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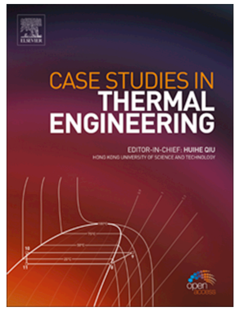

Optimization of thermal comfort, indoor quality, and energy-saving in campus classroom through deep Q learning

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I am the corresponding author (Chi-Chuan Wang) and I certify that all authors have participated sufficiently in the work to take public responsibility for the content. Their contributions have been specified as follows:

Kuan-Heng Yu: Conducts experiment and write the first draft.

Yi-An Chen, Emanuel Jaimes: Conduct the experiment.

Wu-Chieh Wu, Kuo-Kai Liao, Jen-Chung Liao, Kuang-Chin Lu: Supervision and funding..

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Optimization of thermal comfort, indoor quality, and energy-saving in campus classroom through deep Q learning

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Abstract

This study develops a control algorithm for optimization the energy consumption from air-conditioning and exhaust fans through Deep Q-Learning in reinforcement learning. The proposed agent is able to balance indoor air quality (CO_2), thermal comfort, and energy consumption. The algorithm was first trained in a similar environment simulation, and was then applied and tested in a classroom with maximum 72 occupants. Tests were conducted in one month during summer. The effects of outdoor environments and class conditions on the energy-saving and indoor air quality are examined in details. Via agent control, optimization of indoor air quality, thermal comfort, and energy consumption of air-conditioning units and exhaust fans can be achieved. With the same thermal comfort, the agent can offer energy-saving up to 43% when compared to air-conditioning with a fixed temperature of 25 °C, and on average the agent offers about 19% less of the energy consumption. Yet the corresponding CO_2 level is reduced by about 24% with the agent control. Similarly, when compared with a fixed temperature of 26 °C, the agent can offer about 15% lower energy consumption on average and the concentration of carbon dioxide can be reduced by 13% in average.

Keywords: Thermal comfort; Indoor air quality; Energy saving; Reinforcement Learning; Deep Q-Learning

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1. Introduction

Energy consumed by building sector includes residential and commercial end users and accounts for 20.1% total energy consumption worldwide. Among the energy used by building, air conditioning and lighting equipment account for more than 70% of the residential building portion (air conditioning about 45%, lighting about 25%). In tropical and subtropical areas, cooling in buildings is even more essential from the perspective of thermal comfort, particularly in public buildings such as offices, supermarkets, sport centers, etc., where energy consumption accounts for over 56% of building's energy demands [1]. For university campus, an analysis of the energy consumption at China unveiled that the energy consumption of ACs accounts for the most substantial proportion, surpassing 41.8% of the total energy consumption [2]. The thermal environments of campus teaching buildings are quite different from of other types of buildings mainly due to the diference of uncontrollable occupancy. The main objective of air-conditioning is to meet the demand of the thermal comfort for human body [3]. However, the occupancy and AC utilization in each classroom are random, thereby becoming much complicated than those in the buildings with fixed occupancy schedules, like office buildings. Quantitative description of thermal comfort is first proposed by Fanger [4] who developed the Predicted Mean Vote (PMV) mathematical model to correlate the thermal comfort associated with the surrounding environment, and the seven-point thermal sensation scale, including hot, warm, slightly warm, neutral, slightly cool, cool, cold represented by +3, +2, +1, 0, -1, -2, -3, respectively was proposed. Fanger further developed the PMV model to incorporate the Predicted of Percentage Dissatisfied (PPD) to indicate the percentage of people that felt uncomfortable. Since then, many researches had been conducted associated with thermal comfort regarding PMV model (e.g. Auliciems [5], de Dear and Brager [6], Griffiths et al. [7]). Charles [8] made a thorough review of the validity of Fanger's draught model, and concludes that Fanger's draught model can reasonably be applied without concern for serious bias. Mui and Chan [9] and Lin et al. [10] also conducted a thermal comfort study to derive the correlation between outdoor temperature and thermal comfort temperature.

In additional to the energy consumption and thermal comfort, there is also a need to maintain the indoor air quality within acceptable ranges. For typical indoor condition, the carbon dioxide (CO_2) concentration level is one of the main indicator to justify the indoor quality. It is well known that high levels of CO_2 are harmful to human beings. Hence, it is imperative to keep it below certain threshold for improving people's health and efficiency, and creating an environment that encourages talent cultivation. To resolve the complex interactions amid thermal comfort and indoor air quality while balancing the energy consumption of the air-conditioning effectively, a possible way to meet the demand is via artificial intelligence (AI). Some prior studies had been conducted to minimize the CO_2 influence. For instance, Verma et al. [11] employed an AI based building management and information system with multi-agent topology for the energy-efficient building. The design is able to minimize the energy consumption and to maximize the level of comfort. Orosa et al. [12] designed neural networks (NNs) for indoor ambiences with internal covering materials in different buildings. Local thermal comfort conditions and energy consumption subject to internal covering permeability level were calculated. Yet a better indoor ambience along with a lower energy consumption of 20% in the heating, ventilation, and air conditioning (HVAC) systems during the summer season in the first hours of occupation was obtained when permeable coating materials were used. Cheng and Lee [13] proposed a normalized Harris index (NHI) to evaluate the energy saving of different kinds of HVAC controls and the estimated average energy savings percentage and the maximum saving

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rations of AI-assisted HVAC control are 14.4% and 44.04%, respectively. They [14] further developed a predictive model to obtain air conditioning energy consumption data. Comparisons between the predictive and actual data for temperature and humidity were between 95.5 and 96.6%, respectively.

Through the help of AI agents, the foregoing studies can resolve some coupled interactions amid ambiences and thermal environments. However, the thermal environment of the prior studies were quite different from the university campus from several aspects. Firstly, unlike the centralized air-conditioning system applicable for large buildings, the present campus classroom used split type air-conditioning and ventilation fans to regulate the indoor environments. Note that this is often seen in for subtropical campus area. Secondly, depending on the lecture class, the density of occupants varies and may be over crowded in some typical circumstances. Yet, the metabolic rate may change appreciably when the occupants are in focus especially when conducting examinations or tests. In summary, the diversity and complexity of the thermal environments of the campus classrooms require ingenious manipulation to balance the energy consumptions, indoor air (e.g. CO_2), and thermal comfort. Notice that the indoor thermal environments (e.g. CO_2 & thermal comfort) and AC usage are interrelated. The thermal comfort characteristics of occupants in teaching buildings are unique when compared to the occupants in other types of buildings. Hence, the aim of this study is to maintain a thermal comfortable indoor environment in campus classroom with minimum energy consumption of air-conditioning. There were some studies addressing this subject. For example, Huang et al. [15] and Wong and Khoo [16] collected field data on school classrooms and conducted related thermal comfort analysis. Basically, in the subtropical region, the acceptable thermal comfort range is 21.1–29.8°C and the thermal comfort temperature is about 24.7°C. Hsiao and Lin [17] using Fanger's thermal comfort theory as the basis, and derived a model using genetic algorithm to design an expert system. Ku et al. [18] designed an automated thermal comfort control system based on PVM and energy saving particle swarm algorithm to maintain the required PMV value associated with the temperature. Their control methods can maintain the thermal comfort level within ±0.5 at the required temperature.

