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Simulating the Impact of Occupant Behavior on Energy Use of HVAC Systems by Implementing a Behavioral Artificial Neural Network Model

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Abstract

The current methods for simulating building energy consumption are often not accurate, and various types of occupant behavior may explain this inaccuracy. The present study used the EnergyPlus program to simulate the energy consumption of HVAC systems in office buildings. Measured energy data from the offices were used to validate the simulated results. Energy simulation using constant thermostat set point without considering occupant behavior was not accurate. When a behavioral artificial neural network (ANN) model was implemented in the energy simulation, the difference between the simulated results and the measured data was less than 13%. Further simulations demonstrated that adjusting the thermostat set point and the clothing level of the occupants could lead to a 25% variation in energy use in interior offices and 15% in exterior offices. Energy consumption could be reduced by 30% with thermostat setback control and 70% with occupancy control.

Keywords

Data collection, building performance simulation, thermostat set point, clothing level, thermostat setback, occupancy control

1 Introduction

In the United States, 41% of primary energy consumption occurs in buildings, mainly for maintaining a comfortable and healthy indoor environment [1]. Current methods for simulating building energy consumption are often inaccurate, with error ranging from 150% to 250% [2, 3]. Occupants typically use more energy in reality than that predicted by simulations [4]. The discrepancy may be caused by the various types of occupant behavior in buildings [5, 6]. Furthermore, changes in occupant behavior have great potential to reduce building energy consumption [7]. Therefore, it is important to identify an approach for estimating the impact of occupant behavior on building energy consumption.

Occupant behavior in buildings refers to occupants' presence, movement and interactions with building systems such as thermostats, windows, lights, blinds and internal equipment [8]. The existing methods for exploring the effects of occupant behavior on energy consumption are mostly based on questionnaire surveys, case studies and building performance simulations [9]. Building occupants can turn the thermostat set point up or down when they feel cold or hot. However, the occupants' comfortable temperature range may not be the same as that in ASHRAE Standard 55, which further impacts energy use [10, 11]. Similarly, other types of occupant behavior such as occupancy and lighting schedule have been found to vary considerably among buildings [12]. Previous studies have investigated occupant behavior in buildings by using questionnaire surveys and case studies. For example, Haldi and Robinson [13] conducted a field survey over a period of eight years in Switzerland to determine occupants' presence, opening of windows, and raising of blinds. Laurent and coauthors [14] collected window-opening data in 76 dormitory rooms in three residential buildings in order to predict window operation. An et al. [15] carried out a large-scale questionnaire survey of the air conditioner on/off control in 287 residential districts in order to model this occupant behavior with the use of the Designer's Simulation Toolkit in a case study. However, questionnaire surveys and case studies are always time-consuming, and the results for one building may not be applicable to other buildings. Moreover, the estimation of building energy was done mostly during the early design stage, when observing actual occupant behavior is impossible [4]. Therefore, building performance simulation has become a powerful tool for studying the impact of occupant behavior on building energy use.

In the building performance simulation, modeling occupant behavior is challenging because of its complexity [16, 17]. Previous studies have tried to predict the energy consumption in commercial and residential buildings with the use of various occupant behavior models, such as linear regression models [18], logistical regression models [19, 20] and statistical models [21-23]. These behavior models usually consider a single impact factor for building occupant behavior. In recent years, the appearance of a number of novel behavior models has enabled detailed and dynamic modeling of occupant behavior in buildings. For example, stochastic models [24-26] represent occupant behavior as a dynamic process in building performance simulations in both spatial and temporal domains. Agent-based models [27-29] can consider different variables that affect occupant behavior and model the differences among occupants. However, most previous studies have focused on modeling room occupancy schedules [30] and window-opening behavior [7, 13, 14, 31, 32], while neglecting other occupant behavior such as adjusting the thermostat set point. According to a survey of current occupant modeling approaches in building simulations [4], 66% of the researchers modeled the thermostat set point as a daily schedule, while another 16% used a constant for the entire year. Very few researchers have explicitly acknowledged the occupants' interaction with the thermostats [4]. For example, Simona et al. studied the effect of thermostat occupant behavior models on energy use in homes according to a probabilistic approach [32]. Albert and coauthors developed a lightweight and adaptive building simulation framework coupled with an agent-based occupant behavior model to understand the energy effects of comfort related behavior such as adjusting the thermostat set point. [33]. Burak and coauthors developed and implemented a thermostat learning algorithm in seven private offices to save energy use [34]. However, the US Department of Energy Reference Building Models [35] suggested modelling thermostat set point setback in office buildings. A review paper [8] also pointed out the oversimplification of existing behavior models for energy simulation. At present, very few studies have used comfort-related occupant behavior models for energy simulation [9].

Therefore, the purpose of this study is to investigate the impact of adjusting thermostat set point and occupant's clothing level on the energy use of HVAC systems with real measurements and use of an appropriate behavioral model. For this purpose, we first collected energy and occupant behavior data. Then we validated the energy simulation model for a real building and implemented an behavioral ANN model. What is more, the occupant behavior in some other buildings was explored. Finally, we quantified the energy saving potential and impact of occupant behavior for other control strategies.

The layout of this paper is organized as follows: Section 2 presents the methods for collecting data, simulating energy use in the offices and implementing the behavioral ANN model in the simulation program. Section 3 presents the comparison between the measured energy use and simulated results. Section 4 and 5 contain a discussion and conclusions of this study, respectively.

2 Methods

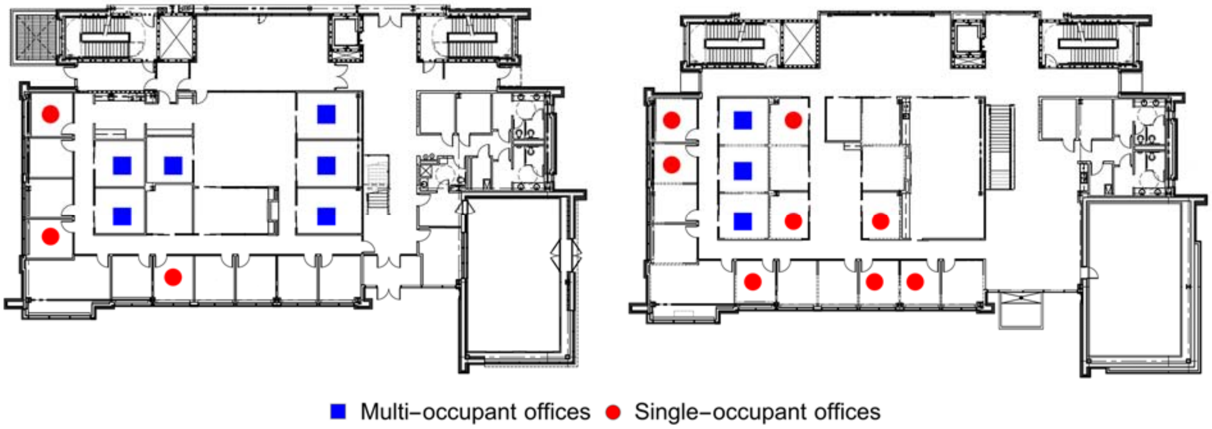
To study the effects of occupant behavior on energy use by HVAC systems, this research collected energy and behavior data in five buildings at Purdue University, Indiana, USA. We used the EnergyPlus program with a behavioral ANN model [10] to simulate the energy consumption of the HVAC systems in the buildings.

