Energy Reports 8 (2022) 7523–7536

Contents lists available at ScienceDirect

Energy Reports

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

Review article

A systematic literature review on smart and personalized ventilation using CO_2 concentration monitoring and control

Ge Song [a], Zhengtao Ai [a], Zhengxuan Liu [a,b,*], Guoqiang Zhang [a,**]

[a] College of Civil Engineering, Hunan University, Changsha, Hunan, 410082, China
[b] Faculty of Architecture and the Built Environment, Delft University of Technology, Julianalaan 134, 2628 BL, Delft, The Netherlands

ARTICLE INFO

Article history:
Received 21 March 2022
Received in revised form 30 April 2022
Accepted 23 May 2022
Available online 11 June 2022

Keywords:
Personalized ventilation
Smart control
CO_2 concentration
Thermal comfort
Energy saving

ABSTRACT

Smart and personalized ventilation systems have been demonstrated with high performance in creating a healthy and energy-efficient indoor environment, but they have been rarely comprehensively summarized and explored in previous studies. With the progressive development of various terminal devices and control technologies, personalized ventilation based on intelligent control is potentially a promising way to achieve efficient control and energy savings in human micro-environments. This study comprehensively summarizes and analyzes the recent studies and common utilization forms of smart ventilation and PV systems that are based on CO_2 concentration control, to pave path and provide some guidelines for their integration application for reducing energy consumption and improving indoor thermal comfort. Research shows that the combination of personalized ventilation and smart ventilation is an essential development for ventilation systems. Smart ventilation with demand control logic based on CO_2 concentration has been mature enough to effectively improve the effectiveness and comfortable performance of personalized ventilation. However, switching from traditional air conditioning systems to personalized ventilation still requires improved sensors and intelligent control algorithms. In addition, this paper also summarizes the exploratory studies and potential application analysis of machine-learning theories to improve intelligent control of personalized ventilation. To this end, this paper identifies future tendencies for advanced theories, integrated systems, and devices in personalized ventilation systems.

Contents

* Corresponding author at: College of Civil Engineering, Hunan University, Changsha, Hunan, 410082, China; Faculty of Architecture and the Built Environment, Delft University of Technology, Julianalaan 134, 2628 BL, Delft, The Netherlands.
** Corresponding author at: College of Civil Engineering, Hunan University, Changsha, Hunan, 410082, China.

E-mail addresses: zhengxuanliu@hnu.edu.cn, Z.liu-12@tudelft.nl (Z. Liu), gqzhang@hnu.edu.cn (G. Zhang).

https://doi.org/10.1016/j.egyr.2022.05.243

1. Introduction

The potential risks of disease transmission using the conventional heating, ventilation and air conditioning (HVAC) systems cannot be overlooked under the current situation of infectious diseases (Guo et al., 2021). In recent years, a plenty of studies have been conducted to decrease these transmission risks (Ding et al., 2020; Faulkner et al., 2022). However, most of the current studies for solving the indoor COVID-19 airborne issues are still focused on how to improve HVAC design solutions to increase the fresh air volume (Pan et al., 2021). In fact, increasing the amount of fresh air only diminishes the concentration of indoor contaminants, instead of removing them from the fountainhead, and it even increases the risks of their mixing with the indoor environment (Santos et al., 2020). Therefore, personalized ventilation (PV) systems should be increasingly appreciated due to the advantageous attributes of ensuring indoor air quality (IAQ), thermal comfort, and effectiveness in preventing the transmission of infectious diseases (Melikov, 2004a). In the practical application, the relatively high investment cost of control flexibility technology and installation improvements has affected the large-scale implementation of PV systems compared to HVAC systems (Zeng et al., 2002). With the advancement of artificial intelligence technology, the costs of smart control methods and strategies will be dramatically decreased in the future (Less et al., 2019). Consequently, the application of available smart ventilation technologies will significantly improve the cost-effectiveness of PV systems, which will become an essential development tendency for future indoor environmental management.

Smart ventilation aims at reducing the unnecessary processing and transport of airflow to save energy and reduce cost (Less et al., 2019; Lu et al., 2010; Homod and Sahari, 2013). Previous studies have demonstrated that smart ventilation has generally a relatively high performance in energy-saving, IAQ, and thermal comfort, thereby owing the huge potential in the future building ventilation (Guyot G et al., 2017). Smart ventilation mainly focuses on more control parameters. A collection of all environmental parameters including human bio-effluents and physiological parameters constitute complex control logic and index for smart ventilation, which results in an increased operating cost of a smart ventilation system due to their randomness and uncertainty. However, selecting and ignoring some control parameters arbitrarily would decrease the performance of a smart ventilation system. A more reliable solution is to combine a PV system which focuses on body micro-environment with smart control strategy of timely feedback, which adjusts the ventilation mode to meet the requirements of human micro-environment (Emmerich and Persily, 2003).

To reduce building energy consumption for cooling and heating, the airtightness of building envelope has been improved, which results in an increased amount of ventilation flow required to maintain a high IAQ (Sjöström et al., 2020; Guyot et al., 2018). The minimum fresh air volume from 7.5 L/s per person (ANSI/ASHRAE, 2019) increased to 10 L/s due to the improvement of demand of occupants (Seppänen O et al., 2012). The demand controlventilation (DCV) logic shows the advantage of energy saving by adjusting the supply flow rate according to the IAQ, occupancy, and weather condition (Laverge et al., 2011; Organization, 2004). The three ventilation levels of indoor environment in design standard in terms of IAQ and thermal comfort, namely from the highest to the lowest, i.e., Category A, B and C (C.C. 1752-1998, 1998). The PV system can be designed to achieve the Category A level with low energy consumption (Melikov, 2004b). And it also can adjust the micro-environment based on the individual demand. The primary objective of PV system is to remove pollutants and ensure air quality, and the advanced objective is to provide a comfortable micro-environment.

There are several review studies about smart ventilation (Guyot et al., 2018; Walker et al., 2021), PV system (Liu et al., 2019; Veselý and Zeiler, 2014), or personal comfort system (PCS) (Zhang et al., 2015; Rawal et al., 2020). Most studies in smart ventilation focus on the system's energy efficiency, in PV system focus on the ability of airflow organization to remove pollutants, and in PCS focus on control methods. However, a summary analysis of the combination has not been covered, which is very important for the combination of the smart control logic with PV system. The application of the control logic of smart ventilation could continually adjust the ventilation system in time, which is also a promising solution for the PV system. In these systems, CO_2 concentration could been chosen as a key control parameter due to its advantages as an indicator of both IAQ and thermal comfort.

The objective of this study is to comprehensively summarize and analyze the recent studies and common utilization forms of smart ventilation and PV systems that are based on CO_2 concentration control, to pave path and provide some guidelines for their integration application for reducing energy consumption and improving indoor thermal comfort. The innovation of this study lies in the individual PV system, based on smart control, especially considering the CO_2 concentration as the control parameter. Another innovation lies in the summary and analysis of the compatibility applications of PV systems, especially considering the combination of smart logic. In addition, this paper summarizes the current existing issues and challenges faced by coupled technologies of PV system and smart control in practical applications, and provides the rational development suggestions to address the identified issues.

The structure of this paper is organized as follows: Section 2 discusses the necessity of selecting CO_2 concentration as control index for judging indoor comfort level, evaluating IAQ and human health, and monitoring ventilation control system; In Section 3, the developments of CO_2 sensor, PV system and smart control equipment are summarized and analyzed; Section 4 presents the current state of development of smart control strategies; Section 5 shows the limitations and future trends for these systems, and Section 6 concludes this study.

2. The necessity of selecting CO_2 concentration as control index

2.1. The role of CO_2 in judging indoor comfort level

The metabolic rate is the only one of the six factors that affect thermal comfort, except for environmental parameters (temperature, humidity, radiant temperature, air velocity, and thermal resistance of clothing), which may cause differences due to individual differences. The amount of CO_2 exhaled is an important indicator that can measure the actual metabolic rate. The production rate of CO_2 is a function of metabolism, which can be empirically written as (Schoeller and Fjeld, 1991; Formenti et al., 2010; Nishi, 1981):

$$M = \frac{21\,(0.23RQ + 0.77)\,Q_{O_2}}{A_D} \tag{1}$$

where M is the metabolic rate (W/m^2); RQ (respiratory quotient) is breathing coefficient, namely the molar ratio of exhaled Q_{CO_2} to inhaled Q_{O_2} (at the average adult's mild or sedentary activity RQ = 0.83), Q_{O_2} is Oxygen consumption (ml/s, at conditions of 0 °C, 101.3 kPa), and A_D is the surface area of DuBois (Liuliu Du et al., 2012):

$$A_D = 0.202H^{0.725}W^{0.425} \tag{2}$$

where W is mass (kg) and H is height (m).

Table 1
CO_2 concentration range requirements in residential buildings.

CO_2 range	Reference	Description
530–1500 ppm	LEED, GREENSHIP (Indonesia, 2014), IGBC (Industry, 2014), Pearl (Council, 2010), KLIMA (Energy Institute Vorarlberg, 2014), NABERS (Nabers, 2010), GPRS (Development, 2011)	Indoor CO_2 concentration in residential buildings according to the Green Building Standard
350–2000 ppm	Kirchner et al. (2006)	The CO_2 concentration in residential buildings fluctuates, but it can reach 6000 ppm in bedrooms from 2:00–5:00 am
>5000 ppm	The American Conference of Governmental Industrial Hygienists (ACGIH, 2011)	The risk of asphyxiation and exceeding metabolic stress
>10 000 ppm	The French Agency for Food, Environmental and Occupational Health Safety (ANSES, 2013)	The risk of cause acidosis to a healthy adult

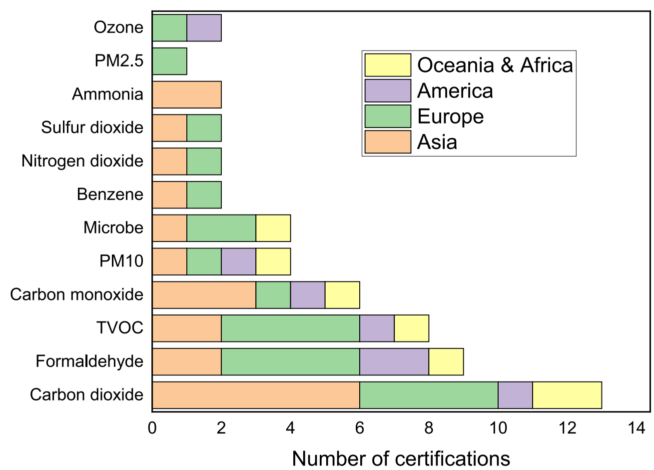

Fig. 1. Indoor air pollutants targeted for indoor air measurement.
Source: Modified from Wei et al. (2015).

ASTM D6245 (ASTM, 2012) mentioned that an adult with an $A_D = 1.8$ m^2 has a normal work metabolic rate of 1.2 met, and a produced CO_2 production rate is 0.0052 L/s; while CO_2 production rate of a children with an $A_D = 1.0$ m^2 in the same condition is 0.0029 L/s. Since the indoor CO_2 concentration may continue increasing due to breath of occupants, it is very important to monitor the indoor CO_2 concentration over time and adjust the ventilation strategy accordingly.

