was presented. Besides, other topics such as the practical design and application of DCV, the estimated energy savings of this technology, the points to be noted in commissioning and simulation, and the various CO_2 sensors for DCV application were also discussed.

In summary, to the authors' best knowledge, all the available reviews on the CO_2-based DCV were published a decade ago and have been outdated in terms of relevant building energy codes, standards, and case studies. Considering the significant standard changes in ventilation requirements and the tremendous research and industry efforts directed towards the enhancement of CO_2-based DCV in the last two decades, there is a practical and compelling need for an updated comprehensive literature review to update the fundamentals of the CO_2-based DCV, quantify the energy savings benefitting from the recent progress, and identify the new challenges to enable the optimal implementation and operation of CO_2-based DCV in commercial buildings.

1.2. Scope and objective

This paper aims at providing a holistic review on the background and technological progress of the CO_2-based DCV in the last two decades, with a focus on the relationship between CO_2 and ventilation "demands" in commercial buildings. The main body of the reviewed literatures was published in the last two decades to feature the state of the art.

In detail, this paper provides the updated background and progresses for the following topics:

- The changes of building energy codes and standards (Section 2)

- The trends of research related to CO_2-based DCV (Section 3).
- The appropriate indoor CO_2 concentration level in the context of standard updates and technological enhancements (Section 4).
- The ventilation “demands” that the CO_2-based DCV fulfils (Section 5).
- The impact of the CO_2-based DCV on IAQ (Section 6).

Various stakeholders are expected to benefit from the 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.

2. Changes of building energy codes and standards related to CO_2-based DCV

Fig. 1 depicts the timeline of the exemplary changes of building energy codes and standards related to the CO_2-based DCV in the last few decades. The building energy codes and ventilation standards depicted in Fig. 1 include the ANSI/ASHRAE Standard 62.1 Ventilation for Acceptable Indoor Air Quality (known as Standard 62 Ventilation for Acceptable Indoor Air Quality before 2004; hereinafter ASHRAE Standard 62.1 or ASHRAE Standard 62) [8], the ANSI/ASHRAE Standard 90.1 Energy Standard for Buildings Except Low Rise Residential Buildings (hereinafter as ASHRAE Standard 90.1) [9], the ANSI/ASHRAE/ICC/USGBC/IES 189.1 Standard for the Design of High-Performance Green Buildings (hereinafter referred to as ASHRAE Standard 189.1) [10], the California Building Energy Efficiency Standards for Residential and Nonresidential Buildings Title 24 (hereinafter California Title 24) [11], and the International Mechanical Code (hereinafter IMC) [12]. It is noted that although the exemplary building energy codes and standards shown in Fig. 1 are widely used in North America, standards and building energy codes in other regions all over the world are also reviewed, including international building energy standard ISO 17772 [13], European building energy standard EN 16798 [14], Australian ventilation standard AS1668.2 [15], Indian IAQ standard ISHRAE 10001 [16], etc. The recommended CO_2 concentration levels are specified in these standards or associated annexes to evaluate perceived air quality. In the informative annexes, ISO 17772 [13] and EN 16798 [14] provide specific limiting concentrations (i.e., CO_2 concentration above outdoor level) for four IAQ categories (category I: 550 ppm; category II: 800 ppm; category III: 1350 ppm; category IV: > 1350 ppm). Comparatively, the recommended CO_2 level for category I according to ISHRAE 10001 is stricter with the concentration of 350 ppm higher than outdoor air CO_2. AS 1668.2 [15] recommends typical CO_2 setpoints are 600–800 ppm and should be selected based on the ambient level of the site and the enclosure characteristics [17].

Despite the many detailed updates as shown in Fig. 1, the following issues are especially worth to be noted:

- Firstly, the recommendations of the CO_2 concentration limit in different standards have led to some misunderstanding about the role of CO_2 in CO_2-based DCV. The CO_2 concentration started to be used as a metric for ventilation by the ASHRAE Standard 62 in 1981. Since then, the CO_2 concentration limit for the building ventilation control had gone through several revisions and was completely deleted from the ASHRAE Standard 62 in 1999. This leads some practitioners to erroneously refer a fixed CO_2 concentration limit to ASHRAE 62.1 [8]. In the meantime, CO_2 concentration limit of 1000 ppm is commonly recommended in different countries standards for the management of generic IAQ concerns and sick building syndrome symptoms [18–20]. However, it is noted that these recommended values are generally provided without sufficient rationales [21]. In the recently released ASHRAE position document on indoor CO_2 [21], it explicitly advised that CO_2 concentration is not a good indicator for general IAQ, at best an indicator of outdoor air ventilation rate per person.

The above examples have shown a lack of understanding about the connection between the indoor CO_2 concentration, ventilation, and indoor air quality while using the CO_2 concentration as a control variable. Therefore, in this review, we would like to summarize and clarify similar fundamental updates regarding the CO_2-based DCV.

- Secondly, the building energy codes and standards started recommending or mandating the DCV for certain circumstances in 1999, which indicates that the DCV is not only a research topic but also a practical and prominent engineering application. For instance, ASHRAE Standard 90.1 has mandated the DCV system for densely occupied spaces and required the DCV system to comply with

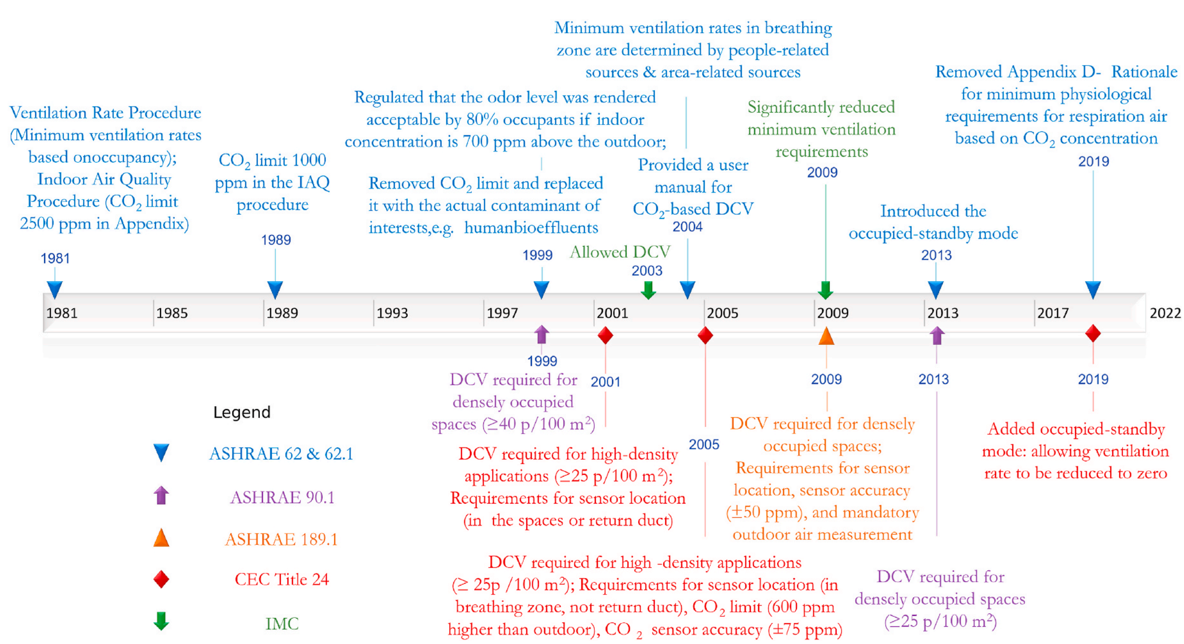

Fig. 1. Timeline of the exemplary standard changes regarding the CO_2-based DCV.

ASHRAE Standard 62.1 since its 1999 version. The DCV has also been adopted by California Title 24 for high-density applications during low-occupancy periods since 2001.

- Thirdly, it is noted that with the building codes and standards being updated regularly, more specific and detailed guidance on the implementation of the CO_2-based DCV tends to be added. For example, while the earliest versions only set requirements for the CO_2 limit, the recent versions in some building codes and standard addenda started to also include the guidance on the accuracy level, placement, and calibration frequency of the CO_2 sensors. Nevertheless, the guidance is still far from enough to achieve the optimal implementation and performance of the CO_2-based DCV technology [4]. For instance, little guidance was presented on how to select the suitable CO_2-based DCV control strategies.

3. Publication collection and thematic analysis

The literatures were collected in the following procedure. First, Google Scholar and Scopus by Elsevier were used as the search engine to find the literatures published in English. The keywords for the search were {CO_2 or occupan*} and {demand control* ventilat*}. To highlight the latest progress, the literatures were restricted to be published after 2000. This yielded a total of 1,098 items in the first place. Then, the literatures in the pool were carefully and manually filtered by removing the irrelevant items falling outside of the working scope. For instance, there exist some significant progresses for CO_2-based DCV in residential buildings [22–25] in the last decade. However, these papers were deemed irrelevant from this review and thus dropped from the list since our focus is more on commercial buildings. This pruning procedure finally yielded 138 papers of interest. The types of the collected items include the journal article, conference paper, project report, thesis, book section, and patent.

To reveal the trends in research, the 138 research papers collected for this study (published after 2000) and the research works analyzed in the previous review papers [4,5] (mainly published before 2000) were carefully reviewed and compared in terms of the publication date and type (e.g., journal articles, conference papers, reports, etc.). The results are visualized in Fig. 2. It is noted that there was a small peak between 1991 and 2000. After 2000, there continues an increasing trend for the relevant papers. The number of publications surged in the last three years probably because the occupant-based controls for the building HVAC systems and healthy building operations gradually gained more attention from the researchers and practitioners.