2.1 Data collection

This research first collected data from the HVAC systems in 20 offices in the Ray W. Herrick Laboratories (HLAB) building at Purdue University, as shown in Figure 1(a). Half of the offices were multi-occupant student offices, and the rest were single-occupant faculty offices. Figure 2 shows the offices used for data collection, which were located on the first and second floors of the three-story building. Eight offices were located in the exterior zone, and the others were located in the interior zone. The areas of the offices ranged from 12.9 m^2 to 21.0 m^2. The height of the ceiling was 3.05 m. The HLAB building used a variable air volume (VAV) system for heating and cooling. Each office had an independent VAV box and a thermostat (Siemens 544-760A) that enabled the building automation system (BAS) to control the air temperature in the room. The occupants could adjust the thermostat set point within the range of 18.3℃ to 26.7℃. In the heating mode, the hot water valve opened, and the air from the air handling unit could be heated by the reheat coil in the VAV boxes. There was a damper in each VAV box to control the supply airflow rate.

(a) (b)

Figure 1. (a) Photograph of the HLAB building, and (b) geometric model of the HLAB building for EnergyPlus simulation



(a) (b)

Figure 2. Layout of (a) the first floor and (b) the second floor of the HLAB building. The dots and squares indicate the single-occupant and multi-occupant offices used for data collection.

This research recorded the supply air temperatures, thermostat set points, damper positions, and room occupancies every five minutes. The lights in each office included ultrasonic and passive infrared sensors (Lutron LOS-CDT 500WH) on the ceiling. The lighting on/off status could signify whether or not the offices were occupied. There were temperature sensors (Siemens QAM2030.010) inside the diffusers in each office to monitor the supply air temperature, which was 43.3±5.5℃ for heating and 15.5±2.8℃ for cooling. We used data loggers (Sper Scientific 800049) in each office to collect the room air temperature and CO_2 concentration data.

We also used a questionnaire to record the clothing level of the occupants when they were inside the offices, and the times at which they adjusted the thermostat set points and their clothing levels. The times at which the occupants arrived at and left the offices were also recorded. For the possible error from the self-reported time, we also used the collected CO_2 concentration data in the office to eliminate the obvious errors.

To avoid bias in data collection and expand the data sample, we also gathered data in four other office buildings on the Purdue University campus: the Materials and Electrical Engineering (MSEE) Building, Lawson Computer Science (LWSN) Building, Stanley Coulter (STAN) Hall and Felix Haas (HAAS) Hall. Each building contained more than 100 offices. The HVAC systems in these four buildings were similar to those in the HLAB building. Each office had an independent VAV box and a thermostat to control the room air temperature. We collected room air temperature, thermostat set point and humidity data in each office. The data were recorded every 15 minutes in the MSEE, STAN and HAAS buildings, and every 10 minutes in the LWSN building. However, the HVAC control strategies in the four buildings differed from the strategy in the HLAB building. The HVAC system operated constantly in the HLAB building, and the occupants could adjust the thermostat set point manually. The LWSN building, by contrast, used thermostat setback that overrode the manual control at night, from 11 pm to 6 am. Meanwhile, the MSEE, HAAS and STAN buildings used occupancy control for the HVAC system in each room in addition to manual control. The purpose of thermostat setback and occupancy control was to save energy. However, these system operations were not directly related to the occupant behavior of adjusting the thermostat set point. We went to these buildings in person and observed the room occupancy status and occupants' clothing levels during the data collection period.

2.2 Simulation of energy use by HVAC systems

We first calculated the supply airflow rate by measuring CO_2 concentration in each office. We assumed a completely mixed balance model in the offices. The ventilation is assumed to be the only air flow path so that the supply air flow rate equaled to return air flow rate. We measured the CO_2 concentration after last occupant left and then there was no CO_2 source inside the office. At that time the initial CO_2 concentration was higher than C_0. The door was closed and the infiltration rate was neglected comparing with supply air flow rate. The indoor CO_2 concentration follows the equation

$$V\frac{dC_i}{dt} = \left(C_0 - C_i\right)Q \tag{1}$$

where V is the room volume, C_i the indoor CO_2 concentration, t the time, C_0 the CO_2 concentration in the supply air, and Q the supply air flow rate. The CO_2 concentration in the return air was equivalent to that in the indoor space C_i. By solving Eq. (1), we obtained

$$Q\,t = -V\ln\frac{C_i - C_0}{C_{i,initial} - C_0} \tag{2}$$

where $C_{i,initial}$ is the initial indoor CO_2 concentration. We used linear regression to obtain the supply airflow rate, Q. We used the CO_2 concentration data in more than 20 days in each office to calculate the supply airflow rate by using Eq. (2). The R^2 was more than 0.95 for the linear regression. We also referred to the damp position in the VAV box monitored in each office and the supply fan speed from the BAS. However, the flow rate estimation may still have uncertainties due to the measurement accuracy of the CO_2 sensor.

Then the sensible heating or cooling rate [36], E, in the offices is

$$E = C_p\rho Q(T_{supply} - T_{room}) \tag{3}$$

where C_p is the specific heat capacity of air, ρ the air density, T_{supply} the supply air temperature, and T_{room} the room air temperature.

Note that the measured heating and cooling rate was only available for the buildings with the BAS and room level recording. The HLAB building was designed and built for such purpose. However, most commercial buildings did not have the BAS and room level recording. What is more, the measured occupant behavior and energy use was only a part of the situation. The simulation can explore more possible situations. The purpose of simulation is to develop a method of using the behavior ANN model to explore the impact of occupant behavior on energy use for more general buildings even without BAS.

This research used EnergyPlus (v8.80) to perform the energy simulation for the HLAB building, with the building geometry model constructed by using SketchUp as shown in Figure 1(b). The interior walls between the offices were gypsum walls, while the interior walls between the offices and the corridor were made of glass. The doors of the exterior offices and interior offices were made of wood and glass, respectively. The windows of the exterior offices could not be opened. Table 1 lists the structure and material properties used for the building envelope in the simulations. The structure information was found in the HLAB building construction drawings and documents. As for the material properties, we used the data from the ASHRAE Handbook – Fundamentals [36]. We also used the actual HVAC system parameters from the building system document such as the maximum capacity and maximum and minimum supply air temperature.

