Building and Environment 237 (2023) 110332

Contents lists available at ScienceDirect

Building and Environment

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

A novel occupant-centric stratum ventilation system using computer vision: Occupant detection, thermal comfort, air quality, and energy savings

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ARTICLE INFO

Keywords:
Occupant-centric control strategy
Occupant detection
Stratum ventilation
Thermal comfort
Energy savings
Computer vision

ABSTRACT

Traditional ventilation and air conditioning systems typically operate on a predetermined schedule with fixed operating parameters. Occupant-centric control (OCC) strategies have been proposed to reduce system operation energy consumption without sacrificing thermal comfort. Indoor occupancy detection in real time is a critical step in successfully implementing the OCC strategy. Thus, the deep learning-based computer vision method was adopted in the first step of the study, and the detection performance and camera position were analyzed in an office scenario. Next, the proposed OCC strategy was used to regulate the supply air parameters and outdoor air volume in stratum ventilation based on the monitored occupant number. The traditional static control strategy was then compared to two control strategies: constant air volume and variable air volume. Occupant detection performance results showed the mean NRMSD for the five most common relative positions of the occupants and camera was 0.1109, with sitting back to camera having the lowest accuracy. Subjective response results demonstrated that, when compared to the traditional control strategy, thermal comfort was improved by 43%–73%, perceived air quality was maintained at an acceptable level, CO_2 concentration was less than 700 ppm, and energy could be saved by 2.3%–8.1%. Furthermore, the lower the occupancy, the greater the improvement in comfort and the greater the energy savings. This research focused on how the stratum ventilation system responds to dynamic changes in occupancy and provided insights into reducing unnecessary energy waste while maintaining comfort.

1. Introduction

According to statistics by the US Department of Energy, building energy consumption accounts for more than 40% of primary energy consumption, with residential and commercial buildings accounting for 28% and 14%, respectively [1]. Heating, ventilation, and air conditioning (HVAC) systems account for 40% of building total energy consumption [2]. Despite the fact that HVAC engineers recognize the importance of energy conservation in HVAC systems, most conventional air conditioning systems typically operate at maximum indoor occupancy and fixed setpoint schedules [3,4]. Mahdavi et al. [5] collected data from three office buildings in Austria and found that the average occupancy of these offices was less than 60% during the most experiment period. Therefore, studies are beginning to shed light on the impact of highly stochastic indoor occupant information on energy consumption. On the one hand, unused or unoccupied space is regulated by the HVAC system, resulting in over-conditioning of rooms and potentially a large amount of wasted energy [6]. On the other hand, occupied space maintains maximum fresh air volume, fixed supply air parameters, or fixed indoor temperature in different occupant information, which does not satisfy the comfort and wastes energy [7].

Thermal comfort and indoor air quality are important factors to consider in HVAC design and should not be overlooked when looking for ways to reduce building energy consumption [8]. The occupant-centric control (OCC) strategy has been proposed to reduce energy consumption, improve occupant thermal comfort, and ensure air quality [9]. The OCC strategy was mentioned in IEA EBC Annex 79, ASHRAE standard 62.1, and ASHRAE handbook [10–12]. The OCC strategy is a control

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https://doi.org/10.1016/j.buildenv.2023.110332
Received 28 February 2023; Received in revised form 16 April 2023; Accepted 18 April 2023
Available online 18 April 2023
0360-1323/

strategy for air conditioning systems that captures indoor environmental parameters and occupant information from the building space and feeds them into the HVAC control system [10]. Both the passive presence and active behavior of occupants affect HVAC start/stop times and operating parameters. OCC strategies are generally divided into two categories: controlling building system operation based on occupant presence, number & position, and predicting preference based on human behaviors (e.g., window opening) to control the operation of building system [13]. In this paper, the first category is adopted to quantify thermal comfort, air quality, and energy savings. According to the review by Xie et al. [14], the case with the OCC strategy can save 22% of air-conditioning energy while improving thermal comfort by 29.1%. The previous study also demonstrated that OCC strategy could create better synergies between indoor air quality, thermal comfort, and energy savings when compared to the conventional control strategy [15].

1.1. Occupant detection

The implementation of an OCC strategy needs to detect indoor occupants. The occupant presence detection method has been used in lighting control systems in various types of buildings [13], whereas the occupant number detection method is still in the early stages of development in building automation systems [13]. Environmental sensors, such as a carbon dioxide sensor and a temperature sensor, only provide rough estimates of indoor occupancy, and the detection accuracy is limited by the sensors' placement. PIR sensor, ultrasonic detector, and pressure sensor are used to detect the presence and number of active occupants [16], but they cannot detect the number of inactive occupants or their locations. Radio frequency identification (RFID) sensor can determine the spatial coordinates of occupants as sensor technology advances [17], but each occupant must wear a specialized tag. The Wi-Fi sensor can identify mobile devices to determine the occupant number [18], but the detection accuracy is influenced by the occupants' devices and living habits.

In light of the shortcomings discussed above, various non-contact sensors, such as camera-based occupant detection technology, have gradually been developed [19]. Computer vision is a combination of camera and deep learning to achieve real-time automatic recognition and tracking of objects instead of the human eye. In general, camera-based deep learning models can predict occupant numbers, positions, and activities with an accuracy range of 80–97%, improving the detection speed, and not interfering with the normal work of occupants [20]. Convolutional neural network (CNN) is the deep learning technology most closely related to image identification [19]. R–CNN [21], Fast R–CNN [22], and Faster R–CNN [23] are object detection methods based on region proposal with high detection accuracy but no real-time detection effect. YOLO algorithm [24] based on CNN can achieve real-time detection with high detection accuracy. Therefore, the YOLO object detection algorithm is used in this study.

1.2. Occupant-centric control strategy studies

With the increased demand for energy savings and the advancement of occupant detection technology, researchers are beginning to investigate the potential application of OCC strategies in HVAC systems. Most researchers use calculation and simulation methods to quantify and compared the performance of OCC strategies to the traditional control strategy based on static schedules. Recently, a few field studies have been conducted to quantify the performance of OCC strategies. Table 1 provides an overview of previous OCC strategy studies. In summary, current studies primarily focus on: 1) controlling the occupied zone temperature and unoccupied zone temperature at different setting values (e.g., temperature setback) [6,25], 2) ensuring the minimum ventilation rate corresponding to the detected occupant number [26], 3) considering both the zone temperature and the ventilation rate [27–30], 4) predicting the indoor human heat load in real time to implement OCC strategies [20], as well as 5) considering the lighting systems [30].

As shown in Table 1, existing studies mainly use OCC strategies to regulate the room temperature to the setting values in the uniform thermal environment, such as mixing ventilation, split-type air conditioners, and energy recovery ventilators. However, no research has been done on the OCC strategy used in a non-uniform thermal environment. The room temperature for a uniform thermal environment is equal to the return air temperature, and the HVAC control system regulates the return air temperature to provide thermal comfort [31]. However, in a non-uniform thermal environment, the difference between the return air temperature and the occupied zone temperature could reach as 4.5 °C [32]. When non-uniform air distribution is regulated based on indoor temperature, it will cause thermal discomfort because the supply parameters are outside the recommended range [32,33]. Therefore, in practical applications, the non-uniform air distribution should dynamically regulate the air supply parameters [34]. In this study, the OCC strategy for a non-uniform thermal environment is optimized by taking supply air parameters and fresh air volume into account, and the performance is quantified by field experiments.

Table 1
Occupant-centric control strategy research review.

Authors	Occupant detection method	Performance test	Building type	Control parameters	Control test	Energy savings	Thermal comfort	Air quality
Tien et al. [6]	CNN Occupant activities	Experiment	Office	Zone temperature & Ventilation duration	Simulation (BES)	Qualitative	Qualitative	/
Choi et al. [30]	CNN Occupant number	Experiment	Office	Temperature setback & Ventilation rate & Lighting	Simulation (EnergyPlus)	10.2% per year	/	/
Meng et al. [25]	FCHD Occupant number	Image dataset	Activity center & Office	Setting temperature	Simulation (TRNSYS)	6.7%	/	/
Tien et al. [20]	CNN Occupant activities	Experiment	Office	Heating load	Simple calculation & Simulation (BES)	Qualitative	/	Qualitative
Pang et al. [29]	Occupant number	/	Office	Temperature setback & Ventilation rate	Simulation (EnergyPlus)	20–45%	/	/
Choi et al. [26]	CNN Occupant number	Experiment	Office	Ventilation rate	Experiment	24–35%	/	Below 1000 ppm
Wang et al. [27]	Video camera & CO_2 sensor Occupant number	Experiment	Office	Air conditioning on/off & Ventilation rate	Experiment	39.4%	Qualitative	/
Kong et al. [28]	Depth & Pressure-based & RFID sensor Occupant number	Experiment	Office	Temperature setback & Ventilation rate	Side-by-side comparison experiment	17–24%	Comfort more than 90%	Neutral greater than 95%

1.3. Stratum ventilation (SV)

Ventilation methods can be classified as fully mixed or non-uniform based on airflow characteristics [35]. In mixing ventilation, a high-speed jet introduces air handled by an air handling unit (AHU) into the room, rolls up the surrounding room air, and creates a uniform thermal environment. Because the AHU handles the load of the entire room, including the load of the unoccupied zone, wasted energy and poor inhaled air quality result. Non-uniform air distribution that only allows the load of the occupied zone has been proposed to save energy consumption of the air conditioning system, and a non-uniform thermal environment has been created. Stratified ventilation is a category of non-uniform ventilation techniques, such as stratum ventilation (SV) [35].

The SV, as shown in Fig. 1, provides fresh air at the head (breathing) level and generates a “sandwich” airflow field in an indoor environment [36]. The thermal neutral temperature of subjects exceeds 27 °C [37,38]. The cooling effect (temperature and airflow) of the conditioned airflow is strongest at the head level, and the situation of “cool head and warm feet” is to provide thermal comfort [37,38]. The thermal comfort indices (PMV, PPD, and PD) meet the requirements of ISO 7730, CR 175–1998, and ASHRAE 55–2020 [37,38]. According to objective measurements [39], the air diffusion performance index (ADPI) is greater than 80%, and the ventilation efficiency is greater than unity. Based on the aforementioned characteristics of this non-uniform air distribution, it can save at least 25–44% of energy over the course of a year when compared to displacement and mixing ventilation [40].

Thus, SV is a comfortable and energy-saving air distribution, which can be used in offices, classrooms, retail shops, and other public buildings [35]. Each air supply inlet in the SV system is responsible for different indoor zones, which are conducive to partitioning regulation based on occupant distribution [41]. The OCC strategy based on occupant detection can further realize the energy savings of the stratum ventilation system. Because of the above three reasons, this study employs stratum ventilation to examine the performance of the OCC strategy in a non-uniform thermal environment.

1.4. Knowledge gaps and contributions

Taking advantage of the features of such an advanced ventilation system, this study proposes an OCC strategy based on computer vision to regulate the stratum ventilation and air conditioning system in real-time, with the goal of creating an acceptable indoor environment while consuming minimal energy. This study primarily addresses the four research questions listed below.

(1) Computer vision technology performance evaluation and optimization solutions for detecting the occupant number in an office environment. In comparison to other studies, this work focuses on the feasibility of applying computer vision based on the YOLO algorithm to office buildings and discusses the recommended installation position and angle of the camera.
(2) The study employs a stratum ventilation system and proposes a design scheme for a real-time occupant-centric control strategy based on occupant number in a non-uniform thermal environment. Existing studies primarily control the zone temperature under the mixing ventilation system and spilt-type air conditioner, all of which result in a uniform thermal environment, to a setting value. However, in a non-uniform environment, such a control strategy will result in supply air parameters outside the recommended comfortable range. This study focuses on the stratum ventilation system (non-uniform air distribution) suitable for the office environment and proposes an OCC strategy that comprehensively takes occupant information, supply air parameters, and fresh air volume into account.
(3) Human trials are carried out to evaluate the thermal comfort performance of the OCC strategy in a stratum ventilation office scenario. The evaluation indies include thermal comfort vote (TCV), thermal sensation vote (TSV), thermal acceptability, thermal preference, and perceived air quality. Other studies primarily assess theoretical values such as predicted mean vote (PMV) and indoor environment parameters, without taking into account practical application effects.
(4) In addition to assessing thermal comfort and air quality, the energy savings potential under the proposed OCC strategy is analyzed. Few studies take into account the three performance metrics of thermal comfort, air quality, and energy-saving potential all at once.