Ferreira et al. [19] proposed a neural network-based predictive control model to optimize thermal comfort and energy consumption of air conditioning. The proposed control strategy mainly consists of three parts, namely, predictive models, cost function and optimization method. Using the Radial Basis Functions Neural Network (RBFNN) to establish the prediction model of the PMV index, they reported energy saving can be more than 50%. Wei et al. [20] used deep reinforcement learning (DRL) for air-conditioning controllers to yield appreciable energy consumption

Until now, most of the AI related studies upon campus ambience focused on the optimization amid the energy consumption by air-conditioning and thermal comfort. However, the indoor air quality (such as CO_2) was not taken into account. The only study to balance these three factors is by Valladares et al. [21] in a small scale laboratory (about 5-7 occupants). They proposed an AI agent that contains a superior PMV and 4–5% less energy consumption while yielding 10% lower CO_2 levels than the current control system. However, the experiment of this study was conducted in a relatively small laboratory with limited occupants. Hence, it is essential to examine the applicability of the AI agent upon a regular size of campus-scale classroom (up to 72 occupants) subject to complex environmental conditions and examine the associated energy-saving potential with and without the help of AI agent in response to thermal comfort and indoor air quality.

2. Experimental setup

The experiments are carried out in a typical classroom of the university campus. No prior settings or specific arrangements of the occupants are made. The students may attend the class lecture or take a test depending on the class type and the students can randomly select the seats at their free will. Yet the number of occupants may vary appreciably subject to lecture courses. The scenario is to reflect actual class conditions and the possible energy-saving potential with and without the presence of agent control.

The basic test apparatus is the same with the prior study in Valladares et al. [21]. However, the experimental test site is an actual classroom containing a certain amount of occupants while the prior experiments were conducted in a laboratory with fewer occupants. The 3-D view and the plane view of the classroom is shown in Fig. 2(a) and 2(b) while the corresponding measuring sensors are also shown in Fig. 2(b). The classroom contains an area of 111.435 m^2 and a height of 4.2 m. It can accommodate up to 72 people with three air-conditioners (AC1-AC3), four exhaust fans (Fan1-Fan4), six temperature and humidity/CO_2 sensors (sensor1-sensor6, S1-S6) and one globe thermometer (GT). The temperature and humidity/CO_2 sensors are installed at a distance of 1300 mm above the ground surface to measure environmental parameters. The air-conditioner controlled by this study is a variable refrigerant flow (VRF) system. The sensor and air conditioning installation points are show in Fig. 2(b). The measurements include dry-bulb temperature, wet-bulb temperature, and the CO_2 level. Generally, the indoor carbon dioxide concentration should not exceed 1000 ppm. To maintain the air-quality, additional ventilation fans are connected to the classroom to lower the CO_2 level. Note that two of the ventilation fans are connected to corridor while the other two are

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installed on the side wall that separates the exterior ambience. The installation and placement of the equipment and sensors are placed on the side walls of the classroom as depicted in Fig. 2(c). The fans connected to the corridor can offer a cooler temperature with a comparatively higher CO_2 level than the one connected to the exterior ambience. The benefit for fans connected to the corridor is to introduce fresh air into the classroom without considerably raising the cooling load of the air-conditioners. This study uses Chunghwa Telecom's Prius smart system that embedded Raspberry PI 3, temperature and humidity/CO_2 sensors and air-conditioners though Wi-Fi as show in Fig. 2(b). The temperature and humidity/CO_2 sensors and air-conditioner measure the environment parameters and related parameters accordingly.

3. Analyzing principle

A deep reinforcement learning (DRL) based controller is developed to optimize the energy consumption of air-conditioning systems in association with thermal comfort and indoor air quality in an actual classroom subject to various ambient conditions. The AI agent adopts reinforcement learning through interaction with the environment, and the process is regarded as a tuple of the Markov Decision Process framework: <S, A, T, R> where S is a finite set of states, A is a finite set of actions, T is the transition function and R is the reward function. To facilitate good decisions in some certain states, a so-called Q function, which represents the total reward expected in the future based on the state S in which it is acting. The Q function has recursive nature and is expressed as:

$$Q(s,a) = r + \gamma \, maxQ(s', a') \tag{1}$$

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Where γ is called discount factor, representing the importance of future rewards. The lower γ is, the more the agent pays attention to the current rewards, and represents whether the rewards in the future might be too far away and insufficient to be connected with the previous or current state decision policy. The agent learns the Q function by rewards which are attainable in interaction with the environment. By introducing a neural network instead of the original Q table, the state is directly associated with the input of the neural network, and the corresponding Q value and actions are obtained through the network, this is called Deep Q Learning. Further details can be described in Valladares et al. [21], and some of the details are addressed in the following.

The system state (S) is a multidimensional vector composed of multiple physical quantities. Through this multidimensional vector, the state of the classroom at a given moment includes indoor temperature, outdoor temperature, thermal comfort PMV, CO_2 concentration, relative humidity, average radiant temperature, and the number of occupants in the classroom. The state vector at time t_1 is expressed mathematically as:

$$s_1 = [T_{in1}, T_{out1}, PMV_1, (CO_2)_1, MRT_1, \# \, people_1, \Delta PMV, \Delta(CO_2)] \qquad (2)$$

Where T_{in} is the indoor temperature, T_{out} is the outdoor temperature, MRT is the mean radiation temperature, ΔPMV and ΔCO_2 are the variation of PMV and CO_2 relative to prior time step. The control actions are collections from all actions, the room temperature is regulated through air- conditioner, and the exhaust fan can introduce fresh air from ambience to reduce CO_2 concentration. The proposed reward function accounts for the following influences: PMV values in the classroom, carbon dioxide concentration values, air-conditioner power consumption, and fan power consumption. The ultimate goal is to obtain a minimum energy consumption while maintaining the PMV in a comfort zone and limiting the carbon dioxide concentration below the threshold value. The algorithm is composed of three different loops, namely the pre-training, training and the control loops. Detailed description of the algorithm can be found in prior study [21].