A word cloud analysis of the publication titles is presented in Fig. 3. A stemming and lemmatization method [26] was used to remove the redundant words and stop words. The top 20 words with the highest frequencies are listed in the left column, with the frequency number annotated right after the word. The unique words that only appear in one column are marked in bold (e.g., "ASHRAE" in Prior 2000 column, and "performance" in Post 2000 column). The numbers next to the Post 2000 column indicate the absolute change in the rankings of the word in Post 2000 column, with the blue upward arrow indicating a ranking rise, and a red downward arrow indicating a ranking drop.

The unique words in the post-2000 column turn out to be "performance," "monitoring," "low," "HVAC," "smart" and "optimization." The words in the post-2000 column that have a significant move-up (larger than 3) are the "occupancy," "simulation" and the words that do not appear in the prior-2000 column (e.g., "monitoring," "low"-cost). What could be safely inferred from the word cloud analysis is that the research trend diversified after 2000, with the practitioners starting to pay attention to computational "simulation," "performance" evaluation, system "monitoring", development of "low"-cost sensors, "smart" "HVAC" control strategy, and "optimization" of energy and ventilation performance. In addition, "occupancy" has become a central point in the CO_2-based DCV, which is aligned with occupant-centric building design and operation in the last decades [27].

The bibliometrics tool VOSviewer [28] was used to further analyze the keywords and identify the associated relationship for the collected studies. Fig. 4 depicts the keyword mining results based on the bibliographic data. The size of the circle represents the occurrence frequency of each keyword while the distance between the circles reflects the co-occurrence probability. Based on a built-in algorithm of VOSviewer, the keywords are clustered into several groups with each group being colored differently. The keywords in the same group (with the same color) tends to be more co-related and share a relevant topic. For example, the keywords in the red group belongs to the topic regarding the field study and sensors while the keywords in the light-blue group are related to the occupancy. The top ten frequent keywords identified from the analysis are "CO_2", "Demand-controlled ventilation", "indoor air quality", "control strategy", "energy saving", "ventilation rate", "simulation", "field study", "CO_2 sensor", and "occupancy estimation".

The structure of the following content is based on the results of keyword identification. Since the CO_2-based DCV is literally defined as the ventilation control strategy that responds to the real-time ventilation "demands" inferred from the indoor "CO_2" concentration, this paper lays its emphasis on the key fundamental components of the DCV, i.e., CO_2 concentration and ventilation demand. 85 research papers that are pertinent to these topics (out of 138 papers collected for the bibliographic analysis) are reviewed in detail in the following sections. For those who are interested in research papers before 2000, please refer to the references [4,5].

To be specific, Section 4 discusses the fundamental basics regarding the indoor CO_2 concentration, e.g., the influencing factors of the indoor CO_2 concentration, and the CO_2 concentration spatial distribution under different scenarios. Section 5 focuses on whether and how the CO_2 could be used as an indicator of the IAQ and Section 6 discusses the impact of the CO_2-based DCV on the IAQ.

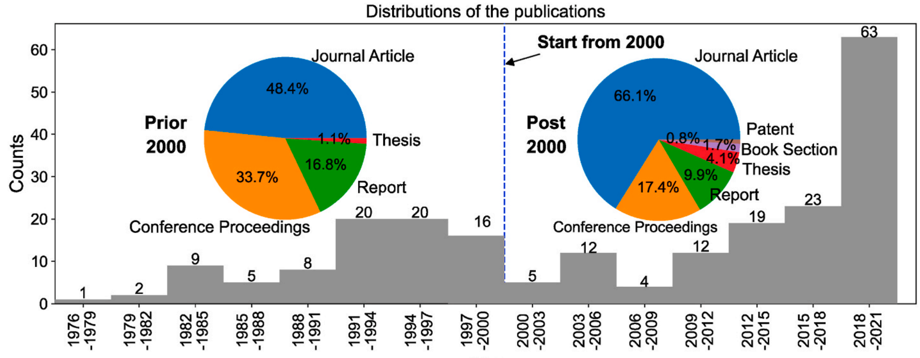

Fig. 2. Distribution of the existing work related to CO_2-based DCV prior to 2000 and post 2000.

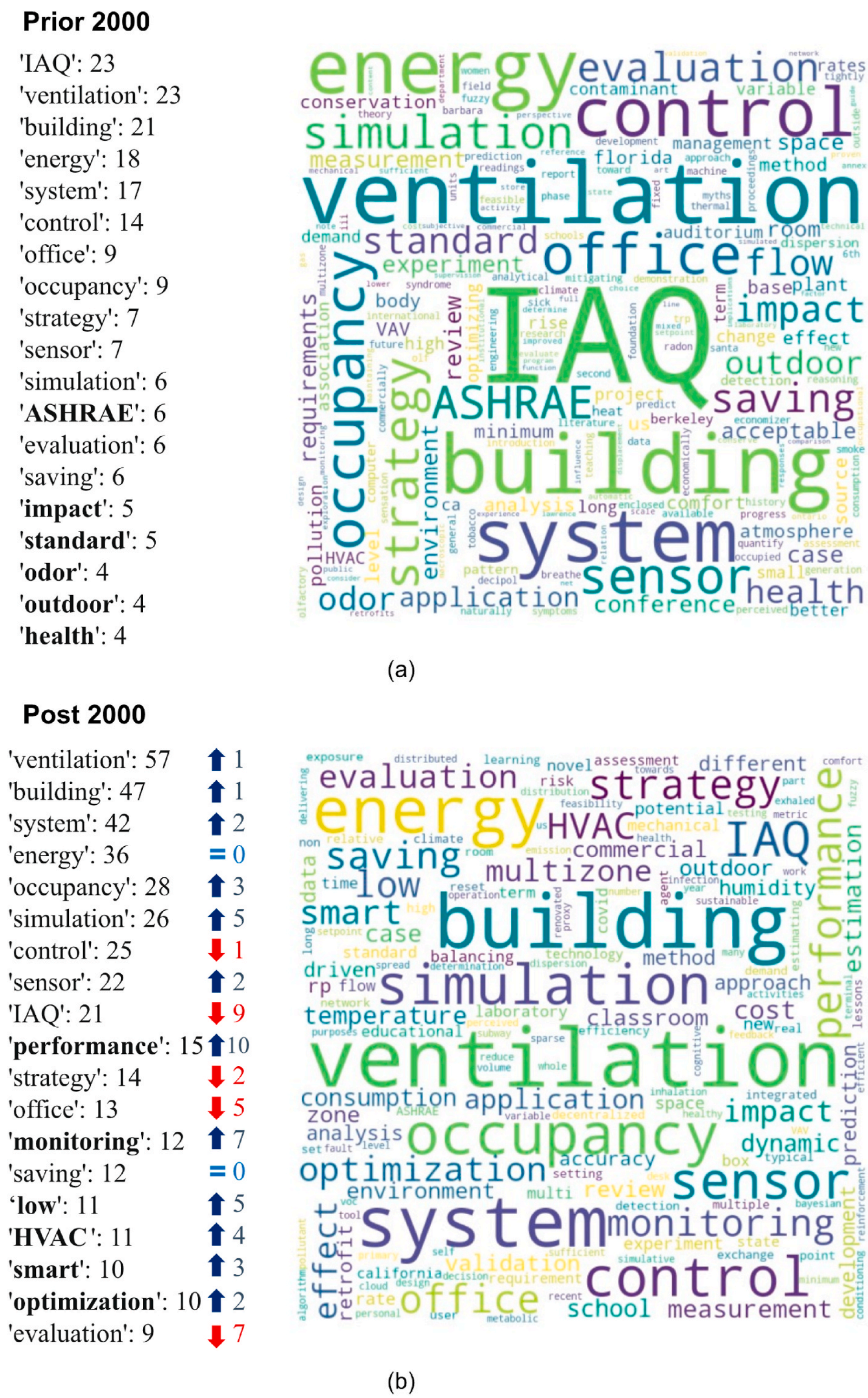

Fig. 3. Word clouds of the publication titles (a) before 2000 (b) after 2000.

4. Indoor CO_2 concentration and its influencing factors

The CO_2 concentration of a single zone could be generally computed from a simplified mass balance equation as shown in Eq. (1), where C_z, C_{oa}, P_z, 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. Solving Eq. (1) would yield to Eq. (2), where C_{ss} is the steady-state indoor CO_2 concentration (ppm). Based on Eq. (2), C_{ss} could be further calculated by Eq. (3).

$$V\frac{dC_z(t)}{dt} = P_z \cdot G + V_z \cdot C_{oa} - V_z \cdot C_z(t), \tag{1}$$

$$C_z(t) = C_{ss} + (C_z(0) - C_{ss})\, e^{-\frac{V_z}{V}t}, \tag{2}$$

$$C_{ss} = C_{oa} + \frac{10^6 G}{V_z / P_z} \quad , \tag{3}$$

It is noted that Eq. (1) is only applicable under specific circumstances and following assumptions: (1) the supply airflow is well-mixed with the

