Data-driven Demand Control Ventilation Using Machine Learning CO_2 Occupancy Detection Method

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Abstract:

Heating, ventilation, and air-conditioning (HVAC) system accounts for approximately 40% of total building energy consumption in the United States. Currently, most buildings still utilize constant air volume (CAV) systems with on/off control to meet the thermal loads. Such systems, without any consideration of occupancy, may ventilate a room excessively and result in a waste of energy. Previous studies show that CO_2-based demand-controlled ventilation methods are the most widely used strategies to determine the optimal level of supply air volume. However, conventional CO_2 mass balanced models do not yield an optimal estimation accuracy. In this manuscript, a data-driven control strategy was developed to optimize the energy consumption of supply fans by feed-forward neural network to predict real-time occupancy as an active constraint. As for the validation, the experiment was carried out in an auditorium located on a university campus. The result shows, after utilizing feed-forward neural network to enhance the occupancy estimation, the new primary fan schedule can reduce the daily ventilation energy by 75% when compared to the current on/off control.

Keywords:

Energy Optimization, HVAC, CO_2, DCV, Occupancy.

1. Introduction

Given that HVAC systems have great impacts on energy consumption and human comfort, researches have been mainly focused on the minimization of HVAC energy use without sacrificing thermal comfort or the optimization of occupants' thermal comfort [1]. Studies show that people in the US and Europe are spending on average 85% to 90% of their time indoors [2]. Since Occupants release latent and sensible heat, indoor thermal conditions change, resulting in an increase of air-conditioning. Human occupants contribute to rising indoor carbon dioxide (CO_2) level which can also indicate how much ventilation is required [3]. This means that human occupants directly affect the HVAC energy consumption as well as indoor air quality (IAQ). Many studies have reported the use of CO_2 concentrations for occupancy prediction and estimation. Davide Cali et al. [4] proposed an algorithm for occupancy detection based on the mass balance equation of indoor CO_2 concentrations. The algorithm provided correct presence profile up to 95.8% of the time while the exact number of occupants was identified with the maximum accuracy of 80.6%. Chaoyang Jiang et al. [5] developed a dynamic model of the occupancy level with which they could estimate the real-time number of indoor occupants based on the CO_2 measurements. They showed the accuracy of up to 94 % with a tolerance of four occupants in an office room. In another study, T. Pedersen et al. [6] proposed a novel plug-and-play occupancy detection method in which they utilized multiple sensory data including CO_2 sensors. Testifying the proposed method in a single room and a three-bedroom apartment resulted in a maximum accuracy of 98% and 78%, respectively. S. Ryu and H. Moon [7] developed a machine-learning occupancy prediction model using indoor and outdoor CO_2 concentration data. By different observation states, they achieved the prediction accuracies ranging from 85% to 93.2%.

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Demand controlled ventilation (DCV) had been initially introduced to conserve energy while maintaining acceptable IAQ by providing outdoor air to a zone based on the actual occupants' demand [8,9]. DCV strategies have been implemented by utilizing occupancy schedules, occupancy counters, CO_2 sensors, temperature and humidity sensors, timers, and occupancy sensors [10]. Many literatures have proven that CO_2-based occupancy detection in DCV systems is a promising approach as CO_2 concentration is a proxy indicator of occupant-related contaminants [11–13]. In addition, CO_2 sensors are affordable, compact, non-intrusive and non-terminal-based. As they are conventionally integrated into standard HVAC systems, almost no additional investments are required in current infrastructures [14]. Several research works have examined the performance of DCV in various types of occupied zones and reported that a well-designed DCV can lead to savings in thermal conditioning and fan operation while meeting IAQ standards [15–19]. Budaiwi and Al-Homoud [16] used theoretical models to show how different CO_2-based ventilation strategies could affect IAQ and cooling energy consumption in a single zone. They proved that more than 50% cooling energy could be saved while maintaining pollutant concentrations within the standard range. Velimir Congradac and Filip Kulic [17] described the use of genetic algorithms (GAs) in CO_2-based control of standard HVAC systems. For different CO_2 concentrations, they reported the maximum cost savings of 21% in chiller and 83% reduced water flow rate through cooling coil. Schibuola et al. [18] used non-dispersive infrared (NDIR) sensors to measure CO_2 concentrations in order to analyse the performance of a DCV system associated with a university library building. It was revealed that the CO_2-based DCV system allowed the reduction of 21% in the airflow rate as well as the total primary energy saving of 33%. Zhongwei Sun et al. [19] presented the on-site implementation and validation of a CO_2-based adaptive DCV strategy in a high-rise building. In comparison with the original fixed outdoor airflow rate control strategy, their proposed DCV strategy saved about 55.8% of outdoor air ventilation energy.

Overall, previous studies have mainly investigated several physical and data-driven occupancy estimation models, disregarding the implementation outcomes on building energy management. Added to this, there have been a plethora of research works focusing on DCV strategies in which only CO_2 concentrations are utilized, but not the number of indoor occupants. This paper quantifies not only the energy savings but also indoor air quality by implementing a dynamic per-occupant DCV strategy, using machine learning techniques based on experimental data. An auditorium, as a densely occupied zone, was selected for the case study to compare the analysis between the proposed method and the proportional DCV strategy recommended by ASHRAE 62.1.