4. Results and Discussion

These present experiments are carried out during active lecture period. The major variants include the number of occupants in the classroom, lecture conditions, outdoor temperature, indoor temperature, indoor humidity, indoor globe ball temperature (radiation temperature), indoor carbon dioxide concentration and energy consumption by air-conditioner and fan. Data is recorded for every 30 seconds while each lecture hour lasts for 50 minutes. However, some lecture hours could last in two consecutive lecture hours with 10 minutes break. The air quality of the class ambience is regarded in good condition when the carbon dioxide concentration is less than 800 ppm; and is acceptable when CO_2 concentration lies between 800 and 1000 ppm; while a concentration exceeding 1000 ppm is unacceptable. From the perspective of thermal comfort, the evaluation is based on PMV, where the comfortable condition is when the PMV falls between ±0.5. The energy consumption is based on the total electricity consumption within 50 minutes of a lecture period. During the experiments, the experimental conditions can be further divided into two categories (the uncontrollable and the controllable):

1. The uncontrollable: weather (sunny, rainy), lecture condition (lecturing, test/examination, number of occupants (24-88 people), outdoor temperature (22-34°C), initial CO_2 concentration, lecture period (1-hr or 2-hr period).

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2. The controllable: constant indoor temperature control (24-27 °C) for air-conditioning for the original control, DQN algorithm automatic control (agent control).

The experiment duration is from May 20, 2019 to June 20, 2019. The lead time for turning on the air-conditioners is 10 minutes prior to the lecture period begins. Yet the front and back door of the classroom are always open and the windows are normally closed. The controlled indoor temperature is between 25 and 26 °C. A total of thirty experiments are performed and the related ambient conditions are listed in Table 1.

Figure 3 shows the test results for all cases sorted with average CO_2 concentration (Fig. 3(a)) or by energy consumption (Fig. 3(b)). Due to the diversity of the test conditions (occupants, outdoor conditions, setting conditions, indoor conditions), there is no definite trend by adding all test results in a specific diagram like Fig. 3(a). However, there is a general trend when sorted with energy consumption as depicted in Fig. 3(b), it appears that normally the lower energy consumption accompanies with the higher the CO_2 concentration. Yet, as seen in Fig. 3(b), cases 16, 22, 23, 24 shows the highest energy consumption. Note that there is a basic difference between cases 16 and cases 22-24 despite these cases are conducting the test and contains comparable occupants. Case 16 is a one-hour test while cases 22-24 are 2-hour test. Hence, the accumulated CO_2 and energy consumption is lower than those of cases 22-24. Hence, only cases 22-24 are used for further subsequent comparisons. It is interesting to know that these cases are for conducting examination test where the occupants are more focused. Apparently, the corresponding value of metabolic equivalent of task (MET) for the occupants during the examination is higher than those during typical lecturing cases. In this regard, more heat is generated from the occupants and requires higher cooling loads from the air-conditioners. This

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can be also made clear from the rise of CO_2 concentration (evaluated as the final CO_2 concentration subtracts the initial CO_2 concentration) are 580, 920, 589, and 381 ppm, respectively. Note that the ventilation fans are not functional when the agent is inactive, meaning that some of the generated CO_2 can only flow out the classroom at the front or back door since these doors are always open. Based on the measurements of Table 1, it is clear that the typical rise of CO_2 concentration is less than 200 ppm for those lecturing classes without agent control. The exceptions are with cases 1, 2, 15, and 29 where the rise of CO_2 concentration is more than 200 ppm. Notice that these cases contain more occupants than the rest lecturing classes. Hence, it generates a comparatively large amount of CO_2 which cannot be expelled effectively without the help of ventilation fan. In fact, the corresponding occupants for these cases are 52, 57, 62, and 52. For the present classroom, the results imply that ventilation fan needs to be functional when the occupants exceed 50. Additionally, case 2 reveals a tremendous rise of CO_2 concentration raise from initial 798 ppm to 1431 ppm for just 1-hour lecture. The result is actually related to a higher indoor setting temperature (26 °C) and a comparatively lower outdoor temperature (27 °C) which results in lighter cooling load of the air-conditioner as can be seen from power consumption. In essence, for typical lecturing class without agent control, the results suggest that the CO_2 concentration is raised appreciably when the occupants exceed 50, and may become even worse with a higher indoor setting temperature. Yet, the rise of CO_2 concentration is even more pronounced for classes having an examination test.

To ease the rise of CO_2 concentration, it is essential to turn on the ventilations fans when needed. The indoor air quality can be improved appreciably by introducing fresh air from the ambience. However, the higher temperature associated with the ambient air inevitably raises the air-conditioner loading. For further elaboration regarding the differences in field tests, it would be more meaningful to compare the test results with similar operational conditions.

The difference in lecture condition, lecturing or conducting examination, is shown in Fig. 4. Note that Fig. 4(a) compares the energy consumption for different lecture types under similar conditions while Fig. 4(b) compares the final CO_2 concentration. The final carbon dioxide concentration and energy consumption for classes conducting examination test is normally higher than that in lecture period. This is because that during the examination period the occupants' metabolism will be more active for being highly focused with devoted thinking, and the higher the metabolic rate is, the more CO_2 is produced from the human body. As a consequence, the average CO_2 concentration and energy consumption in a testing period far exceeds that of the lecture period.

Yet, based on the values of physical activity levels (M) from compendium of [22], the metabolic rate M during examination is estimated to be about 30-50% higher than in quiet lecture condition. The difference between CO_2 concentration between lecturing and examination is generally qualitatively in line with the measurements. In the meantime, the CO_2 accumulation is further accentuated with time, this can be made clear from case 18 where the test is conducted in 2-hour periods, and the corresponding CO_2 level may exceed 1800 ppm.

Consecutive lecture periods contains a 2-hr lecture with a short 10 minutes break in between. Fig. 5 shows that the difference in energy consumption between the first and the second hour along with the corresponding CO_2 concentration. Note that cases 6 and 7 are without agent control and cases 8 and 9 are under agent control. Apparently, with or without agent control, the second hour consumes less energy than the first hour. This is because the compressor loading is comparatively heavy at the first hour since the room temperature is higher when the lecture starts. On the other hand, the CO_2 concentration at the second hour is considerably higher than the first hour due to accumulation effect.