Table 1. Structure and material properties of the HLAB building for the simulation

Constructions	*Layers (from exterior to interior)*	*Thickness (mm)*	*Conductivity (W/m K)*	*Density (kg/m^3)*	*Specific heat (J/kg K)*
Exterior window	Clear float glass	6	0.99	2528	880
	Air cavity	13	0.026	1.225	1010
	Clear float glass	6	0.99	2528	880
Exterior wall 1	Brick	92.1	0.89	1920	790
	Air cavity	60.3	0.026	1.225	1010
	Rigid insulation	50.8	0.03	43	1210
	Exterior sheathing	12.7	0.07	400	1300
	CFMF stud	152.4	0.062	57.26	964
	Gypsum board	15.9	0.16	800	1090
Exterior wall 2	Aluminum panel	50.8	45.28	7824	500
	Rigid insulation	50.8	0.03	43	1210
	Exterior sheathing	12.7	0.07	400	1300
	CFMF stud	152.4	0.062	57.26	964
	Gypsum board	15.9	0.16	800	1090
Interior gypsum wall	Gypsum board	15.9	0.16	800	1090
	Metal stud	92.1	0.06	118	1048
	Gypsum board	15.9	0.16	800	1090
Interior glass wall/door	Glass	6	0.99	2528	880
Interior wood door	Wood	44.45	0.15	608	1630

To enable comparison of the simulated results with the measured data, our simulations used actual weather data collected at a weather station at the Purdue University Airport, which was 1.5 km away from the HLAB building. The data were collected hourly and included outdoor air temperature, dew point temperature, relative humidity, air pressure, wind speed, wind direction, etc. As for the solar radiation data, we used the data measured on the roof of the HLAB building from the BAS.

Since each office had an independent thermostat that allowed occupants to adjust the set point temperature, our simulations defined each office as a thermal zone. Other indoor spaces on each floor were merged and simulated as one thermal zone. There were a total of 47 thermal zones in the simulation model. For all the offices in this study, we set the room temperature according to the actual thermostat set point from the BAS at each moment when validating the simulation program. We then implemented the behavioral ANN model [10] for simulating the occupant behavior of adjusting the thermostat set point and clothing level.

We used the lighting status from the BAS to determine the room occupancy in the single-occupant offices. For the multi-occupant offices, we used questionnaires to record the arriving and leaving times of each occupant every day.

In building energy simulation, occupant behavior is one of the uncertainties in the building energy analysis [37]. When validating the simulation program, we used the actual thermostat set points, occupancy schedules and clothing level information. For prediction of energy use, we used the behavioral ANN model [10], which is expressed as:

$$\text{Behavior occurrence} = f\,(\text{air temperature, relative humidity, clothing insulation, metabolic rate}) \tag{4}$$

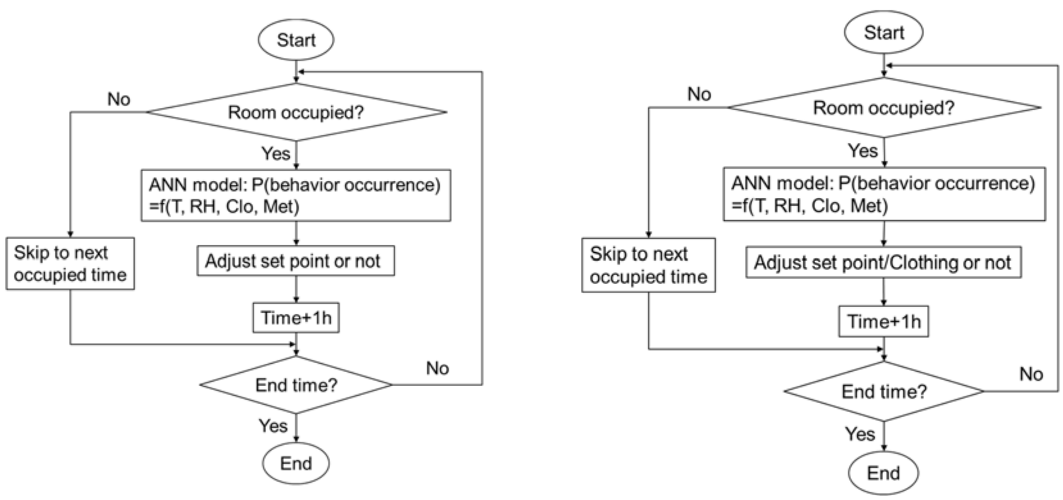
where f is the behavioral ANN model trained with the use of the collected data.

We assumed that that the office occupants could actively adjust the thermostat set point for their comfort, because the cost of maintaining a comfortable environment is typically not on their minds. What is more, according to the PMV thermal comfort model, six parameters have an impact on thermal comfort. Our measurements showed that the surface temperature of the surrounding walls was almost the same as room air temperature. Our measurements also showed that the air velocity in the offices was less than 0.2m/s. Therefore, the behavioral ANN model had four input parameters: air temperature, relative humidity, clothing insulation, and metabolic rate. For the metabolic rate, the occupants could sit or walk inside their offices, and the corresponding metabolic rates were 60W/m^2 and 115W/m^2, respectively, according to the ASHRAE Handbook [36]. So we assumed that when the occupant arrived the office, the metabolic rates were 115W/m^2 and after that, it was 60W/m^2. Other factors such as individual mood was not considered because of the complexity and difficult of collection and verification.

For the behavioral ANN model, the number of layers were three. The number of neurons in the hidden layer was ten. We trained the behavior ANN model with 1254, 1382 and 2303 behavior data points collected from the ten offices in the winter, summer, and the shoulder seasons, respectively. The overall training accuracy of the ANN model in predicting behavior was 87.5%. More detailed information about the ANN model can be found in [10].

Figure 3 shows the simulation process with the behavioral ANN model. When the simulation starts, the program first checks whether the office is occupied, since the behavior occurs only when there is an occupant inside the office. If so, the behavioral ANN model calculates the probability of behavior occurrence. With this probability, the program decides whether or not to adjust the thermostat set point. The differences between the single-occupant and multi-occupant offices lie in two aspects. First, previous studies [10, 38] demonstrated that behavior occurrence in response to a feeling of discomfort was different in multi-occupant offices than in single-occupant offices. We found that most occupant in single-occupant offices only took off clothes when entering the offices. When they stayed in the office and felt uncomfortable, they usually adjust the thermostat set point to make they feel more comfortable without considering others. However, in the multi-occupant offices, although some occupants in the same office felt uncomfortable, they were unsure whether others felt the same. Therefore, typically, they compromised and did not adjust the thermostat set point. Instead, they adjusted their clothing level to make them feel comfortable. While occupants could adjust the thermostat set point or their clothing level in multi-occupant offices, clothing adjustment would impact the thermal comfort of the occupants but not the building energy use.