2. Materials and methods

2.1. Test environment and equipment

The test environment used in this study was an auditorium located on a university campus. Fig. 1 depicts the 3D layout of the zone; this auditorium is designed for the maximum seating capacity of 182 and mostly holds scheduled lecture classes and seminars. It has the volume and floor area of 1,400 m^3 and 306 m^2, respectively. There are three entrances to the zone whereas the window per wall ratio is zero. The conditioned air is delivered by six supply diffusers mounted on the suspended ceiling while the room's air is returned and relieved by one sidewall as well as four ceiling-mounted square extract grilles. Per ASHRAE standard 62.1-2016 [20], CO_2 sensors are located not only in the zone, but inside the supply and return ducts. Red marks shown in Fig. 1 are the exact location of these sensors.

Fig. 2 is the schematic diagram of the HVAC system associated with this auditorium. It comprises a standalone primary fan as well as a recirculation system. The primary fan receives 100% outdoor air and distributes to multiple zones including the auditorium. In spite of the VFD, this fan is currently operating between two fixed control positions, occupied and unoccupied mode. The primary air is modulated by a ventilation air damper, supplied to the zone as fresh ventilation air, and then mixed with the conditioned air by the recirculation system. The recirculation system fully operates with no shutdown (CAV type), while the primary fan is on full operation during occupied mode and on 70% operation during unoccupied mode. The occupied mode schedule is set from 6:00 a.m. to 9:00 p.m.

excluding weekends and holidays. During occupied mode the ventilation air damper is fully open, introducing about 1,000 L/s of outdoor air. During unoccupied hours, the ventilation air damper position goes down to 0% so that no outdoor air is supplied to the auditorium. Due to mass balance, the zone relief air damper position is proportional to the ventilation air damper position. Thus, the relief damper closes while the zone is unoccupied, meaning that only the recirculation system is in the loop.

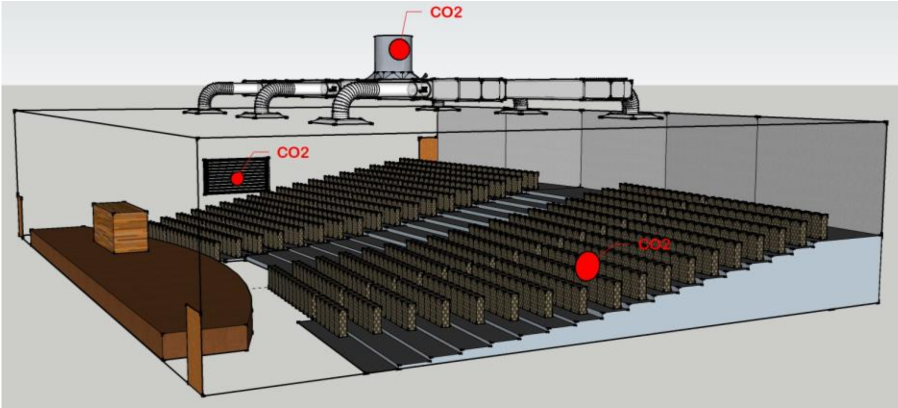

Fig. 1. An overview of the test environment.

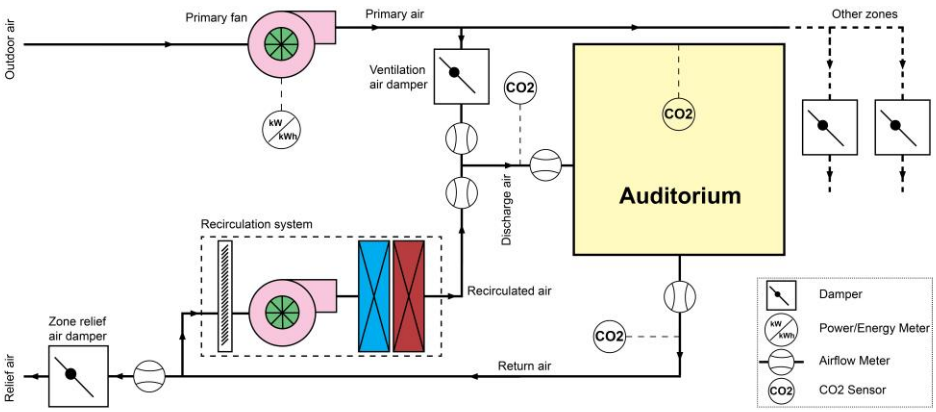

Fig. 2. The schematic of HVAC system serving the auditorium.

2.2. Data and sensor type

The data acquisition system, as Fig. 3 represents, consist of one power/energy meter sensor, three CO_2 sensors, an IoT gateway, the cloud platform and its dashboard. All the integrated sensors are capable of wireless communication via Bluetooth low energy (BLE) technology. The power meter is connected to the primary fan, measuring power factor, active power (kW) and energy consumption (kWh). It can cover the voltage range of 90-600 VAC with 0.5% accuracy. The CO_2 sensors are non-dispersive infrared (NDIR) type, which measure a range of 0 to 5000 ppm with ±5% of reading accuracy. The cloud dashboard is capable of showing both historical and real-time data that can also be downloaded for further processing.