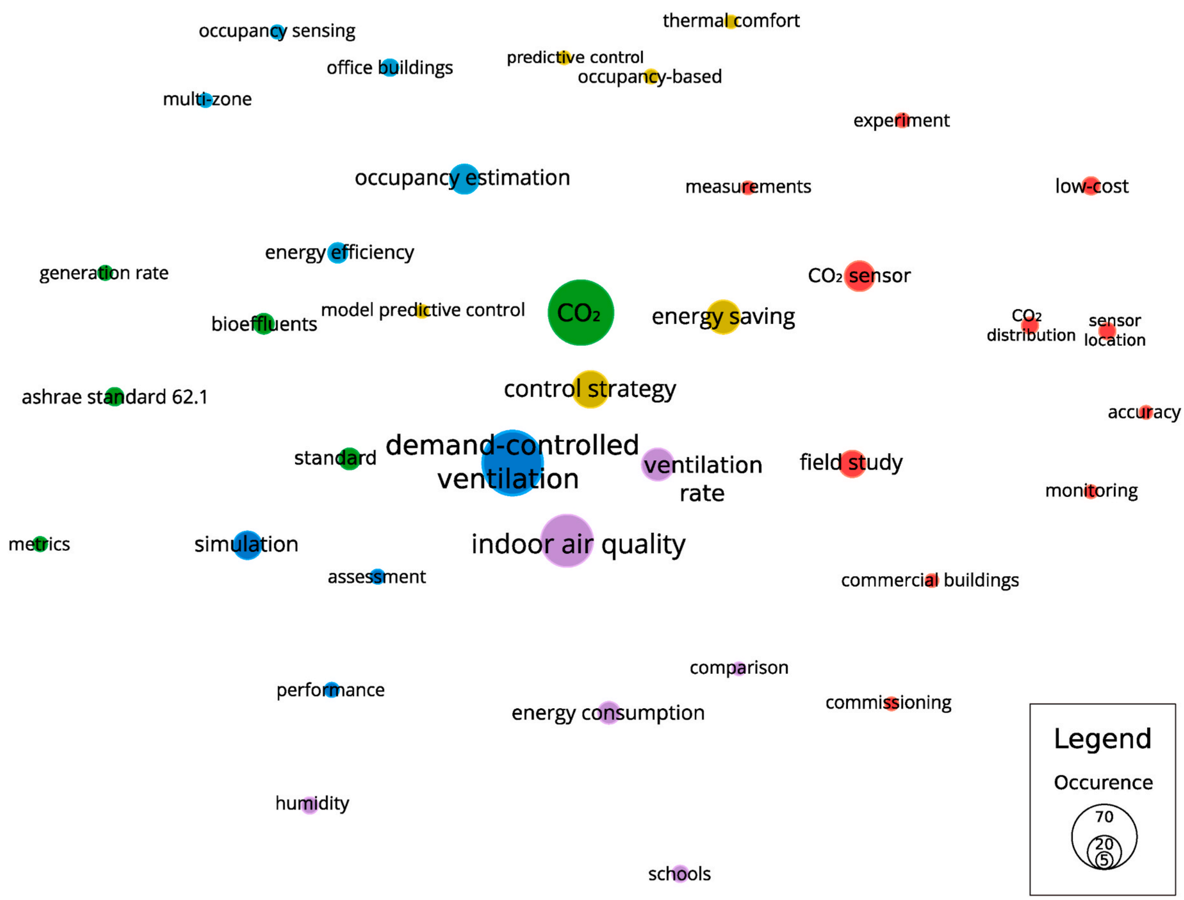

Fig. 4. Results of the keyword mining analysis based on the studies published after 2000.

indoor air; (2) the building occupants are the only invariant CO_2 production source and the indoor CO_2 is diluted only by the ventilation; (3) the infiltration (exfiltration) airflow and the airflow between the adjacent zones (when applicable) are neglectable; (4) the outdoor CO_2 concentration is constant. (5) the influence of the zone temperature on the CO_2 concentration is neglectable.

Recently, Persily et al. [29] proposed a metric based on the ventilation rate per person to estimate the indoor CO_2 concentrations in different ventilated space types at a given time, which was derived from Eqs. (2) and (3). An online tool [30] was developed to calculate both the steady-state CO_2 concentration, and the dynamic CO_2 concentration at the other time interval based on the space-specific inputs such as the ventilation rate per person, space geometry, and the occupancy according to ASHRAE Standard 62.1–2019 [9].

As presented in Eqs. (1)–(3), the indoor CO_2 concentration is closely related to the ventilation rate, occupant number, and CO_2 generation rate per person. These relationships are further discussed respectively in Sections 4.1-4.3. However, when it comes to the real operation in commercial buildings, other factors such as the transient nature of airflows inside the building, multi-zone layout, different ventilation schemes, and dynamic and stochastic occupant behaviors also deliver an influence on indoor CO_2 concentration distributions [31]. The issues related to the CO_2 concentration spatial distribution are detailed in Section 4.4.

4.1. Ventilation rate

As described in Eq. (3), the indoor CO_2 concentration is related to the ventilation rate per person. For example, in an office space, the steady-state CO_2 concentration of 1000 ppm corresponds to the design per-person ventilation rate of 8.5 L/(s·p) assuming that the outdoor air CO_2 concentration is 400 ppm and the CO_2 generation rate per person is 0.3 L/(min·person). However, it is noted that the ventilation rate per person usually changes with the zone occupancy and space type per requested by the updated ASHRAE Standard 62.1 ventilation rate procedure (VRP). The VRP prescribes minimum zone-level OA rates for different building space types and procedures to find system-level OA intake rates. Starting from ASHRAE Standard 62.1–2004, the minimum ventilation rate is calculated as the sum of the occupant- and area-related components (as shown in Eq. (4)). This leads to the issue that the relationship between the zone occupant number and the corresponding steady-state CO_2 concentration is nonlinear. Therefore, the use of a fixed CO_2 setpoint may not comply with the VRP [32], considering that the zone occupancy is usually dynamic in practice. In addition, the standard stipulates that different space types should have different design per-person ventilation rates, and thus the steady-state CO_2 concentration will be quite different from 1000 ppm [33]. The curve in Fig. 5, which is derived from Eq. (3), depicts the relationship between the per-person ventilation rate in different spaces and the steady-state CO_2 concentration. For a meeting room that is designed based on the updated ASHRAE Standard 62.1 VRP, the fixed CO_2 setpoint control of 1000 ppm would lead to the under-ventilation during the low occupancy period but over-ventilation under the design occupancy.

$$V_{bz} = V_{bz-P} + V_{bz-A} = R_p P_z + R_a A_z \quad , \tag{4}$$

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.

As noted, the steady-state CO_2 assumption is often invalid in real

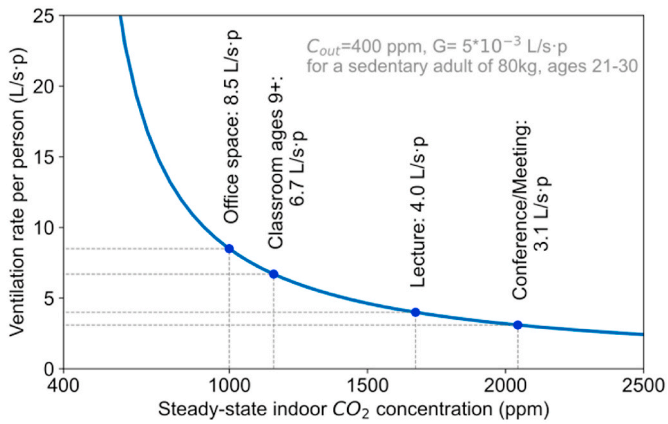

Fig. 5. Relationship of the per-person ventilation rate based on ASHRAE 62.1–2019 VRP [9] and corresponding steady-state CO_2 concentration.

building operations due to the dynamic supply airflow rate and occupant behaviors. As a result, the actual ventilation rate of a particular zone in a multi-zone ventilation system might not satisfy the code requirement. The problem of over-ventilation or under-ventilation is mostly owing to the potential air balancing issues between the zone terminals (e.g., improper zone terminal damper control). Zhao [34] compared several different outdoor airflow control sequences of a multi-zone VAV system in a 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 over-ventilation and under-ventilation 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. [35] developed a physical model for the airflow network using 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. [36] built a data-driven model for the duct branch system to control the damper's angle based on the desired airflow rate. The proposed black model did not require 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 over-ventilation problem.

Although the relationship between the indoor CO_2 concentration and ventilation rate is complicated in real building operations, many studies published in the last two decades still used CO_2 as a trace gas to estimate the ventilation rate and evaluate the ventilation performance. Chan et al. [37] used the steady-state method to estimate the per-person ventilation rate based on the daily maximum CO_2 concentration (measured in an interval of 15 min) for a multi-zone system with 94 classrooms in California, USA. The estimation results demonstrated that the 25 classrooms with CO_2-based DCV had good ventilation performances compared to the non-DCV systems. Oliveira et al. [38] estimated the ventilation rate of a single test room using the CO_2 concentration decay method. The results were in a good agreement with the air change rate (ACH) tests, with a coefficient of variation of 16.5% for an average ACH value of 0.55/h. Batterman et al. [39] reviewed different methods to determine the ventilation rate based on CO_2 sensing in classroom buildings. Four methods with relevant applications, including the steady-state, transient mass balance, build-up, and decay methods, were summarized. Their result suggested that if the accurate occupancy information was available, the transient mass balance method would provide the most accurate ventilation rate estimation compared to other methods. However, if the occupancy measurement was not available, the CO_2 concentration trends should be carefully examined to determine whether the steady-state or build-up method should be selected. Since different sources of uncertainties affect the estimation accuracy, Kabirikopaei [40] assessed the error propagation for three different methods, steady-state, build-up, and decay methods, in classroom buildings. The study shows that the steady-state method has the least uncertainty among the three methods. Considering different sources of uncertainties (e.g., measurement uncertainties), Hou et al. [41] applied Bayesian Markov Chain Monte Carlo method to estimate the ventilation rate using CO_2 sensors in school buildings. Macarulla et al. [42] used the stochastic differential equations based on the CO_2 mass balance to obtain the ventilation flow rates in a room by introducing uncertainty elements.