The purpose of this study is to evaluate the applicability of the OCC strategy based on computer vision to a non-uniform thermal environment from a variety of perspectives. It could serve as a reference for building HVAC designers when applying the OCC strategy to the non-uniform thermal environment in offices. It will help advance research into occupant detection methods, occupant-centric control strategies, demand-controlled ventilation, energy savings in buildings, and indoor thermal comfort.

2. Occupant-centric control strategy based on computer vision

2.1. Overview of research methodology

Fig. 2 depicts an overview of the research method and framework. To begin, this study employs an occupant detection method based on a deep learning algorithm (YOLOv5 occupant detection model released in June 2021, Section 2.2.1), assesses detection performance in an office

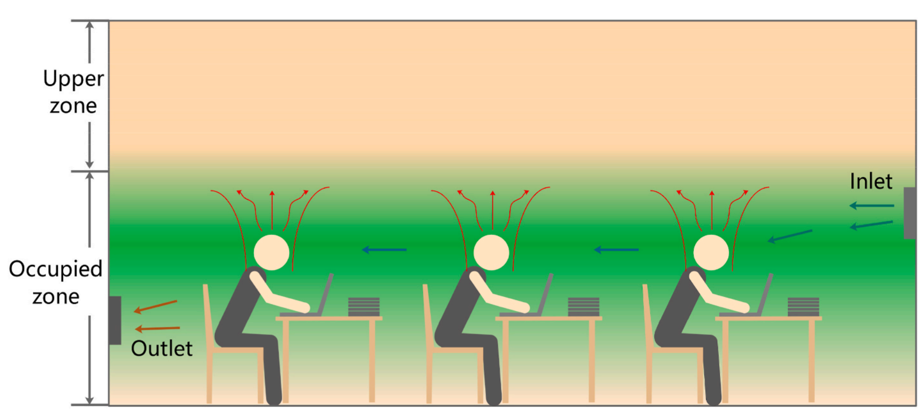


Fig. 1. Indoor air distribution under the stratum ventilation.

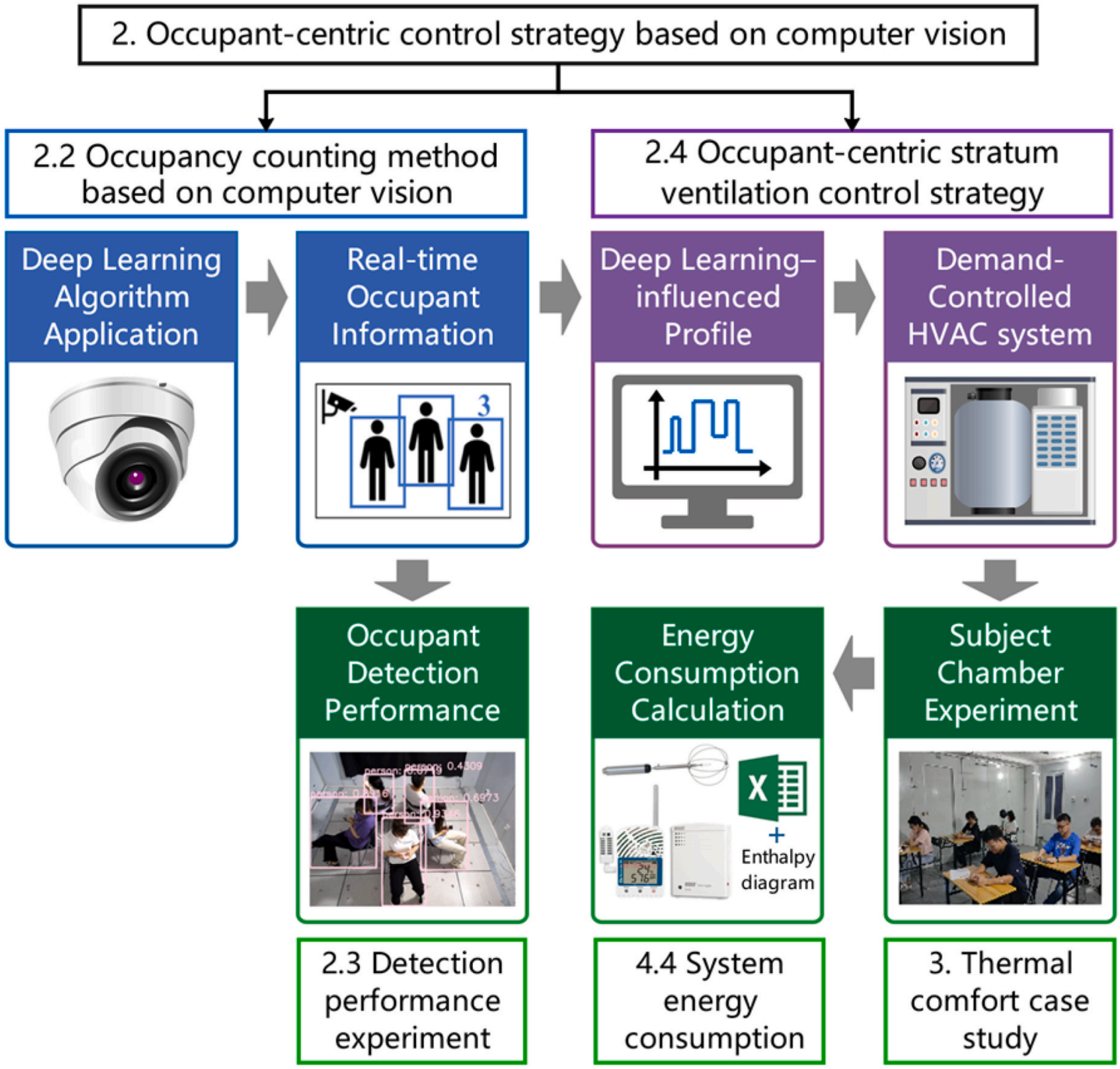


Fig. 2. Overview of the research method and framework.

environment (Section 2.3). Second, a deep learning-influenced profile (DLIP) based on indoor occupant data is created (Section 2.2.2). Following that, an occupant-centric stratum ventilation control strategy is proposed based on the proportion integration differentiation (PID) control principle (Section 2.4). Furthermore, the thermal comfort and air quality created by the OCC strategy is evaluated by the subjective experiment (Section 3). Finally, the results of occupant detection (Section 4.1), thermal comfort (Section 4.2), air quality (Section 4.3), and energy consumption (Section 4.4) are adopted comprehensively to assess the overall performance of the proposed OCC strategy.

2.2. Occupancy counting method based on computer vision

2.2.1. YOLO algorithm

The object detection algorithm based on CNN concludes two types of object detection architecture: one-stage and two-stage. From the entire image, one-stage predicts directly bounding boxes and class probabilities. However, two-stage predicts final bounding boxes and class probabilities one by one by using region proposal to generate potential bounding boxes from the full image. R–CNN [21], Fast R–CNN [22], and Faster R–CNN [23] are based on region proposal with high detection accuracy but no real-time detection effect. The YOLO algorithm processes the full images and reduces the object detection problem to a simple regression problem. There is no region proposal and no separate calculation for each region of interest (ROI), and the detection accuracy and detection speed are greatly improved by using GPU parallel processing to calculate the response map [24]. Another one-stage object detection method is the single shot multibox detector (SSD) [42]. SSD detects objects using multi-scale feature map, which can achieve real-time detection. The YOLOv5 algorithm used in this study also makes use of the multi-scale feature map concept. Because the methods described above were both trained on very large image datasets, their detection performance is excellent.

YOLO stands for "you only look once," which means that you can predict the locations and classes of objects by looking only once. This paper employs version 5.0 of the YOLOv5 algorithm to achieve simple and efficient detection performance. The central idea is to directly predict bounding boxes and class probabilities from input images using a CNN structure. Input, backbone, neck, and head are all parts of the network structure. In the prediction phase, the image is divided into three scale grid cells, each with three initial anchor boxes. Then, based on the location and the contained image of each grid cell, the coordinates (x, y) of each anchor box center relative to the grid cell center, width w and height h, confidences and class probabilities are predicted.

The confidence is the intersection over union (IOU) of the anchor box and the ground truth box if the anchor box contains the object. Finally, non-maximum suppression (NMS) based on distance-IOU (DIOU) is used to screen the optimal bounding box of each detection object in the image. In the training phase, according to the ground truth boxes of the training set, the dimensions of the three initial anchor boxes corresponding to the three scales are obtained by the k-means clustering algorithm. The loss function is a regression problem, and the gradient descent method is used to minimize the loss function.

The YOLO algorithm has been generally adopted to detect occupancy in buildings in recent years [30,43–46], with detection accuracy ranging from 80% to 97%. The YOLO algorithm has been constantly optimized since 2016, and version 5.0 of YOLOv5 was released on June 23, 2021. YOLOv5 is more flexible, accurate, and fast in detection than previous versions. As a result, this study employs YOLOv5 version 5.0, which includes four models: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Because the network depth and width of the four models differ, so do the detection speed and accuracy. Although YOLOv5s object detection speed is faster and YOLOv5x detection speed is slower, the difference in occupant detection accuracy in the office environment is not significant. The occupant detection system for occupant-centric HVAC system of office buildings must meet the requirements of real-time detection and long-term operation. In this study, the YOLOv5s-5.0 algorithm is chosen, and the MS COCO dataset with 80 classes is used to train the model. Fig. 3(a) depicts the detection process.

2.2.2. Deep learning–influenced profile

According to the detected occupant number by the mentioned algorithm, the deep learning-influenced profile (DLIP) [20] is shown in Fig. 3(b). To reduce operation costs, it is recommended that the air conditioning system's regulation period is set to 10 min [47], and the number of occupants is set to the modal number 1 min before the air

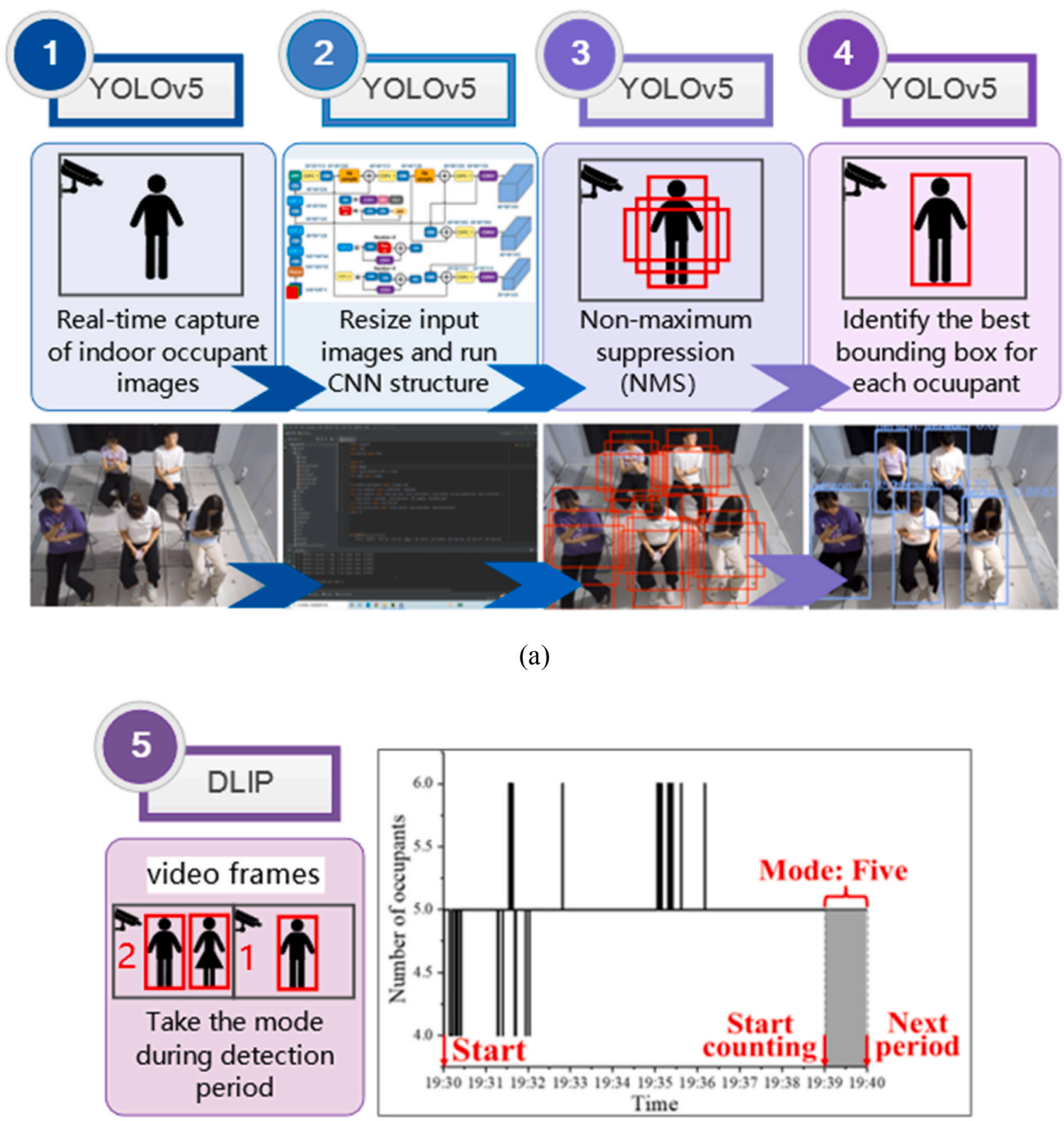


Fig. 3. The occupant detection algorithm (a. The process of algorithm; b. A method for outputting DLIP from real-time detection results).

conditioning system's regulation [48]. DLIP will be used to generate the occupant heat emission curve over time. In the calculation of the cooling load, the metabolic rate of typing, 1.1 met [49], is chosen to stand for the metabolic rate of office activities. Then, the cooling capacity that the air conditioning system should provide over time is generated. Thus, the operating parameters of the HVAC system can be automatically adjusted based on occupant information, and the control strategy is detailed in Section 2.4. As a result, DLIP is used to provide input parameters to the proposed OCC strategy in this study.