Note that if the room was occupied for less than 5 minutes, such occupancy time would not appear in the simulation. We collected the room occupancy data every 5 minutes, and in the simulation the time step was 5 minutes. What is more, in our previous study [10], we already found that when feeling uncomfortable immediately after entering the office, occupants preferred to adjust the thermostat set point after some time had passed. So in the simulation, we updated the occupant behavior every hour. Therefore, if the room is only occupied by a short time, no occupant behavior occurred.



(a) (b)

Figure 3. Energy simulation process with the behavioral ANN model for (a) single-occupant office and (b) multi-occupant office.

With the above methods of data collection, we collected the energy-related data and occupant behavior data from the HLAB building to learn the actual energy use and occupant behavior pattern. We also gathered the occupant behavior data from other four buildings to avoid bias in data collection and expand the data sample. Then with the methods of energy simulation, we built the HLAB building model with actual material and structure information for the simulation program. We used the actual parameters of the HVAC system, outdoor weather data and occupant behavior to validate the simulation. Finally, with the methods of implementing the behavioral ANN model [10], we simulated the impact of stochastic occupant behavior such as adjusting thermostat set point and clothing level on heating and cooling rate of the HVAC system. We could obtained the simulated energy and their variations in various conditions.

3 Results

This section first compares the heating and cooling rate by the HVAC system for the offices in the HLAB building as simulated with the use of actual behavior, with the behavioral ANN model, and with constant thermostat setting. The measured data are also used for comparison.

3.1 Comparison of energy simulations with and without the behavior model

It was necessary to validate the building performance simulation program, since there are many uncertainties in energy simulations [25]. We first validated the energy simulation program with energy use data measured in the HLAB building for a one-month period in each of the four seasons of 2018: winter from January 15 to February 14, spring from March 12 to April 12, summer from June 9 to July 9, and fall from October 11 to November 9. Figure 4 shows the outdoor temperature from January to November of 2018 at Purdue University. The mean outdoor temperatures were -4.5□, 5.2□, 23.4□ and 7.2□, respectively, in the four seasons.

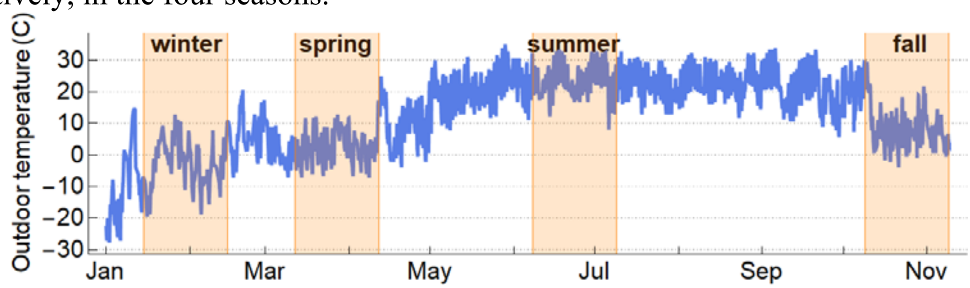


Figure 4. Outdoor temperature from January to November of 2018. The shaded regions represent the simulated time windows.

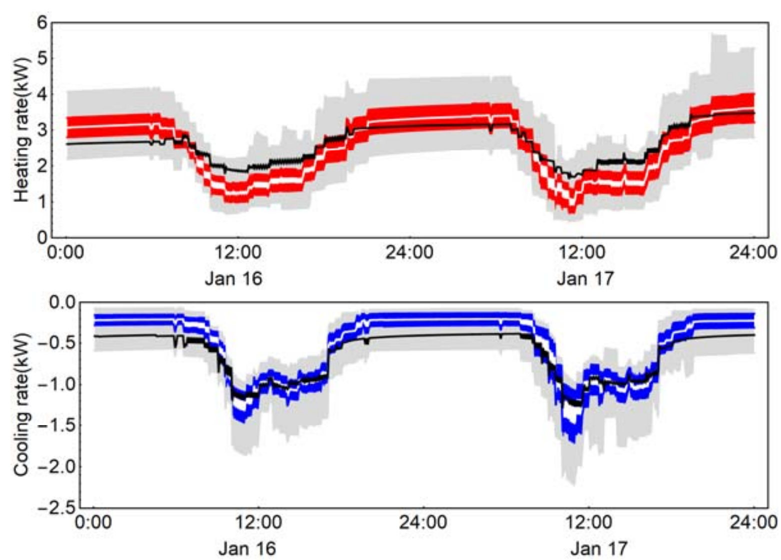
To validate the simulation program, we used the collected actual behavior data from BAS and questionnaire and fed the behavior data in each tine step into EnergyPlus. We compared the simulated and measured energy use in all the offices in the four seasons. On January 30 and October 29, the HVAC system was shut down, but these shutdowns were not reflected in the simulation; therefore, the differences were significant. With the exception of those two days, the maximum error between simulated energy use and actual data was less than 13%, as shown in Table 2. The errors may have arisen from many factors such as door opening. In the simulations we assumed that the office door was closed, but this may not have been the case. If the door was opened, the measured energy use in the office would have increased because of infiltration. What is more, the door were not totally air tight, which added uncertainty to the measured heating and cooling rate.

Table 2. Comparison between simulated and measured energy use in all the HLAB offices for a one-month period in each of the four seasons.

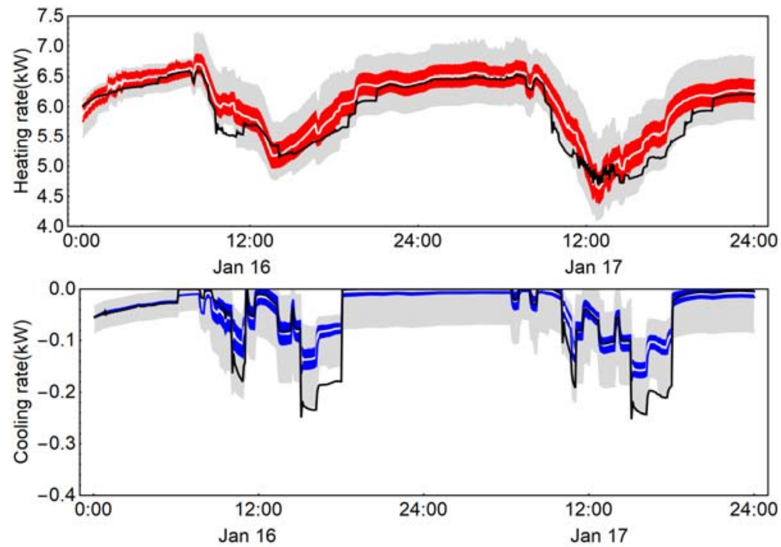
Season	Measured heating energy use (kWh)	Normalized measured heating energy use (kWh/m^2)	Simulated heating energy use (kWh)	Normalized simulated heating energy use (kWh/m^2)	Error	Measured cooling energy use (kWh)	Normalized measured cooling energy use (kWh/m^2)	Simulated cooling energy use (kWh)	Normalized simulated cooling energy use (kWh/m^2)	Error
Winter	5,314	19.9	5,156	19.3	3%	998	3.7	870	3.3	13%
Spring	2,833	10.6	2,719	10.2	4%	2,261	8.5	2,041	7.7	10%
Summer	2,102	7.9	1,945	7.3	7%	2,726	10.2	2,565	9.6	6%
Fall	3,183	11.9	3,083	11.6	3%	1,205	4.5	1,315	4.9	9%