4.2. Occupancy level

Many studies have proven a strong correlation between the indoor CO_2 concentration and occupancy level. Meanwhile, they also pointed out that there could be a time delay for the change in CO_2 concentration with regard to the occupancy change. In practice, this time delay typically depends on the zone volume, zone airflow characteristics, and the relative distance of a CO_2 sensor and the CO_2 sources [43–48]. Meyn et al. [47] reported an average lag of 10–20 min for the CO_2 concentration change following an increase in occupancy among all the zones in a multi-zone office building. In contrast, Rahman et al. [49] saw a time delay of 30–45 min for six ventilation schemes, e.g., on-off control and proportional control. The time delay of the change in CO_2 concentration is mainly due to the CO_2 dispersion time rather than the sensor response time [49]. In a simulation-based study, Lu et al. [50] found that the lag of the change in CO_2 concentration is more evident in the space with a highly dynamic occupancy profile due to the diffusion and mixing mechanics of CO_2. Franco et al. [44] demonstrated the correlation between the CO_2 concentration and occupancy profiles through a synthetic variable defined as the zone volume available per person from the experimental data in classrooms.

Due to the potential correlation, numerous studies have been proposed to investigate estimating the zone occupancy using the CO_2 measurement, considering that the zone occupancy is a necessary input for some of the DCV control strategies. As one of the earliest studies, Ke et al. [51] determined the zone occupancy using both transient form and steady-state form of the CO_2 mass balance equation to facilitate building ventilation controls. The results showed that the transient equation followed the actual occupancy precisely with a time lag of approximately 3 min while the steady-state equation produced enormous errors. Using similar transient CO_2 mass balance equations, Calì et al. [52] conducted a CO_2-based occupancy estimation in two office buildings and one residential building. The predicted occupant number was imprecise with an average accuracy of 69% and the highest accuracy of 80.6% in the experiment, while the predicted occupancy presence was mostly accurate (i.e., the average accuracy of 88% and the highest accuracy of 95.8%). The results also suggested that the estimation was highly dependent on the input parameters such as the airflow rate through windows/inner doors/infiltration, and the outdoor CO_2 concentration. Similar approaches (i.e., the steady-state and transient mass balance equations) were also adopted by other studies [53–55].

Considering the significant uncertainties of some critical parameters such as the infiltration rate, Wolf et al. [56] proposed a stochastic differential method to estimate the room occupancy. This method is unique because a noise term was added to the mass balance equation to address the uncertainties of the infiltration airflow rate, inter-zonal ventilation airflow rate, and the sensor errors. Pantazaras et al. [57] constructed a CO_2 state-space model using the system identification method to estimate room occupancy. In spite of the innovation, the results of this method, however, showed that the state-space model had a worse performance compared to the transient physical-based model if the training data was limited. Jorissen [58] developed a detailed multi-zone airflow model in Modelica to estimate the zone occupancy with CO_2 sensor readings. Some uncertain parameters (e.g., the per person CO_2 generation rate) were tuned to make sure that the estimated occupancy matched the measured occupancy as closely as possible.

Apart from the aforementioned physical-based methods, the data-driven approaches were also widely studied to estimate room occupancy. For instance, Basu et al. [59] predicted the 15-min average occupant number in large classrooms as a function of indoor CO_2 concentration using the ensemble least squares regression. In the pre-processing stage, the task-driven sparse non-negative matrix factorization was used to denoise the CO_2 data for learning a non-negative low-dimensional representation. The proposed method estimated the exact occupant number with an accuracy level of only 15%. Alam et al. [60] developed a dynamic neural network model for the occupancy estimation. The estimation accuracy, which was evaluated with the normalized root mean square error (NRMSE), varied between 4% and 23%. The results suggested that the accuracy was heavily dependent on the frequency of the occupancy variations. Besides, the system factors such as the data sampling interval and sensor accuracy would also influence the estimation accuracy. Arief-Ang et al. [61] proposed several decomposition-based algorithms with a zero pattern adjustment to estimate the occupancy number using a single CO_2 sensor. This method was tested in an academic staff room with up to 4 occupants and a cinema theatre with up to 300 occupants. The testing results suggested that the proposed method had a high average accuracy level of approximately 90% for the low occupancy case compared to a modest average accuracy level of approximately 50% for the high occupancy case. Szczurek et al. [62] predicted the occupant number using a k-Nearest Neighbors (k-NN) algorithm from 60-min long segment datasets of CO_2 concentration. The results showed that the occupant number could be successfully determined with an accuracy level of 98% and a mean error of 0.5 person. However, how this method was performed in the case with a large occupant number, or a lower data sampling rate (less than 60 min) was not introduced. Taheri et al. [63] estimated the occupancy number using the predicted CO_2 concentration by the Multilayer Perceptron algorithm. Rahman et al. [64] explored a Bayesian Markov Chain Monte Carlo algorithm to recognize the number and distribution of occupants in a multi-room office building using indoor CO_2 concentrations. The presented inference-based approach did not require a large amount of data for model training in advance; instead, it only relied on a single type of environmental measurement, i.e., the indoor CO_2 concentration, for prediction. The results of a parametric study showed that the prior probabilities of input parameters such as the supply airflow rate, activity level of occupants, and outdoor CO_2 concentration all had an impact on the estimation accuracy, but the effects of these factors were not as significant as that of the uncertainty level of the CO_2 reading. The estimated occupancy conformed to the actual occupancy within a modest range (i.e., 43.5%) due to the fluctuations and uncertainty in CO_2 measurements and time delays in the dynamic Bayesian process [49].

While all of the studies reviewed above only used the CO_2 concentration as a sole predictor for the occupancy presence/occupant number, some recent studies started to investigate taking advantage of multiple environmental sensors, including CO_2 sensors, to serve this purpose. Meyn et al. [47] developed novel sensor fusion algorithms to further enhance the accuracy of occupancy estimation based on the information collected from the passive infrared (PIR) sensors and the digital video cameras, along with the CO_2 sensors. The results showed that the average accuracy of occupant counting could be increased from 30% to 79% with this algorithm. For the occupancy presence scenario, the sensor fusion algorithm based on motion detection and CO_2 measurements could enable the prediction accuracy to be improved from 54% to 98% [55].

Table 2 lists a summary of the case studies which investigated predicting the building occupancy based on CO_2 sensing. In general, the performances of these methods were relatively modest, rendering a huge potential for improvement. For the physical-based approaches, the estimated occupancy from the steady-state method had a significant delay, which led to a serious underestimation/overestimation for the

Table 2
Summary of the occupancy estimation studies using CO_2 sensing.

Reference	Year	Approach	Building Type	Simulation/ Experiment	Estimation Accuracy	Maximum occupancy	Occupancy estimation interval
[51]	1997	Physical-based (transient, steady-state mass balance equations)	Office/ Conference room	Simulation	Transient: Track well with the occupancy changes with a small time lag of 3 min; Steady-state: Large underestimation (up to 12.9 per·h) and overestimation (up to 6.3 per·h)	15/50 per	15 min
[47]	2009	Data-driven (Kalman-filter, sensor fusion of CO_2, motion, and video sensing)	Multi-zone office buildings	Experiment	Mean accuracy building level: 89% Mean accuracy zone level: 79%	20 per	10 min
[52]	2014	Physical-based (transient mass balance equations)	Office/ Residential building room	Experiment	Mean accuracy: 69%; Up to 80.6%	2 per	Don't know
[59]	2015	Data-driven (Ensemble Least Square Regression with data denoise pre-processing)	Classroom	Experiment	Accuracy: 15%	42 per	15 min
[58]	2017	Physical-based (detailed multi-zone airflow model)	Office	Experiment	Qualitatively the occupancy estimation agrees well with the measured values.	16 per	Continuous
[60]	2017	Data-driven (artificial neural network)	Office	Simulation	Normalized root mean square errors vary in 4%–23%	8 per	1 min
[61]	2017	Data-driven (decomposition-based method)	Staff room/ Theatre	Experiment	Mean accuracy for staff room: 90%; Mean accuracy for theatre: 50%;	4/300 per	1 min
[62]	2018	Data-driven (k-Nearest Neighbors classification)	Classroom	Experiment	Mean accuracy: 98%; mean error: 0.15 per.	9 per	60 min
[49,64]	2018	Data-driven (Bayesian Markov chain Monte Carlo algorithm)	Office	Experiment	Mean accuracy: 33%–45%	6 per	3 min
[53,57]	2018	Physical-based (transient mass balance equations); Grey-box (CO_2 state-space model)	Theatre	Experiment	Root mean square error for physical-based method: 12 per Root mean square error for grey-box method: 18 per	300 per	Don't know
[56]	2019	Grey-box (stochastic differential equations based on mass balance)	Office	Experiment	Root mean square error: 0.72 per	4 per	5 min

occupant number in a given space. In contrast, the transient methods could enhance the prediction accuracy under the condition where the uncertain parameters were properly determined. Multiple data-driven algorithms were investigated in the case studies, but it was found that the prediction accuracy was generally subject to the size of the dataset, as well as its sampling interval, occupancy profile, and uncertainty level of the CO_2 sensor. So far, there lacks a generalized method to estimate the occupant number with high accuracy for different scenarios. It is also noted that although some specific studies [62] could achieve an estimation accuracy as high as 98%, its estimation interval, however, was 60 min, which was far from satisfactory. Such a coarse interval made it nearly impossible to integrate this method into actual control applications.