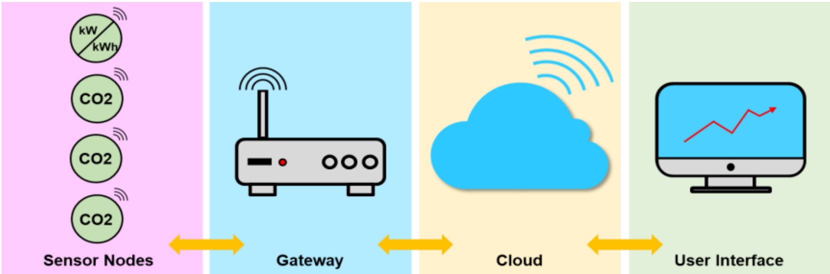

Fig. 3. The IoT-based data acquisition system.

Aside from the IoT platform, the building management system (BMS) is set to store the airflow rate data. The collected data of both IoT and BMS systems along with the ground truth occupancy readings are eventually lumped together for analysis. The experimental data were collected and monitored on a 15-minute time interval, from September 27th, 2019 to January 7th, 2020. The number of occupants in the auditorium was manually counted and then cross-checked with the class schedule provided by the university personnel.

2.3. Occupancy estimation

In this section we briefly describe three occupancy estimation models: steady-state approximation, transient, and feed-forward neural network. Steady-state approximation and transient models are categorized as physical models because they are derived from mass balance equations. The feed-forward neural network is a type of artificial neural network (ANN).

2.3.1. Physical models

For the auditorium space, a mass balance model was used to describe the change of CO_2 within the zone, following Eq. (1) [21].

$$v\frac{dC_z}{dt} = P_z G + V_{dz}C_{dz} - V_r C_r, \qquad (1)$$

where v is the auditorium volume (L), C_z is the CO_2 concentrations in the auditorium (ppm/10^6), P_z is the number of occupants in the auditorium (person), G is the average rate of CO_2 generation per person (L/s.person), V_{dz} is the zone discharge airflow rate to the auditorium (L/s), C_{dz} is the CO_2 concentrations in the zone discharge air (ppm/10^6), V_r is the return airflow rate (L/s), and C_r is the CO_2 concentrations in the return air (ppm/10^6).

Equation (2) shows the mass balance at the air handler unit (AHU),

$$V_{dz}C_{dz} = (V_r - V_e)C_r + V_{oz}C_{oz}, \qquad (2)$$

where V_e is the relief airflow rate (L/s) and V_{oz} is the outdoor airflow rate (L/s). Eq. (2) assumes the CO_2 concentration in the relief air equals to that of the return air.

Upon substituting Eq. (2) into Eq. (1), the zone CO_2 mass balance equation becomes Eq. (3),

$$v\frac{dC_z}{dt} = P_z G + V_{oz}C_{oz} - V_e C_r, \qquad (3)$$

Although Eq. (3) is solvable via simple integration, it is more convenient to either adopt steady-state approximation or to use the transient method, according to ASHRAE 62.1-2016 [20].

Assuming the CO_2 concentration in the auditorium has reached a steady-state, the equation drops the derivative term and becomes Eq. (4), and the estimated zone occupancy, $P_{z,\text{est}}$ can be calculated by Eq. (5) using steady-state approximation.

$$P_z G + V_{oz}C_{oz} - V_e C_r = 0 \qquad ,(4) \qquad\qquad P_{z,\text{est}} = \frac{V_e C_r - V_{oz}C_{oz}}{G}, \qquad (5)$$

The transient method assumes the CO_2 derivative to be the rate of change of concentration between the current and previous sampling instants, expressed as Eq. (6). The zone estimated occupancy then can be calculated by Eq. (7),

$$\frac{dC_z}{dt} \approx \frac{C_z^i - C_z^{i-1}}{\Delta t} \qquad ,(6) \qquad\qquad P_{z,\text{est}}^i = \frac{V_e C_r - V_{oz}C_{oz}}{G} + v\frac{C_z^i - C_z^{i-1}}{G\Delta t}, \qquad (7)$$

where Δt is the timestep in second and i is the current step.

2.3.2. Artificial neural network model

ANNs are machine learning tools that process the data like a human brain. ANNs can build linear and nonlinear models for time series. They are widely accepted as effective tools for fitting functions [22]. This study utilizes a two-layer feed-forward neural network (FFNN) to approximate nonlinear relationships between inputs and outputs. FFNN consists of layers of processing units, denoted as neurons. The basic elements in FFNN are neurons arranged by the input, output and hidden layers. Input layers read in a signal to the network and hidden layers pass the signal through the network through weighted connections. In this network every hidden neuron receives inputs in the form of weighted signals from the previous layer plus a bias and flows to the output layer in one direction. By using the Sigmoidal activation function in Eq. (8), the network output is described as Eq. (9) [23].

$$f(x) = \frac{1}{1+e^{-x}} \quad ,(8) \qquad \textit{and} \qquad y_k = f\left(\sum_{j=1}^{M} u_{jk} \cdot f\left(\sum_{i=1}^{N} w_{ij} x_i + \theta_j\right)\right) + \theta_k \,, \quad (9)$$