The effect of outdoor temperature on the energy consumption is depicted in Fig. 6(a) and the CO_2 level is also shown in the figure. With the rise of outdoor temperature, the COP of the air-conditioning system is considerably reduced which leads to a much higher energy consumption. Fig. 6(b) compares energy consumption and CO_2 level in different outdoor climates (sunny or rainy). The relative humidity in rainy days is comparatively high and requires more moisture removal from the air-conditioner to reach the same setting point temperature. In this regard, rainy day always consume more energy to maintain the indoor setting point. Weather, type of classroom condition, the number of occupants, outdoor temperature, initial CO_2 concentration and lecture period all impose some impacts on the agent control, the following are established under the same conditions for comparison.

Figure 7 compares the original control method with fixed indoor temperature of 25 °C in association with other similar but uncontrollable conditions. When the outdoor temperature is low, the agent will adjust the air-conditioner to 27 °C provided the thermal comfort in terms of PMV is met. Through this manipulation, appreciable energy saving by reducing the compressor loading can be achieved. Note that the agent also take care about the ventilation fan to offer a lower CO_2 level than the one without agent control where no ventilation fans are used to regulate CO_2 level. Despite additional energy is consumed with the presence of the ventilation fans when agent is in control, the CO_2 level with agent control is apparently lower. In essence, when the outdoor temperature or the indoor CO_2 concentration is high, the agent will turn on the exhaust fan to draw in the external air that leads to increase of the indoor temperature and an increased loading of the air-conditioner. Upon agent control, the resultant energy consumption is comparable or lower than that of the fixed temperature of 25 °C. Compared with the fixed temperature of 25 °C, the average energy saving of the agent control is about 19% (with a maximum saving of 43%), and the average CO_2 concentration is reduced by about 24%.

Figure 8 compares the control methods of the agent and the fixed temperature control of 26 °C having similar but different conditions. Analogously, the one with agent control shows superior performance to the one without agent control either in the aspects of CO_2 level or energy consumption. Compared with the fixed temperature of 26 °C, the average energy saving of the agent is about 15% (with a maximum saving of 21%), and the average CO_2 concentration is reduced by about 13%.

5. Conclusions

In this study, Deep Q-Learning is used to incorporate with a deep reinforcement learning algorithm for optimization subject to energy consumptions from air-conditioning and exhaust fans, thermal comfort, and indoor air quality (CO_2) in a classroom having maximum occupants up to 72. The classroom contains a rectangular area of 111.435 m^2, and a height of 4.2 m. Three split-type air conditioners, 4 exhaust fans, 6 temperature and humidity/CO_2 sensors and 1 globe ball thermometer are installed in the classroom. With comparable thermal comfort amid the original control and the proposed agent control, the effects of outdoor condition, class types (lecturing or conducting examination), and lecturing period on the indoor air quality and energy consumption with and without the help of agent is examined in details through thirty experiments. Based on the foregoing discussions, the following conclusions are drawn:

1. For the similar ambient conditions, it is found that the CO_2 concentration and energy consumption for the class conducting examination is much higher than that with lecturing

due to higher metabolic rate of the occupants. In fact, the CO_2 can even reach a level of 1800 ppm during examination.

2. Under consecutive period of classes, when the outdoor temperature is higher than the air conditioner setting, the energy consumption of the first lecture will be much higher than the second class. When the outdoor temperature is lower than the air conditioner setting, the indoor temperature of the first lecture period is still lower than the air conditioner setting temperature, therefore the energy consumption of the first and second lecture periods is comparable to the first period.
3. With the similar ambient conditions while maintaining the same thermal comfort, the DRL Agent algorithm can offer energy-saving up to 43% when compared with the air-conditioning with a fixed temperature of 25 °C. On average, the energy saving with agent is about 19%. Yet the corresponding CO_2 level is reduced by about 24% with the presence of agent control.
4. Similarly, when compared with a fixed temperature of 26 °C, the agent can offer about 15% less energy consumption on average and the average concentration of carbon dioxide can be reduced by 13%.

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Tables

Table 1

Environmental conditions for the experimental cases.

Case	Weather	Lecture Type	Occupant No.	(Lecture Period) PMV	Control Type	Initial CO_2 Concentration (ppm)	Power Consumption (kWh)	Final CO_2 Concentration (ppm)	Setting Temperature (°C)	Avg. Outdoor Temperature (°C)
1	Rainy	Lecture	52	(1)+0.19	Fixed 26°	694	2.6423	988	26	24.5
2	Sunny	Lecture	57	(1)-0.16	Fixed 26°	798	2.2711	1431	26	27
3	Sunny	Test	57	(1)-0.32	Fixed 25°	786	1.127	1044	25	24
4	Sunny	Lecture	24	(1)-0.43	Fixed 25°	554	1.7132	766	25	23
5	Sunny	Lecture	27	(1)-0.38	Fixed 25°	523	1.6175	764	25	26.5
6	Sunny	Lecture	45	(1)-0.03	Fixed 26°	650	4.0461	773	26	31
7	Sunny	Lecture	45	(2)-0.11	Fixed 26°	600	3.2388	887	26	30
8	Sunny	Lecture	47	(1)-0.33	Agent	833	3.4617	1010	24-27	28.5
9	Sunny	Lecture	47	(2)-0.23	Agent	1018	2.0667	1046	24-27	28.5
10	Sunny	Lecture	52	(2)+0.14	Fixed 26°	1183	2.706	1227	26	25.5
11	Sunny	Test	<54	(2)-0.35	Fixed 25°	1238	1.5678	1506	25	24
12	Sunny	Lecture	47	(2)-0.07	Fixed 26°	907	1.2753	1046	26	23.5
13	Sunny	Test	55	(1)-0.23	Fixed 25°	551	4.3711	1036	25	32
14	Sunny	Test	26	(1)-0.05	Fixed 26°	550	1.0977	801	26	25