4.3. CO_2 generation rate

The CO_2 generation rate from occupants in buildings is calculated using Eq. (5), which is related to the occupants' body size and their activity level. The CO_2 generation rate, for an average size ($A_D = 1.8\ m^2$) sedentary ($M = 1$ met) adult with a respiratory quotient (RQ) of 0.83, is about 0.005 L/s.

$$G = \frac{0.00276 A_D \cdot M \cdot RQ}{0.23RQ + 0.77} \tag{5}$$

where G is the CO_2 generation rate per person in L/(s·p); A_D is the DuBois surface area in m^2; M is the physical activity level in met. RQ is the respiratory quotient, which is the ratio of the volumetric CO_2 generation rate to the rate at which oxygen is consumed.

In the last decades, several new approaches have been proposed for estimating the CO_2 generation rate with detailed inputs. Tajima et al. [65] developed some equations based on the Japanese subjects' exhaled breath data, with factors such as the occupant's height, weight, gender, age, and physical activities being taken into account. Persily et al. [66, 67] proposed a new method for estimating the CO_2 generation rate with a thorough consideration of the impacts of the occupant characteristics. The method is derived from the principles of human metabolism and energy expenditure [30]. The considered factors include sex, age, height, weight, body size (body mass), fitness level, diet composition, etc., many of which were not considered in Eq. (5). Eq. (6) from Persily et al. [67] is a general form and Eq. (7) shows a special scenario under an air pressure P of 101 kPa and a temperature T of 273 K. This method has been described and integrated into the informative appendix ab to ASHRAE 62.1–2019 [8] but still pending a public review.

$$G = 0.000211 \cdot RQ \cdot BMR \cdot M \cdot \frac{T}{P}\ , \tag{6}$$

$$G = 0.000484 \cdot BMR \cdot M\ , \tag{7}$$

where BMR is the basal metabolic rate of the individual, which typically constitutes 45%–70% of the daily energy expenditure and is primarily a function of age, sex, body size, and body composition. In order to facilitate the use of these equations, Persily et al. [67] summarized the CO_2 generation rates of several typical space types in buildings as shown in Table 3. This table uses the default occupancy levels and outdoor air ventilation rates from ASHRAE Standard 62.1–2019 [8], and assumes air change rates for a dwelling, and *met* values from compendium [68].

As depicted in Fig. 6, the CO_2 generation rates are compared between the newly proposed NIST method and the method currently adopted by the ASHRAE [69] for different metabolism levels. ASHRAE Standard 62.1 currently uses a value of 0.0084 cfm/(met·p) to estimate the generation rate of CO_2. As shown in Fig. 6, the discrepancies between the two estimations vary significantly with the space type and metabolism level. The smallest difference is 0.85% for occupants in the lobby with a 1.4 metabolism rate while the largest difference exceeds 68% for occupants in a child's bedroom with a 2.0 metabolism rate. The values marked in *italics* in Table 3 are the cases with the smallest difference for a given space type between this new NIST approach and the ASHRAE method. Most of these smallest differences are less than 10% and are for the cases with a metabolism rate of 1, which is a typical value used in building applications. For the common space types in buildings such as office, conference room, lecture classroom, and residence, the discrepancies are 0.95%, 0.95%, 6.00%, and 0.95% with a metabolism rate of 1.2, 1.0, 1.0, and 1.0, respectively, which indicates the ASHRAE method is acceptable for these cases. These metabolism rate values are

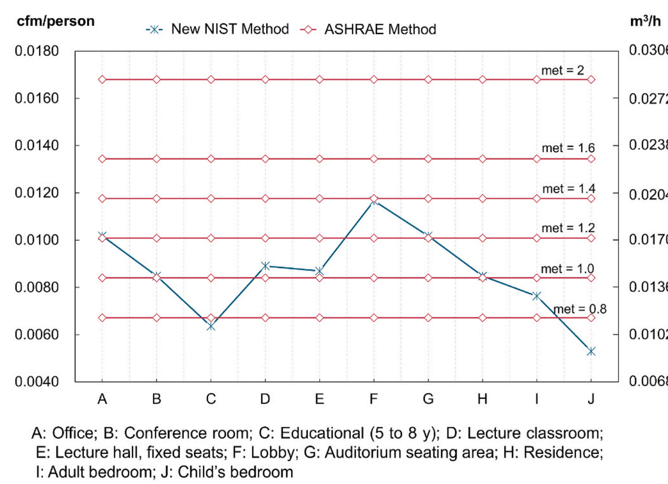

Fig. 6. The Comparison of the CO_2 generation rates calculated from the new NIST method and the current method adopted by ASHRAE [67].

Table 3
The Comparison of the CO_2 generation rates calculated from the new NIST method and the current method adopted by ASHRAE [67].

Space type	Average CO_2 generation rate (NIST)		Percentage differences between the CO_2 generation rates currently adopted by the ASHRAE handbook (0.0084 cfm/(p·met)				
	L/(s·p)	cfm/p	Met				
			1.0	1.2	1.4	1.6	2.0
Office	0.0048	0.0102	21.14%	*0.95%*	−13.47%	−24.29%	−39.43%
Conference room	0.004	0.0085	*0.95%*	−15.87%	−27.89%	−36.90%	−49.52%
Educational (5–8 y)	0.003	0.0064	*−24.29%*	−36.90%	−45.92%	−52.68%	−62.14%
Lecture classroom	0.0042	0.0089	*6.00%*	−11.67%	−24.29%	−33.75%	−47.00%
Lecture hall, fixed seats	0.0041	0.0087	*3.48%*	−13.77%	−26.09%	−35.33%	−48.26%
Lobby	0.0055	0.0117	38.81%	15.67%	*−0.85%*	−13.24%	−30.60%
Auditorium seating area	0.0048	0.0102	21.14%	*0.95%*	−13.47%	−24.29%	−39.43%
Residence	0.004	0.0085	*0.95%*	−15.87%	−27.89%	−36.90%	−49.52%
Adult bedroom	0.0036	0.0076	*−9.14%*	−24.29%	−35.10%	−43.21%	−54.57%
Child's bedroom	0.0025	0.0053	*−36.90%*	−47.42%	−54.93%	−60.57%	−68.45%

Note: This table is calculated at 273 K and 101 kPa for the selected spaces of interest.

commonly used for both building CO_2-based simulations and modelling.

A recent study showed that the per-person CO_2 generation rate was greater for the occupants doing cognitive tasks than those with relaxed activities [70]. This implies that the alternative method could also consider the psychological factors while determining the CO_2 generation rate.

4.4. CO_2 concentration spatial distribution

One limitation of Eqs. (1)–(3) is that they could only be applied to the well-mixed assumption. However, in reality, the actual indoor CO_2 concentration is usually unevenly distributed in the space under the mixed ventilation mode. This could be due to multiple factors such as the dynamic occupant movement and uneven air distribution, which could be caused by the diffuser location, thermal plumes, and temperature gradients. A good understanding of the indoor CO_2 concentration spatial distribution could provide helpful guidance on the optimal CO_2 sensor location.

However, only limited studies on this topic were reviewed in the NIST review paper [4]. Ruud et al. [71] conducted a test in the conference room. The results revealed that the CO_2 reading from the wall-mounted CO_2 sensors was nearly identical to the CO_2 concentrations measured at the room exhaust. However, the wall-mounted sensor reading was observed to have a shorter delay compared to the measurement of the exhaust air. The well-mixed CO_2 distribution in this study was achieved possibly because the design supply airflow rate as enforced by the building code was much higher 30 years ago. Another study [72] concluded that a good mixing could be achieved in the room with closed doors, and therefore the sensor location was not critical. But the testing was carried out in a residential room; hence the conclusion was less referenceable for the commercial DCV applications.

Over the last twenty years, simulation and field tests have been conducted to study the CO_2 concentration spatial distribution under different ventilation schemes. For the mixed ventilation (i.e. ventilation from ceiling diffuser), Mui et al. [73] measured the CO_2 concentration at 12 different locations in an office room with a VAV system. The room CO_2 concentration was controlled below a fixed setpoint. The results showed that 75% of the 12 locations had an acceptable CO_2 concentration, i.e., controlled below the setpoints. The largest deviation from the average CO_2 concentrations measured at the 12 locations at all sampling times was 24.8%. Fisk et al. [74] evaluated the spatial variability of CO_2 concentrations within six meeting rooms in a commercial building. The maximum CO_2 concentration deviations from the space average at different spots are 14.7%, 6.9%, 4.0%, 7.8%, 3.8%, and 13.9%, respectively for six different meeting rooms. The results also suggested that the measurement at return-air grilles may be preferred to the measurement at wall-mounted locations because the CO_2 concentrations at return grilles did not vary much. Rackes [75] studied the spatial variation of CO_2 concentration in a typical office setting using the CONTAM simulation. The results suggested that the spatial variation was not large in the case study; hence the authors stated that improving the CO_2 sensors accuracy is perhaps more important than capturing the spatial distribution. Instead of using the zonal model as Rackes [75] did with CONTAM, Pei et al. [76,77] used the Computational Fluid Dynamic (CFD) tool to study the spatial distribution of CO_2 in a building with the DCV system. In this study, multiple influencing factors such as the ventilation system (displacement vs. mixing), air change rate, and occupant densities were considered in the simulation. For the mixed ventilation, the horizontal and vertical CO_2 distributions were fairly uniform, while for the displacement ventilation, the CO_2 stratification was obvious with the high occupancy scenario. Melikov [78] measured the CO_2 concentration in a meeting room at both the room exhaust and locations near the occupants. A difference of 20% was found in the average CO_2 concentration. A testing conducted by Pantelic et al. [79] showed that the concentration surrounding a single occupant was around 200–500 ppm higher than the background CO_2 concentration.