2.2. The impact of CO_2 concentration on IAQ and human health

More than 65% of green building standards from European, African, Asian and American consider the CO_2 concentration as the main indoor pollution parameter (as shown in Fig. 1) (Wei et al., 2015).

The standards for indoor CO_2 concentration in residential buildings and the effects on human are shown in Table 1. The response of occupants to CO_2 concentration is not sensitive enough to identify its variable signals as to other environmental parameters such as temperature, humidity, and airflow, etc., which is difficult for them to adjust the indoor ventilation timely even if the indoor CO_2 concentration has reached a level harmful to health. Korsavi et al. (2020) evaluated the occupant react of 29 naturally ventilated classrooms and 805 primary school students in the UK. When all occupant-related factors were in favor of air quality, the mean CO_2 concentration level maintained below 900 ppm. When none of the occupant-related factors were in favor of IAQ, the mean CO_2 concentration exceeded 1300 ppm. Seppänen OA and Mendell (1999) studied the impact of CO_2 concentration in offices and commercial buildings on health. With nearly 20 studies and more than 30,000 subjects, they found that the probability of sick building syndrome would increase when the per capita ventilation rate was less than 10 L/s, and the prevalence would decrease when the ventilation rate increased to between 10 L/s and 20 L/s per capita. Excessive CO_2 concentration also affected cognition. Haverinen and Shaughnessy (2011) studied on the correlation between classroom ventilation rate and the academic achievement of the students. The study measured CO_2 levels in 100 fifth-grade classrooms in 100 schools in the US, and estimated the ventilation rate based on the CO_2 concentration. The ventilation rates of 87 classrooms were found to be lower than the recommendations of the ASHRAE 62 standard. The survey showed that the cognitive ability of the students was linearly related to ventilation rate. The passing rate of math test was increased by 2.9% and the number of students passing the reading test was increased by 2.7%, with every 1 L/s increase in ventilation rate per person when the ventilation rate reached 0.9–7.1 L/s per person.

The increase of CO_2 concentration will also affect the human cardiovascular system, respiratory system, and central nervous system. Vehvilainen et al. (2016) studied the physiological parameters of four subjects in the office environment in response to CO_2 concentration, and found that when the CO_2 concentration reached 900 ppm to 2800 ppm, the heart rate of the subjects fluctuated and the blood circulation resistance increased. The CO_2 concentration passed through the human epidermis and subjectively reported symptoms of drowsiness then increased. Stricker et al. (1997) tested 22 subjects in a bedroom with a CO_2 concentration of 3000 ppm, where the concentration raised up to 4500 ppm at night. It was found that the bedroom CO_2 concentration did not affect the respiratory response and had no effect on subjectively assessed headaches, fatigue and attention, but it affected the excretion of phosphate and bone metabolism in the body. In that study, the authors observed that long-term exposure to $\geq$10,000 ppm may cause bone loss. Xanthopoulos et al. (2013) conducted a subjective perception test on the impact of CO_2 concentration in environmental chamber on 10 subjects and found that when the indoor CO_2 concentration reached 3000 ppm, the subjects felt tired and unpleasant, with a poor intellect performance, and their ability to concentrate was reduced. They also found that when the CO_2 concentration reaches 5000 ppm, the diastolic blood pressure rises. Gortner et al. (1971) performed experiments on 12 subjects in a basement environment with a CO_2 concentration of 6500 ppm to 12 000 ppm for 42 days, and reported that the pH value of the subjects' blood decreased (blood acidity increased). Sliwka et al. (1998) tested 4 subjects in a space with CO_2 concentration of 12 000 ppm for 23 days and found that subjective headaches increased, and brain blood flow had sudden increases. When the CO_2 concentration rises to more than 70,000 ppm, it is no longer possible to conduct long-term experiments on humans. Staying in a high-concentration

CO_2 environment for 10 to 20 min increases the heart rate, blood pressure, respiratory rate, and acidic blood (Sechzer et al., 1960; Woods et al., 1988; Bailey et al., 2005; Diaper et al., 2012). Compared to the short-term high-concentration exposure in some industry or public buildings, the accumulation of CO_2 concentration in residential buildings usually hurts the health of occupants chronically, which may be more harmful.

The harm of excessive CO_2 concentration is long-term and chronic, and the change of indoor CO_2 concentration is unstable. The untimely response of the human body to the hazards of CO_2 concentration increases the risk of long-term exposure to high-concentration CO_2 environments. Compared to other environmental parameters, CO_2 concentration is more necessary to use smart control logical to monitor and control according to the occupants in time.

2.3. The role of CO_2 concentration in ventilation control system

DCV is a specific type of smart ventilation, which has been applied for many years before the concept of smart ventilation appeared. It focuses on the demand of occupants, which can be marked by CO_2 concentration. Therefore, the DCV based on CO_2 concentration has an advantage for the improving indoor environment and individual comfort level, as well as saving energy (Emmerich, 1997; Schell and Shim, 1998; Persily, 1997). The ventilation standard ASHRAE 62 (Tucker, 1992) calculates the ventilation rate based on indoor CO_2 concentration as:

$$V_{OZ} = \frac{N_Z}{(C_Z - C_O)} \tag{3}$$

where V_{OZ} is the outdoor airflow required by a zone (L/s), N_Z is the CO_2 generation in the zone (L/person), C_Z is CO_2 concentration in the zone (ppm), and C_O is outdoor CO_2 concentration (ppm). N_Z is usually defined as the product of the body activity constant C and the number of people P_Z in the zone:

$$N_Z = C \times P_Z \tag{4}$$

The early DCV system used almost only CO_2 concentration as the control parameter. It should be noted that, pollutants such as tobacco, radon and CO (Emmerich SJ et al., 2005) should be controlled and removed from the sources, rather than relying on ventilation dilution (Wouter Borsboom T et al., 2016). IEA defines the type of pollutants that should be controlled by demand, namely (1) obviously transient or variable pollutants, (2) known to exceed the maximum emissions, and (3) unpredictable and unable to be controlled from the sources (Mansson et al., 1997). Since CO_2, as a kind of bio-effluents, does not cause direct harm to the human body when its concentration is not too high and it is easy to measure, it has become the most commonly used control index in ventilation strategies (Persily A, 1990).

In literature (Caillou S et al., 2014), CO_2 concentration was used as a tracking gas to determine whether occupants are available in residential buildings. If the CO_2 concentration higher than 600 ppm, it means there were occupied indoors. According to ASHRAE Standard 62.1-1989-2001 and ASHRAE 62.1 2004–2010, the CO_2-based DCV developed because of the change of CO_2 concentration requirements (Nassif, 2012). The ventilation requirement of the old version of the standard was defined as 7.08 L/s for outdoor air per person; and regardless of the number of occupants, the upper limit of indoor CO_2 concentration remains at 1050 ppm. In the new version of this standard, as shown in Fig. 2, the indoor CO_2 concentration changes with the number of occupants, which in turn determines the change of ventilation requirement. It can easily be seen that the new version of the standard makes building ventilation more energy-efficient.

The development of the concept and technology of DCV is mature, combined with the development of intelligent control technology, it can almost achieve timely, high-efficiency, energy-saving and other high-performance application goals in overall indoor environment. In order to achieve more refined, clean, and energy-saving personalized ventilation requirements, applying the existing CO_2-based DCV technology to the use of PV is a superior solution. This paper termed it as "Demand Control Personalized Ventilation" (DCPV). CO_2 sensor, PV air terminal devices (PVATD), and smart control logic are the three key factors for the development of DCPV. It is worth discussing and clarifying how to improve the existing PV systems.

3. The development of CO_2 sensor, PV system and control equipment

3.1. The development of CO_2 sensor on control indoor environment

The concept of ventilation control based on CO_2 concentration was proposed at least 1916, but the first CO_2 sensor was designed to use on ventilation control until 1990 (Schell and Int-Hout, 2001). Considering the cost and accuracy, the ventilation control normally uses two technologies for CO_2 detect: Non-Dispersive Infrared Detection (Dinh et al., 2016) and Photo-Acoustic CO_2 Sensors (Sherstov et al., 2020). The principle of Non-Dispersive Infrared Detection is to obtain the CO_2 concentration by measuring the CO_2 absorption to the corresponding frequency infrared, which is cheaper and larger. And of Photo-Acoustic is based on the photoacoustic effect of gas, by selecting a specific light source and sound wave detection equipment (such as a microphone) to achieve high-sensitivity sensing of one or more gases, which is more expensive and smaller.

The common range of CO_2 concentration in thermal comfort research and experiment environment control is 600–800 ppm or 700–900 ppm according to ASHRAE standard 62.1. Choi and Loftness (2012) performed experiments to analyze the correlation between skin temperature and overall thermal sensation, the correlation between heart rate and thermal sensation (Choi et al., 2012), and the difference in thermal comfort under immersive virtual environment and indoor environment conditions (Nassif, 2012). CO_2 sensors (Telarire 6004) were used in their experiments to control indoor CO_2 concentration to be 600–800 ppm and thus to maintain the stability of the experimental conditions. International Energy Agency (2020) used CO_2 sensors (Telarire 6004) to control the indoor CO_2 concentration to be between 700–900 ppm to study the influence of body local thermal sensation on the overall thermal sensation. Yeom et al. (2019) used CO_2 sensors to control the indoor CO_2 concentration to be between 700 and 900 ppm to analyze the difference of thermal sensation in two different environments. An adaptive DCV control strategy for multi-zone ventilation systems in super high-rise buildings was established based on CO_2 sensors (Sun et al., 2011).

Another way to enroll CO_2 sensor on indoor environment control strategy is to predict room occupancy schedules (Kusiak and Li, 2009). Nagy et al. (2015) used humidity sensors, air temperature sensors (Thermostat), and CO_2 sensors to measure the occupancy time and the amount of lighting required. Ryu and Moon (Ryu and Moon, 2016) used indoor and outdoor CO_2 concentrations and lighting system power consumption to develop occupancy prediction models through hidden Markov models (HMM algorithms). Using the indoor CO_2 concentration such as 1st order shifted difference of CO_2, indoor CO_2 moving average (15 min), indoor CO_2 change rate (15 min), indoor and outdoor CO_2 concentration ratio to compare model accuracy, it was concluded that the indoor and outdoor CO_2 concentration ratio was more accurate to predict the indoor occupancy. In

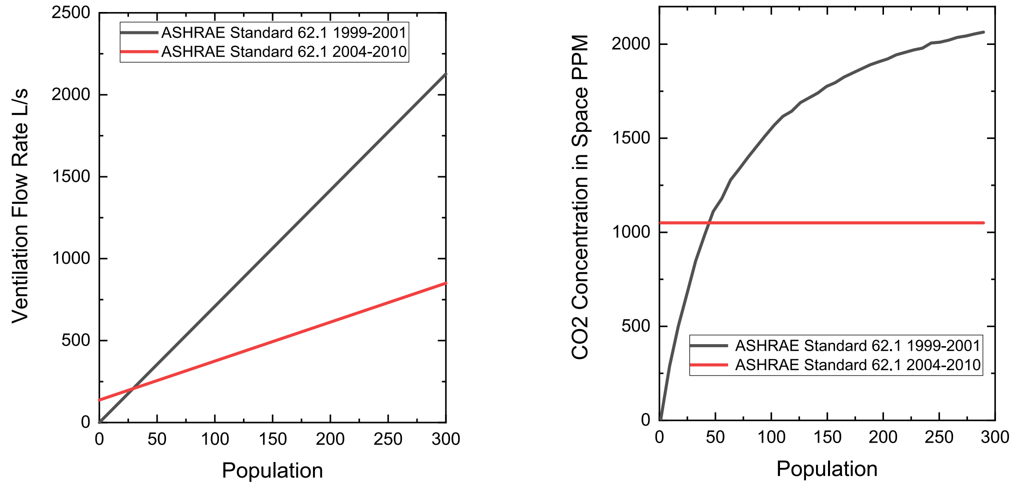

Fig. 2. ASHRAE Standard 62.1 1989–2001 and ASHRAE Standard 62.1 2004–2010 ventilation rate requirements and CO_2 concentration requirements with pollutant concentration.
Source: Modified from Nassif (2012).

order to overcome the limitation of sensor monitoring at fixed locations, Jin et al. (2018) proposed an automatically moving sensing system to monitor IAQ. The system consists of temperature sensor (MCP9808), lighting sensor (SI1145), CO_2 sensor (K-30), PM2.5 sensor (SEN0177), and organic volatile matter sensor (TGS2620). Compared to traditional fixed-point monitoring devices, this monitoring device showed better performance in both cost and accuracy.