2.3. Detection performance experiment

In order to quantify the detection performance of the YOLOv5s-5.0 algorithm in an office scenario, the experiment was carried out in an experimental chamber designed to simulate a multi-person office with five to six occupants. As shown in Fig. 4, the office measures 3.8 m in length, 3.8 m in width, and 2.6 m in height. The occupant detection experiments in this study evaluated the detection effects of six relative positions of occupants and camera (Section 4.1). There were a total of 6 experimental conditions and a total of 15 subjects, 5 subjects for each experiment. The experiments lasted 6 days, with one experimental condition per day and three groups of subjects tested each day. Each group of subjects collected 1 h of experimental data for each experimental condition, detection results were recorded every 10 s, and 1080 data were screened for each experimental condition. The subjects were not controlled except for the sitting posture orientation. In a thermal comfort experiment with occupant-centric stratum ventilation, the performance of occupant detection was also evaluated.

The camera was mounted on the side wall near the ceiling (approximately 2.5 m high) in order to capture a large portion of the room. The HIKVISION camera, which captures 2560 × 1440 frames at 25 frames per second, captures the distribution of occupants in real time. The camera is linked to a computer, which runs the deep learning algorithm described in section 2.2.1 to generate the occupant detection results, which are saved in real time in an Excel file. The experiment computer was outfitted with an NVIDIA GeForce RTX 2060 graphics card and 16 GB of RAM. The actual number of occupants at a time is determined by viewing the detection processes' output video files, which are then compared to the predicted number of occupants at a time.

Accuracy, recall, F-measure, and normalized root mean square deviation (NRMSD) are commonly used detection performance indices to provide more in-depth performance information, which is essential for occupant-centric HVAC systems. This study focuses on the differences in the detection performance of the algorithm across different studies in the Results and Discussion section. NRMSD as a standardized evaluation index can be compared with the findings of other studies [50]. As a result, the NRMSD is chosen as a performance metric to assess accuracy [51]. The difference between the actual and predicted values is represented by NRMSD, and the closer it is to zero, the closer the algorithm detection value is to the true value, and the more accurate the detection. The NRMSD calculation equation is shown in Equation (1).

$$NRMSD(x,y) = \frac{\frac{\|x-y\|}{\sqrt{K}}}{\max(z) - \min(z)} \tag{1}$$

where, $x = [x_1, \ldots, x_K]$ is a vector of K predicted numbers of occupants, $y = [y_1, \ldots, y_K]$ is a vector of K actual numbers of occupants, K is the number of samples collected for the detection performance experiment, $z = [x^T, y^T]^T$, $\|.\|$ is the Euclidean norm.

2.4. Occupant-centric stratum ventilation control strategy

Compared with other ventilation systems, stratum ventilation system (Section 1.3) can improve thermal comfort and air quality with reducing energy consumption. Vertical temperature stratification is observed in a room with stratum ventilation [36], which creates a non-uniform thermal environment. Each air supply inlet is responsible for different indoor zones, which aids in the partition regulation of the office space. The stratum ventilation system is chosen as the regulation object of the occupant-centric control (OCC) strategy in light of these features.

According to Goyal et al. [52], controlling the operating parameters of air conditioning system has a decreasing impact on energy savings in the following order: 1) supply airflow rate and supply air temperature, 2) return air ratio, and 3) air temperature after being conditioned by a surface air cooler. As a result, the supply airflow rate and supply air temperature of stratum ventilation is chosen as the regulating parameters of the OCC strategy.

The OCC strategy employs a closed-loop negative feedback control system, with the main control equipment being air damper opening, fan frequency and coil cooling capacity in the air handling unit (AHU). As shown in Fig. 5(a), when the number of occupants changes during the detection period, the corresponding parameters are regulated to satisfy the dynamic changes of indoor cooling load and fresh air cooling load according to the HVAC system control strategy and calculation formulas. This research focuses on two OCC control strategies of the HVAC system. The first is a constant air volume control strategy, in which the total air volume remains constant throughout the regulation process while the

(a) (b)

Fig. 4. Experimental scenarios and camera positions (a. Occupant detection experiment scenario; b. Stratum ventilation experiment scenario).

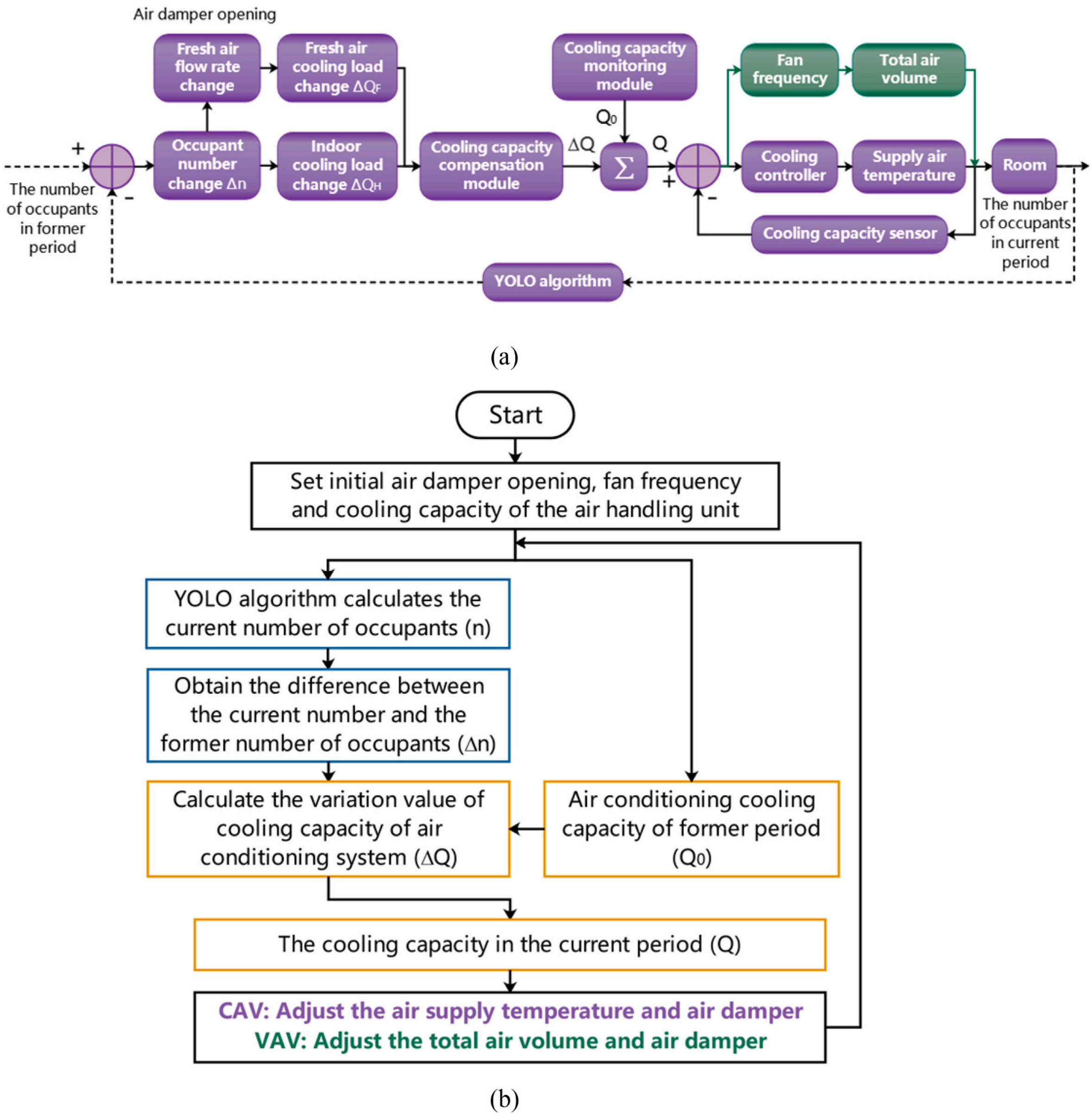


Fig. 5. The occupant-centric control strategy (a. Schematic diagram; b. Process of the air conditioning system regulation).

supply air temperature changes continuously. The second strategy is variable air volume control strategy, in which the supply air temperature remains constant while the total air volume changes continuously. The fresh air volume for both strategies varies with the occupant number and meets the requirements of ASHRAE Standard 62.1 [11]. Table 2 displays the most important control variables for the two OCC strategies. For the current period, negative feedback regulation of cooling capacity is implemented using two types of control equipment for supply air parameters and fresh air volume.

ASHRAE Standard 62.1 recommends determining the breathing zone outdoor airflow (V_{bz}) based on the number of occupants (n) and the floor area (A_z), as shown in Equation (2), and the zone outdoor airflow (V_{oz}) based on Equation (3) [11]. In this study, a single-zone system is used, so the outdoor air intake flow (V_{ot}) equals the zone outdoor airflow (V_{oz})

Table 2
Key control variables for the OCC strategies.

Control parameters and equipment		Conventional control strategy (Baseline)	Constant air volume control strategy (CAV)	Variable air volume control strategy (VAV)
Supply air parameters	Supply air temperature	Constant/Maximum	Change with the occupant number	Constant/Maximum
	Total air volume	Constant/Maximum	Constant/Maximum	Change with the occupant number
Control equipment	Supply air temperature	Cooling coil maintains constant	Cooling coil dynamical regulation	Cooling coil maintains constant
	Total air volume	Fan frequency maintains constant	Fan frequency maintains constant	Fan frequency dynamical regulation
Fresh air volume		Constant/Maximum	Change with the occupant number	Change with the occupant number
Control equipment		Air damper maintains constant	Air damper dynamically regulates the fresh air volume (see Equations (2) and (3))	

[11]. The number of occupants (n) is determined using the computer vision detection method described in section 2.2. Because the air distribution is stratum ventilation, the zone air distribution effectiveness (E_z) is taken as 1.4 [36]. The additional coefficient of air leakage in the ventilation system is 10% [53]. The simulation office of the experiment chamber should have the outdoor airflow rate required per unit area (R_a) of 0.3 L/s/m^2 and the outdoor airflow rate required per occupant (R_p) of 2.5 L/s/p [11].

$$V_{bz} = R_p \times n + R_a \times A_z \tag{2}$$

$$V_{oz} = V_{ot} = V_{bz}/E_z \tag{3}$$

Stratum ventilation creates a non-uniform thermal environment. As a result, the total cooling load of an indoor occupied zone ($Q_{occupied}$) is calculated by Equation (7), which differs from that of a uniform environment.

$$G_F = 1.1 \times 10^{-3} \times V_{ot} \times \rho \tag{4}$$

$$Q_F = G_F \times (h_o - h_r) = 1.1 \times 10^{-3} \times \left((R_p \times n + R_a \times A_z) \,/\, E_z \right) \times \rho \times (h_o - h_r) \tag{5}$$

$$Q_H = n \times \varphi \times (q_1 \times X + q_2) \tag{6}$$

$$Q_{occupied} = ECLF_{occ} \times Q_H + Q_F + ECLF_{ex} \times Q_E \tag{7}$$

where, G_F is the fresh airflow rate/outdoor airflow rate, kg/s; ρ is the air density, kg/m^3; Q_F is the fresh air cooling load, kW; h_o is the outdoor air enthalpy, kJ/kg; h_r is the return air enthalpy, kJ/kg; Q_H is the human total heat load, kW; φ is the clustering coefficient; q_1 is the human sensible heat load, kW/person; X is the cooling load coefficient of the human sensible heat load; q_2 is the human latent heat load, kW/person; $ECLF_{occ}$ is the human effective cooling load coefficient in a non-uniform environment, 0.85 is recommended for the stratum ventilation [36]; $ECLF_{ex}$ is the effective cooling load coefficient of cooling loads except for the human body, 0.8 is recommended for the stratum ventilation [36]; Q_E is the room cooling loads other than the human total heat load, kW.