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Case	Weather	Lecture Type	Occupant No.	(Lecture Period) PMV	Control Type	Initial CO2 Concentration (ppm)	Power Consumption (kWh)	Avg. CO2 Concentration (ppm)	Setting Temperature (℃)	Avg. Outdoor Temperature (℃)
15	Sunny	Lecture	62	(1)-0.26	Fixed 25°	522	3.7194	923	25	30.5
16	Sunny	Test	60	(1)-0.11	Fixed 25°	555	6.2166	1003	25	33
17	Sunny	Lecture	56	(3)+0.21	Fixed 26°	1378	1.4675	1493	26	32.5
18	Sunny	Test	<55	(2)-0.42	Fixed 25°	1426	3.5836	1906	25	31.5
19	Sunny	Lecture	45	(2)-0.42	Fixed 25°	917	3.7204	984	25	30.5
20	Sunny	Lecture	47	(2)-0.23	Agent	866	3.035	887	24-27	31.5
21	Sunny	Lecture	18	(1)-0.16	Agent	600	0.9787	668	24-27	23.5
22	Sunny	Test	55	(1-2)-0.32	Fixed 25°	551	7.9547	1471	25	31.5
23	Sunny	Test	60	(1-2)-0.12	Agent	550	6.7651	1130	24-27	30
24	Sunny	Test	60	(1-2)-0.15	Agent	512	8.03	893	24-27	31
25	Sunny	Lecture	52	(2)-0.03	Agent	600	2.6503	845	24-27	31.5
26	Sunny	Lecture	50	(2)-0.17	Fixed 26°	977	3.31	1108	26	30.5
27	Sunny	Lecture	52	(2)+0.14	Fixed 26°	1175	2.9685	1227	26	25.5
28	Sunny	Lecture	47	(2)-0.02	Agent	1178	2.6499	1130	24-27	24
29	Sunny	Lecture	52	(1-2)+0.17	Fixed 26°	694	5.35	1107	26	25
30	Sunny	Lecture	47	(1-2)-0.31	Agent	642	4.23	898	24-27	23.5

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Figures

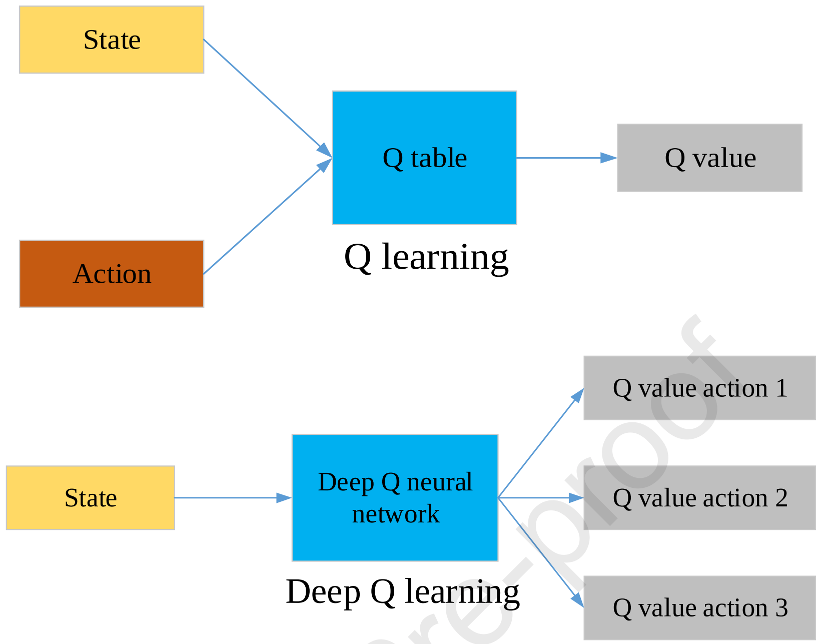

Fig. 1. Q learning vs Deep Q learning.

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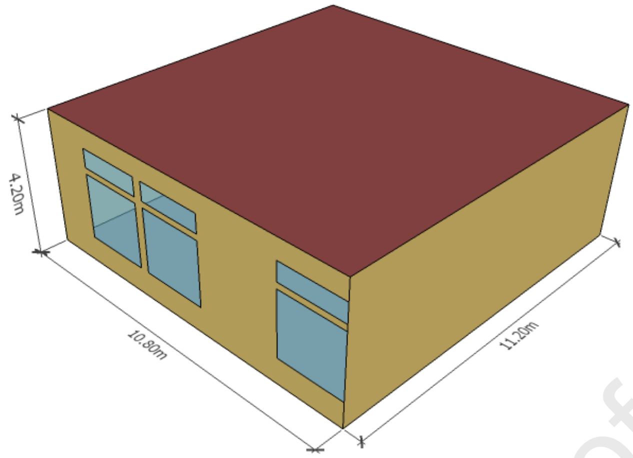
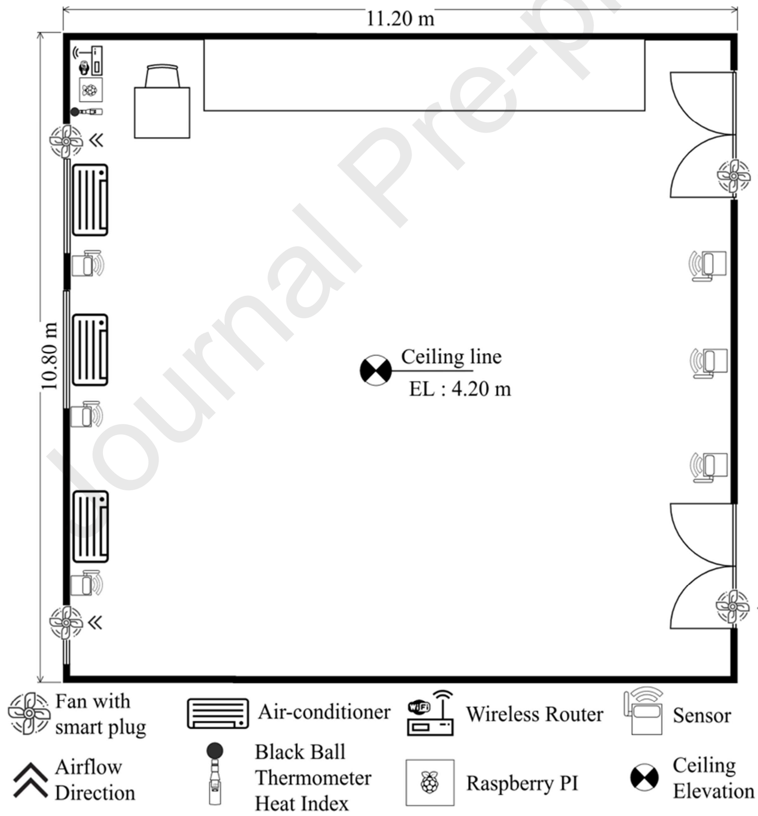


(a) 3D view of the classroom



(b) Schematic of the equipment installation (AC unit, fan, sensor, Raspberry Pi) in testing environments

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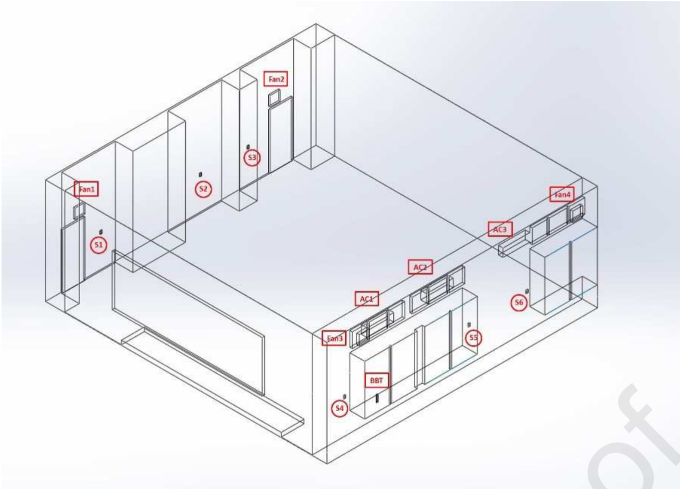

(c) Locations of the measured sensors.