Here, $f(x)$ is the Sigmoidal activation function, y is the output of the network, w and u are the scaler weights, and θ is the bias. N and M are the number of inputs and the number neurons in the hidden layer, respectively. In this study, the neural network model was built using MATLAB deep learning toolbox [24]. The inputs to the algorithm are the CO_2 concentrations in the zone, discharge air, and return air; also, the ventilation rate of the discharge, outdoor, and return; and the schedule of classes specifying when the zone is likely to be occupied. The training function was selected to be Bayesian regularization backpropagation which minimizes the mean squared error (MSE) between the predicted and observed values. The number of hidden layer neurons was determined by the number of inputs by the following relationship as $M = 2N + 1$ [25]. The only output of the model is the estimated number of occupants inside the zone. We utilize all collected data measured from September 27th, 2019 to January 7th, 2020, leaving data from September 30th to October 4th for future validation. A summary of FFNN design parameters and inputs are listed in Table 1.

Table 1. Summary of FFNN design parameters and inputs.

Network Type	*FFNN*
Inputs parameters	CO_2 concentrations (ppm), ventilation rates (L/s), class schedule
Targets	number of occupants
Training Algorithm	Bayesian regularization
Number of Neurons	15
Performance	MSE

2.4. Indoor CO_2 concentration standards and guidelines

In most cases indoor CO_2 concentrations never reach 5,000 ppm to pose a health risk. Previously, the ASHRAE Standard 62-1989 [26] recommended indoor CO_2 level of 1,000 ppm to satisfy comfort criteria. This recommendation was later dropped in the ASHRAE Standard 62-1999, eliminating an absolute level of 1,000 ppm CO_2. Instead, a 700 indoor/outdoor CO_2 concentration differential was established [27]. Previous studies have shown that outdoor CO_2 concentrations typically range from 300 to 500 ppm. Therefore, indoor CO_2 concentration between 1,000 ppm to 1,200 ppm for sedentary occupants is an acceptable indoor air quality indicator [28]. This study used indoor CO_2 concentration of 1,200 ppm as a guideline to build proposed DCV controls discussed in the next sections.

2.5. Implementation of DCV using CO_2

Ventilation and IAQ principles permit the utilization of DCV to control outdoor air ventilation rate. Under the principles of ASHRAE Standard 62.1-2016 an effective ventilation prerequisite of a zone is dependent on the number of occupants and the floor area. Equation (10) gives the minimum required outdoor airflow.

$$V_{bz} = R_p P_z + R_a A_z \,, \qquad (10)$$

where V_{bz} is the required outdoor fresh airflow in the breathing zone, R_p is the outdoor airflow rate required per person, P_z is the number of people in the ventilation zone during use, R_a is the outdoor airflow rate per unit area, and A_z is the occupiable floor area of the breathing zone.

2.5.1. Proportional control

Based on the zone CO_2 concentration measurement, the ventilation rate can be adjusted proportionally between the minimum and the outdoor value. A proportional control system can be applied to outdoor air dampers to modulate the outdoor airflow. Equation (11) calculates the outdoor airflow introduced by a proportionally controlled outdoor air damper [21].

$$V_{oz} = \frac{C_z - C_{z,\min}}{C_{z,\mathrm{des}} - C_{z,\min}} (V_{oz,\mathrm{des}} - V_{oz,\min}) + V_{oz,\min}\,, \qquad (11)$$

where C_z is the measured zone CO_2 concentration (ppm/10^6), $C_{z,\min}$ is the indoor CO_2 concentration when the zone is unoccupied (ppm/10^6), $C_{z,\mathrm{des}}$ is the indoor CO_2 concentration when the zone has the design level of occupancy (ppm/10^6), $V_{oz,\mathrm{des}}$ is the ventilation rate at the design level of occupancy (L/s), and $V_{oz,\min}$ is the ventilation rate when the zone is unoccupied (L/s).

2.5.2. Dynamic per-occupant controls

Using either the two physical models or the FFNN model, it is possible to calculate the minimum ventilation rate by Eq. (10) according to the number of occupants. Both steady-state approximation and transient models calculate the breathing zone population using the air properties that can be easily obtained by data-loggers. The FFNN model requires more computing power, yet it is achievable through implementing a dedicated system.

3. Results and discussion

The occupancy estimation resulted from using the physical models, Eq. (5) and Eq. (7), and the FFNN model are presented in this section. This study used a typical Monday – Friday school week in 2019 for validation of the models. Both physical models calculated the occupancy level using the data obtained within this validation period. The FFNN model was trained using data obtained from the entire experiment period, excluding the days used for validation.