The cooling capacity of the former period is Q_0, the variation value of cooling capacity of air conditioning system due to change in the occupant number is ΔQ (see Equation (8)), and the cooling capacity to be provided by the system in the current period is Q (see Equation (9)). Fig. 5(b) depicts the process of the air conditioning system regulation.

$$\Delta Q = \frac{\Delta Q_{occupied} \times (h_r - h_s)}{(h_N - h_s)} + \Delta Q_F = \frac{ECLF_{occ} \times \Delta Q_H \times (h_r - h_s)}{(h_N - h_s)} + \Delta Q_F \tag{8}$$

$$Q = Q_0 + \Delta Q \tag{9}$$

where, h_N is the indoor air enthalpy, kJ/kg; h_s is the supply air enthalpy, kJ/kg.

3. Thermal comfort case study

3.1. Experimental conditions

To quantify the thermal comfort performance of the OCC strategy proposed above, the thermal comfort experiment was carried out in a controlled climate chamber at the Sino-Nordic Research Center for Indoor Environment and Energy in Xi'an, China during summer (July 2021). The chamber's dimensions are 4.8 m (length), 5.4 m (width), and 2.6 m (height), with a floor static pressure box of 0.22 m. The average per capita occupied area of an ordinary office is 4 m^2/person, implying that a maximum occupancy of 6 occupants is possible [54]. The air supply temperature, the air supply speed, the fresh air to return air ratio, and the total air volume can all be artificially adjusted.

Fig. 6 depicts the interior layout of the experimental chamber. The chamber is divided into two rows of seats according to the location of the air supply inlets and airflow characteristics, with a total of six seats. According to the recommendation of the studies related to stratum ventilation [36,55], the first row of seats should be 2.1 m away from the air intakes in order to avoid draft. Two air supply inlets (0.2 m × 0.2 m) are located 1.25 m above the floor, and two air return outlets (0.2 m × 0.2 m) are located 0.5 m above the floor. As measuring points, measuring points 1, 2, 3 around three occupants and measuring point 4 in the center of the chamber occupied zone were chosen.

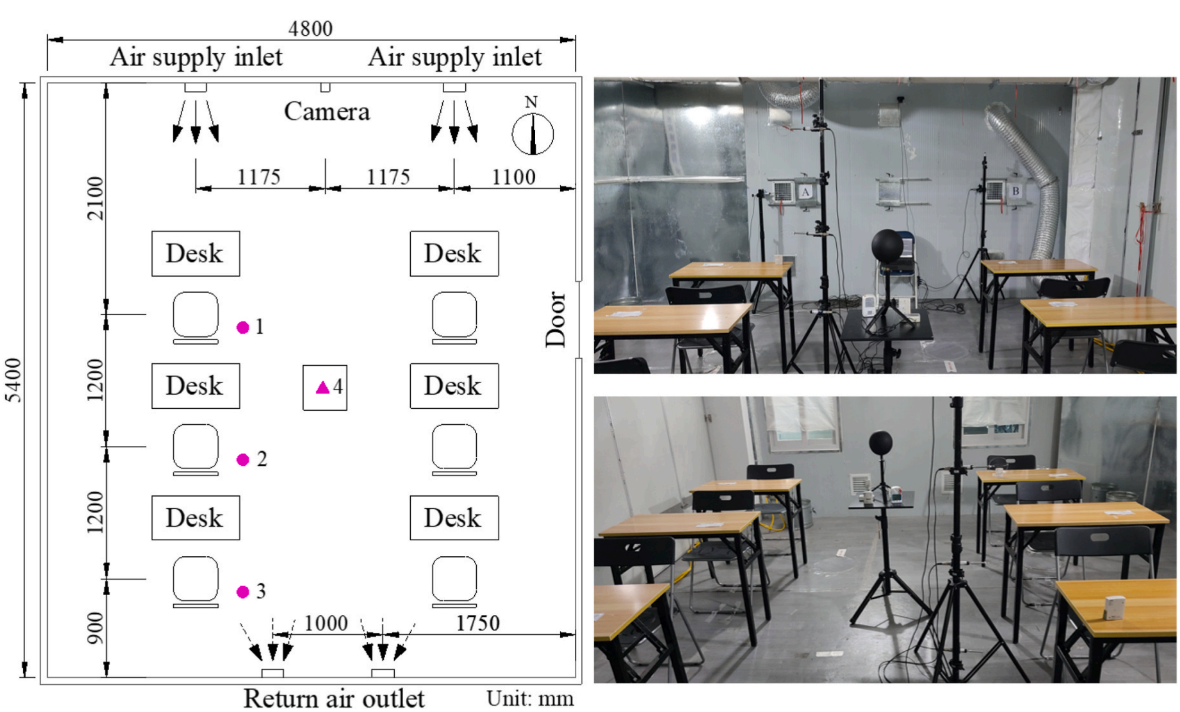


Fig. 6. The indoor layout of the experimental chamber.

The breathing zone is in the head region of the occupant, between 0.8 m and 1.4 m above the floor, so measurement point 4 for CO_2 concentration is located in the center of the chamber occupied zone, approximately 1.1 m above the floor [38,55]. The experimental instruments and measurement details are shown in Table 3.

The experiment included three comparison conditions to quantify comfort performance under the OCC strategy: the baseline control strategy, the variable air volume (VAV) control strategy, and the constant air volume (CAV) control strategy. In the comparison conditions, three experimental conditions were set up to investigate the comfort performance under the three indoor occupancy conditions. Table 4 depicts the experimental conditions. The baseline control strategy maintained the same supply air parameters and fresh air volume while changing the occupant number. The supply air parameters and fresh air volume changed with the occupant number under the VAV and CAV control strategies. The stratum ventilation system increases the air movement around the occupants. The combination of the indoor ambient temperature of 27 °C and the situation of "cool head and warm feet" is intended to fulfill the thermal comfort needs of the occupants. Cheng et al. [55] recommended that when the supply air temperature of the stratum ventilation is not lower than 20 °C, more than 80% of people feel comfortable at a room temperature up to 27 °C. Thus, the CAV and VAV control strategies maintained the thermal environment temperature in the occupied zone at 27 ± 0.5 °C throughout the experiment, and the measured relative humidity was 48 ± 6%. Table 4 displays the specific experimental parameters.

3.2. Thermal comfort equation

Fanger proposed the thermal comfort equation, which describes the energy balance of human body under steady-state conditions [12], see Equations 10–13. According to Fanger's thermal comfort equation, the human thermal comfort can be determined by four environmental factors (air temperature t_a, relative humidity, mean radiant temperature $\bar{t}_r$, and air velocity V) plus two personal ones (clothing insulation I_{cl} and metabolic rate M) [56].

$$M-W=3.96\times10^{-8}f_{cl}\left[(t_{cl}+273)^4-(\bar{t}_r+273)^4\right]+f_{cl}h_c(t_{cl}-t_a)$$
$$+3.05[5.73-0.007(M-W)-p_a]+0.42[(M-W)-58.15]+0.0173M(5.87-p_a)+0.0014M(34-t_a) \tag{10}$$

where, W is the rate of mechanical work accomplished, W/m^2; f_{cl} is the clothing area factor, dimensionless; t_{cl} is the mean temperature of the outer surface of the clothed body, °C; h_c is the convective heat transfer coefficient, W/(m^2·K); p_a is the water vapor pressure in ambient air, kPa.

$$t_{cl}=35.7-0.0275(M-W)-R_{cl}\{(M-W)-3.05[5.73-0.007(M-W)-p_a]-0.42[(M-W)-58.15]-0.0173M(5.87-p_a)-0.0014M(34-t_a)\} \tag{11}$$

where, R_{cl} is the thermal resistance of clothing, (m^2·K)/W.

$$h_c=\left\{\begin{array}{cc}2.38(t_{cl}-t_a)^{0.25} & 2.38(t_{cl}-t_a)^{0.25}>12.1\sqrt{V}\\ 12.1\sqrt{V} & 2.38(t_{cl}-t_a)^{0.25}<12.1\sqrt{V}\end{array}\right\} \tag{12}$$

$$f_{cl}=\left\{\begin{array}{cc}1.00+0.2I_{cl} & I_{cl}<0.5clo\\ 1.05+0.1I_{cl} & I_{cl}>0.5clo\end{array}\right\} \tag{13}$$

3.3. Human subjects

Twelve subjects were recruited randomly to participate in the subjective experiment. Table 5 displays the physiological characteristics of the subjects. Subjects wore typical summer indoor clothing, including normal trousers, short sleeves, socks, shoes, and underwear, with a total thermal resistance of 0.49 clo. Twelve subjects were divided into groups based on the occupant number in the various conditions described in Table 4, and all twelve subjects took part in nine conditions. The experiments for each condition were carried out on different days, but they were all carried out at the same time.

3.4. Experimental procedure

After arriving at the experimental site, the subjects rested in the waiting room for 20 min. After entering the chamber, the subjects were exposed to the thermal environment for 100 min. Subjects remained in a sitting position for 20 min of adaptation and 10 min of rest to adapt to the thermal environment without completing questionnaires. During the remaining 60 min, subjects were asked to complete six identical questionnaires. As shown in Fig. 7, the questionnaires were administered at 10-min intervals, and the same group of subjects was guaranteed to change seats three times in the same condition to experience the local thermal environment in three rows of positions at different distances from the air supply inlets. Throughout the experiment, the subjects were not informed of any environmental parameters and were not permitted to discuss the contents of the experimental questionnaires.

3.5. Questionnaires

Questionnaires are the most direct method of evaluating the thermal environment. Online questionnaires were used to assess the subjects' overall thermal sensation, thermal comfort, thermal acceptability, thermal preference, and perceived indoor air quality. The questionnaire was designed in accordance with the ASHRAE standard [57]. Thermal sensation was graded on a seven-point scale, with −3 = cold, −2 = cool, −1 = slightly cool, 0 = neutral, +1 = slightly warm, +2 = warm, +3 = hot being the highest. Thermal comfort was graded on a 5-point scale, with −2 being uncomfortable, −1 being slightly uncomfortable, 0 being no feeling, +1 being slightly comfortable, and +2 being comfortable. Thermal acceptability was graded on a 5-point scale, with −2 being very unacceptable, −1 being slightly unacceptable, 0 being just unacceptable, +1 being slightly acceptable, and +2 being very acceptable. Thermal preference was measured using a three-point scale: 1 = cooler,

Table 3
Experimental instruments.

Instruments	Parameters measurement	Sampling rate	Accuracy & Range
HOBO data loggers (HOBO U12-012, Onset, Bourne, USA)	Average room temperature and relative humidity in the occupied zone & Return air temperature at the two return air outlets	Every minute	±0.35 °C −20 - +70 °C ±2.5% & 0–95% RH
Swema anemometers (Swema 03+, SWEMA, Sweden)	Air supply velocity and temperature at 0.1, 0.6, 1.1, and 1.7 m in the vertical direction around the occupants & Air supply velocity and temperature at the two air supply inlets	10 Hz	±0.03 m/s 0.05–3.0 m/s ±0.3 °C 10–40 °C
RTR-576 data loggers (T&D Corporation, Nagano, Japan)	CO_2 concentration in the occupant breathing zone	Every minute	±50 ppm 0–9999 ppm
Black bulb thermometer (HQZY-1, Beijing, China)	Black globe temperature	Every minute	±0.5 °C −20 - +80 °C
Wireless temperature and heat flux recorders (JTRO1Z, Beijing, China)	Heat flux density of six walls and two windows	Every minute	±0.2 °C ±5%

Table 4
Experimental conditions (Mean ± Standard Deviation).