We also conducted field testing in a large office room located on the campus of an American university during July 27th and August 7th, 2020. Due to the Coronavirus disease 2019 (COVID-19) pandemic, the occupancy density of the office was extremely low (approximately 4 people for an area of 210 m^2). The CO_2 concentrations at various locations were collected from four ExTech CO210 sensors (i.e., Sensor 2, 5, and 7), three HOBO MX1102A sensors (i.e., Sensor 1, 3, 4, and 7), and two CO_2 sensors installed at the return vent with readings available from the building automation system (BAS). The ExTech CO210 sensor has a detection range between 0 and 9,999 ppm, with an accuracy level of $\pm$ (5% of reading + 50) ppm and resolution of 1 ppm; while the HOBO MX1102 sensor has a detection range between 0 and 5000 ppm, with an accuracy level of $\pm$ (5% of reading + 50) ppm and resolution of 1 ppm. All the sensors were calibrated before deployment. The layout of the office room, locations of the CO_2 sensors and supply/return vents, and the CO_2 measurement results were presented in Fig. 7. As shown, the CO_2 concentration was highly unevenly distributed depending on the location of the sensor. On August 5th, 2020, the percentage difference of the maximum and minimum CO_2 concentration could vary from 6% to 24%.

Table 4 summarizes some studies of investigations on the indoor spatial variability of CO_2 concentration. It is concluded that the CO_2 distribution is closely related to the ventilation control scheme, occupancy level, and air change rate per hour (ACH). As summarized from the case studies, for the mixed ventilation, the CO_2 concentration deviation from the space average or between the measurement points was generally smaller than 20% under a higher ACH, except for the space that was closely prominent to the occupants. Non-uniform spatial distribution of CO_2 was mostly observed for the cases with a low ACH and/or large room volume. Several studies [4,73,74,76,77,80] indicated that the CO_2 concentration near the exhaust grille (or return vent) could represent the breathing zone concentration with a reasonable accuracy. For the displacement ventilation, a vertical CO_2 stratification was highly likely to occur, with the dividing height highly sensitive to the occupancy level. The CO_2 concentration at the intake of the return/exhaust duct was much higher than that of the breathing zone for this type of ventilation scheme.

5. The nexus of CO_2 concentration and ventilation demands

In this section, the potential of using CO_2 as an indicator for different ventilation "demands" is discussed. Section 5.1 elaborates on why and how the CO_2 concentration could serve as an indicator to control the odor under a certain level due to its proven correlation with the bioeffluents. Section 5.2 reviews the correlation studies of CO_2 concentration with the other common indoor contaminants besides the bioeffluents.

5.1. Bioeffluent

Bioeffluent, which is the byproduct of human metabolism, is the most primary "demand" in the CO_2-based ventilation controls. In as early as the mid-1800s, Pettenkofer [83] first discovered that the bioeffluents generated by occupants could cause IAQ issues in the indoor space. In a recent study, Zhang et al. [84] conducted comparative experiments and concluded that the moderate concentration of bioeffluents, but not sure whether CO_2, was the actual cause of deleterious effects on occupants during typical indoor exposures. In one experiment, the exposure of occupants to a high CO_2 concentration at or below 3000 ppm did not exert significant effects on perceived air quality, acute health symptoms, or cognitive performance. In contrast, in another comparative experiment, a much higher bioeffluent concentration and CO_2 concentration (over 3,000 ppm), which were resulted from a reduced ventilation rate, had significantly deteriorated the perceived air quality, aroused acute health symptoms, and worsened the cognitive performance. It is noted that currently there is a controversy on whether

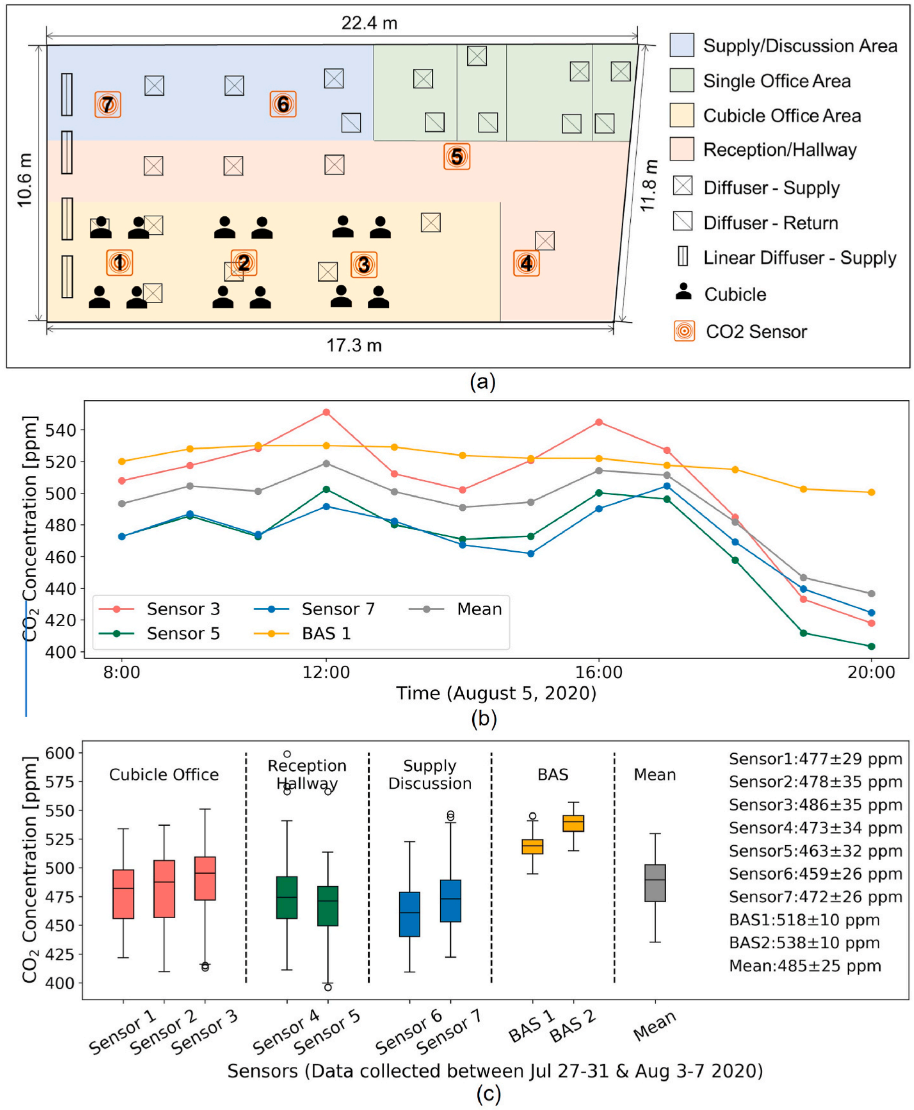

Fig. 7. (a) The layout of the office room and the locations of the CO_2 sensors and supply/return vents; (b) The hourly CO_2 distributions of four selected sensors on a given day; (c) The boxplots of the hourly CO_2 concentrations of the nine sensors for ten days.

the CO_2 itself should be considered a pollutant that affects human cognitive performance and decision making at a certain concentration level [85–87]. Some studies [87–90] find effects of higher CO_2 concentrations (between 1000 and 5000 ppm) on the cognitive performance while other studies [91–93], where confounding factors were controlled, find no effects on this outcome. Considering CO_2 is commonly associated with other bioeffluents that may have effects on health, it is challenging to verify whether CO_2 itself is directly responsible for the health effects [19,94].

The criterion for per-person ventilation rate required in ASHRAE Standards 62.1 is mainly based on the perception of the odor with an 80% occupancy satisfaction [43]. Many sources have indicated that a ventilation rate of about 7.5 L/s per person could control the human body odor effectively, such that 80% of the occupants would find it acceptable [4,18,95]. When the outdoor CO_2 concentration is 400 ppm, the odor acceptability level corresponds to an equivalent steady-state CO_2 concentration of 1050 ppm, which is commonly used as a control limit.

As the most primary “ventilation demand”, the bioeffluents can be indirectly controlled by the CO_2 concentration owing to the assumption that the CO_2 generation rate is roughly proportional to the odor generation rate. Lin et al. [43] evaluated the validity of this underlying assumption through a comprehensive literature review. The conclusion was that this relationship is valid and independent of the level of physical activities and the steady-state assumption [18]. Based on this correlation, the indoor CO_2 concentration can be used as a signifier or a proxy to maintain an acceptable bioeffluent concentration in a CO_2-based DCV. As mentioned in Section 4.2, the steady-state CO_2 equation is often used to estimate the zone occupancy in CO_2-based DCV strategies. 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 equation is effective to calculate the required OA flow rate to maintain an acceptable level of bioeffluent concentration. In other words, while the required airflow based on the steady-state equation does not exactly track the source strength of bioeffluents due to transient effects, it generally guarantees an acceptable bioeffluent concentration [96,97]. On the contrary, for the ventilation reset strategies from direct occupant counting sensing technologies [98] (known as occupancy-centric control (OCC) [99]), the ventilation performance regarding the bioeffluent concentration still largely unknown, although these strategies react to the occupancy level faster. For example, when people just stay in a room for a short period, the bioeffluent concentration or CO_2 concertation may not be varied much, which will not trigger any HVAC system reaction in CO_2-based

Table 4
Summary of the indoor CO_2 concentration spatial distribution.