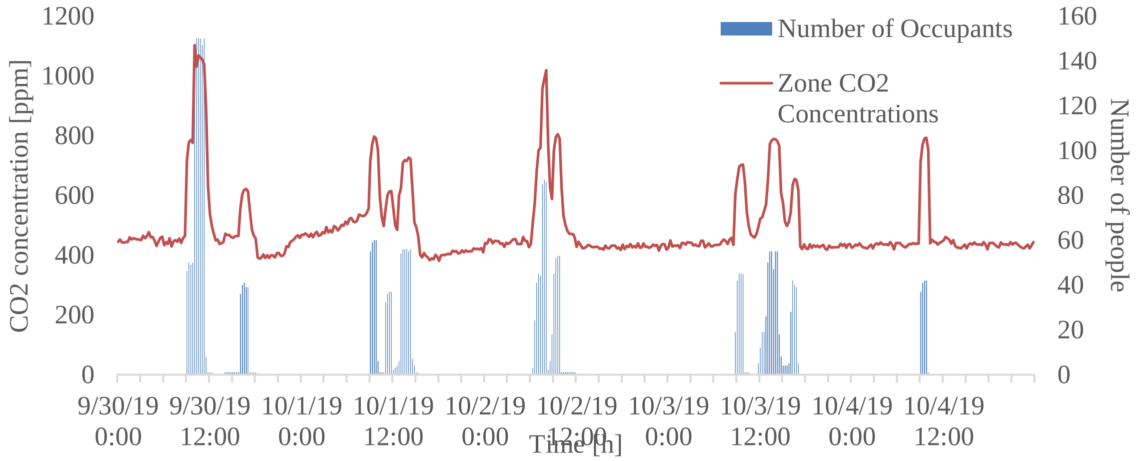

Fig. 4. The zone CO2 concentrations and occupancy level.

3.1. Current zone CO_2 concentrations and occupancy

Figure 4 shows the current zone CO_2 concentrations and the occupancy level in the auditorium over 5 working days, from September 30th to October 4th, 2019. The average breathing zone CO_2 concentrations during occupied mode of AHU are 508 ppm. The statistics also shows that the average zone CO_2 concentrations while classes are in session and not in session are 697 ppm and 439 ppm, respectively. The peak occupancy level is 150 people, occurring in the morning on September 30th, due to a large seminar. The average number of occupants during occupied mode is 47 people and the average number of occupants during unoccupied mode is 0 people. The average occupants in the validation period is 7.76 people. The average ventilation rate during occupied mode is about 1000 L/s and 0 L/s during unoccupied mode.

3.2. Occupancy prediction model performance

The occupancy estimation models described were evaluated using ASTM D5157 Standard Guide for Statistical Evaluation of Indoor Air Quality Models. This standard provides three statistical tools for evaluating the accuracy of IAQ model predictions as suggested by [29] and [3]. We calculated the values using the Eq. (12) and Eq. (13), which are summarized in Table 2 and assessed the model performance using what are suggested by ASTM guideline [30]. Fig. 5 shows the scatter plot between the models' estimated occupancy and the observed occupancy.

$$r = \frac{\sum_{i=1}\left[\left(P_z^i - \overline{P}_z\right)\left(P_{z,\mathrm{est}}^i - \overline{P}_{z,\mathrm{est}}\right)\right]}{\sqrt{\sum_{i=1}\left(P_z^i - \overline{P}_z\right)^2}\sqrt{\sum_{i=1}\left(P_{z,\mathrm{est}}^i - \overline{P}_{z,\mathrm{est}}\right)^2}}, \quad (12) \qquad NMSE = \frac{1}{N\,\overline{P}_z\,\overline{P}_{z,\mathrm{est}}}\sum_{i=1}^{N}\left(P_{z,\mathrm{est}}^i - P_z^i\right)^2, \quad (13)$$

where P_z is the observed occupancy, $\overline{P}_z$ is the average of the observed occupancy, $P_{z,\mathrm{est}}$ is the estimated occupancy, $\overline{P}_{z,\mathrm{est}}$ is the average estimated occupancy, and N is the number of observations. These parameters should be within certain ranges as shown below.

1. The correlation coefficient, calculated using Eq. (12), shall be 0.9 or greater;
2. The best fit regression line between the estimation and observed data should have a slope between 0.75 and 1.25 and an intercept less than 25 % of the average observed value;
3. The normalize mean square error (NMSE), calculated using Eq. (13) should be less than 0.25.

Table 2. Performance summary of the occupancy prediction models.

Modeling Techniques	r	slope	intercept	NMSE
ASTM Criteria	>0.9	0.75-1.25	less than 25% of average occupancy (1.94 people)	<0.25
Steady-State Approximation	0.85	1.07	5.56	1.60
Transient Method	0.86	0.85	3.86	1.56
FFNN	0.98	1.00	0.97	0.23