Cases	Occupant number (person)	Nominal supply air temperature (°C)	Nominal supply air speed (m/s)	Nominal fresh air volume (m^3/h)	Measured supply air temperature (°C)	Measured supply air speed (m/s)	Measured room temperature (°C)	RH (%)
CAV	2	23.0	2.30	37	23.1 ± 0.2	2.34 ± 0.12	27.2 ± 0.3	46
CAV	4	22.0	2.30	51	22.0 ± 0.3	2.32 ± 0.16	27.3 ± 0.2	50
CAV	6	21.0	2.30	65	21.2 ± 0.1	2.37 ± 0.10	27.1 ± 0.4	42
VAV	2	21.0	1.70	37	20.9 ± 0.2	1.74 ± 0.13	26.8 ± 0.3	48
VAV	4	21.0	2.10	51	21.0 ± 0.1	2.09 ± 0.14	26.9 ± 0.4	47
VAV	6	21.0	2.30	65	20.8 ± 0.3	2.28 ± 0.11	27.2 ± 0.2	54
Baseline	2	21.0	2.30	65	20.8 ± 0.2	2.32 ± 0.10	25.0 ± 0.2	51
Baseline	4	21.0	2.30	65	21.0 ± 0.1	2.28 ± 0.15	26.3 ± 0.1	50
Baseline	6	21.0	2.30	65	20.7 ± 0.3	2.29 ± 0.10	27.1 ± 0.2	53

Table 5
Subjects' physiological characteristic parameters.

Gender	Age (years)	Height (m)	Weight (kg)	Body mass index (kg/m^2)	Number of subjects
Males	24.3 ± 1.9	1.79 ± 0.06	74.6 ± 7.5	23.3 ± 1.6	6
Females	23.2 ± 0.8	1.62 ± 0.06	53.3 ± 10.1	20.4 ± 4.4	6
Total	23.8 ± 1.5	1.71 ± 0.11	63.9 ± 14.0	21.8 ± 3.5	12

0 = no change, and +1 = warmer. On a 5-point scale, perceived indoor air quality was rated as −2 = clearly unacceptable, −1 = slightly unacceptable, 0 = neutral, +1 = slightly acceptable, and +2 = clearly acceptable.

3.6. Statistical analyses

This study used the Shapiro-Wilk normality test, and normality was rejected when the p-value was less than 0.05. To determine whether the variances were homogeneous, the Levene test was applied. One-way ANOVA was used when the data was normally distributed, and the variances were homogeneous. The paired samples *t*-test was used when the data were normally distributed, and the variances were not homogeneous. The paired samples Wilcoxon signed rank test was used when the data did not fit a normal distribution. This study used a significance level of 0.05 and a confidence level of 95%. There was no significant difference ($p > 0.05$) between the two-questionnaire data in Stages 2, 4, and 6, indicating that the subjects' perceptions of the thermal environment remained stable. As a result, the questionnaire data from these three stages were used for data analysis and discussion in section 4.

4. Results and discussion

4.1. Occupant detection accuracy based on computer vision

The activity state of office occupants was simulated in section 2.3 detection performance experiment. Meanwhile, the occupant detection data of six relative positions were collected, which were standing, sitting back to the camera, sitting facing the camera, sitting back to each other, sitting left to the camera, and sitting right to the camera. The data after being filtered were used for detection performance analysis. Fig. 8(a) depicts examples of occupant detection in the experimental environment.

Fig. 8(b) depicts the data analysis of the occupant detection results. When it comes to sitting postures, the occupant number of sitting back to the camera primarily varies between 4 and 5. As shown in Fig. 8(c), there is an example of misjudgement when occupants are close to the camera, which is caused by different parts of the body being covered by each other. The average predicted number of occupants for the remaining four sitting postures is very close to 5, and the detection accuracy is better than that of back-to-camera detection. Because the occupants remain active during the experiment and the light source is on the side wall, there is a misjudgement of the shadow as an occupant during the detection process in the case of standing posture, as shown in Fig. 8(c).

According to the calculated NRMSD values, sitting facing the camera performed the best, with an NRMSD of 0.0599, while sitting back to the camera has the worst effect, with an NRMSD of 0.2580. The database trained with the YOLOv5s algorithm can be optimized based on the above calculation results and reasons for misjudgements. In the office, the average NRMSD of the six relative positions is 0.1461. Without taking into account sitting back to the camera, the average NRMSD of the five relative positions is 0.1109. As a result, the detection accuracy can be improved by adjusting the relative position, height, and angle of the camera. When using this algorithm in the office, it is recommended that the camera be installed at ceiling height near the side wall to capture images of occupants facing the camera. When tables, chairs, and computers obscure a large area from occupants in the camera's field of view, it is recommended that the camera capture images of the occupants' bodies side.

The occupant detection data was also collected in the occupant-centric stratum ventilation thermal comfort experiment. Fig. 9(a) depicts some occupant detection examples during testing. Fig. 9(b) depicts the detection performance, with an NRMSD of 0.0526 and predicted and actual values that are generally similar. The main causes of counting errors are occupant occlusion and occupant occlusion by tables and chairs. In previous studies, the detection method combining CO_2 concentration and Bayesian inference model had a time delay of 20–25 min [58], the NRMSD of a combination of door counter sensor and PIR sensor

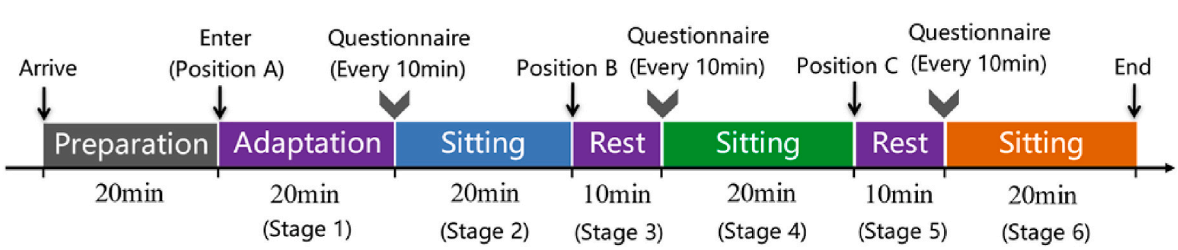


Fig. 7. Experimental procedure.

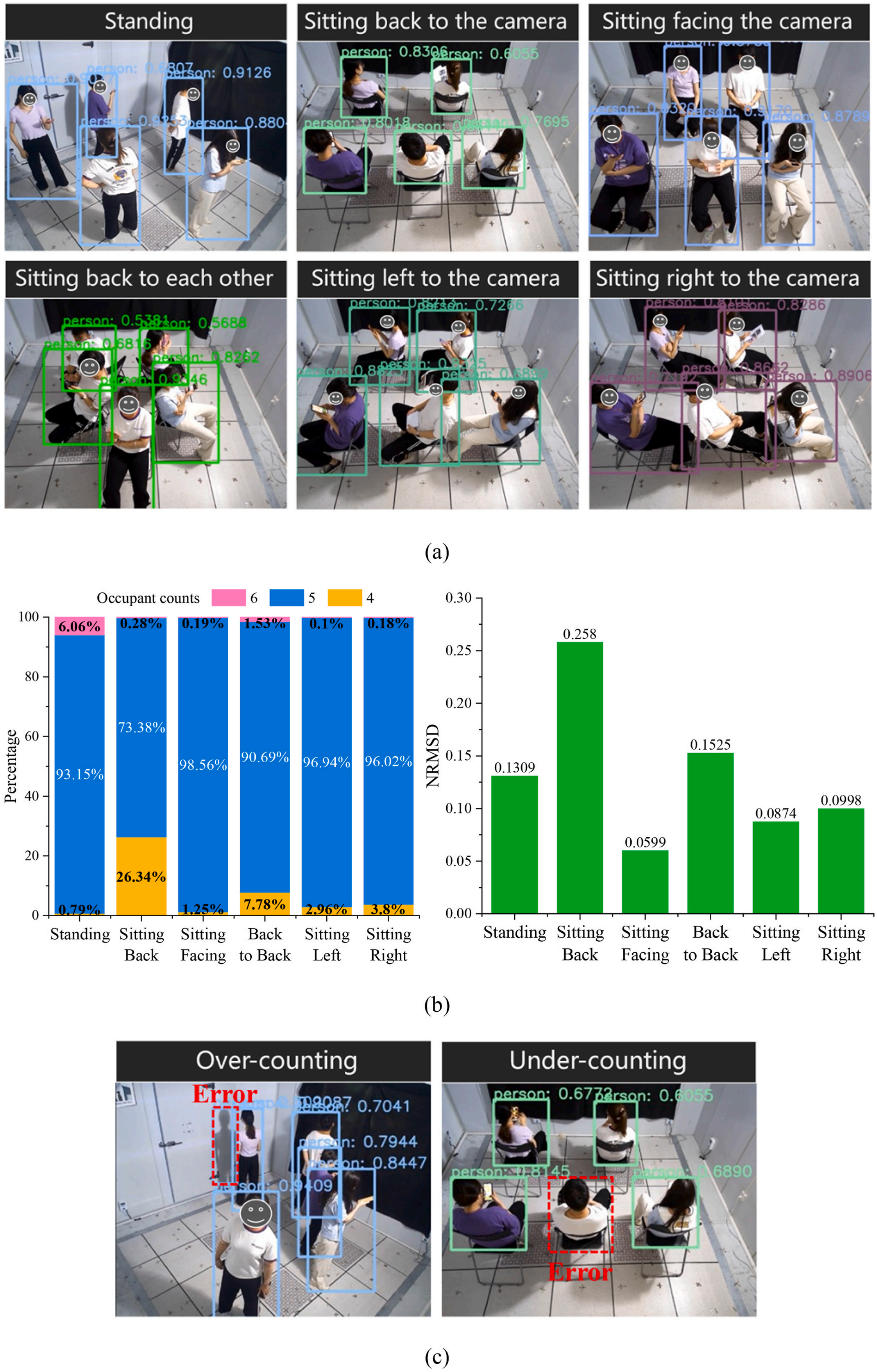
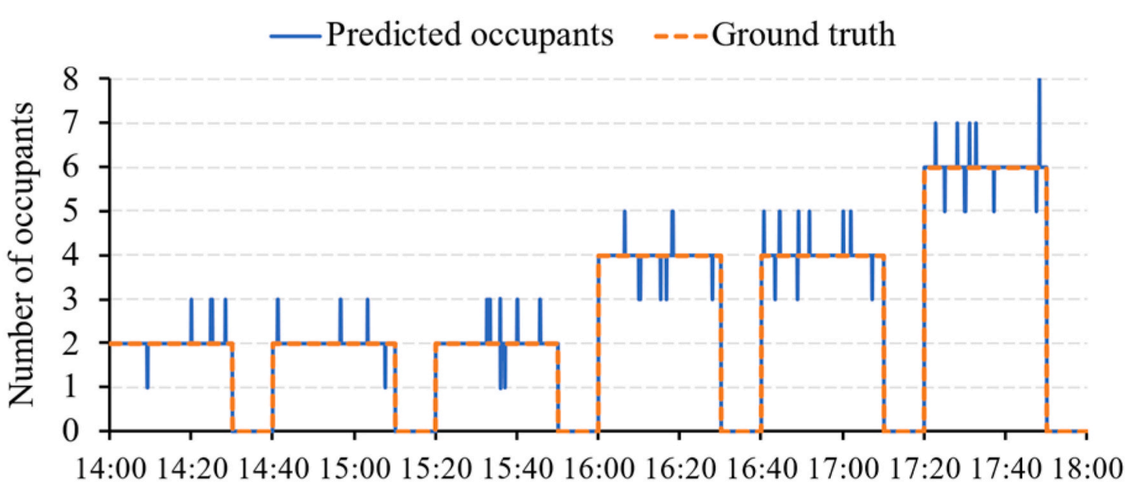


Fig. 8. The occupant detection results (a. Examples of experimental environment; b. Data analysis; c. Examples of algorithmic misjudgements).

(a)



	Experiment I	Experiment II	Experiment III
NRMSD	0.0713	0.0811	0.0633
Total	0.0526		

(b)

Fig. 9. Occupant detection during thermal comfort experiment (a. Examples of occupant detection; b. Detection performance).

was 0.113 [59], the NRMSD of a Wi-Fi sensor-based occupant detection method was 0.096 [18], and the NRMSD of a generative adversarial network-based method is 0.1424 [60]. In comparison to the other methods mentioned, the YOLOv5 algorithm-based occupant counting method has no time delay, and the detection performance is accurate and stable. Thus, it can be used in the OCC strategy to reduce lag in control signal transmission to mechanical equipment.

Furthermore, unlike environmental sensors, motion sensors, and radio frequency sensors, which can only detect the occupant number, computer vision technology can detect partition detection. As a result, it can be combined with the stratum ventilation characteristic of supply air inlet partitioning to implement partition control. The YOLOv5 algorithm-based occupant detection method serves as a reference for dynamic input parameters of the OCC strategy in offices.