The indoor environment control based on CO_2 sensors has significant energy saving potential. Dong and Lam (2013) proposed a real-time occupancy predictive model based on CO_2 sensors in combination with other parameters like air temperature, relative humidity, sound, light and human motion, to control the smart ventilation system. It is estimated that DCV based on CO_2 sensors can save between 20% and 70% of energy consumption in densely populated spaces with variable occupancy, such as the various halls, theaters and cinemas (Emmerich SJ, 2001). Wachenfeldt et al. (2007) compared the performance of two ventilation control strategies based on CO_2 sensor in two Norway schools: (1) demand-controlled displacement ventilation (DCDV) and (2) traditional constant air volume (CAV) mixed ventilation. Compared with CAV, the use of DCDV resulted in a decrease of ventilation volume by 65%–75%. Furthermore, CO_2 sensors play an important role in smart reconstruction of old building ventilation systems. Schibuola et al. (2018) evaluated the energy saving and comfort requirements of a ventilation system controlled by a CO_2 sensors in a reconstructed historic building in Venice. A CO_2 sensor was installed in the return air duct of each room, the measured average CO_2 concentration was directly fed back to the fan controller, and the fresh air flow was controlled by changing the fan frequency. The results showed that the annual air volume supplied by the CO_2 sensor based ventilation system was reduced by 21% and the related energy consumption was reduced by 33%. In addition, CO_2 sensors were used to conduct experimental evaluations of energy consumption for two occupancy-based control strategies of HVAC systems in commercial buildings (Goyal et al., 2015).

The application of CO_2 sensors in indoor environment control can be divided into two categories: (1) for air quality monitoring, and (2) for tracking the behavior of the occupants. Since the CO_2 sensors are mostly used in traditional ventilation systems, where the test area is too uncertain to capture personal CO_2 exhalation, few studies have been conducted to monitor the individual CO_2 concentration exhale and personal demand. This is mostly due to the uncertainty of occupant actions and the install way of CO_2 sensors. The CO_2 sensors used in ventilation control are usually installed in the occupied space, and collect the cumulative CO_2 concentration throughout the room. It is difficult to install CO_2 sensors in the breathing area of the each occupant, and the HVAC system cannot provide a ventilated environment that meets individual demand. The PV system can solve the problem of individual ventilation demand, but the installation of the CO_2 sensors and the accuracy of non-contact measurement are still the difficulties that need to be overcome at present. In PV's research and applications, measurement of CO_2 concentration are mostly based on contact sensors. The sensors are usually fixed to the breathing zone with tape or microphones for experimental research. Pantelic et al. (2020a) used A LI-COR CO_2 Gas Analyzer (Model LI-820, LI-COR, Lincoln, NE, USA) and the low-cost CO_2 sensing network, consisting of Telaire, T6713 CO_2 module (Mouser Electronics, Mansfield, TX, USA) to figure out the relationship between different sensors location. It was found that the CO_2 inhalation zone concentration levels were between 200 and 500 ppm above the background, and the test value also influenced by the posture, nose geometry, and breathing pattern of occupants. Researchers are more concerned about the application effect of PV in ensuring the IAQ in the breathing zone that assume individual needs are static. But the actual application goal is that PV can be adjusted autonomously according to the monitored CO_2 concentration, which is a very lacking research direction in the PV research field.

3.2. PV air terminal devices (PVATD)

The air terminal devices (ATD) is used for PV to supply personalized air and control the airflow rate and flow direction closed to the breathing zone of occupants, which originated from the desk environment adaptive system in 1988, consists of nine parts: desktop supply module, desktop control panel, desktop supply nozzle, radiant heating panel, task light, flexible supply duct, recirculated room air, desk and personal computer. Among them, the desktop supply modules, desktop supply nozzle, and recirculated room air are the basic components of all personalized air supply terminal devices (Bauman F and Baughman, 1998).

Melikov (2004a) proposed desk integrated PV terminals like Movable Panel (MP), Computer Monitor Panel (CMP), as shown

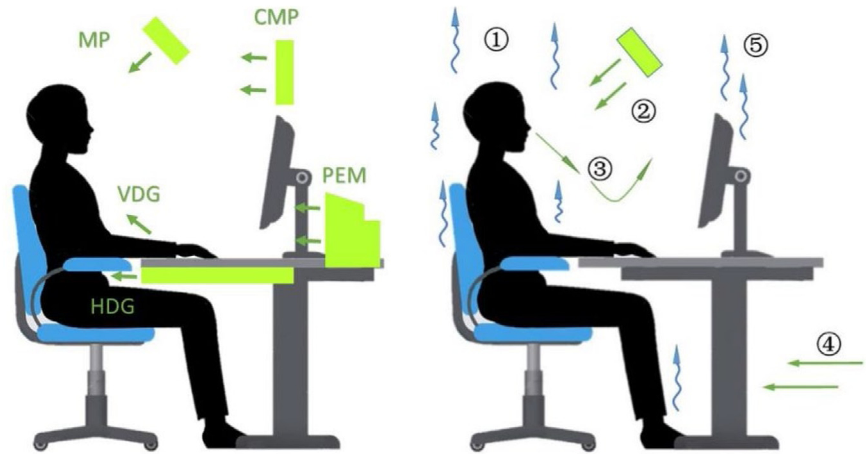

Fig. 3. Desk PV system. (a) Air supply terminal devices (ATD), Movable Panel (MP), Computer Monitor Panel (CMP), Vertical Desk Grill (VDG); Horizontal Desk Grill (HDG), Personal Environments Module (PEM). (b) Air convection around the human body: ①Free convection, ②Personalized airflow, ③Breathing flow, ④Ventilation flow, ④Heat flow.
Source: Modified from Melikov (2004a).

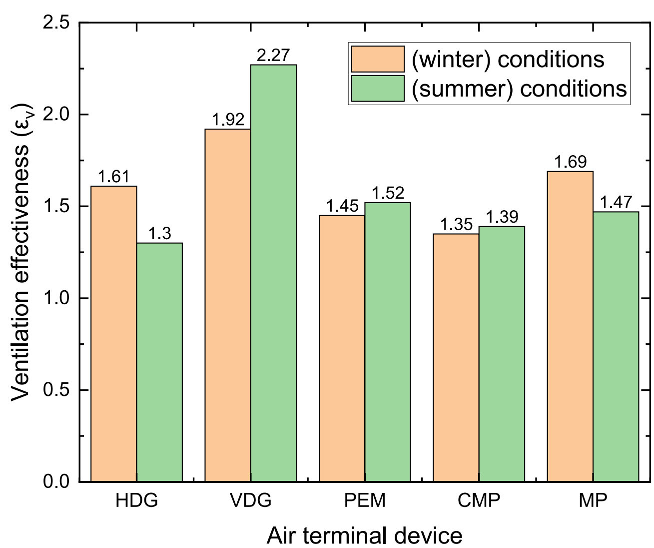

Fig. 4. Comparison of ventilation efficiency of five ATDs under winter and summer conditions. The indoor air temperature and relative humidity is 20 °C and 30% in winter, and 26 °C and 30% in summer. The supply PV system works at a temperature of 20 °C and humidity of 30% (Bolashikov et al., 2003b).

in Fig. 3. Melikov et al. (2002) evaluated the performance of the five PVATDs using the parameter ventilation efficiency (ε_V):

$$\varepsilon_V = \frac{C_R - C_S}{C_P - C_S} \tag{5}$$

where C_R is the pollutant concentration in the exhaust indoor air, C_S is the pollutant concentration in the supply indoor air, and C_P is the pollutant concentration in the inhalation zone.

Another parameter used in that study was the personal exposure efficiency (ε_P):

$$\varepsilon_P = \frac{C_{I,0} - C_I}{C_{I,0} - C_{PV}} \tag{6}$$

where $C_{I,0}$ is the concentration of pollutants in the inhaled air without PV, C_I is the concentration of pollutants in the inhaled air, and C_{PV} is the concentration of pollutants in the personalized air.

The effect of PVATD is examined by decreasing the part of exhaled air that is re-inhaled. It can be found that the exposure efficiency increases with the ATD air supply rate, and the exposure efficiency of VDG is the best among all ATDs, which reaches 0.6. However, as the air flow rate increases, the VDG may result in an intensified cooling sensation of the facade. Fig. 4 shows the comparison of the ventilation efficiency of these five ATDs in winter (20 °C, RH 30%) and summer (26 °C, RH 30%) conditions. Bolashikov et al. (2003a), Melikov et al. (2003) had developed the PV system with the freshness of air reaching more than 20 times as that provided by mixing ventilation, and the supply air temperature can be 6 °C lower than mixed ventilation in cooling conditions. The PV system is effective in reducing sick building syndrome, but it may cause thermal discomfort and dryness (Melikov and Kaczmarczyk, 2012). Therefore, the flow rate of the PVATD should be controlled at the necessary minimum value, at which the supply flow is strong enough to break the plume of free convection layer of the human body (Khalifa et al., 2009; Russo et al., 2009).

The impact of airflow from ATD on skin is significant since it is close to the breathing area. How to improve the ventilation efficiency while reducing the negative impact is a key problem. This problem can be effectively solved by improving the performance of PVATD. Khalifa et al. (2009) developed a new type of PV nozzle in combination with ergonomic and aesthetic, as shown in Fig. 5. This nozzle performed well in ventilation efficiency. The ventilation effectiveness could reach up to 7 when it provided 2.4 l/s, a significant improvement from traditional nozzles, which usually offered less than 2.

In order to make the airflow distribution more efficient, the orifice plate of the air outlet is also designed, and a new type of ceiling PVATD is designed using CFD simulation, as shown in Fig. 6 (Yan J et al., 2017). The outlet area of the channel at the edge of the device is smaller than the inlet, which accelerates the airflow speed and form an air curtain on the entire airflow edge to prevent the airflow diffusion. The inner air holes is just the opposite with the edge holes, with the outlet larger than the inlet.