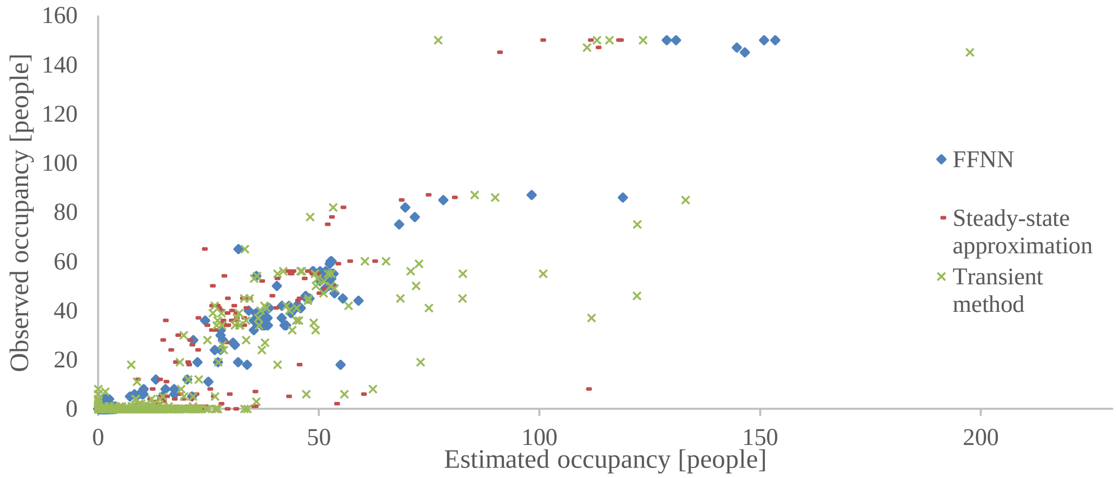

Fig. 5. Scattered plot showing the performance of occupancy prediction models.

The steady-state approximation model gives the correlation coefficient of 0.85. The best fit regression line has a slope of 1.06 and an intercept of 5.58, which is 72% of the average measured occupancy. The NMSE is calculated to be 1.60. The best fit line is close to unity, which suggests the model well estimates the overall trend of the change of occupancy. However, an intercept of 5.58 means that the model tends to underestimate the number of occupants by 5 to 6 people and the correlation coefficient is not within the recommended guideline. NMSE also suggests that the model does not yield a satisfactory result. The transient model has the correlation coefficient of 0.86. Its best fit regression line has a slope of 0.86 and an intercept of 3.86, which is 50% of the average measured occupancy. The NMSE is 1.56. The transient model only is fractionally better than the steady-state model in terms of correlation coefficient. The slope is within the guide, but both the intercept and NMSE are not satisfactory. This shows that the transient model, though provides a better result, is still not an optimal option to estimate the occupancy level. The FFNN model has the correlation coefficient of 0.98. Its best fit regression line has a slope of 1 and an intercept of 0.97, which is 12% of the average measured occupancy. The NMSE is 0.23. All evaluation metrics are within the guideline's recommendation. The result suggests that the FFNN model successfully estimates the occupancy level and it is the best modeling technique among what we have tested.

3.3. Comparison of ventilation rates

The CO_2-based DCV methods were compared with the schedule-based on/off control that is currently being implemented. The current on/off control and the proportional control do not consider the occupancy level directly. Instead, the proportional control uses 1,200 ppm as the reference CO_2 concentration. On the other hand, the zone occupancy is utilized by the dynamic per-occupant control strategies, following the minimum ventilation rate per person by ASHRAE standard. For a school lecture hall, ASHRAE 62.1-2016 demands ventilation rate of 3.8 L/s per person and 0.3 L/s per square meter of the floor area [20].

A close-up view of the day of October 3rd is shown in Fig. 6. It is evident that CO_2-based DCV strategies gave lower ventilation rates when the AHUs were in occupied mode. When the AHU was in unoccupied mode the current on/off control strategy produced no ventilation due to the closure of the outdoor air damper. Other strategies are required to give a minimum of unoccupied ventilation per ASHRAE standards.

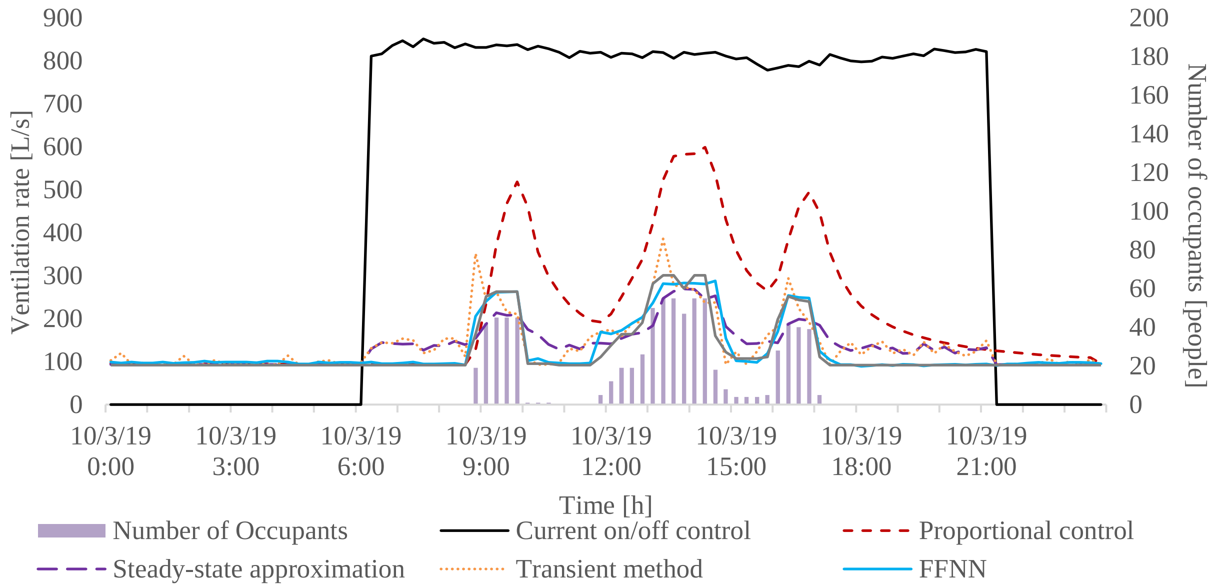

Fig. 6. Simulated ventilation rates under different control strategies for October 3rd.