Fig. 2. Schematic of the test site, the related equipment/sensors, and the locations of the sensors; the space contains up to 72 occupant seats.

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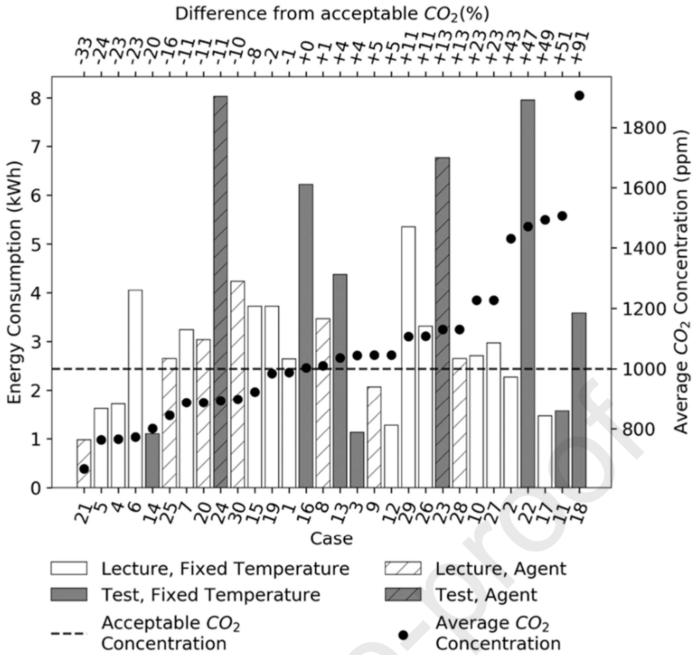
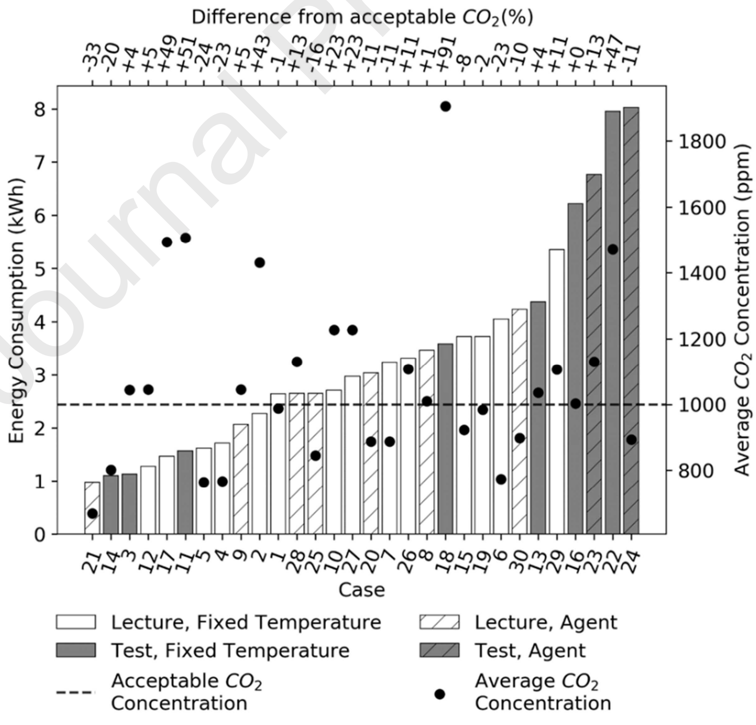
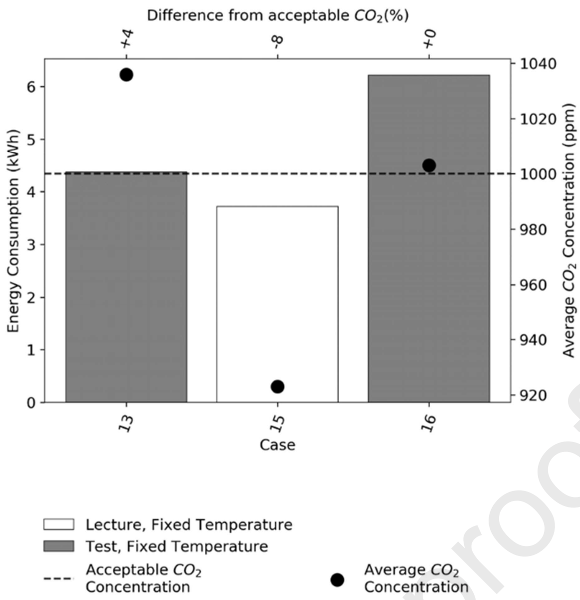


(a) Test results for all cases sorted by average CO_2

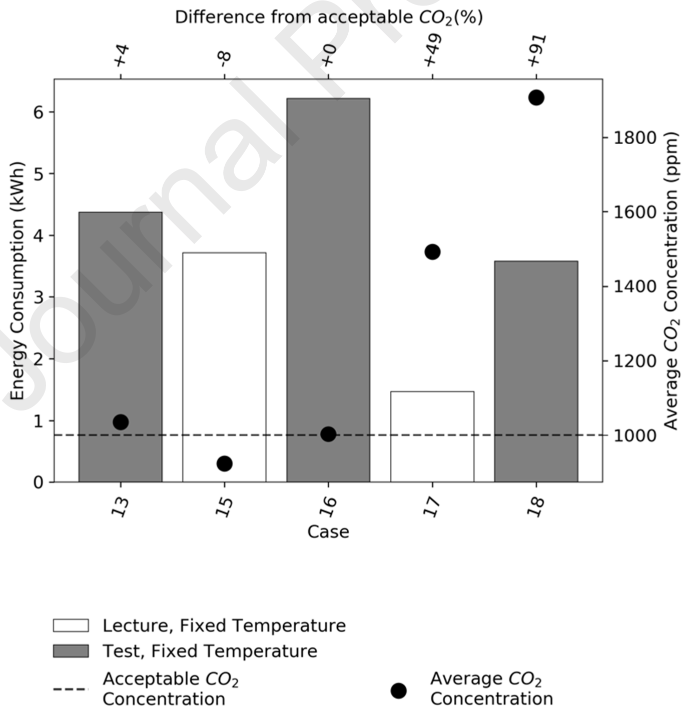


(b) Tests cases sorted by energy consumption

Fig. 3. Test results for all cases sorted by (a) CO_2 consumption; (b) Energy Consumption.