After validating the EnergyPlus program, we ran the simulations with the behavioral ANN model and compared the simulated results with the measured energy use. Because of the randomness of the occupant behavior, every simulated result with the behavioral ANN model was different. If we had run only a few simulations, they may not have been representative and could not have covered all the possible ranges. Therefore, we ran the simulations with the behavioral ANN model for 200 times. We used a box whisker chart to display the simulated results, since this type of chart can illustrate the mean and standard deviations (SD) for various simulations.

Figures 5 shows the heating and cooling rate in the 11 offices in the interior zone, the nine offices in the exterior zone, and all the offices combined, for two selected days in winter, respectively. The white lines represent the mean of the simulated results. The boxes represent the mean plus and minus the SD of the simulated results. The whiskers represent the upper and lower bounds of the simulated results. As Figure 5 shows, the results simulated with the behavioral ANN model match the measured data closely. The maximum and mean difference between the simulated results and measured data was 10% and 6%, respectively. The simulated results with the behavioral ANN model also indicate the energy use variation due to the occupant behavior. At any time, the variations in energy use could reach ±1 kW and ±0.5 kW, respectively, for heating and cooling in the interior zone, and ±0.5 kW and ±0.2 kW, respectively, in the exterior zone, as the gray bars shown in Figures 5 and 6. The relative variation was the ratio between the absolute variation and the heating or cooling rate. And these variations accounted for more than 25% of the total energy consumption of the HVAC system in the interior zone and more than 15% in the exterior zone. Therefore, adjusting the thermostat set point had a greater impact on energy use in the interior offices than in the exterior offices.



(a)



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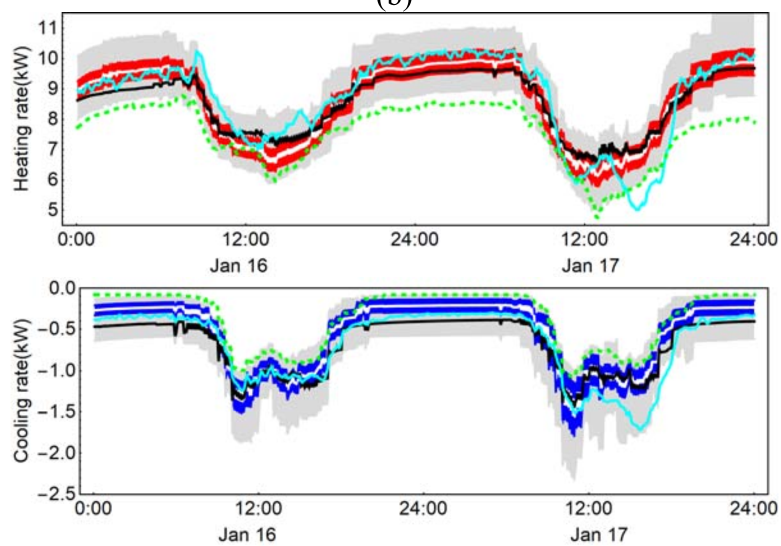

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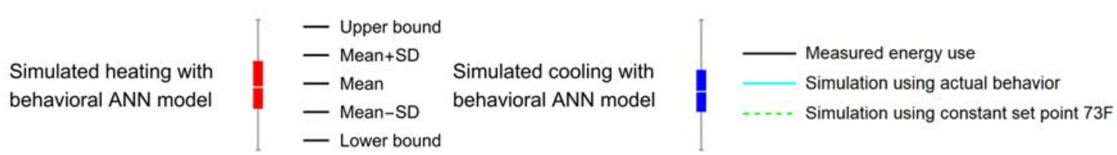


Figure 5. Comparison of total heating and cooling rate on two selected days in winter for (a) 11 offices in interior zone, (b) 9 offices in exterior zone, and (c) all the 20 offices.

Figures 5(c) and 6 compare the simulated and measured energy use on the two selected days in winter and summer, respectively. The simulations used the behavioral ANN model, constant temperature set point, and actual behavior. The results that were simulated with the use of actual occupant behavior were closest to the measured data, which is completely understandable. The simulations with the behavioral ANN model also performed well. Most of the time, the measured energy fluctuated within the lower and upper bounds predicted by the behavioral ANN model. However, the simulation with constant thermostat set point exhibited a large discrepancy with the experimental data. The relative error was as large as 30%. The reason was that some occupants set the thermostat set point much higher or lower than 22.8□ (73□) in order to feel comfortable. They did not reset the thermostat when they left the office, and this behavior wasted considerable energy. That is why the measured energy use was higher than the predicted energy using constant thermostat set point, to some extent [4].