The proportional control strategy produces the most ventilation airflow among the DCV strategies because it continues to ventilate the zone even when there is no occupancy. Also, the proportional control reacts slowly to the change of occupancy when people enter and leave the zone, creating a huge saving opportunity due to over-ventilation. The average ventilation rate when the AHU is in occupied mode using the proportional control is 246 L/s, and 103 L/s when the AHU is in unoccupied mode.

The dynamic control strategies react to the changes of occupancy quickly. When there are no occupants in the zone, the controls modulate the outdoor air damper to the minimum required. Compared to on/off control and proportional control strategies, the dynamic control strategies all have the advantage of being able to yield ventilation savings. Among them, the FFNN model gives the lowest average ventilation rate because of its estimation accuracy. The steady-state approximation method gives the second lowest ventilation rate; however, this is because it tends to underestimate the number of occupants. Therefore, it is less accurate in predicting the occupancy level as mentioned in the last section. The transient model produces comparable average ventilation rate to that of the steady-state approximation method. The reason is both steady-state and the transient models predict almost the same average occupancy level in the day. The only difference is that the transient model predicts the number with better accuracy in terms of NMSE shown in previous section.

The average ventilation rates using the steady-state approximation, the transient model, and the FFNN model when the AHU is in occupied mode are 183 L/s, 187 L/s, and 155 L/s, respectively. During the time when the AHU is in unoccupied mode, the numbers are 94 L/s, 100 L/s, and 99 L/s, respectively.

3.4. Effects on CO_2 Concentrations

The effect on zone CO_2 concentrations using different DCV strategies was modeled by Eq. (3). Fig. 7 shows the change of zone CO_2 concentrations on the day of October 3rd, along with the 1,200-ppm guide mentioned in section 2.4. It can be seen that CO_2-based DCV strategies increase the overall CO_2 concentration due to the decrease of ventilation rates. None of the DCV strategies cause the peak CO_2 level to be higher than the guideline.

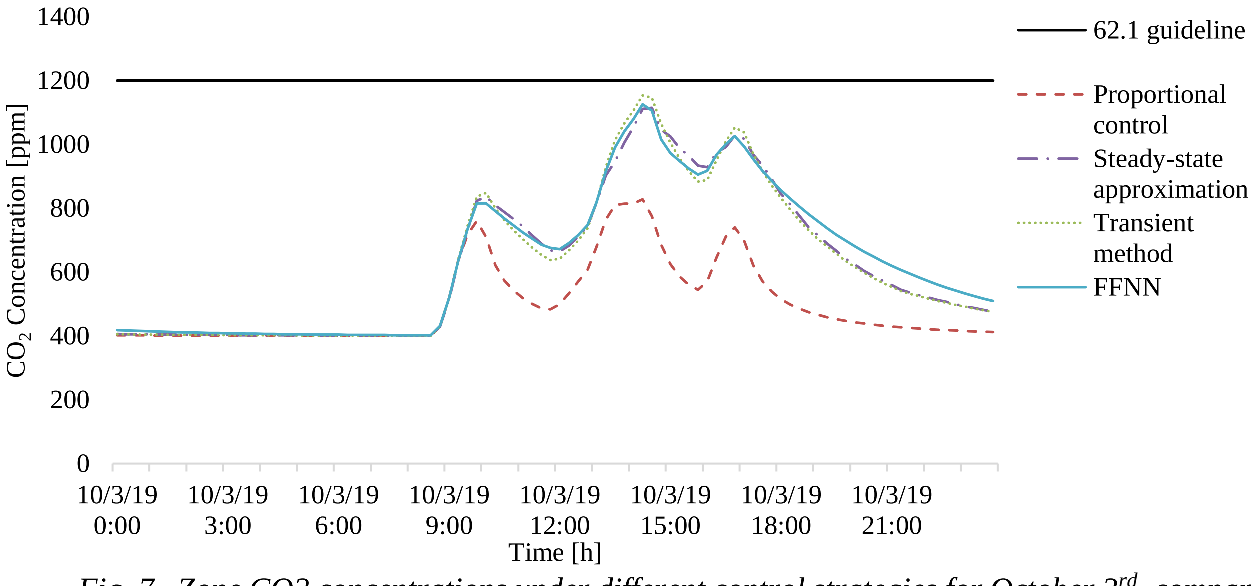

Fig. 7. Zone CO2 concentrations under different control strategies for October 3rd, compared with the level recommended by ASHRAE 62.1.

The proportional control method results in an average of 530 ppm during occupied mode, and 408 ppm during unoccupied mode. The CO_2 concentration of 530 ppm is 2.5% and higher that the current average zone CO_2 concentration during occupied mode, and the number is 8% lower during unoccupied mode.