Reference	Year	Simulation /Experiment	Ventilation Scheme	Building type	Occupancy Profile	Room Volume (RV)/Ventilation Rate/Air Change Rate Per Hour	CO_2 Concentration Deviations[a]
[73]	2005	Experiment	Mixed ventilation (MV)	Office room	High occupancy density	ACH = 0.6–1/h	24.8%
[74]	2010	Experiment	Mixed ventilation	Six meeting rooms	High occupancy density	RV = 46–160 m^3	3.8–14.7%
[81]	2010	Experiment	Mixed ventilation	Experimental chamber	4 m^2/per	RV = 17.75 m^3; ACH = 0.72–1.61/h	3.3–5.7%
[75]	2017	Simulation	Mixed ventilation	Four office rooms	22 m^2/per	ACH = 1.5–5/h	4–13%
[38]	2019	Experiment	Natural ventilation	Experimental chamber	Don't know	RV = 32.4 m3 ACH = 0.55%	Within 10%
[76,77]	2019	Simulation	Mixed ventilation; Displacement ventilation	Office room	Low/high occupancy density (18/3.6 m^2/per)	RV = 55 m^3; ACH = 2.5,5/h	DV: 7–20% MV: 2–5%
[78]	2019	Experiment	Mixed ventilation	Meeting room	High occupancy density (2 m^2/per)	RV = 50 m^3; ACH = 4/h	19.5%
[82]	2020	Experiment	Natural ventilation	Office room	Don't know	ACH is small	50%
[79]	2020	Experiment	Mixed ventilation	Office room	One person in the room	RV = 77 m^3; ACH = 4/h	31–77%
N/A	2020	Experiment	Mechanical ventilation	Office room	Low occupancy density (due to COVID19)	ACH = 0.25–0.4/h	6%–24%

[a] Please be noted that there currently lacks a scientific and validated index to measure the uneven CO_2 concentration spatial distribution. The case studies summarized in this table used different indexes to quantify the spatial variability (e.g., CO_2 concentration deviations from the space average, CO_2 concentration deviations between different measurement points, etc.); hence the results should only be considered a qualified reference and could not be used for a quantified apples-to-apples comparison.

DCV. However, if the OCC does not consider the delay, the HVAC system with OCC will act differently.

5.2. Other contaminants

The relationship between the concentrations of CO_2 and other contaminants mainly depends on whether the sources of the other contaminants are occupant-related [4]. In other words, the indoor CO_2 concentration may not provide any useful information on the concentrations of occupant-independent sources. Many recent studies have investigated this limitation on the use of CO_2-based DCV for such a purpose.

Table 5 summarizes the relationship between the CO_2 concentrations and other contaminants obtained through the field studies. The contaminants being investigated included the volatile organic compounds (VOC), nitrogen dioxide (NO_2), radon, PM2.5 (particles less than 2.5 µm in diameter), and trihalomethanes (tTHM). Szczurek et al. [100] measured the CO_2 concentrations and total volatile organic compounds (TVOCs) in a university classroom. A correlation analysis was conducted to examine the relationship in a timespan of one day and 30 min. The results showed that there were no obvious or constant relationships between CO_2 concentrations and TVOCs for both scenarios, which indicated that the CO_2 concentration could not convey any information about the TVOCs. Nevertheless, Han et al. [55] found a strong connection between the CO_2 measurements and the volatile organic compound (VOC) concentrations from several tests in an office building where the occupancy-based ventilation control was deployed. Although this finding might be case-specific, it showed a potential to reduce the need for expensive VOC monitoring equipment in terms of IAQ control during a regular building operation. Afroz et al. [101] also reported that the VOC concentrations measured in several university library rooms largely followed the trend of CO_2 concentration in a one-year field study. The possible reason for these two studies with a confirmed correlation of CO_2 and VOC is that the VOC concentration is implicitly associated with

Table 5
Summary of the relationship of indoor CO_2 concentration and other contaminants in field studies.

Contaminant Type	Reference	Year	Building Type	Measurement Period	Data Interval	Correlation Statement
VOC/TVOC	[100]	2015	University classroom	9 days in winter	30 min; 1 day	• The co-variation of CO_2 and TVOCs measurements conveyed different information about IAQ as a function of time.
	[55]	2020	Office	7 a.m.-5 pm in 3 days	1 min	• A strong link between CO_2 measurements and VOC concentration profiles was found in several tests.
	[101]	2020	University library	1 year	5 min	• The VOC concentration largely follows the trend of CO_2 concentration despite the fact that concentration levels are not the same. • A reasonable positive relationship exists in different zones.
	[102]	2020	Office	6 months	1 h	• A weak positive correlation was seen between CO_2 and TVOCs.
NO_2	[102]	2020	Office room	6 months	1 h	• This relationship between increased ventilation and higher ingress of NO_2 can be observed. • A weak negative correlation was seen between CO_2 and NO_2.
tTHM	[103]	2020	Swimming facility	Occupied hours in 7 days	20 min	• A statistically significant relationship was found between the two (Pearson's correlation equals to 0.38), but this relationship is far from linear.
Radon	[111]	2004	Lecture theatre	1 day	30 min	• An inverse relationship between CO_2 and radon is seen when CO_2-based DCV is deployed.
	[112]	2020	University classroom	1 day	30 min	• A weak negative relationship between CO_2 and radon was identified.
Particles	[113]	2020	Primary school classroom	1 day	30 s	• No statistical relationship between CO_2 and PM2.5 was seen on the observation day.

occupancy level, e.g., through the usage of VOC-originated products. Stamp et al. [102] conducted long-term IAQ monitoring in an office building and observed a weak positive correlation between CO_2 and TVOCs. Apart from the correlation with VOCs/TVOCs, the relationship of the indoor CO_2 concentrations of and NO_2 was also investigated in this research. A weak negative relationship was identified due to the ingress of the NO_2 from the outdoor with increased ventilation. Nitter et al. [103] investigated the correlation between the CO_2 concentration and trihalomethanes (tTHM) concentration in a swimming pool facility. A statistically significant relationship was found between the two concentrations (Pearson's correlation equals 0.38), but this relationship was far from linear.

Besides, the indoor CO_2 concentration was also used as a proxy for the infection risk of COVID-19 and other respiratory diseases in the indoor space [104–106]. In these studies, the indoor CO_2 concentration acted as an indicator of rebreathed fraction of indoor air (i.e., the fraction of inhaled air that was exhaled by someone else in the space). However, there are a few assumptions for using this correlation due to the distinct characteristic of the CO_2 and virus-latent aerosols [107]. For example, the pathogen particle is more likely to lose infectivity in aerosols, while CO_2 is only lost to ventilation. In addition, the virus-containing particles are only emitted by the infected person while everyone emits CO_2. Based on some HVAC operation guidelines during the COVID-19 pandemic [108–110], the CO_2-based DCV system are recommended to be disabled during an epidemic [108,109] or overruled to force the ventilation system to operate at full speed (e.g., reset the CO_2 setpoint to 400 ppm [110]).

6. The impacts of the CO_2-based DCV on IAQ

In Section 6.1, how the CO_2-based DCV impacts the concentration of the indoor air contaminants, as well as the selection of an appropriate sensor fusion algorithm, is discussed. Section 6.2 talks about the impact of CO_2-based DCV on indoor humidity control.

6.1. Indoor air contaminants

Although the CO_2 concentration is not a good indicator for the major indoor contaminants that are unrelated to the occupants, the impacts of the DCV on these contaminants were investigated in both simulation-based studies and field tests. Table 6 shows a summary of the CO_2-based DCV impact on the indoor air contaminants.

Rackes [114] investigated the impact of DCV on different indoor air contaminants through a Monta Carlo simulation across six cities in the U.S. office buildings. The inputs to the IAQ model (e.g., emission rate, infiltration rate, etc.) were randomly selected from the distributions that characterize real U.S. offices. The results showed that the DCV had a minor influence on ozone or particles due to the large non-ventilation loss mechanisms. However, the DCV had a significant impact on VOCs, especially in colder climates, due to a lower average infiltration rate. De Jonge et al. [115] investigated the impact of a DCV system on the indoor VOC levels in an apartment using the dynamic VOC model in CONTAM [116]. The simulation results showed the total yearly dose of exposure to VOC was 10% higher in the DCV case than that of the conventional ventilation case.

Gram et al. [113] field investigated the impact of DCV on indoor contaminants in a primary school. The field measurements showed that the concentration of formaldehyde exceeded the limit recommended in guidelines during lunchtime and non-operating hours. The formaldehyde level only came to a normal range when the ventilation airflow rate was increased, which indicated that the formaldehyde was generated indoors. The formaldehyde concentration was thus recommended as a marker for DCV control along with the CO_2 concentration to ensure that the occupant-generated and non-occupant-generated pollutants could both be controlled simultaneously. Besides, the PM2.5 level measured in the classrooms was mostly very low. No correlations between the indoor PM2.5 level and ventilation airflow rate were found, except for a period with an unusually high outdoor PM2.5 level. Therefore, it is not recommended to involve the PM2.5 sensor for DCV control in primary schools if the outdoor PM2.5 level is low. Another field study in a university auditorium [117] revealed that the increase in PM10 and TVOC concentrations was insignificant when the ventilation rate was reduced to 50% of the design level. However, considering that the ventilation rate could be reduced to an even smaller value in a DCV application, whether this conclusion would still be true under the extremely low-ventilation scenario is yet to be verified.

6.2. Humidity

Some studies also look into the impact of the DCV on the indoor humidity level. Schibuola et al. [119] checked the relative humidity level in a university library with a CO_2-based DCV system in Venice, Italy. The results suggested that the DCV only had a small negative impact on the indoor humidity level. During the whole-year monitoring,

Table 6
Summary of the DCV impact on the indoor air contaminants.