To further improve the air quality in the breathing area, Faulkner D et al. (2003) improved a desk-edge-mounted ventilation device based on Melikov's PVATD (as shown in Fig. 7). The system provided an airflow rate of 3.5–6.5 l/s, and its air change effectiveness could reach 1.5 h^{-1}, which could increase the air supply rate by 50% in the breathing area (Niu et al., 2007).

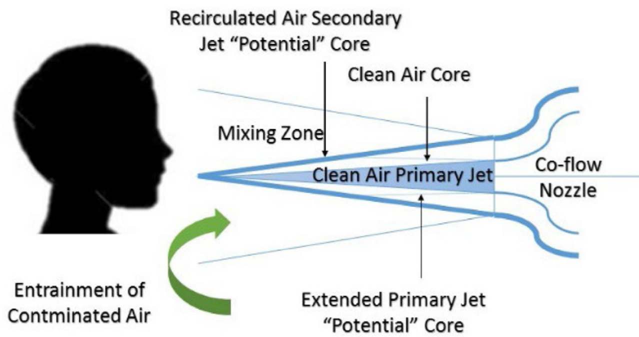

Fig. 5. Low mixing co-flow nozzle.
Source: Modified from Khalifa et al. (2009).

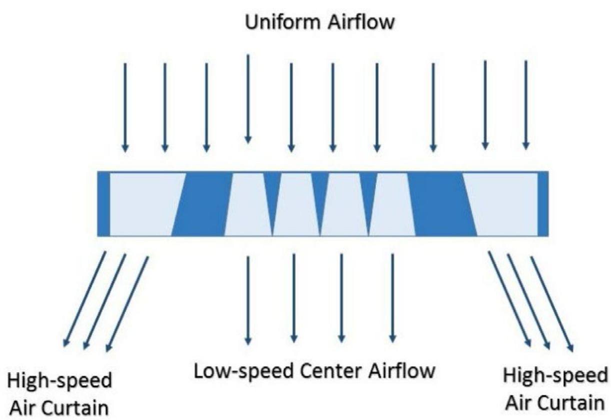

Fig. 6. Designed register.
Source: Modified from Yan J et al. (2017).

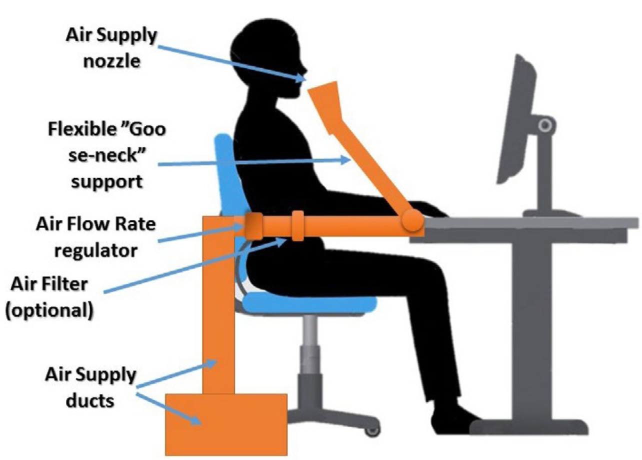

Fig. 7. Desk-edge-mounted ventilation device.
Source: Modified from Faulkner D et al. (2003).

Li et al. (2010) studied the potential of improving the thermal comfort of indoor occupants when the PV system was used in combination with the under-floor air distribution (UFAD) system in hot and humid areas. The experimental device of the proposed PV system is shown in Fig. 8.

Although the PVATD provides fresh air directly to the breathing zone, it may cause discomfort due to the airflow being too close to the face. Yang et al. (2010) found that a combination

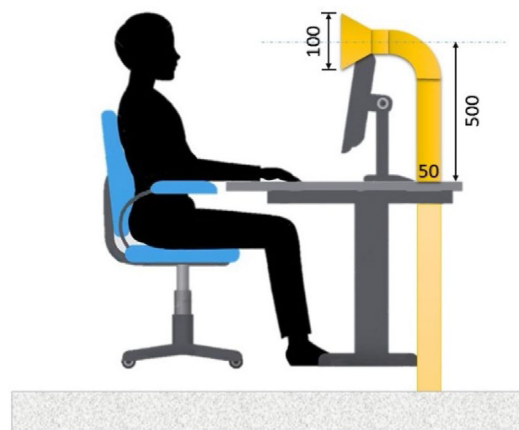

Fig. 8. Desk-mounted PVATD in the FEC workstation.
Source: Modified from Li et al. (2010).

of ceiling and desktop PVATD with mixing ventilation had an excellent overall performance. Makhoul et al. (2013) found that ceiling-mounted PV nozzle combined with desk-mounted fans had a good performance to reduce the negative effect of thermal plume generated by the occupants, as shown in Fig. 9, and also reduced energy saving by 13% when compared with mixing ventilation systems.

Lan et al. (2013) used the PVATD in the bedroom for sleeping people as shown in Fig. 10, and they measured the physiological parameters of the subjects and found that even if the PV supply air temperature was higher than the ambient air temperature, the subjects still felt cool. The bedside PV devices can also be used as a potential ventilation method to remove pollutions if it had flexible control system based on sleeping comfort.

The development of PV systems is a consequence of the increasing demand for IAQ and thermal comfort, as well as the exploration of its unique air rate threshold. In addition, the control strategy of the PV systems is more worth exploring due to the demand for flexibility.

PV systems have better performance in reducing the spread and dispersion of small particles than other ventilation systems (Liu et al., 2007). Melikov and Kaczmarczyk (2012) studied the effects of indoor air flow on perceived air quality (PAQ) and sick building syndrome based on 124 human subjects. Their study found that increased local ventilation rates improved IAQ and relieved building syndrome symptoms, which was the foundation for the later development of PV. Liu et al. (2007) simulated the particle dispersion associated with the use of PV by considering three cases with different airflow speeds: (a) no airflow, (b) 32 m^3/h of personalized airflow, and (c) 32 m^3/h of mixed supply airflow from the ceiling. After studying the air temperature field and pollutant concentration field in these 3 cases, it was found that personalized airflow was effective to remove particles smaller than 2 μm, but PV was not effective if the particles were larger than 7.5 μm.

Because PV forms a special ventilation area on the surface of human body, it has great energy saving potential compared with traditional ventilation. Fig. 11 shows the energy savings, ventilation effectiveness, and lower pollution of breathing zone compared with normal ventilation systems of the two PV systems proposed by Sekhar et al. (2005) and Makhoul et al. (2015). The performance of a low-mix coaxial nozzle installed on the ceiling, which provided a vertical jet of fresh air to the breathing area of users, was studied by Makhoul (2012). The nozzle was integrated with a diffuser that has a variable air supply angle for fluid positioning. Compared to traditional nozzles, the efficiency of this

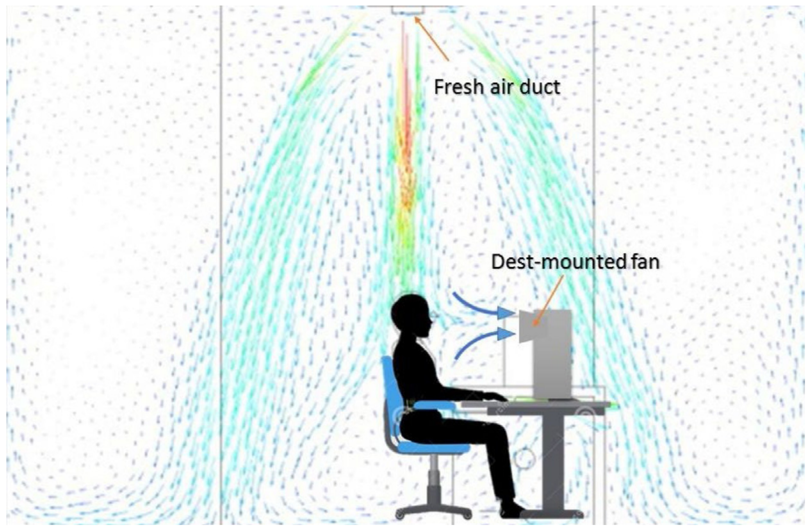

Fig. 9. Ceiling-mounted PV nozzle.
Source: Modified from Makhoul et al. (2013).

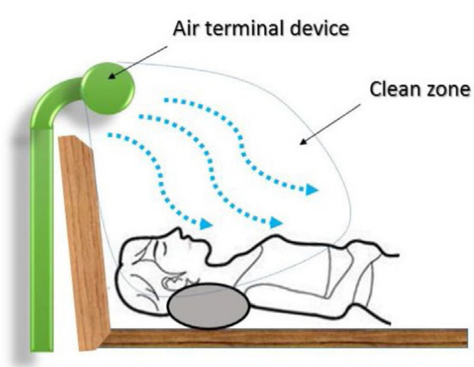

Fig. 10. Bedside PV system.
Source: Modified from Lan et al. (2013).

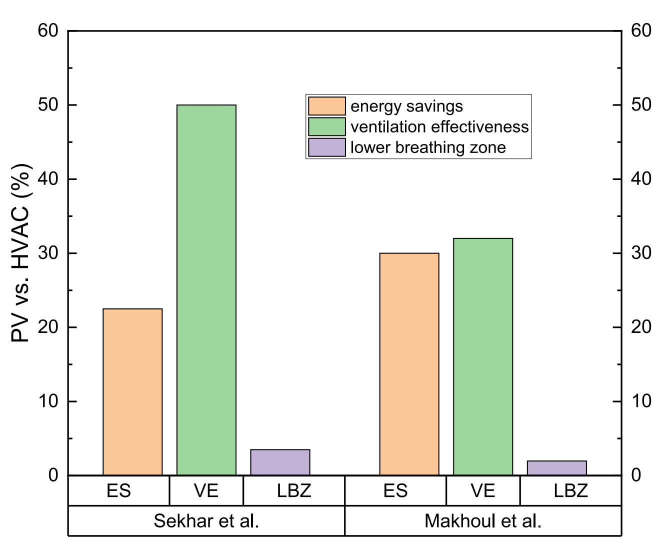

Fig. 11. Comparison chart of energy saving, ventilation effectiveness, and temperature reduction in the breathing zone from the studies of Sekhar et al. (2005) and Makhoul et al. (2015).

coaxial nozzle when providing the same amount of clean air could be increased by 3–4 times, while also achieving a comfortable effect and saving energy by 30%. Yang et al. (2010) specifically analyzed the energy consumption performance of the ceiling PV device in hot and humid areas. Results showed that the ceiling PV system and mixed ventilation could reduce cooling power when used together, and the ceiling PV device had better heat dissipation effect and can reduce total energy consumption compared with desktop ventilation and mixed ventilation. Tham et al. (2004) compared two kinds of air supply modes, one of them was personalized supply with air temperature at 20–23 °C when the indoor air temperature was 26 °C, and another was purely mixing ventilation mode with the room air temperature controlled at 23 °C. It was found that the former could reduce the cooling load by 29.5% and energy consumption by 27%. Kaczmarczyk J et al. (2006) found the all ATDs that proposed by Melikov (2004a) had obviously positive effects on human comfort and air quality, and the circle movable showed the best performance. Due to uniform airflow distribution, lower jet velocity and turbulence intensity, this ATD provided higher comfort and air quality. The energy saving rate of several typical PV devices shown in Fig. 12.