The FFNN model leads to the highest average CO_2 concentrations among the per-occupant strategies, which is expected as it produces the lowest average ventilation rates. The numbers are 671 ppm and

445 ppm, 30% higher and 1% lower than the current CO_2 ppm readings during occupied and unoccupied mode, respectively. The steady-state and the transient models result in similar average CO_2 concentrations since they have comparable average ventilation rates as described in section 3.3. During occupied mode the steady-steady and the transient models yield 646 and 660 ppm, respectively. These numbers are 25% and 28% higher than the current CO_2 ppm measurements. During the unoccupied mode the numbers are 425 ppm and 426 ppm. They are both about 3.6% lower than the current average value.

3.5. Energy saving analysis

The current energy baseline due to auditorium ventilation is about 703 kWh/day and our experiment shows a linear relationship between the primary ventilation flow and the primary air fan power consumption. The R-squared between the primary ventilation airflow and the fan power is 0.93, as a result from Fig. 8. Thus, the percentage reduction in ventilation rates can be used to estimate the percentage energy saving. Results on energy savings of each DCV strategies with respective to the current strategy are summarized in Table 3. The maximum energy saving was achieved by utilizing FFNN for occupancy detection in dynamic per-occupant control. The saving percentage is about 75%. The physical model occupancy detection methods yield similar energy savings. The saving percentages are 74% for steady-state approximation and 73% for the transient method. It should be noted that the steady-state method tends to underestimate the occupancy. This is the main reason that it results in a higher energy saving. Proportional control does not use the occupancy estimation and therefore only 59% reduction of energy is achieved.

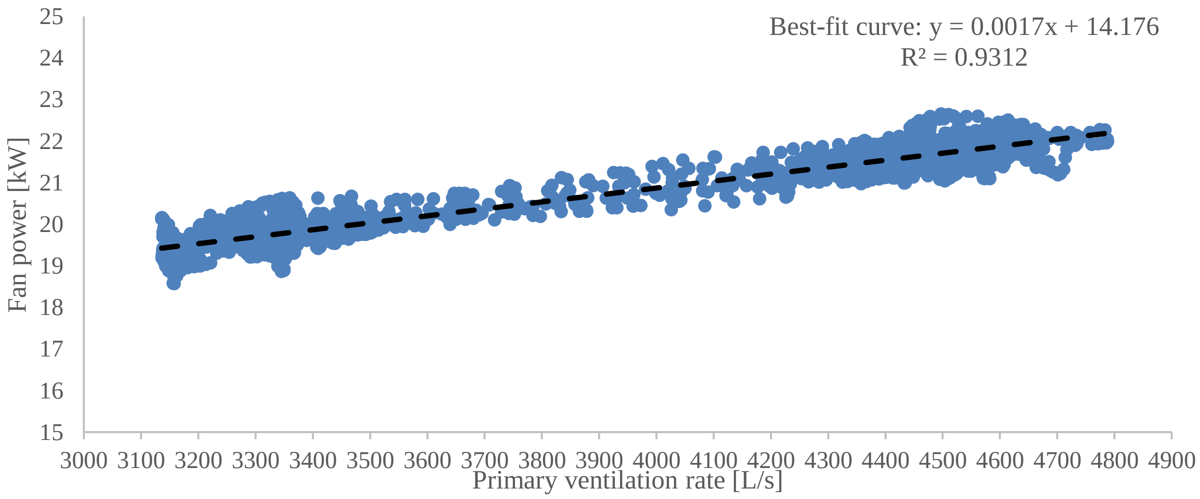

Fig. 8. Linear relationship between primary ventilation rate and primary fan power.

Table 3. Summary of ventilation energy savings under different control strategies, comparing to the baseline.

Modeling Techniques	*Average daily ventilation fan energy [kWh/day]*	*Saving compared to baseline [%]*
Baseline	*703*	*0%*
Proportional	*289*	*59%*
Steady-State Approximation	186	*74%*
Transient Method	193	*73%*
FFNN	176	*75%*

4. Conclusion and perspectives

This study investigated the benefit of implementing machine learning algorithms in CO_2-based DCV methods. The two-layer feed-forward neural network can be used to estimate the occupancy, which was proven through a case study. Comparison among the four tested methods demonstrated that the application of ANN in the per-occupant DCV can result in 75% energy savings against the baseline, about 39% against the proportional control, and 5% to 9% against the physical models. All strategies can maintain indoor CO_2 concentrations below 1,200 ppm, which means they are all effective energy saving strategies while dealing with occupancy ventilation. Further research shall include the analysis of effects on human comfort when implementing excessive reduction in ventilation airflow.

Nomenclature

C	CO_2 concentrations, (ppm/10^6)
G	average rate of CO_2 generation per person, (L/s.person)
P	number of occupants, (person)
V	airflow rate, (L/s)
v	volume, (L)

Subscripts and superscripts

bz	Breathing zone
des	Design level
dz	Discharge to the zone
e	Relief
est	Estimated
i	Current step
min	Minimum level
oz	Outdoor to the zone
r	Return
z	Zone

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