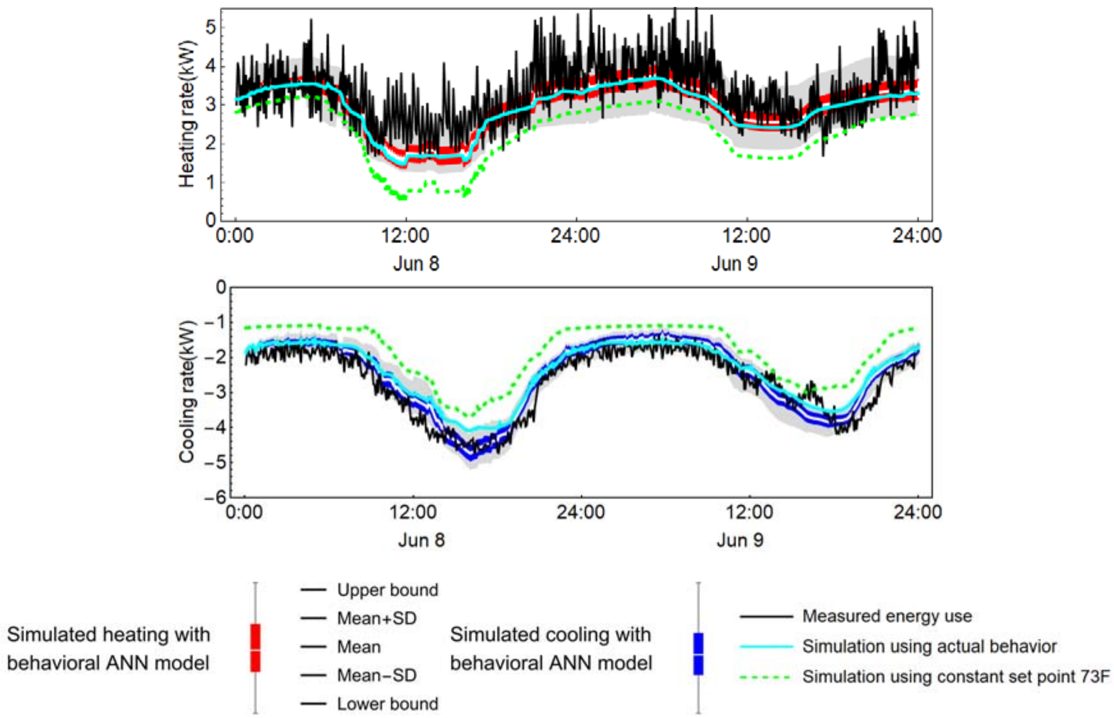


Figure 6. Comparison of heating and cooling rate in all the 20 offices for the two selected days in summer

Note that Figure 6 portrays a large fluctuation in the actual heating energy use in summer. When we checked the heat exchanger in the HLAB building, we found that although the water temperature set point was 54.4□, the supply water temperature fluctuated greatly and could sometimes be as high as 76.7□. This water-temperature control issue caused the fluctuation in the heating energy use in the HLAB building.

Figure 7 summarizes the measured energy use and the results of the simulations using actual behavior and the behavioral ANN model, for a one-month period in each of four seasons. In winter and in the shoulder seasons (spring and fall), the heating energy was greater than the cooling energy, and vice versa in the summer. Furthermore, in the winter and shoulder seasons the variation in energy use due to occupant behavior was greater for cooling than for heating. Meanwhile, the variation in energy use in the summer was smaller than in other seasons. This difference occurred because heating energy in the summer was mostly used when the interior offices were unoccupied and in the exterior offices at night. In these cases, occupant behavior seldom affected the energy use of the HVAC system.

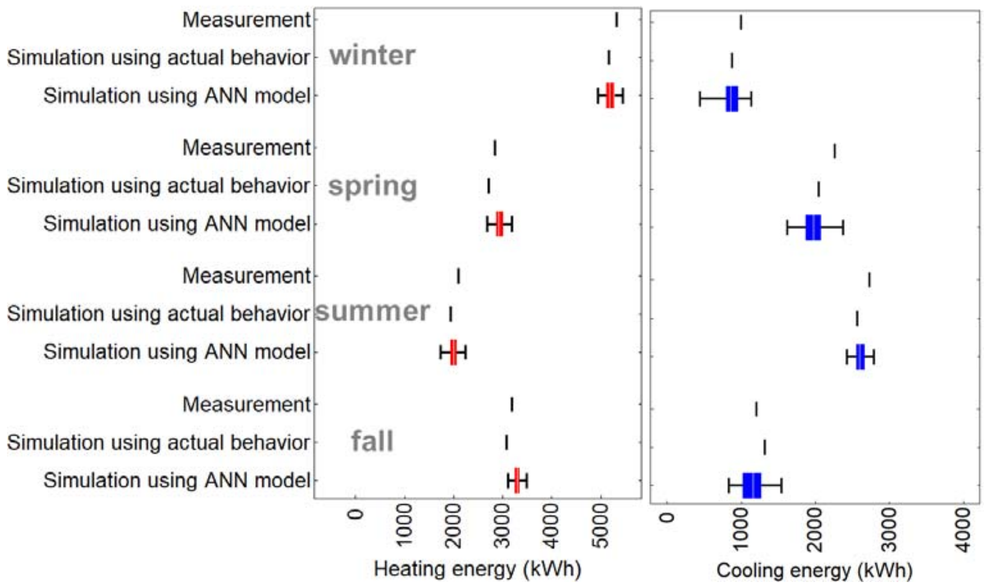
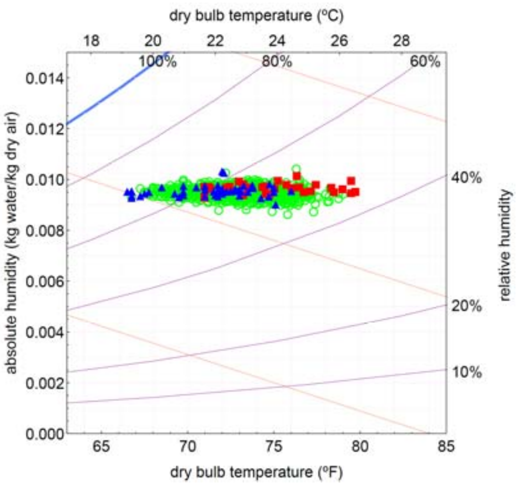


Figure 7. Comparison of measured and simulated total energy use in the HLAB offices for a one-month period in each of the four seasons.

3.2 Simulation using the data collected in the four buildings

After analyzing the impact of occupant behavior on energy use by the HVAC system in the HLAB building, we analyzed the occupant behavior in the other four buildings. We used the BAS in the four buildings to collect room air temperature, thermostat set point and humidity data. Changes in the thermostat set point represented raising or lowering of the set point by occupants. Figures 8(a), (c) and (e) display the collected behavior data in psychrometric charts for the summer, fall and winter, respectively, of 2018. The colors and shapes of the dots represent different kinds of behaviors. We obtained 1259 data points for a period of ten days in the summer, 3415 data points for a thirty-day period in the fall, and 1758 data points for a fourteen-day period in the winter. Since the data collection time in summer was limited, the humidity ratio variation was small, and the data were more concentrated. We used these parameters to train the behavioral ANN model [10] for the four buildings. Figures 8(b), (d) and (f) show the comfort zones predicted by the behavioral ANN model in the three seasons, respectively. The blue zone illustrates the temperature and humidity ranges which 88% of the occupants did not adjust the thermostat set point or their clothing level; the green and orange zones represents the conditions under which 76% and 15% of the occupants made no adjustments, respectively. The lower and upper bounds of the absolute humidity in the comfort zones were the minimum and maximum of the absolute humidity found in the data. A comparison of the comfort zones with those obtained from the HLAB building [10] reveals that the comfortable temperature range was larger in the four buildings. For an 80% comfortable rate, the temperature ranged from 20□ to 25.6□ in the four buildings in summer, whereas the range for the HLAB building was from 21.1□ to 24.4□ [10]. The occupant behavior occurrence in the four buildings was lower than that in the HLAB building, which led to a wider comfort zone in the four buildings.