4.2. Thermal environment evaluations

4.2.1. Thermal sensation vote

According to the IEA EBC Annex 79 document, not taking into account information such as occupant activity patterns during building operation may cause an uncomfortable indoor environment [10]. As shown in Fig. 10(a), there are significant differences in thermal sensation votes for different occupant numbers under the baseline control strategy. The smaller the occupant number, the further away from neutral thermal sensation. As a result, the two-way interaction between occupants and buildings must be considered. And to achieve a high level of comfort, it should combine the occupant information with control algorithms [10]. In this study, occupant information is combined with the ventilation system control algorithm to improve thermal comfort.

The thermal sensation under the CAV control strategy was increased by 0.89 (two occupants indoors), 0.57 (four occupants), and 0.03 scale units (six occupants), respectively, when compared to the baseline control strategy. The thermal sensation under the VAV control strategy was increased by 1.09 (two occupants), 0.59 (four occupants), and 0.02 scale units (six occupants), respectively. The average values of thermal sensation votes improved from slightly cool (−1) to close to neutral (0). Thus, the control strategy of supply air parameters changing with occupant number is beneficial to improving thermal sensation. Kong et al. also confirmed that the occupant-centric control strategy improved thermal sensation, with a mean thermal sensation vote of 0.06 [28]. For only two occupants indoors, there is a significant difference in thermal sensation votes between the CAV and VAV control strategies.

4.2.2. Thermal comfort vote

Huizenga et al. investigated the thermal comfort of 215 buildings using conventional ventilation and air conditioning systems operating with fixed operating parameters, and results reported that only 11% of the buildings had more than 80% of occupants who were satisfied with the temperature of the workspace, with an average building satisfaction of 59% [61]. As shown in Fig. 10(b), there are significant differences in thermal comfort votes for different occupant numbers under the baseline control strategy. The results also confirm that the thermal environment's comfort needs to be improved based on the occupant number.

Occupants are equivalent to heat sources and have a significant impact on the indoor ambient temperature. As shown in Table 4, the baseline control strategy reduced the indoor ambient temperature by

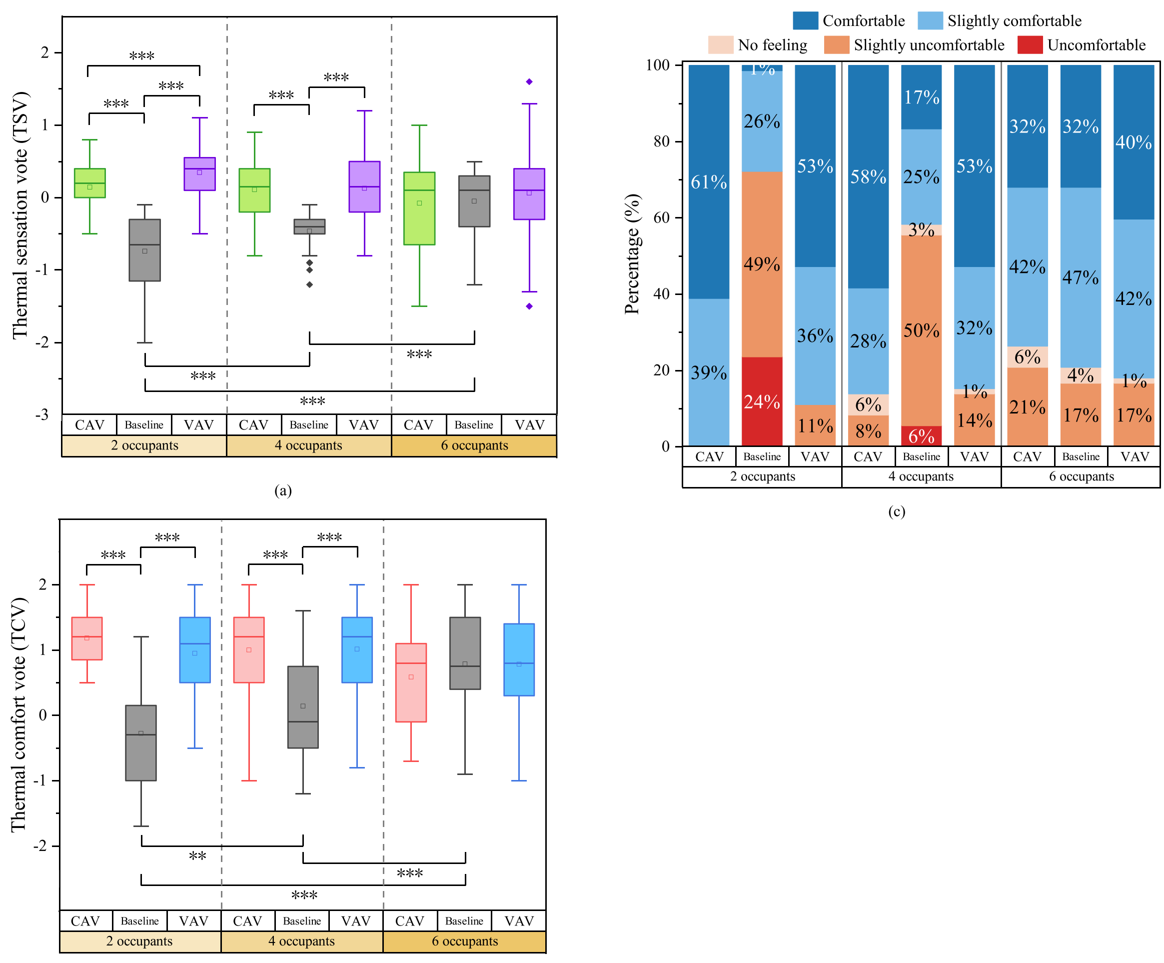


Fig. 10. The Voting results (a. Overall thermal sensation; b. c. Overall thermal comfort).

0.8 °C and 2.1 °C for two and four occupants, respectively, compared to the maximum occupancy (six occupants). If the occupant number is less than the maximum occupant number under the baseline control strategy, the indoor ambient temperature and the thermal comfort will be significantly reduced. As shown in Fig. 10(c), thermal discomfort increases with the difference from the maximum occupant number. Thus, when compared to the baseline control strategy, the CAV control strategy increased thermal comfort by 1.46 (improved by 73%) and 0.86 (improved by 62%) scale units for two and four occupants, respectively. Thermal comfort under the VAV control strategy was increased by 1.23 (improved by 44%) and 0.87 (improved by 43%) scale units for two and four occupants, respectively.

As shown in Fig. 10(c), more than 80% of the votes fell within the no feeling and comfort ranges when using the CAV and VAV control strategies. Kong et al. also confirmed that the occupant-centric control strategy can improve thermal comfort, with approximately 70% of thermal comfort votes falling within the comfortable range, with an average thermal comfort vote of +1.40 [28]. The CAV and VAV control strategies can moderately improve thermal comfort. However, when combined with the thermal sensation results (see Fig. 10(a)), the CAV control strategy slightly outperforms the VAV control strategy for the same number of occupants, because the indoor thermal condition under stratum ventilation is more sensitive to the supply air temperature than the supply air volume [62].

4.2.3. Thermal acceptability and thermal preference

The thermal environment is acceptable when the thermal acceptability is greater than 80%, according to the ASHRAE standard 55 recommendation [57]. As shown in Fig. 11(a), 79%–94% of the votes fell within the slightly acceptable and acceptable ranges using the CAV and VAV control strategies. The voting results showed that occupant-centric control strategies can achieve the requirement of an acceptable thermal environment, but thermal acceptability for the conventional control method (Baseline) was 46%–77%.

Thermal acceptability was improved by 48% (two occupants), 18% (four occupants), and 2% (six occupants), when compared to the baseline control strategy. Thermal acceptability was increased by 39% (two occupants), 22% (four occupants), and 8% (six occupants). The findings demonstrated that the lower the occupancy, the greater the improvement in thermal acceptability. The main reason for this is that the greater the difference between the total cooling load of the occupied zone and the system cooling capacity, the less thermally acceptable the subjects are. The thermal acceptability can be significantly improved when the system operating parameters and the total cooling load of the occupied zone are matched (CAV and VAV). Therefore, the degree of improvement in thermal acceptability highly depends on the accuracy of the occupant detection algorithm.

As shown in Fig. 11(b), all nine experimental conditions exist for subjects who want the thermal environment to become colder or warmer, indicating that subjects' thermal preferences differ [63]. The voting results for those who want the thermal environment to become warmer account for approximately 57% (two occupants) and 43% (four occupants), under the baseline control strategy. This is because of a mismatch between the system operating parameters and the occupied zone's dynamic total cooling load, resulting in a cold indoor thermal environment. The percentages of votes indicating a desire to change the thermal environment for the CAV control strategy were 29% (two occupants) and 20% (four occupants) lower than Baseline. The VAV control strategy received 21% fewer votes (two occupants) and 17% fewer votes (four occupants) than Baseline.

4.3. Indoor air quality

The fresh air volume remains constant under the baseline control strategy, while the CO_2 concentration fluctuates in steps, increasing with the occupant number. The CO_2 concentration measurement point was

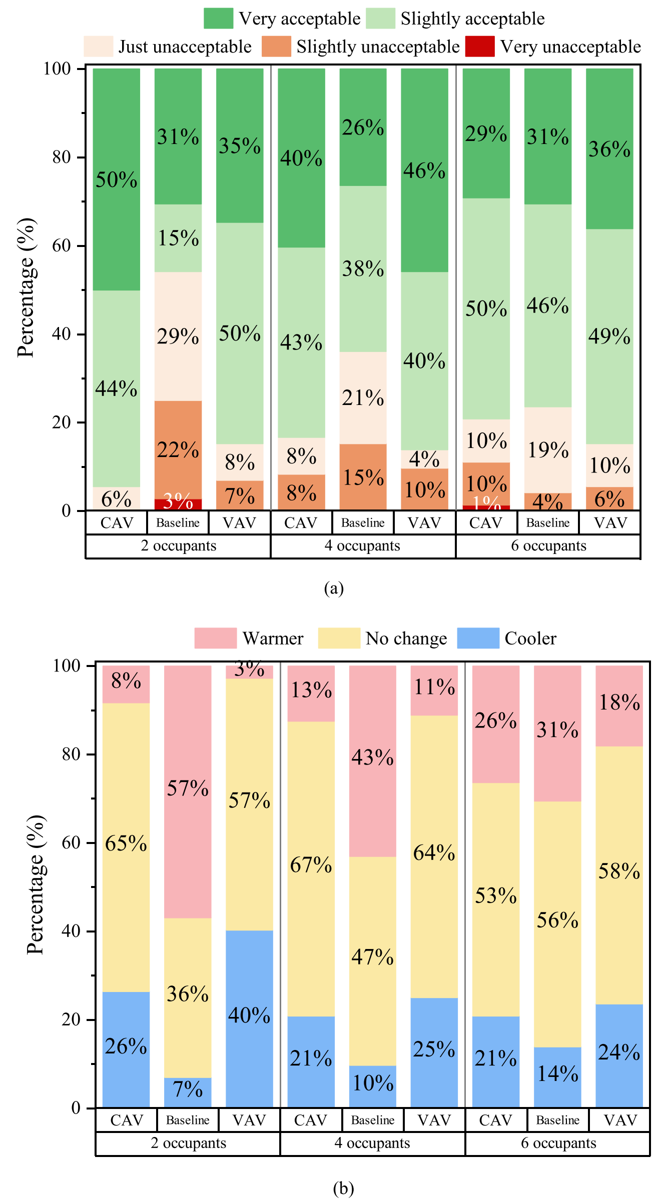


Fig. 11. The Voting results (a. Thermal acceptability; b. Thermal preference).

located in the center of the chamber's occupied zone, approximately 1.1 m above the floor (in breathing zone) [38,55]. When the fresh air volume was set to its maximum value, the perceived air quality votes under Baseline were higher than those under CAV and VAV, ranging from 1.2 to 1.6 (significantly acceptable). The CO_2 concentration ranged from 663 to 700 ppm for the CAV control strategy, and the perceived air quality votes were between 0.8 and 1.1 (acceptable). The CO_2 concentration fluctuated between 624 ppm and 685 ppm for the VAV control strategy, and the perceived air quality votes ranged from 0.2 to 1.0 (acceptable). The ventilation rate is reduced by 43% (two occupants) and 22% (four occupants) under CAV and VAV when compared to six occupants. According to the above findings, the baseline control strategy operating at maximum ventilation rate can over-ventilate, which is detrimental to building energy savings.