(a) Comparison of energy consumption for lecture and test.



(b) Comparison of average. CO_2 for lecture and test.

Fig. 4. Effect of lecture type, lecturing or conducting test, on the energy consumption and average CO_2 concentration level.

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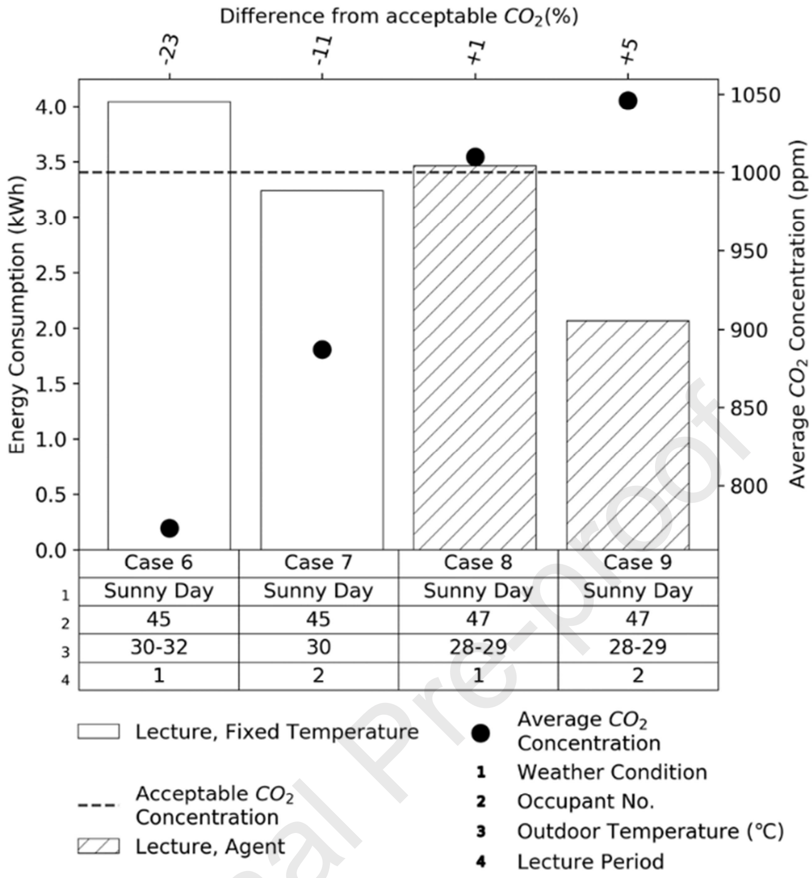

Fig. 5. Effect of lecture period, first hour or the second hour, on the energy consumption and average CO2 concentration level.

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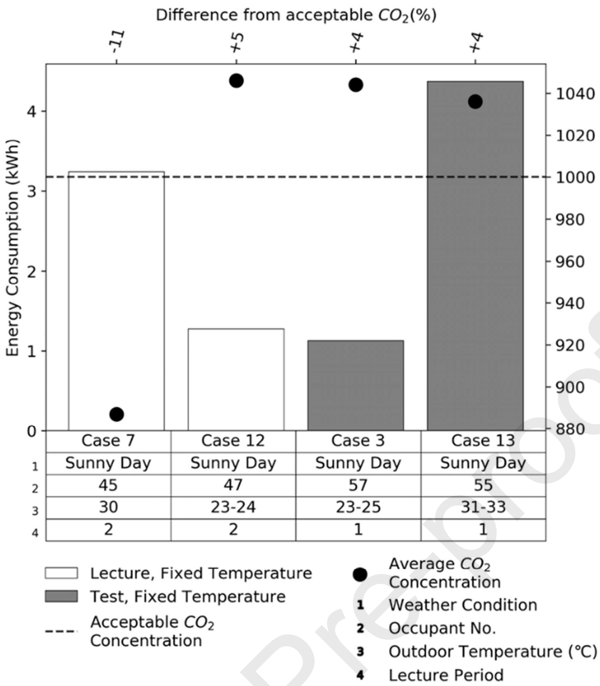
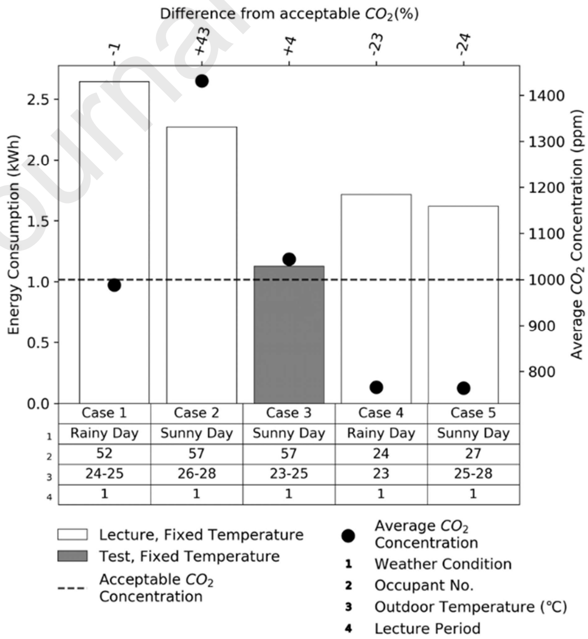


(a) Effect of the outdoor temperature.



(b) Effect of outdoor humidity.

Fig. 6. Effect of outdoor conditions on the energy consumption and average CO_2 concentration level.