dry bulb temperature (ºC)
18
20
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absolute humidity (kg water/kg dry air)
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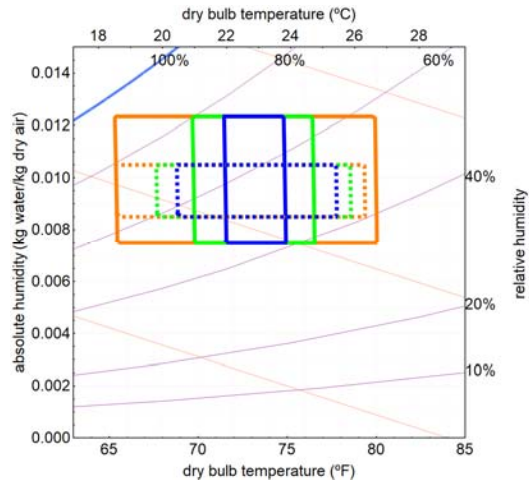
dry bulb temperature (ºF)

(a)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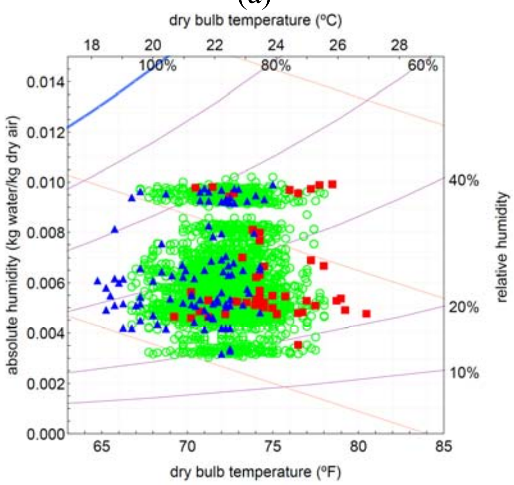
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dry bulb temperature (ºF)

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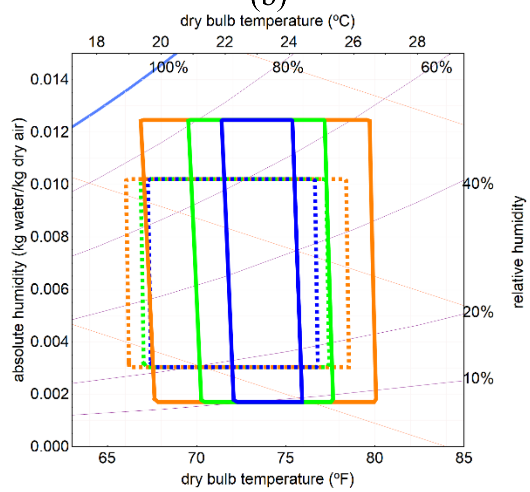
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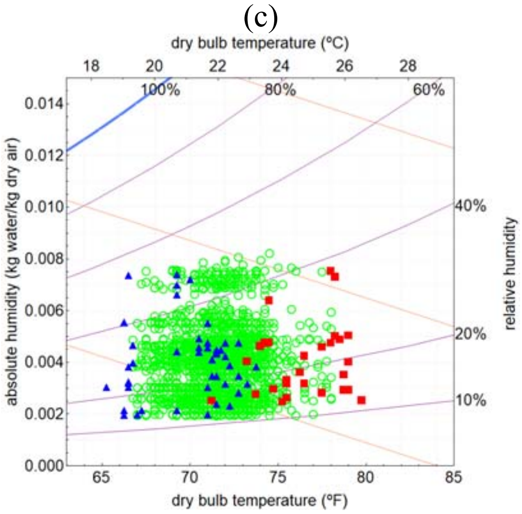
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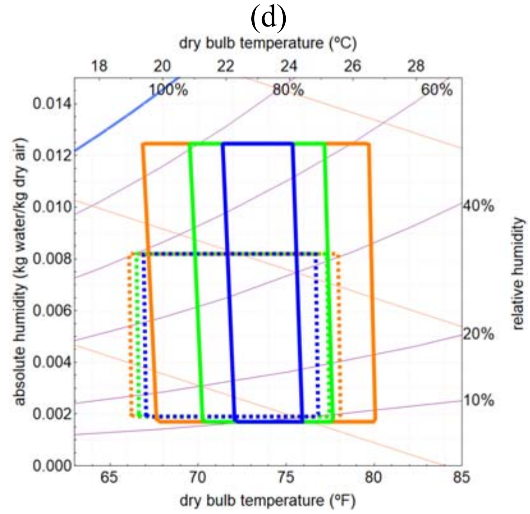
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dry bulb temperature (ºF)

(f)

Figure 8. Collected behavior data (left) and comfort zone (right) obtained with the behavioral ANN model: (a) and (b) summer, (c) and (d) fall, and (e) and (f) winter.

We found that the comfort zone in the four buildings was different from that in the HLAB building. Previous studies [39, 40] have also found that using different thermal comfort models could affect the prediction of building energy consumption. Therefore, we trained the behavioral ANN model with a different set of data and used this model to simulate the impact of occupant behavior on energy use in the HLAB offices. We compared the energy simulations for one typical year in the HLAB offices between differently trained models. The weather data was typical meteorological year (TMY3) for the energy simulation, and the other settings were the same as we used in Section 3.1. Table 3 compares the energy use predicted by the different behavioral ANN models in the HLAB offices for a one-year period. The simulation using the model trained by the data in the four buildings exhibited greater variation than the simulation using the model trained by the data in the HLAB building. This difference was due to the lower behavior occurrence and wider comfort zone as shown in Figure 8. Lower behavior occurrence indicates higher tolerance for the indoor environment. At high or low air temperatures, occupants may adjust the set point less frequently. The new, wider comfort zone means that the ranges in possible thermostat set point and room air temperature were larger, so that the energy use would be more extreme. Therefore, the impact of occupant behavior on energy use increased.

Table 3. Comparison of simulated total energy use with different behavioral ANN models in the HLAB offices for a one-year period.