Fig. 12 shows that the 2-occupants condition has significantly lower perceived air quality votes than 4 occupants and 6 occupants in the VAV control strategy. According to the subjects' interviews, perceived air quality was related not only to fresh air volume but also to the indoor thermal environment. The VAV control strategy had a lower CO_2 concentration than CAV, but its perceived air quality is lower. This is

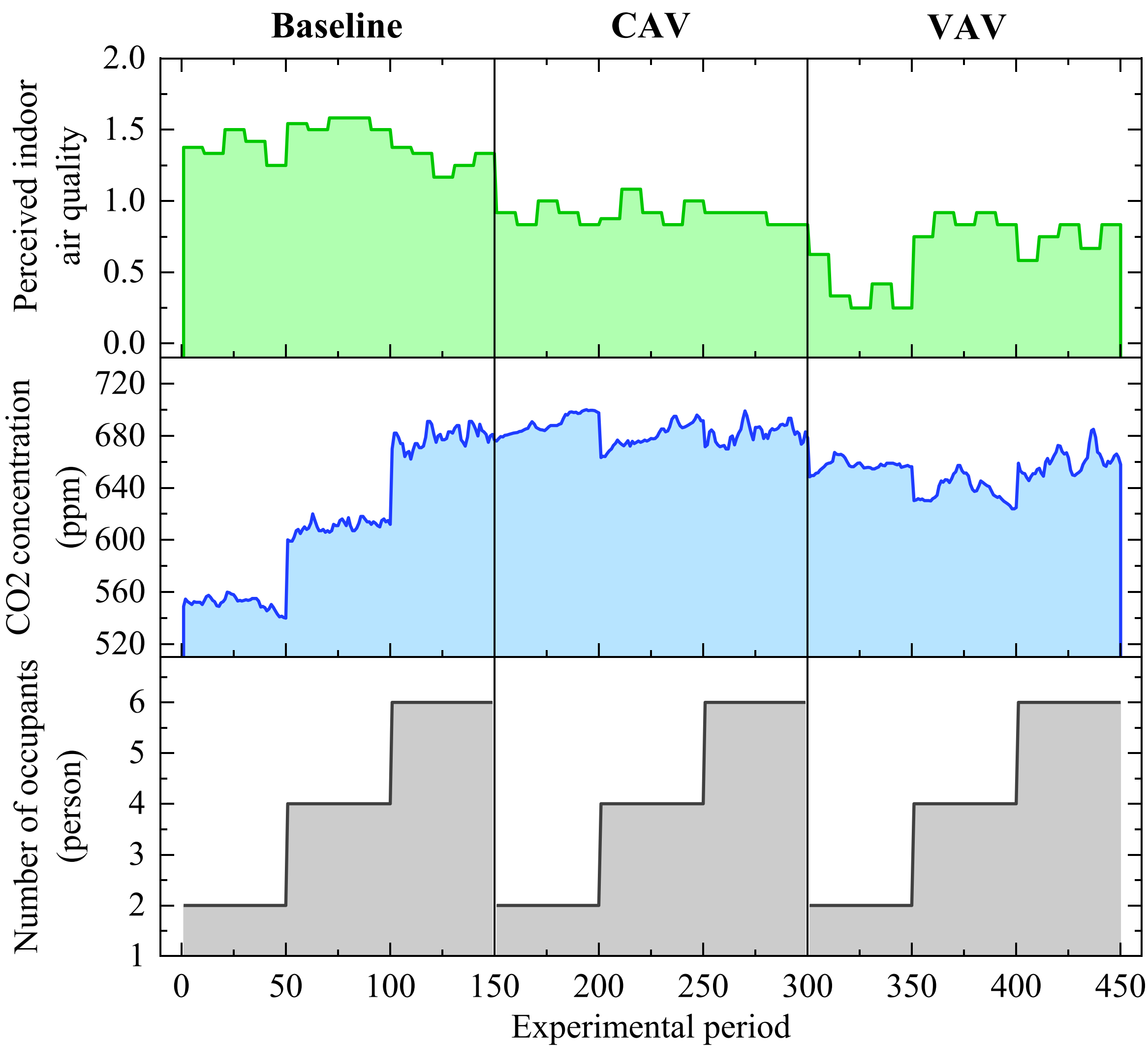


Fig. 12. Perceived indoor air quality and CO_2 concentration.

because the air supply velocity of VAV was lower than CAV's. It could reveal that the perceived air quality is related to the indoor thermal environment. As a result, the CAV control strategy slightly outperforms VAV in air quality.

In summary, even though the fresh air volume was adjusted based on the occupant number, the air quality was all at an acceptable level, and the CO_2 concentration was all below 700 ppm, ensuring the inhaled air quality. Choi et al. [26] calculated the ventilation rate based on the detected occupant number and concluded that indoor CO_2 concentrations could be properly maintained through field experiments. Similar findings were confirmed in this study, which, when combined with perceived air quality votes, indicated that air quality can be guaranteed. According to previous research, the ventilation efficiency of stratum ventilation was 1.4 [36], which is higher than that of the traditional ventilation system. Furthermore, because fresh air was directly supplied to the occupants' breathing zones, it costed less fresh air volume to maintain the same level of inhaled air quality as the traditional ventilation system. The proposed OCC strategy combined with stratum ventilation allows for more efficient utilization of fresh air volume.

4.4. System energy consumption

The total energy consumption (E) on the cooling side of the system is composed of the fan effective power (E_{fan}) and the electric energy of air conditioning system (E_{cond}) consumed by the indoor cooling load and the fresh air cooling load [12,54], as shown in Equation (14) and Equation (15).

$$E = E_{fan} + E_{cond} = E_{fan} + \left(G_S \times c_p \times (T_r - T_s) + G_F \times c_p \times (T_o - T_r)\right) / COP \tag{14}$$

$$E_{fan} = P \times Q = \left(\Delta p_m \times l + \sum \zeta \times \frac{v^2 \rho}{2}\right) \times Q \tag{15}$$

where, G_S is the supply airflow rate, kg/s; c_p is the constant pressure specific heat capacity, 1.004×10^3 J/(kg·K); T_r is the return air temperature, K; T_s is the supply air temperature, K; G_F is the fresh/outdoor airflow rate, kg/s; T_o is the outdoor air temperature, 305.15 K, the value of which refers to the outdoor average temperature of the outdoor weather station during the experiments in Xi'an (107°40′-109°49′ E, 33°42′-34°45′ N), China; COP is the cooling coefficients of performance, 3.0 [28]; P is the fan total pressure in order to compensate the pressure loss, Pa; Q is the fan volume flow rate, m^3/s; Δp_m is the pressure loss per unit duct length, Pa/m, value reference handbooks [12,54]; l is the duct length, m; $\sum \zeta$ is the summation of local loss coefficients in the duct section, value reference handbooks [12,54]; v is the air velocity in the duct where a local pressure loss occurs, m/s; ρ is the air density, kg/m^3.

By entering the supply air parameters and indoor parameters obtained from the experiment, the system total energy consumption can be calculated. Fig. 13 shows that the CAV and VAV control strategies can reduce energy consumption by 3.0% and 8.1%, respectively, under the 2-occupants condition when compared to the baseline control strategy. The calculated energy savings under the CAV and VAV control strategies for the 4-occupants condition are 2.3% and 2.8%, respectively. The results revealed that the energy savings potential is highly dependent on the accuracy of the detection algorithm, because the algorithm can help identify when and how the occupied zone needs to be conditioned and ventilated. The proposed OCC strategy approaches energy savings of 2.3–8.1% while improving thermal comfort and ensuring indoor air quality, based on the results of thermal environment evaluations and indoor air quality. The experimental site is in Xi'an, China, which has a warm-temperate semi-humid continental monsoon climate, and the energy savings can be used as a reference value for areas in the same climate zone.

This research focuses on calculating the energy savings potential in the occupied zone of adjusting supply air parameters and the fresh air volume based on the different occupant numbers. There are also unoccupied zone and building unoccupied modes for the OCC strategy with a 24 h cycle, which will save more energy than the traditional fixed schedule control strategy. A small change in occupancy can save anywhere from 2.3% to 8.1% of energy. Larger fluctuations in occupancy will further reduce energy consumption in buildings with multiple small offices. When controlling the indoor ambient temperature and the outdoor airflow rate in a small office based on the occupant number, the energy simulation results showed a 7.9% reduction in annual energy consumption [30]. Another study results reported that the OCC strategy could save up to 45% of the energy when simulating the energy consumption of an entire building with medium-sized offices [29].

4.5. Discussion on performance analysis of occupant-centric control strategy

The accuracy of occupant detection affects thermal comfort and the potential for building energy efficiency. When combined with the OCC strategy and stratum ventilation, the YOLO algorithm with an NRMSD of 0.0526 makes it easier to implement demand-driven HVAC operations. In contrast to the traditional control strategy of fixed supply air parameters and maximum fresh air volume, this paper integrates occupant information detected by computer vision with the operation of stratum ventilation and air conditioning system (non-uniform thermal environment), taking into account the two-way interaction between occupants and building. According to thermal environment evaluations and indoor air quality, the proposed OCC strategy has practical effects in improving thermal comfort (43%–73%), ensuring air quality (below 700 ppm), and reducing system energy consumption (2.3%–8.1%). The PID control strategy is used by thermostats in some existing buildings to control indoor temperature [64]. Some OCC strategies studies have reached similar conclusions, but they all regulate the indoor temperature to a constant value based on occupant number in a uniform thermal environment, rather than directly regulating the supply air temperature and total air volume, so this study is more applicable to a non-uniform environment for the following reasons.

The proposed OCC strategy has three advantages over the indoor temperature-based control strategy: 1) The detected change in the occupant numbers in an occupied zone in real-time can directly predict HVAC system regulation values. Thus, the lag of thermal environment regulation (see Fig. 14) caused by the distance between the occupied zone and the indoor temperature sensor is reduced. 2) When non-uniform air distribution is regulated based on indoor temperature, it causes thermal discomfort because the supply parameters are outside the recommended range [32,33]. 3) According to the dynamic

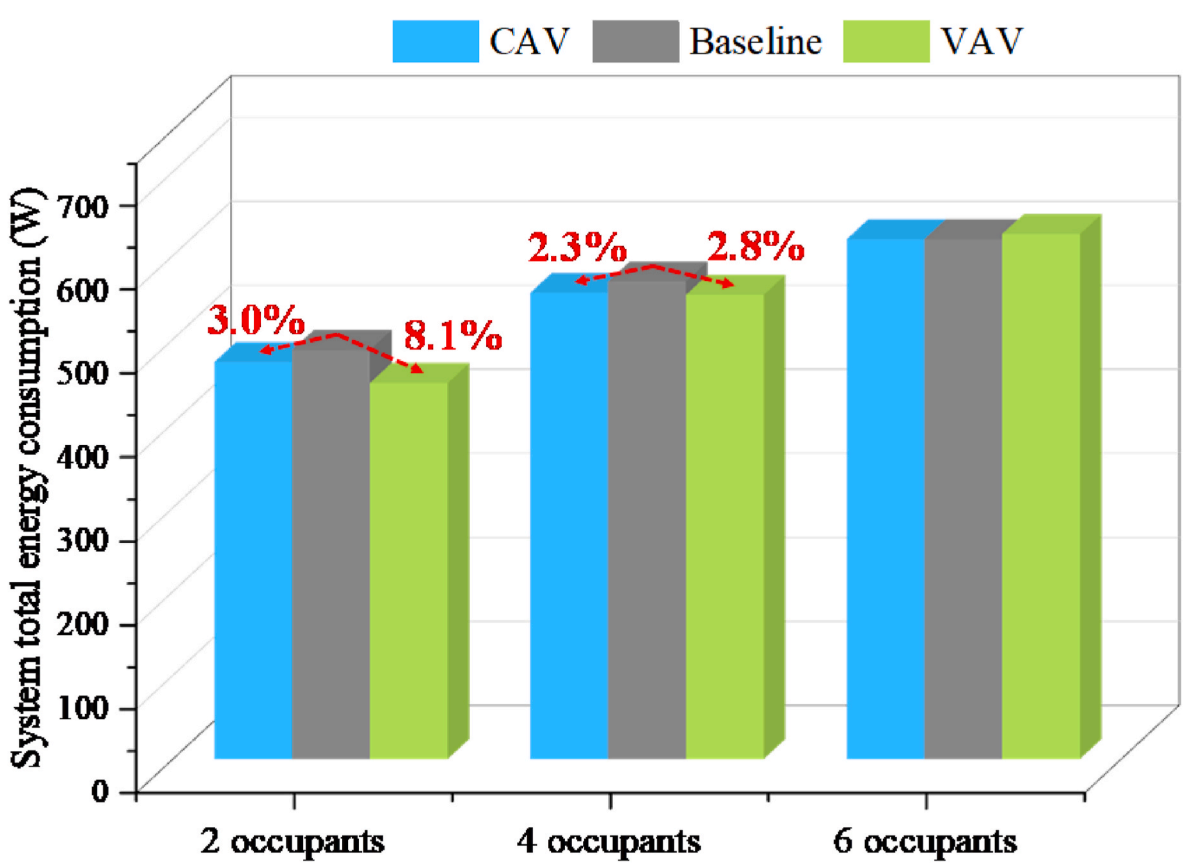


Fig. 13. System total energy consumption.