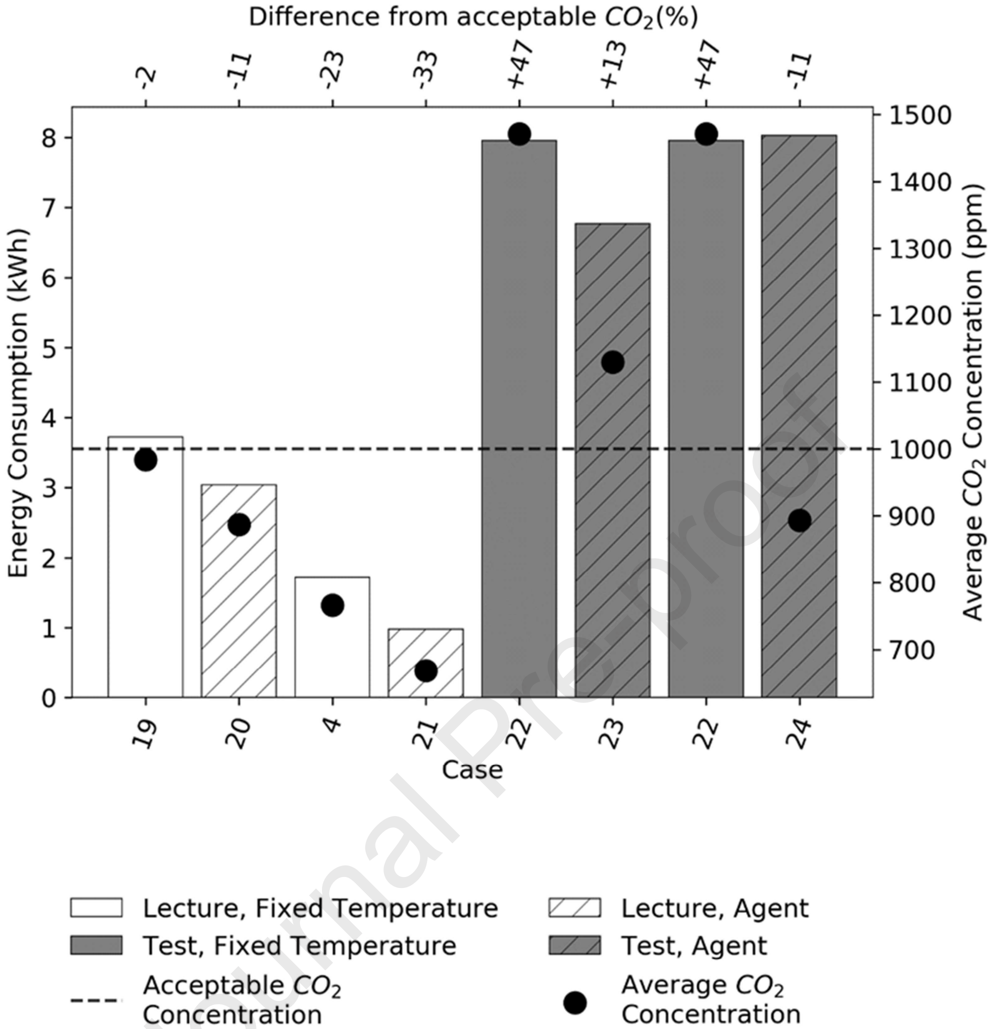


Fig. 7. Comparison of energy consumption and CO_2 concentration for air-conditioning between a fixed temperature 25° air-conditioning control and agent control.

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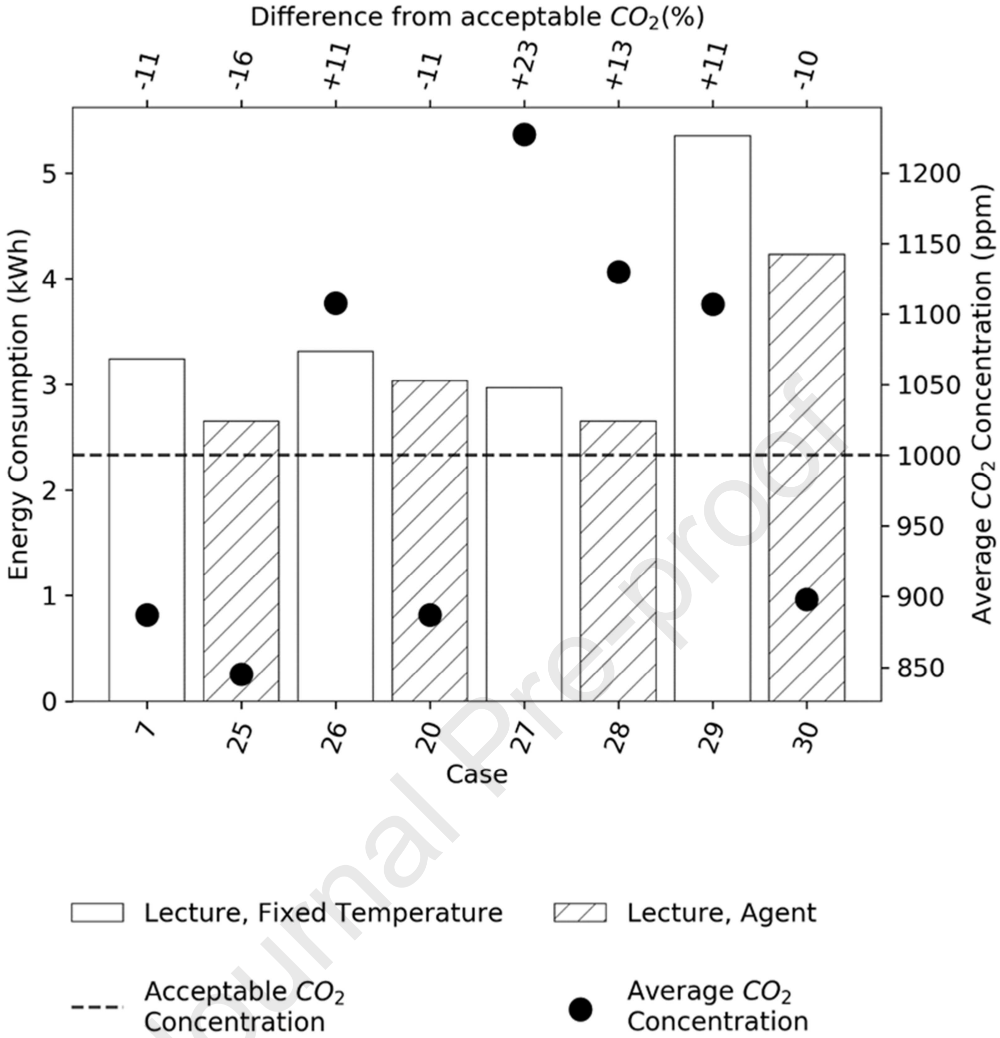

Fig. 8. Comparison of energy consumption and CO_2 concentration for air-conditioning between a fixed temperature 26° air-conditioning control and agent control.

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Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

The authors declare that they have no conflict of interest

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