It is easy to see that the two main advantages of PV system are the ability to remove pollution and energy-saving. However, the biggest disadvantage of PV system is too closed to human body that is easy to cause thermal discomfort due to the air velocity, which request the flexible and timely control logic. As a consequence, there is huge prospects of combining PV and smart control strategies.

4. Development of smart ventilation control logic

The control system of smart ventilation works through calculating the required ventilation rate based on the indices recognized by the relevant sensors, which then adjusts the operation status of the ventilation system in time to achieve the goal of energy saving and high performance.

For natural ventilation, the control system adjusts the window opening according to outdoor weather condition, indoor air temperature and humidity, CO_2 concentration, airflow speed and other parameters (Rinaldi et al., 2017). For mechanical ventilation, the control system changes the opening of the fan speed, the area of the air inlet and outlet, or the fan operating frequency, etc. (Fisk and De Almeida, 1998).

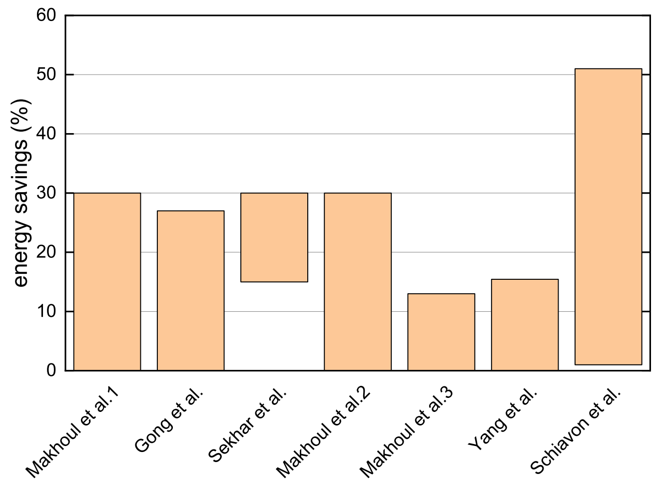

Fig. 12. Comparison chart of energy saving rate based on different researchers of Makhoul (2012), Tham et al. (2004), Sekhar et al. (2005), Makhoul et al. (2015), Makhoul et al. (2013), Yang et al. (2010), and Schiavon et al. (2010).

4.1. Application of machine learning (ML) technology in predicting indoor environmental state based on CO_2 concentration

Smart ventilation systems have been improved in recent years with the development of big data and artificial intelligence technology. As a branch of artificial intelligence, ML has great application potential in smart ventilation control strategies. ML algorithms are a type of algorithm that obtains rules from data through classification or regression analysis, and uses the rules to predict unknown data, which include two major categories, namely supervised learning (Welling, 2011) and unsupervised learning (Barlow, 1989). In the field of ventilation, supervised learning is mostly used to predict indoor occupancy based on user behavior data to calculate ventilation demand, and unsupervised learning is used to find users behavior (Peng et al., 2018). ML technology relies on big data and requires the collection and establishment of a complete database system for repeated training of the model. Independently of the algorithm, the objective is to find quantifiable potential connections among seemingly unrelated parameters through a large number of parameters in the training database (Song et al., 2022). Therefore, the main purpose of ML as an approach is to achieve the demand calculation purpose in ventilation module.

The control indicators referenced by ML-based smart ventilation control strategies are usually divided into two categories: occupancy rate and thermal comfort. Artificial Neural Networks (ANN), Hidden Markov Models (HMM) (Tokuda et al., 2000), Decision Tree (DT) (Safavian and Landgrebe, 1991), Random Forest (RF), Logistic Regression (LR) (Kleinbaum et al., 2002), K-nearest Neighbor (KNN), and Support Vector Machine (SVM) (Zhang et al., 2006) can strengthen the correlation between indoor environmental parameters and user behavior. CO_2 concentration as a product of occupant, has become an important reference indicator for ML prediction algorithm.

The Predicted Mean Vote (PMV) function for thermal comfort models tend to produce large errors (Luo et al., 2015), when they are used to deal with individual differences or mixed-mode indoor spaces due to their lack of self-correction capabilities (Zhou et al., 2020). Due to its self-learning ability, machine learning is likely to be the common method for predicting 3-point or 7-point scales of comfort level in the future (Kim et al., 2018a; Luo et al., 2020). The application of ML in indoor environment studies is shown in Table 2.

4.2. The necessary of combining smart control with PV based on CO_2concentration

Control logic is one of the most important components of the PV system. The control strategy design is mainly based on the air temperature, velocity and direction of the personalized airflow. In principle, increasing the temperature of the PV airflow requires increasing simultaneously the airflow speed to maintain the convective heat dissipation of the human body, but the increase in the airflow speed in the PV device usually takes away more heat and causes the air temperature dropping (Faulkner et al., 2003). Therefore, the PV system should be designed to adjust to the transient response to micro-environment. Many control systems and sensors in smart ventilation can cooperate with the PV system to form an effective personalized and smart ventilation control system (Chaudhuri et al., 2019).

Office is one of the places with the strongest demand for PV devices due to the long occupied time and the high population density. Most of existing PV devices consider the working state of human body in a static sitting position. The free convection boundary layer around the human body will affect the personalized airflow (Melikov, 2004b). The PV devices attached to the office desk are designed to be able to break the free convection boundary layer of the human body and thus to deliver clean or cooled air to the breathing area. At the same time, it needs to cooperate with the personalized comfort system to provide heating or cooling local thermal environment according to the thermal sensation of different parts of the human body to improve the comfortable state during office work (Rawal et al., 2020). The office PV system based on CO_2 sensor not only considers the air quality in the breathing area, but also determines the on/off state of the system depending on the detected human signal.

Compared to the office areas, the occupied density in bedrooms is low, but the sleeping environment has higher requirements for the IAQ and thermal environment (Lan et al., 2016). Since usually only the head is outside the quilt during sleep, the PV strategy of the bedroom is mainly targeted for the human head. However, previous studies on human thermal sensation in the awake state suggested that the thermal sensation in the head has a stronger effect than other parts of the body (Nunneley, 1983; Nunneley and Maldonado, 1982). Zhou et al. (2014) investigated the effects of bedside PV on human sleep air quality by evaluating environmental parameters, subjective feelings and human physiological parameters, and found that people who awake up after sleep were more sensitive to their surrounding environment than usual. However, special attention should be paid to the noise caused by PV system to the elderly (Namba et al., 2004).

No matter which kind of PV system, the application of smart control logic will be the future development trend. The concept of smart PV system based on CO_2 concentration as shown in Fig. 13.

PV system for smart control based on CO_2 concentration can be classified into 6 steps. Step 1 relies on the development of CO_2 sensors and measurement technology. In the case of IAQ, the selection of the measurement position is critical to the accuracy of the results. In the case of metabolic rate, beyond the measurement position, the accuracy of non-contact CO_2 sensors technology is also very important (Pantelic et al., 2020b). Step 2 is implemented according to the standard. The implementation of step 3 requires the support of artificial intelligence algorithms. There is no more accepted heat balance equation for calculating thermal comfort in the micro-environments. However, the rapid development of machine learning algorithms and their widespread use in the field of thermal comfort has led to greater flexibility and energy efficiency of smart ventilation systems. Steps 4, 5 and 6 are calculated and adjusted for different

Table 2
The application cases of different ML methods.

ML method	References	Research objects
ANN	Mozer (1998)	Developed residential comfort control system; Predicted occupancy Evaluated model's accuracy
KNN	Scott et al. (2011)	Developed a heating controller system: PreHeat Predicted the occupancy activity Realized energy-saving
SVM	Kadouche R and Abdulrazak (2010)	Predicted occupancy rate Realized energy-saving
DT, HMM	Ryu and Moon (2016)	Comparison of prediction accuracy based on the four parameters of indoor CO_2 concentration, 1st order shifted difference of CO_2, indoor CO_2 moving average, indoor CO_2 rate of change, and indoor and outdoor CO_2 concentration ratio.
HMM	Chaney et al. (2016)	Predicted occupancy based on CO_2 concentration
SVM, RF	Singh et al. (2018)	Developed a occupancy prediction method based on CO_2 concentration with an accuracy of 98.4%
ANN	Javed et al. (2018)	Predicted the comfort level and occupancy based on CO_2 concentration; Reduced the energy consumption by 19.8%
HMM	Ryu and Moon (2016), Chaney et al. (2016), Dong and Lam (2014) and Kleiminger et al. (2014)	Predicted the occupancy rate
ANN	Yang et al. (2012), Mamidi et al. (2012) and Ekwevugbe et al. (2013)	Predicted the occupancy rate
SVM, KNN, RF	Cosma and Simha (2019)	Predicted 3-points comfort level
ANN, RF	Chaudhuri et al. (2019)	Predicted thermal sensation
KNN, RF, and SVM	Lu et al. (2019)	Predicted 7-points comfort level
Bagging, ANN and SVM	Wu et al. (2018)	Predicted thermal comfort Compared the accuracy of each algorithm
LR, DT, GBM, GPC, RF, and SVM	Kim et al. (2018b)	Predicted users' behavior of using heating and cooling systems
RF	Chaudhuri et al. (2018a)	Predicted 3-points comfort level based on physiological parameters
Extreme Learning Machine (ELM) and SVM	Chaudhuri et al. (2018b)	Predicted thermal sensation

systems and different comfort requirements and background environments. The following section will focus on the development and research status of these six segments and discusses the development trends and application possibilities of smart PV systems based on CO_2 concentration.

5. Discussions, limitations and future trends

The importance of CO_2 concentration as an indicator in guiding formulating ventilation strategies was summarized in this study. The development of CO_2 sensors, the relevant regulations on CO_2 concentration in green building standards, and the role of CO_2 concentration in calculating ventilation requirements was also comprehensively reviewed in this study. And PV system as a new type of ventilation method has achieved high performance in ventilation efficiency, energy saving and preventing the spread of diseases, but it needs more flexible control to supply the comfort environment. Based on available information, it is necessary and desirable to combine smart ventilation control strategy with PV systems. Previous studies on PV systems mainly focus on IAQ. It may ignore some uncomfortable issues caused by the personalized airflow. Studies on smart ventilation pay more attention on the flexible control. There are still no studies trying to combine smart control system with PV system, especially based on CO_2 concentration.

It was found that the development of CO_2 sensors is essential to promote the intelligence and efficiency of PV systems since newer sensors could provide more accurate data. The control principle on which also requires an improved comfort model that pays more attention to individual differences. Traditional PMV model can no longer meet the performance requirements of PV systems. Therefore, it is easy to overlook the comfort potential of the PV systems in addition to their advantages in providing fresh air and personalized cooling and heating.