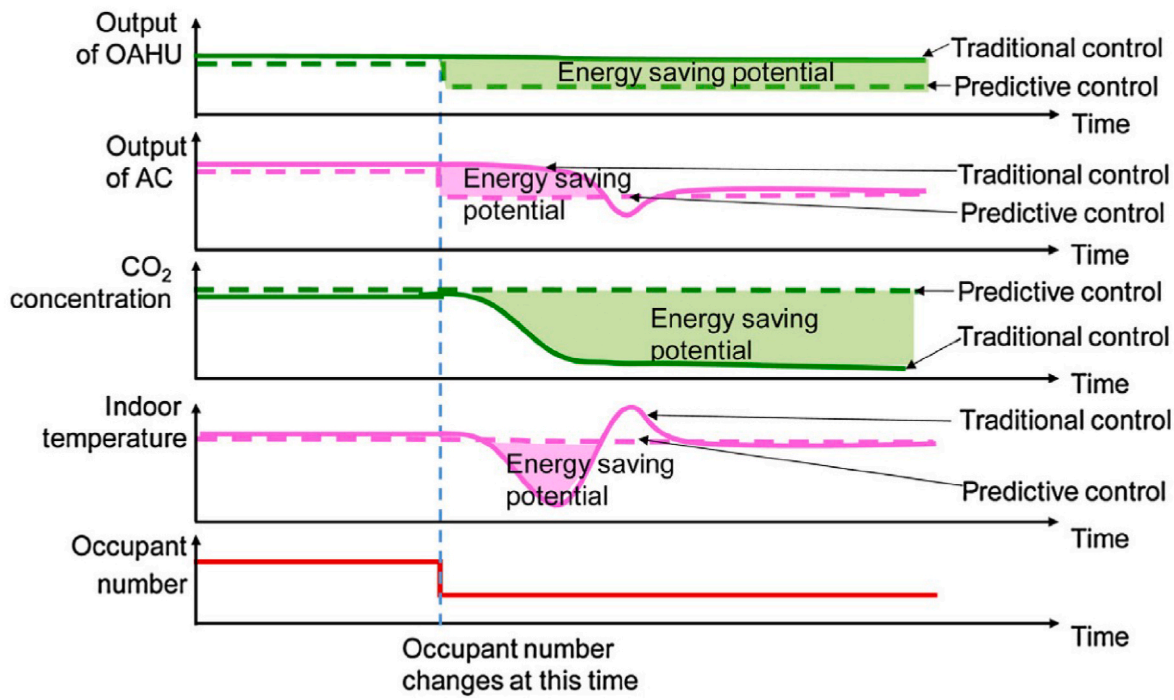


Fig. 14. The benefits brought by the OCC predictive control compared with traditional control strategy [27].

occupancy, adjusting the air supply parameters and fresh air volume is beneficial to ensure indoor comfort in a non-uniform environment (thermal acceptability greater than 80% & CO_2 concentration less than 700 ppm). Some studies regulated the fresh air volume based on the indoor CO_2 concentration [65]. There is also the issue with the regulation lag (see Fig. 14). And the placement of CO_2 sensor significantly affects the improvement of indoor air quality. However, the proposed OCC strategy directly regulates the fresh air volume based on the occupant number detected in real time. Indoor temperature and CO_2 concentration regulation delays will result in energy waste and thermal

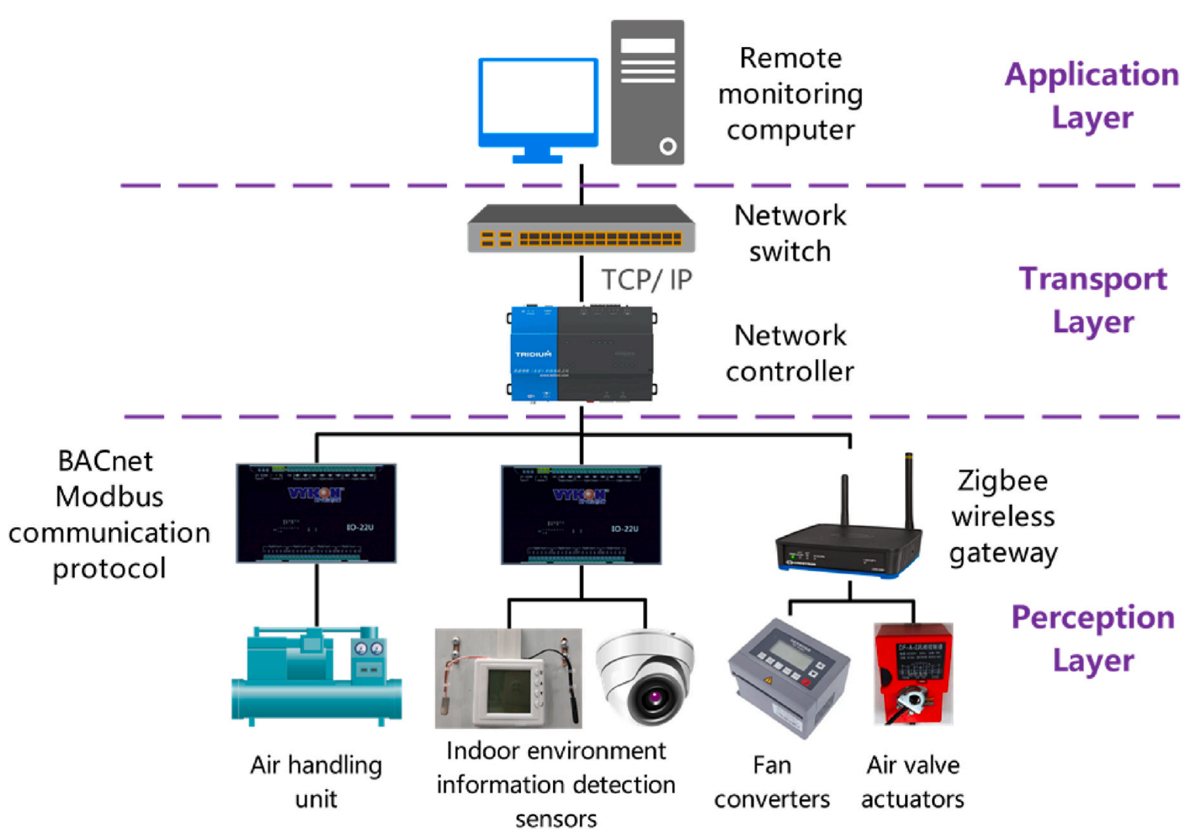


Fig. 15. Distributed control system architecture.

discomfort.

Unevenly distributed temperature in different regions accounted for 43% of people dissatisfied with the temperature in more than 600 buildings [66]. This study's occupant-centric control method can adjust supply air parameters based on the occupant number in different partitions, meet the cooling demand in different zones, and create a comfortable and energy-efficient thermal environment in occupied zones. At the same time, for more efficient use of the air supply jet, occupants can adjust the supply air opening and supply air direction of the stratum ventilation according to their thermal preference to better meet personalized thermal comfort [67].

4.6. Automatic control system based on IOT architecture

The OCC strategy can be implemented through a building automatic control system. As shown in Fig. 15, the occupant detection method based on the computer vision, the occupant-centric control strategy, and the stratum ventilation system can use the Internet of Things (IOT) to realize the distributed control system architecture in practical applications. The indoor environmental information detection sensors send the indoor occupant information and environmental parameters to the computer, which analyses the indoor occupancy information using the occupant detection algorithm described in section 2.2 and then outputs the HVAC system operation parameters using the OCC strategy described in section 2.4. The transport layer sends control signals to the field controller as well as the wireless gateway, which sends the signals over a short distance to the air handling unit, fan converters, and air valve actuators to allow the HVAC equipment's operation parameters to be adjusted.

4.7. Practical applications

Lin et al. [36] mentioned that when the supply air path of stratum ventilation is within 6 m, it can meet the requirements of thermal comfort and air quality for office and classroom occupants, providing a reference for building system design. The supply air path in this paper is 5.4 m, and the results show that the proposed OCC strategy also meets the requirements of thermal comfort and air quality. Therefore, the proposed OCC strategy is appropriate for public buildings consisting of multiple offices or classrooms and supply air paths no longer than 6 m. The OCC strategy is recommended to be combined with a camera-based occupant detection method and better suited for buildings with monitoring systems. The proposed OCC strategy is also applicable to other air distributions that result in a non-uniform thermal environment (e.g., displacement ventilation and column attachment ventilation). However, the capabilities for improvement must be investigated and compared further.

The results show that both CAV and VAV control strategies can satisfy thermal comfort and air quality, giving occupants more options. Therefore, occupants who prefer air movement in the occupied zone will benefit from the CAV strategy with constant supply air speed. The VAV strategy with demand-controlled supply air speed is appropriate for occupants who prefer uniform temperature distribution in the horizontal direction in the occupied zone. However, the system complexity should be considered when designing the ventilation system. Additional regulating components, such as dampers, adjustable fans, or secondary temperature regulation devices, are required to implement the OCC strategy. As a result, a compromise between energy efficiency and economy is required.

4.8. Limitations and future work

First, more research into occupant detection is required. The experimental study differs from the actual working environment, and the detection performance will be evaluated in the actual environment using the experimental results. Second, only the zone-occupied scenario was used to calculate the energy-saving potential of the OCC strategy. There are two scenarios for the OCC strategy: zone unoccupied and building unoccupied modes. The number of occupants in the entire office building fluctuates more. In the follow-up, the annual energy savings of the OCC strategy will be quantified in conjunction with the preceding two points.

5. Conclusions

The paper presents a pilot study of how stratum ventilation systems can respond to dynamic changes in indoor occupancy to minimize system energy consumption, improve human thermal comfort, and ensure indoor air quality. The performance of the occupant detection method based on computer vision and thermal comfort, air quality, and the energy savings potential of an occupant-centric stratum ventilation system are the two main issues addressed. Analyzing and discussing the experimental results yields the following conclusions.

(1) Computer vision based on CNN is adopted to detect the occupant number. The average NRMSD of the six relative positions of occupants and camera is 0.1461, and the accuracy of sitting back to the camera is the lowest. The stratum ventilation office application scenario has an NRMSD of 0.0526, and the predicted values tend to be close to the actual values. According to the experiment results, the suggested camera position should be installed at ceiling height near the side wall to capture images of facing the camera or the occupants' bodies side.
(2) Two OCC strategies, CAV and VAV, are proposed for adjusting supply air parameters and fresh air volume of the stratum ventilation (non-uniform thermal environment) based on the occupant number and compared to the traditional baseline control strategy. The subjective response experiment results demonstrate that the two strategies improve thermal sensation by 0.57–1.09, thermal comfort by 43%–73%, and thermal acceptability by 18%–48%.
(3) The ventilation rate is reduced by 22% and 43% for different occupancy under both control strategies, compared to the traditional control strategy. However, the perceived air quality of both strategies is maintained at an acceptable level of 0.2–1.1, and the CO_2 concentration is maintained below 700 ppm.
(4) The system energy consumption on the cooling side can be reduced by 2.3%–8.1% by adjusting the system operating parameters based on occupant number in the stratum ventilation system.
(5) The experimental results and conclusions fully demonstrate that the lower the occupancy, the more obvious the improvement in thermal comfort and the more energy saved, but also the ability to guarantee inhaled air quality. Thus, the accuracy of occupant detection significantly affects thermal comfort as well as the building energy-saving potential.

CRediT authorship contribution statement

Bin Yang: Supervision, Funding acquisition, Conceptualization. **Yihang Liu:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Pengju Liu:** Investigation, Formal analysis, Data curation. **Faming Wang:** Writing – review & editing. **Xiaogang Cheng:** Writing – review & editing, Supervision. **Zhihan Lv:** Writing – review & editing, Supervision.

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.

Data availability

Data will be made available on request.

Acknowledgements

This research was grateful for the support of the National Natural Science Foundation of China (No. 52278119).

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