Contaminant Type	Reference	Year	Building Type	Simulation/ Field Test	Impacts
Formaldehyde	[113]	2020	Primary school classroom	Field test	• Formaldehyde concentration exceeds the guideline limit outside the operating hours or within the operating hours during lunchtime.
VOC/TVOC	[118]	2003	Office, classroom, conference room, lecture hall, fast food restaurant	Simulation	• The indoor VOC levels increased by a factor of two to three, but the absolute concentrations were still relatively low based on the assumed emission rates.
	[114]	2013	Office	Simulation	• TVOC daytime means increased by 7–10% and peaks increased by 10–14%, depending on the city.
	[115]	2019	Apartment	Simulation	• The total yearly dose of exposure of the simulated VOC is 10% higher than the conventional ventilation system.
	[117]	2020	University auditorium	Field test	• The increase of TVOC concentrations is insignificant when the ventilation rate is reduced from 100% to 50%.
Particles	[113]	2020	Primary school classroom	Field test	• No significant impacts were seen on the PM2.5 and its concentration in the classrooms is mostly very low
	[114]	2013	Office	Simulation	• In most cases, implementing DCV uniformly decreases PM2.5 and PM10 daytime means and peaks, with median decreases of about 3–4%.
	[117]	2020	University auditorium	Field test	• The increase of PM10 concentrations is insignificant when the ventilation rate is reduced from 100% to 50%.
Ozone	[114]	2013	Office	Simulation	• The impact on the ozone concentration differences is small and no more than 5 ppb at the median level for either peak or mean.

the indoor relative humidity level fell in the range of 40–60% for 97% of the time in summer and for 90% of the time during winter. In contrast, a field study carried out in Minnesota, U.S., showed an improvement in the indoor humidity control achieved by the CO_2-based DCV by analyzing the BAS data and conducting a survey on occupant's perspectives on the indoor humidity [120]. Generally, in the climate zone where outdoor air plays a dominant effect on the indoor relative humidity (i.e., driving the relative humidity down in winter and up in summer), reducing the outdoor airflow rate could moderate its impact on the indoor humidity level.

7. Concluding remarks and future directions

This review covers important and urgent topics regarding the nexus of the indoor CO_2 concentration and ventilation "demands" underlying the CO_2-based DCV in commercial buildings, but also identifies many limitations with potential improvement suggestions for further research. The conclusions and future directions are summarized in the following sections.

7.1. Conclusion remarks

This paper first gives a direct overview of how this technology involves. The changes of building codes and standards related to CO_2-based DCV in the last forty years were presented. In addition, a bibliometrics analysis was conducted to identify the major working scope as well as the research trends at different times. The top ten topics in the last two decades are "CO_2," "Demand-controlled ventilation," "indoor air quality," "control strategy," "energy saving," "ventilation rate," "simulation," "field study," "CO_2 sensor" and "occupancy estimation."

In Section 4, we reviewed the publications regarding the fundamental updates for the indoor "CO_2" concentration. The relationship of the indoor CO_2 concentration and its major influencing factors such as ventilation rate, occupant CO_2 generation rate, and occupancy level are discussed. The characteristic of CO_2 concentration spatial distributions in different scenarios is summarized. The major takeaways are summarized as follows, and these fundamental updates are critical for developing the CO_2-based DCV in commercial buildings.

- After the version of ASHRAE Standard 62.1–2004 VRP, the ventilation rate per person changes with the building occupancy, which leads to the corresponding steady-state CO_2 concentration having a nonlinear correlation with the number of occupants. Therefore, using a fixed CO_2 setpoint may not be code compliant for the VRP since it could only satisfy the requirements at a single occupancy level.
- Whether the required ventilation rate could be achieved for terminal zones in the multi-zone systems depends on the zone terminal local airflow controls.
- The ventilation rates could be estimated based on CO_2 sensing using different methods, including the steady-state, transient mass balance, build-up, decay, and Bayesian inference methods. Different methods have distinctive application scenarios and existing studies have provided certain guidance on how to select the method. For example, the steady-state method should only be applied after the CO_2 levels reached an equilibrium concentration. The transient mass balance method needs accurate occupancy information. The build-up method requires a stepwise increase in occupancy and is always sensitive to the selection of time period. In order to accurately estimate the ventilation rates from CO_2 sensing, one needs to carefully evaluate the CO_2 and occupancy data fidelity (such as availability, interval, noise), and then select the appropriate estimation methods based on the applicable conditions.
- Apart from the physical-based methods, the data-driven methods and grey-box methods are developed to estimate the occupant number from the CO_2 sensing. However, there are no generalized methods to estimate the occupancy number with high accuracy for different scenarios.
- New approaches for estimating the occupant CO_2 generation rate were proposed. The new NIST approach is promising, which considers more influencing factors, including sex, age, height, weight, body size (body mass), fitness level, diet composition. In addition, the input parameters such as body size are easy to estimate than the body area in the old approach. A comparison of the new NIST approach and conventional ASHRAE method is presented. The discrepancies between the new and ASHRAE methods are minor for the common space types in buildings such as office, conference room, lecture classroom, and residence.
- The uneven distribution of CO_2 concentration in space has been noted in many case studies. This issue is usually related to room geometry, ventilation scheme, occupancy level, and air change rate. For the mixed ventilation mode, the CO_2 concentration deviation from the space average or between the measurement points is generally less than 20% under a higher ACH except for the area closely prominent to the occupants. Non-uniform spatial distributions of CO_2 were observed with low airflow rates and large room volumes

In Section 5, we reviewed the publications on whether CO_2 could represent all the ventilation "demands." The salient conclusions are listed as follows:

- The bioeffluents can be indirectly controlled by the CO_2 concentration owing to the assumption that the CO_2 generation rate is roughly proportional to the odor generation rate. The main purpose of CO_2-based DCV is to maintain the bioeffluent concentration using CO_2 concentration as an indicator. Despite the relatively low prediction of physical-based steady-state models, the steady-state equation is often used in CO_2-based DCV strategies and an acceptable level of bioeffluent concentration could be achieved.
- While indoor CO_2 concentrations are associated with the perception of human bioeffluents and the level of acceptance of their odors, they do not provide an overall indication of IAQ, especially for the cases where the major indoor contaminants are unrelated to the occupants. As noted by the recently released ASHRAE position document on indoor CO_2 [21], CO_2 is not a good indicator of IAQ, nor any other concentration. The correlation statements of the CO_2 concentration and contaminants are summarized in Table 5. In particular, the impact of the DCV on the volatile organic compounds (VOC) concentration is large. Due to the bioeffluents emitted by humans and the other VOCs from human activities, VOC sensors might be correlated with the occupancy while containing the information from the non-occupant contaminant sources. Therefore, the sensor fusion of CO_2 and VOC sensors might be a promising direction for addressing this limitation. The sensor fusion hardware and software need to be developed for optimizing IAQ levels [121]. Another research question arising from this is how much energy saving could be reduced by further controlling those non-occupant related contaminants. Preliminary work has been done for the residential buildings [122,123], but the answers for the commercial buildings are largely unknown.

In Section 6, we summarized the impacts of the CO_2-based DCV on the IAQ. The key takeaways are outlined as follows:

- The impacts of DCV on different containments are different. The impact on the VOC/TVOC is larger than the particles and ozone, probably due to the large non-ventilation loss mechanisms of the latter.
- The impact of DCV on the humidity level seems not obvious from the existing case studies.

7.2. Future directions

- Compared to the VRP, the fixed setpoint CO_2-DCV could result in over-ventilation when the zone occupancy is high and under-ventilation when the zone occupancy is low. Further investigations should be conducted to study whether non-compliance with the standard in different occupancy levels leads to potential side effects (e.g., energy waste, IAQ and health related issues) using the fixed setpoint CO_2-DCV.
- Although the ventilation rate could be estimated from CO_2 sensing with different approaches, it is noted that most of the existing methods do not consider the uncertainties such as the measurement errors and CO_2 generation rate. Therefore, future work should be conducted to facilitate a better understanding of the uncertainties associated with different estimation methods and develop novel estimation methods that are robust under different sources of uncertainties.
- The uneven CO_2 distribution increases the uncertainties in the design and operation of the CO_2-based DCV. Considering that only a limited number of CO_2 sensors will be installed per zone in practice due to the cost, there is a need for more in-depth research to provide detailed guidance of optimal CO_2 sensor locations in different scenarios. Experiments should be conducted to assess the potential impacts from this uncertainty on the operation of the CO_2-based DCV.
- The ventilation reset control strategies from direct people counting sensing technologies have been a research hotspot recently. Although these strategies could react to the dynamic occupancy faster than the CO_2-based DCV strategies and bring potential energy savings, the ventilation performance (e.g., maintaining an acceptable bioeffluent level) is still largely unknown. There exist limited comparative studies between the CO_2-based DCV strategies and the DCV strategies from people counting using other sources. Future research needs to compare the energy-saving potential and ventilation performance of DCV using these two types of sensing technologies.
- It is still no clear how CO_2 itself is linked with health effects at low concentration levels. Although some studies show CO_2 might not be the direct pollutant causing the deleterious effects on occupants, this topic is still controversial in the literature and requires additional fundamental research. Confounding factors should be measured or controlled to identify whether CO_2 itself is directly responsible for the health effects [19].

7.3. Next step

DCV control and operation strategies, associated sensor technologies (e.g., CO_2 sensor, airflow sensor), and performance evaluation are also critical topics in CO_2-based DCV as identified from keyword mining in Section 3. In an ongoing work [124], we have extended our review to CO_2-based DCV control strategies with a focus on:

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

CRediT authorship contribution statement

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

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