According to previous studies, PV has high performance in VE and ES, for example, VE and ES can reach improvements of up to 50% and 30%, respectively. Applied to the current global epidemic of COVID-19, the advantages of PV to reduce the risk of airborne disease spread are more prominent. The thermal discomfort caused by its strong effect on the human micro-environment needs more attention. Compared to the normal ventilation systems, PV is more sensitive to the factors affecting airflow such as the relative position of PVATD and human body, the direction of personalized airflow, the shape of air outlet, the size of wind speed, etc. Conventional methods for evaluating thermal comfort performance of ventilation systems are not adequate

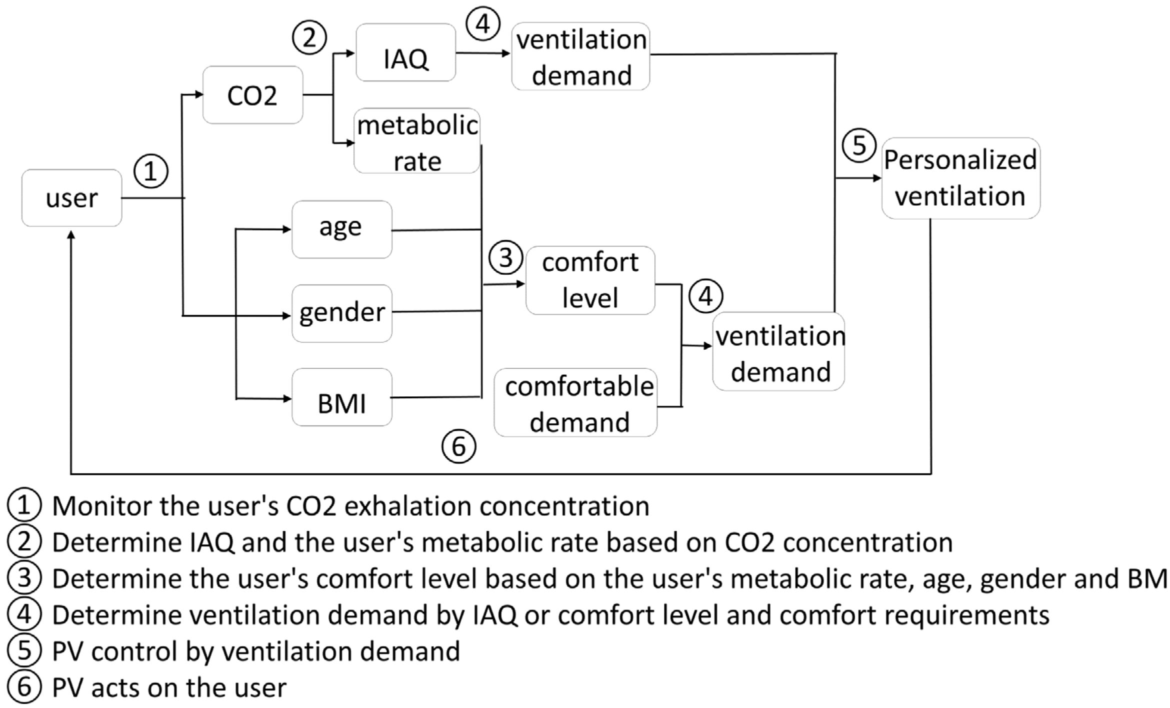

Fig. 13. The concept of smart PV system based on CO_2 concentration.

for PV systems. The more precise thermal comfort model for PV should be developed immediately. For example, the ventilation demand control based on human physiological parameters. This is not only a challenge for sensor technology for monitoring physiological parameters, but also for the ventilation demand models developed based on physiological parameters.

As an important parameter in the DCV research, CO_2 concentration has accumulated mature research results. And it also plays an important role in physiological parameter to measure the metabolic rate of the occupants. Therefore, CO_2 concentration could be the preferred choice to investigate the combination of PV system and smart control based on physiological parameters.

However, PV systems based on CO_2 concentration are currently in the experimental phase and few studies have fully integrated CO_2 concentration as an evaluation indicator for thermal comfort and IAQ. This paper is therefore limited to providing only a concept and future trends in PV systems and their technical implement ability, and does not go into detail about a particular practical CO_2 smart personalized ventilation system.

6. Conclusions

This paper summarizes the theoretical basis and practical application of smart and PV system based on CO_2 concentration, especially: (1) the necessity of CO_2 concentration as a ventilation system control parameter, (2) the development status of PV system, (3) intelligence application of control technology for PV system. With the global spread of the coronavirus, the PV system could effectively avoid the shortcomings of the central air-conditioning system that the virus cannot be isolated due to its personalized characteristics, and thus it has a great application prospect. However, this also requires the improvement of sensitive control systems and efficient control strategies.

Most PV systems consider the possible comfort or discomfort caused by the interaction of between the system wind field with the human micro-environment, but few studies do not focus on the comfort willingness of the users and the individual differences. In addition, previous studies did not consider collecting user application feedback in order to adjust the air supply status of the entire system in time according to user's requirements. Therefore, the construction of human comfort feedback system and effective ventilation strategy should be reconsidered in the studies of PV system.

All the investigated smart control systems, sensors or machine learning strategies, have demonstrated the huge prospects for the integration with PV systems. However, chaotic control logic and comfort indicators that are difficult to quantify have become the main obstacles to the development of smart PV systems, resulting in PV systems still staying in traditional ventilation modes, and the related studies are mostly centered on equipment such as ducts, vents, installation location, etc. A flexible and smart control method is more necessary to improve the performance of PV system, which could supply comfort micro-environment, reduce building energy consumption, and improve indoor environment.

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.

References

ACGIH, 2011. Documentation of the threshold limit values and biological exposure indices.
ANSES, 2013. Concentrations de CO2 Dans L'Air Intérieur Et Effets sur la SantÉ - Avis de L'Anses - Rapport D'Expertise Collective. Édition scientifique.
ANSI/ASHRAE, A.S., 2019. Ventilation and acceptable indoor air quality in residential buildings.
ASTM, 2012. Standard Guide for using Indoor Carbon Dioxide Concentrations to Evaluate Indoor Air Quality and Ventilation. American Society for Testing and Materials (D6245-07), West Conshohocken, PA.
Bailey, J.E., Argyropoulos, S.V., Kendrick, A.H., Nutt, D.J., 2005. Behavioral and cardiovascular effects of 7.5% CO2 in human volunteers. Depress. Anxiety 21, 18–25.
Barlow, H.B., 1989. Unsupervised learning. Neural Comput. 1 (3), 295–311.
Bauman F, C.T., Baughman, A., 1998. Field study of the impact of a desktop task/ambient conditioning system in office buildings.

Bolashikov, L.N.Z., Melikov, A.K., Kaczmarczyk, J., P.O, 2003a. Fanger New air terminal devices with high efficiency for personalized ventilation application. In: Proceedings of the 7th International Conference on Healthy Buildings, 7-11 2003, Singapore.
Bolashikov, Z.D., Nikolaev, L., Melikov, A., Kaczmarczyk, J., Fanger, P.O., 2003b. Personalized ventilation: Air terminal devices with high efficiency. Proc. Health Build. 2, 850–855.
Caillou S, H.N., Laverge, J., et al., 2014. Development of an evaluation methodology to quantify the energy potential of demand controlled ventilation strategies. In: 35th AIVC Conference: Ventilation and Airtightness in Transforming the Building Stock To High Performance. AIVC, pp. 587–596.
C.C. 1752-1998, 1998. Ventilation for Buildings—Design Criteria for the Indoor Environment. Bruxelles.
Chaney, J., Hugh Owens, E., Peacock, A.D., 2016. An evidence based approach to determining residential occupancy and its role in demand response management. Energy Build. 125, 254–266, 08/01/ 2016.
Chaudhuri, T., Soh, Y.C., Li, H., Xie, L., 2019. A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings. Appl. Energy 248, 44–53, 08/15/ 2019.
Chaudhuri, T., Zhai, D., Soh, Y.C., Li, H., Xie, L., 2018a. Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology. Energy Build. 166, 391–406, 05/01/ 2018.
Chaudhuri, T., Zhai, D., Soh, Y.C., Li, H., Xie, L., 2018b. Thermal comfort prediction using normalized skin temperature in a uniform built environment. Energy Build. 159, 426–440, 01/15/ 2018.
Choi, J.-H., Loftness, V., 2012. Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations. Build. Environ. 58, 258–269, 12/01/ 2012.
Choi, J.-H., Loftness, V., Lee, D.-W., 2012. Investigation of the possibility of the use of heart rate as a human factor for thermal sensation models. Build. Environ. 50, 165–175, 04/01/ 2012.
Cosma, A.C., Simha, R., 2019. Machine learning method for real-time non-invasive prediction of individual thermal preference in transient conditions. Build. Environ. 148, 372–383, 01/15/ 2019.
Council, A.D.U.P., 2010. The Pearl Rating System for Estidama – Building Rating System – Design & Construction. version 1.0.
Development, 2011. The green pyramid rating system.
Diaper, A., Nutt, D.J., Munafò, M.R., White, J.L., Farmer, E.W., Bailey, J.E., 2012. The effects of 7.5% carbon dioxide inhalation on task performance in healthy volunteers. J. Psychopharmacol. 26, 487–496.
Ding, J., Yu, C.W., Cao, S.-J., 2020. HVAC systems for environmental control to minimize the COVID-19 infection. Indoor Built Environ. 29, 1195–1201.
Dinh, T.-V., Choi, I.-Y., Son, Y.-S., Kim, J.-C., 2016. A review on non-dispersive infrared gas sensors: Improvement of sensor detection limit and interference correction. Sensors Actuators B 231, 529–538, 08/01/ 2016.
Dong, B., Lam, K.P., 2013. A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting. Build. Simul. 7, 89–106.
Dong, B., Lam, K.P., 2014. A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting. Build. Simul. 7, 89–106, 02/01 2014.
Ekwevugbe, T., Brown, N., Pakka, V., Fan, D., 2013. Real-time building occupancy sensing using neural-network based sensor network. In: 2013 7th IEEE International Conference on Digital Ecosystems and Technologies (DEST). pp. 114–119.
Emmerich, A.K.S.J., 1997. Persily literature review on CO2-based demand-controlled ventilation. ASHRAE Trans. 103 (pt 2), 229–243.
Emmerich, S.J., Persily, A.K., 2003. State-of-the-art review of CO2 demand controlled ventilation technology and application.
Emmerich SJ, P.A.K., 2001. State-of-the-Art Review of CO2 Demand Controlled Ventilation Technology and Application. Diane Publishing Company.
Emmerich SJ, E.S.J., Gupte, A., et al., 2005. Modeling the IAQ Impact of HHI Interventions in Inner-City Housing. US Department of Commerce, National Institute of Standards and Technology.
Energy Institute Vorarlberg, 2014. Klima:Aktiv Bauen Und Sanieren Kriterienkatalog WohngebäUde Neubau. version 5.1.
Faulkner, C.A., Castellini, Jr., J.E., Zuo, W., Lorenzetti, D.M., Sohn, M.D., 2022. Investigation of HVAC operation strategies for office buildings during COVID-19 pandemic. Build. Environ. 207, 108519.
Faulkner, D., Fisk, J.W., Sullivan, P.D., Lee, M.S., 2003. Ventilation efficiencies and thermal comfort results of a desk-edge-mounted task ventilation system. United States: N. p. 2003. Web.
Faulkner D, F.W.J., Sullivan, D.P., et al., 2003. Ventilation efficiencies and thermal comfort results of a desk-edge-mounted task ventilation system. Indoor Air (Supplement 8) 14 (LBNL-53798).
Fisk, W.J., De Almeida, A.T., 1998. Sensor-based demand-controlled ventilation: a review. Energy Build. 29, 35–45, 12/01/ 1998.
Formenti, F., Constantin-Teodosiu, D., Emmanuel, Y., Cheeseman, J., Dorrington, K.L., Edwards, L.M., et al., 2010. Regulation of human metabolism by hypoxia-inducible factor. Proc. Natl. Acad. Sci. 107, 12722–12727.
Gortner, D.A., Messier, A.A., Heyder, E., Schaefer, K.E., 1971. The Effects of Elevated Atmospheric CO2 on Acid-Base Balance and Red-Cell Electrolytes of FBM Submarine Crew Members. Naval Submarine Medical Center.
Goyal, S., Barooah, P., Middelkoop, T., 2015. Experimental study of occupancy-based control of HVAC zones. Appl. Energy 140, 75–84, 02/15/ 2015.
Guo, M., Xu, P., Xiao, T., He, R., Dai, M., Miller, S.L., 2021. Review and comparison of HVAC operation guidelines in different countries during the COVID-19 pandemic. Build. Environ. 187, 107368.
Guyot, G., Sherman, M.H., Walker, I.S., 2018. Smart ventilation energy and indoor air quality performance in residential buildings: A review. Energy Build. 165, 416–430, 04/15/ 2018.
Guyot G, S.M., Walker, I., et al., 2017. Residential smart ventilation: a review.
Haverinen, M.D.J., Shaughnessy, R.J., 2011. Association between substandard classroom ventilation rates and students' academic achievement. Indoor Air 21 (2), 121–131.
Homod, R.Z., Sahari, K.S.M., 2013. Energy savings by smart utilization of mechanical and natural ventilation for hybrid residential building model in passive climate. Energy Build. 60, 310–329, 05/01/ 2013.
Indonesia, G.B.C., 2014. GREENSHIP for New Building. version 1.2,.
Industry, C.o.I., 2014. IGBC Green New Buildings Rating System. version 3.0.
International Energy Agency, 2020. Buildings a Source of Enormous Untapped Efficiency Potential. Int Energy Agency, [Online]. Available https://www.iea.org/topics/buildings [Accessed 20 2020].
Javed, A., Larijani, H., Wixted, A., 2018. Improving energy consumption of a commercial building with IoT and machine learning. IT Prof. 20, 30–38.
Jin, M., Liu, S., Schiavon, S., Spanos, C., 2018. Automated mobile sensing: Towards high-granularity agile indoor environmental quality monitoring. Build. Environ. 127, 268–276, 01/01/ 2018.
Kaczmarczyk J, M.A., Bolashikov, Z., et al., 2006. Human response to five designs of personalized ventilation. Hvac R Res. 12 (2), 367–384.
Kadouche R, C.B., Abdulrazak, B., 2010. User's behavior study for smart houses occupant prediction. Ann. Telecommun.-Ann. Télécommun. 65 (9–10), 539–543.
Khalifa, H.E., Janos, M.I., Dannenhoffer, J.F., 2009. Experimental investigation of reduced-mixing personal ventilation jets. Build. Environ. 44, 1551–1558, 08/01/ 2009.
Kim, J., Schiavon, S., Brager, G., 2018a. Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control. Build. Environ. 132, 114–124, 03/15/ 2018.
Kim, J., Zhou, Y., Schiavon, S., Raftery, P., Brager, G., 2018b. Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. Build. Environ. 129, 96–106, 02/01/ 2018.
Kirchner, S., et al., 2006. Observatoire de la QualitÉ de L'Air Intérieur - Campagne Nationale Logements - Etat de la QualitÉ de L'Air Dans Les Logements Français. (Rapport final), CSTB.
Kleiminger, W., Mattern, F., Santini, S., 2014. Predicting household occupancy for smart heating control: A comparative performance analysis of state-of-the-art approaches. Energy Build. 85, 493–505, 12/01/ 2014.
Kleinbaum, D.G., Dietz, K., Gail, M., Klein, M., Klein, M., 2002. Logistic Regression. Springer.
Korsavi, S.S., Montazami, A., Mumovic, D., 2020. Indoor air quality (IAQ) in naturally-ventilated primary schools in the UK: Occupant-related factors. Build. Environ. 180, 106992, 08/01/ 2020.
Kusiak, A., Li, M., 2009. Optimal decision making in ventilation control. Energy 34, 1835–1845, 11/01/ 2009.
Lan, L., Lian, Z.W., Lin, Y.B., 2016. Comfortably cool bedroom environment during the initial phase of the sleeping period delays the onset of sleep in summer. Build. Environ. 103, 36–43, 07/01/ 2016.
Lan, L., Lian, Z., Zhou, X., Sun, C., Huang, H., Lin, Y., et al., 2013. Pilot study on the application of bedside personalized ventilation to sleeping people. Build. Environ. 67, 160–166, 09/01/ 2013.
Laverge, J., Van Den Bossche, N., Heijmans, N., Janssens, A., 2011. Energy saving potential and repercussions on indoor air quality of demand controlled residential ventilation strategies. Build. Environ. 46, 1497–1503, 07/01/ 2011.
Less, B.D., Dutton, S.M., Walker, I.S., Sherman, M.H., Clark, J.D., 2019. Energy savings with outdoor temperature-based smart ventilation control strategies in advanced California homes. Energy Build. 194, 317–327.
Li, R., Sekhar, S.C., Melikov, A.K., 2010. Thermal comfort and IAQ assessment of under-floor air distribution system integrated with personalized ventilation in hot and humid climate. Build. Environ. 45, 1906–1913, 09/01/ 2010.
Liu, W., Lian, Z., Zhao, B., 2007. A neural network evaluation model for individual thermal comfort. Energy Build. 39, 1115–1122, 10/01/ 2007.
Liu, J., Zhu, S., Kim, M.K., Srebric, J., 2019. A review of CFD analysis methods for personalized ventilation (PV) in indoor built environments. Sustainability 11, 4166.
Liuliu Du, S.B., Godwin, Christopher, Chin, Jo-Yu, Parker, Edith, Breen, Michael, Brakefield, Wilma, Robins, Thomas, Lewis, Toby, 2012. Air change rates and interzonal flows in residences, and the need for multi-zone models for exposure and health analyses. Int. J. Environ. Res. Public Health 9 (12), 4639–4661.

Lu, J., Sookoor, T., Srinivasan, V., Gao, G., Holben, B., Stankovic, J., et al., 2010. The smart thermostat: using occupancy sensors to save energy in homes. In: Presented At the Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems. Zürich, Switzerland.
Lu, S., Wang, W., Lin, C., Hameen, E.C., 2019. Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884. Build. Environ. 156, 137–146, 06/01/ 2019.
Luo, M., Cao, B., Damiens, J., Lin, B., Zhu, Y., 2015. Evaluating thermal comfort in mixed-mode buildings: A field study in a subtropical climate. Build. Environ. 88, 46–54, 06/01/ 2015.
Luo, M., Xie, J., Yan, Y., Ke, Z., Yu, P., Wang, Z., et al., 2020. Comparing machine learning algorithms in predicting thermal sensation using ASHRAE comfort database II. Energy Build. 210, 109776, 03/01/ 2020.
Makhoul, A., 2012. Ceiling-mounted fresh air personalized ventilator for occupant-controlled microenvironment. In: Proceedings of the ASME 2012 International Mechanical Engineering Congress and Exposition; IMECE 2012.
Makhoul, A., Ghali, K., Ghaddar, N., 2013. Desk fans for the control of the convection flow around occupants using ceiling mounted personalized ventilation. Build. Environ. 59, 336–348, 01/01/ 2013.
Makhoul, A., Ghali, K., Ghaddar, N., 2015. Low-mixing coaxial nozzle for effective personalized ventilation. Indoor Built Environ. 24, 225–243.
Mamidi, S., Chang, Y.-H., Maheswaran, R., 2012. Improving building energy efficiency with a network of sensing, learning and prediction agents. In: Presented at the Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems - Volume 1. Valencia, Spain.
Mansson, L.G., Svennberg, L.A., Liddament, M., 1997. A Summary of IEA Annex 18. Demand Controlled Ventilating Systems. Technical Synthesis Report, AIVC.
Melikov, A.K., 2004a. Personalized ventilation. Indoor Air 14, 157–167.
Melikov, A.K., 2004b. Personalized ventilation. Indoor Air 14 (Suppl 7), 157–167.
Melikov, A.K., Cermak, R., Majer, M., 2002. Personalized ventilation: evaluation of different air terminal devices. Energy Build. 34, 829–836, 09/01/ 2002.
Melikov, A.K., Kaczmarczyk, J., 2012. Air movement and perceived air quality. Build. Environ. 47, 400–409, 01/01/ 2012.
Melikov, R.C.A.K., Kovar, O., Forejt, L., 2003. Impact of airflow interaction on inhaled air quality and transport of contaminants in rooms with personalized and total volume ventilation. In: Proceedings of the 7th International Conference on Healthy Buildings, 7-11 2003, Singapore.
Mozer, M.C., 1998. The neural network house: An environment hat adapts to its inhabitants. In: Proc. AAAI Spring Symp. Intelligent Environments.
Nabers, 2010. NABERS indoor environment for offices data collection guidance document.
Nagy, Z., Yong, F.Y., Frei, M., Schlueter, A., 2015. Occupant centered lighting control for comfort and energy efficient building operation. Energy Build. 94, 100–108, 05/01/ 2015.
Namba, S., Kuwano, S., Okamoto, T., 2004. Sleep disturbance caused by meaningful sounds and the effect of background noise. J. Sound Vib. 277, 445–452, 10/22/ 2004.
Nassif, N., 2012. A robust CO2-based demand-controlled ventilation control strategy for multi-zone HVAC systems. Energy Build. 45, 72–81.
Nishi, Y., 1981. Chapter 2 measurement of thermal balance of man. In: Cena, K., Clark, J.A. (Eds.), Studies in Environmental Science, Vol. 10. Elsevier, ed, pp. 29–39.
Niu, J., Gao, N., Phoebe, M., Huigang, Z., 2007. Experimental study on a chair-based personalized ventilation system. Build. Environ. 42, 913–925, 02/01/ 2007.
Nunneley, R.J.M.S.A., 1983. Head and or/torso cooling during simulated cockpit heat stress. Aviat. Space Environ. Med. 54, 496–499.
Nunneley, D.C.R.S.A., Maldonado, R.J., 1982. Head-temperature effects on physiology, comfort and performance during hyperthermia. Aviat. Space Environ. Med. 53, 623–628.
Organization, I.S., 2004. Ergonomics of the Thermal Environment—Analytical Determination and Interpretation of Heat Stress using Calculation of the Predicted Heat Strain, ISO Standards 7933, ed. International Standards Organization Geneva, Switzerland.
Pan, Y., Du, C., Fu, Z., Fu, M., 2021. Re-thinking of engineering operation solutions to HVAC systems under the emerging COVID-19 pandemic. J. Build. Eng. 43, 102889, 11/01/ 2021.
Pantelic, J., Liu, S., Pistore, L., Licina, D., Vannucci, M., Sadrizadeh, S., et al., 2020a. Personal CO 2 cloud: laboratory measurements of metabolic CO 2 inhalation zone concentration and dispersion in a typical office desk setting. J. Expos. Sci. Environ. Epidemiol. 30, 328–337.
Pantelic, J., Liu, S., Pistore, L., Licina, D., Vannucci, M., Sadrizadeh, S., et al., 2020b. Personal CO2 cloud: laboratory measurements of metabolic CO2 inhalation zone concentration and dispersion in a typical office desk setting. J. Expos. Sci. Environ. Epidemiol. 30, 328–337.
Peng, Y., Rysanek, A., Nagy, Z., Schlüter, A., 2018. Using machine learning techniques for occupancy-prediction-based cooling control in office buildings. Appl. Energy 211, 1343–1358, 02/01/ 2018.
Persily, A.K., 1997. Evaluating building IAQ and ventilation with indoor carbon dioxide. ASHRAE Trans. 103 (pt 2), 193–204.
Persily A, D.W.S., 1990. The relation of CO 2 concentration to office building ventilation. In: Air Change Rate and Airtightness in Buildings. ASTM International.
Rawal, R., Schweiker, M., Kazanci, O.B., Vardhan, V., Jin, Q., Duanmu, L., 2020. Personal comfort systems: A review on comfort, energy, and economics. Energy Build. 214, 109858.
Rinaldi, A., Roccotelli, M., Mangini, A.M., Fanti, M.P., Iannone, F., 2017. Natural ventilation for passive cooling by means of optimized control logics. Procedia Eng. 180, 841–850, 01/01/ 2017.
Russo, J.S., Dang, T.Q., Khalifa, H.E., 2009. Computational analysis of reduced-mixing personal ventilation jets. Build. Environ. 44, 1559–1567, 08/01/ 2009.
Ryu, S.H., Moon, H.J., 2016. Development of an occupancy prediction model using indoor environmental data based on machine learning techniques. Build. Environ. 107, 1–9, 10/01/ 2016.
Safavian, S.R., Landgrebe, D., 1991. A survey of decision tree classifier methodology. IEEE Trans. Syst. Man Cybern. 21, 660–674.
Santos, A.F., Gaspar, P.D., Hamandosh, A., Aguiar, E.B.d., Guerra Filho, A.C., Souza, H.J.L.d., 2020. Best practices on HVAC design to minimize the risk of COVID-19 infection within indoor environments. Braz. Arch. Biol. Technol. 63.
Schell, M., Int-Hout, D., 2001. Demand control ventilation using CO∼2. ASHRAE J. 43, 18–29.
Schell, S.C.T.M.B., Shim, R.O., 1998. Application of CO2-based demand-controlled ventilation using ASHRAE Standard 62: optimizing energy use and ventilation. ASHRAE Trans. 104 (2), 1213–1225.
Schiavon, S., Melikov, A.K., Sekhar, C., 2010. Energy analysis of the personalized ventilation system in hot and humid climates. Energy Build. 42, 699–707, 05/01/ 2010.
Schibuola, L., Scarpa, M., Tambani, C., 2018. CO2 based ventilation control in energy retrofit: An experimental assessment. Energy 143, 606–614, 01/15/ 2018.
Schoeller, D.A., Fjeld, C.R., 1991. Human energy metabolism: what have we learned from the doubly labeled water method? Annu. Rev. Nutr. 11, 355–373.
Scott, J., Brush, A.J.B., Krumm, J., Meyers, B., Hazas, M., Hodges, S., et al., 2011. PreHeat: controlling home heating using occupancy prediction. In: Presented at the Proceedings of the 13th International Conference on Ubiquitous Computing. Beijing, China.
Sechzer, P.H., Egbert, L.D., Linde, H.W., Cooper, D.Y., Dripps, R.D., Price, H.L., 1960. Effect of CO2 inhalation on arterial pressure, ECG and plasma catecholamines and 17-OH corticosteroids in normal man. J. Appl. Physiol. 15, 454–458.
Sekhar, S.C., Gong, N., Tham, K.W., Cheong, K.W., Melikov, A.K., Wyon, D.P., et al., 2005. Findings of personalized ventilation studies in a hot and humid climate. HVAC R Res. 11, 603–620, 10/01 2005.
Seppänen O, B.N., Goeders, G., et al., 2012. Existing Buildings, Building Codes, Ventilation Standards and Ventilation in Europe. Final HEALTHVENT WP5 report.
Seppänen OA, F.W.J., Mendell, M.J., 1999. Association of ventilation rates and CO2 concentrations with health andother responses in commercial and institutional buildings. Indoor Air 9 (4), 226–252.
Sherstov, I.V., Vasiliev, V.A., Karapuzikov, A.I., Zenov, K.G., 2020. Comparative studies of photo-acoustic gas analyzers based on tunable CO2 lasers with external and intracavity detector arrangement. Infrared Phys. Technol. 105, 103170, 03/01/ 2020.
Singh, A.P., Jain, V., Chaudhari, S., Kraemer, F.A., Werner, S., Garg, V., 2018. Machine learning-based occupancy estimation using multivariate sensor nodes. In: 2018 IEEE Globecom Workshops (GC Wkshps). pp. 1–6.
Sjöström, S., Klintenäs, E., Johansson, P., Nyqvist, J., 2020. Optimized model-based control of main mine ventilation air flows with minimized energy consumption. Int. J. Mining Sci. Technol. 07/08/ 2020.
Sliwka, U., Krasney, J.A., Simon, S.G., Schmidt, P., Noth, J., 1998. Effects of sustained low-level elevations of carbon dioxide on cerebral blood flow and autoregulation of the intracerebral arteries in humans. Aviat. Space Environ. Med. 69, 299–306.
Song, G., Ai, Z., Zhang, G., Peng, Y., Wang, W., Yan, Y., 2022. Using machine learning algorithms to multidimensional analysis of subjective thermal comfort in a library. Build. Environ. 212, 108790, 03/15/ 2022.
Stricker, S., Bourgeau, M., Fonberg, E., Parent, D., 1997. Physiological responses to elevated carbon dioxide levels in buildings. Indoor Built Environ. 6, 301–308, 09/01 1997.
Sun, Z., Wang, S., Ma, Z., 2011. In-situ implementation and validation of a CO2-based adaptive demand-controlled ventilation strategy in a multi-zone office building. Build. Environ. 46, 124–133, 01/01/ 2011.
Tham, S.C.S.K.W., Cheong, D.K.W., Gong, N., 2004. A case study of quantitative energy efficiency of personalized ventilation in the tropics. In: Proceedings of ROOMVENT 2004, 5–8 September, Coimbra, Portugal.
Tokuda, K., Yoshimura, T., Masuko, T., Kobayashi, T., Kitamura, T., 2000. Speech parameter generation algorithms for HMM-based speech synthesis. In: 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No. 00CH37100). pp. 1315–1318.

Tucker, W.G., 1992. Ventilation for Acceptable Indoor Air Quality. Rpt. for Jan-Aug 92. Environmental Protection Agency, Air and Energy Engineering Research Lab, Research Triangle Park, NC (United States).

Vehvilainen, T., Lindholm, H., Rintamaki, H., Paakkonen, R., Hirvonen, A., Niemi, O., et al., 2016. High indoor CO2 concentrations in an office environment increases the transcutaneous CO2 level and sleepiness during cognitive work. J. Occup. Environ. Hyg. 13, 19–29.

Veselý, M., Zeiler, W., 2014. Personalized conditioning and its impact on thermal comfort and energy performance–A review. Renew. Sustain. Energy Rev. 34, 401–408.

Wachenfeldt, B.J., Mysen, M., Schild, P.G., 2007. Air flow rates and energy saving potential in schools with demand-controlled displacement ventilation. Energy Build. 39, 1073–1079, 10/01/ 2007.

Walker, I., Guyot, G., Sherman, M., Jordan, C., 2021. Residential smart ventilation: A review.

Wei, W., Ramalho, O., Mandin, C., 2015. Indoor air quality requirements in green building certifications. Build. Environ. 92, 10–19, 10/01/ 2015.

Welling, M., 2011. A First Encounter with Machine Learning. University of California, Irvine, CA, p. 12.

Woods, S.W., Charney, D.S., Goodman, W.K., Heninger, G.R., 1988. Carbon dioxide-induced anxiety: behavioral, physiologic, and biochemical effects of carbon dioxide in patients with panic disorders and healthy subjects. Arch. Gen. Psychiatry 45, 43–52.

Wouter Borsboom T, D.G.N.W., Logue, J., et al., 2016. Technical Note AIVC 68 Residential Ventilation and Health. INIVE EEIG, Belgium.

Wu, Z., Li, N., Peng, J., Cui, H., Liu, P., Li, H., et al., 2018. Using an ensemble machine learning methodology-bagging to predict occupants' thermal comfort in buildings. Energy Build. 173, 117–127, 08/15/ 2018.

Xanthopoulos, P., Pardalos, P.M., Trafalis, T.B., 2013. Linear discriminant analysis. In: Robust Data Mining. Springer, ed, pp. 27–33.

Yan J, Z.Q., Liang, Y., et al., 2017. Modeling and implementation of electroactive smart air-conditioning vent register for personalized HVAC systems. IEEE Access 5, 1649–1657.

Yang, Z., Li, N., Becerik-Gerber, B., Orosz, M., 2012. A Multi-Sensor Based Occupancy Estimation Model for Supporting Demand Driven HVAC Operations, Vol. 44.

Yang, B., Sekhar, C., Melikov, A.K., 2010. Ceiling mounted personalized ventilation system in hot and humid climate—An energy analysis. Energy Build. 42, 2304–2308, 12/01/ 2010.

Yeom, D., Choi, J.-H., Kang, S.-H., 2019. Investigation of the physiological differences in the immersive virtual reality environment and real indoor environment: Focused on skin temperature and thermal sensation. Build. Environ. 154, 44–54, 05/01/ 2019.

Zeng, Q., Kaczmarczyk, J., Melikov, A., Fanger, P.O., 2002. Perceived air quality and thermal sensation with personalized ventilation system. In: Proceedings of Roomvent, pp. 61–64.

Zhang, H., Arens, E., Zhai, Y., 2015. A review of the corrective power of personal comfort systems in non-neutral ambient environments. Build. Environ. 91, 15–41.

Zhang, H., Berg, A.C., Maire, M., Malik, J., 2006. SVM-KNN: Discriminative nearest neighbor classification for visual category recognition. In: 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06). pp. 2126–2136.

Zhou, X., Lian, Z., Lan, L., 2014. Experimental study on a bedside personalized ventilation system for improving sleep comfort and quality, 23, pp. 313–323.

Zhou, X., Xu, L., Zhang, J., Niu, B., Luo, M., Zhou, G., et al., 2020. Data-driven thermal comfort model via support vector machine algorithms: Insights from ASHRAE RP-884 database. Energy Build. 211, 109795, 03/15/ 2020.