	Simulated heating energy use				Simulated cooling energy use			
Model used in simulation	Mean (kWh)	Normalized Mean (kWh/m^2)	Variation (kWh)	Normalized variation (kWh/m^2)	Mean (kWh)	Normalized Mean (kWh/m^2)	Variation (kWh)	Normalized variation (kWh/m^2)
ANN model of the HLAB building	34,205	128.3	2,718	10.2	15,908	59.7	2,128	8.0
ANN model of the four buildings	32,398	121.5	3,427	12.9	14,380	53.9	1,742	6.5
Difference	5.3%	5.3%	26%	26%	9.6%	9.6%	18%	18%

3.3 Simulation of setback and occupancy control

The above results show that occupant behavior had a major impact on building energy consumption, and we were able to simulate the impact. Section 2.1 demonstrated that the four buildings used thermostat setback and occupancy control to reduce energy use by the HVAC systems. Since the HLAB building did not use such strategies, it was interesting to determine how much energy could be saved with thermostat setback control and occupancy control. We simulated a typical year in the HLAB offices and compared the simulated results with and without the use of these control strategies. The schedule for setback was from 6 am to 11 pm. The schedule for occupancy control was the same as the actual lighting occupancy schedules collected from the BAS in each HLAB office. We still used the behavioral ANN model to simulate the impact of occupant behavior on energy use.

Figure 10 shows the simulated results under different control strategies in the 20 HLAB offices for two selected days in summer. The red and blue bars represent the heating and cooling energy use, respectively. When setback was used, the energy use at night was zero, but it was very large when the HVAC system started to work in the morning. Setback did not have a significant impact in daytime. In comparison with thermostat setback, using only occupancy control in each HLAB office reduced energy use to a greater extent. This occurred because most of the HLAB offices were unoccupied; the professors and students may have been working in other locations. However, these energy saving results were not typical and may not be applicable to other office buildings.

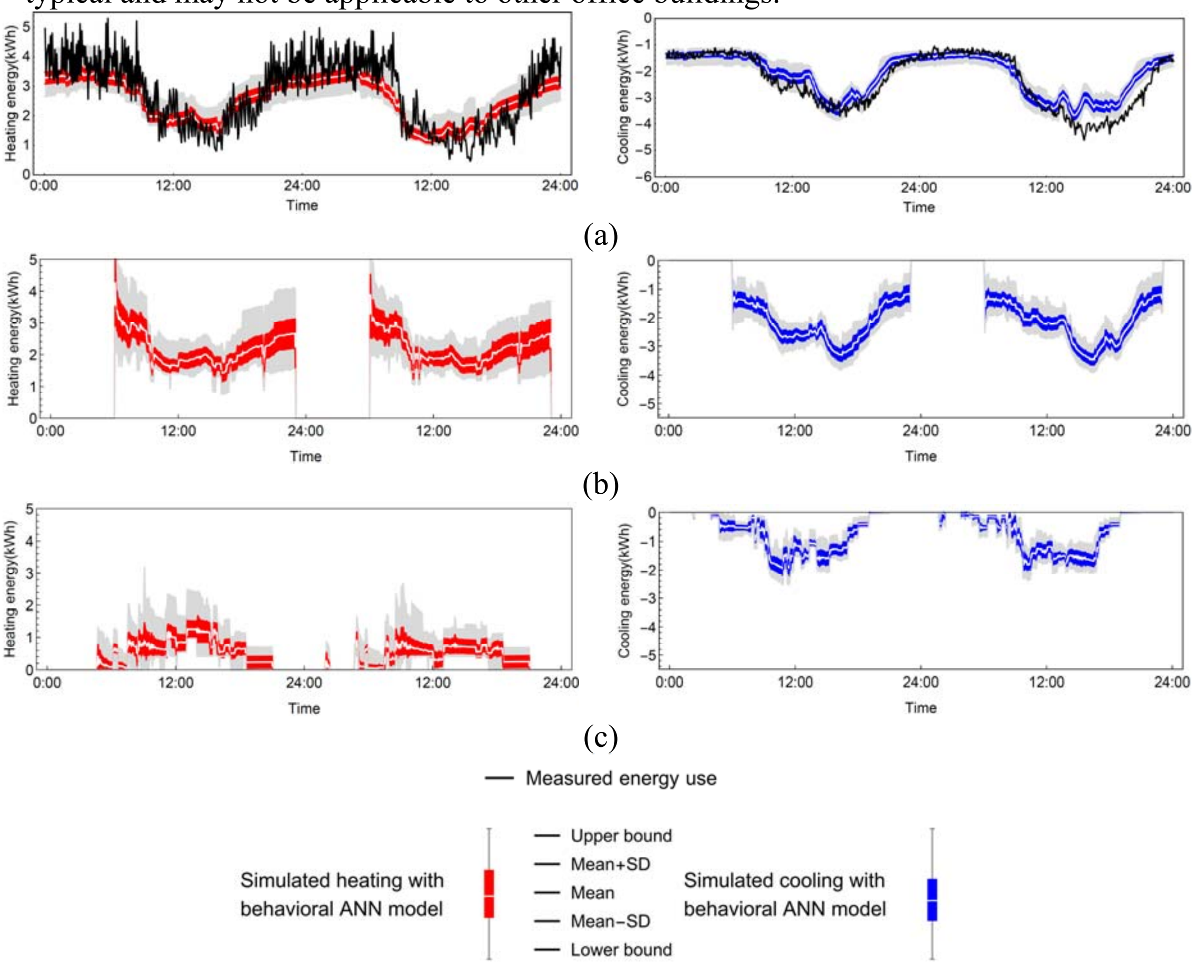

Figure 10. Comparison of measured and simulated heating (left) and cooling (right) energy use under different control strategies in the HLAB offices for two selected days in summer: (a) existing 24-hour constant-temperature control strategy; (b) thermostat setback; and (c) occupancy control

Table 4 summarizes the simulated total energy use under different control strategies in the HLAB offices for a one-year period. Currently, the occupants can set the thermostat set point within the range of 18.3ºC to 26.7ºC and adjust it freely when they feel uncomfortable. When the occupants leave the office, the setting does not change, and the room condition is maintained in that state. The simulated energy use with thermostat setback could reduce heating energy use by 36% and cooling energy use by 20% in the HLAB offices over a period of one year. Meanwhile, occupancy control could reduce heating energy use by 71% and cooling energy use by 73% over a one-year period. Previous studies found that thermostat setback could save energy around 20% to 30% [41-43], and the occupancy control could save 20% to 70% [44-47]. The energy saving was also related to the building type, HVAC system type and outdoor climate. Table 4 also shows that the variation in energy use was smaller for both thermostat setback and occupancy control, but the relative variation was larger than under the current strategy. This occurred because the energy use was zero at night for thermostat setback and during unoccupied times for occupancy control. Therefore, the impact of occupant behavior on energy use with thermostat setback and occupancy control was significant.

Table 4. Comparison of simulated total energy use under different control strategies in the 20 HLAB offices for a one-year period.

	Simulated heating energy use					Simulated cooling energy use				
Control strategy	Mean (kWh)	Normalized mean (kWh/m^2)	Variation (kWh)	Normalized variation (kWh/m^2)	Relative variation	Mean (kWh)	Normalized mean (kWh/m^2)	Variation (kWh)	Normalized variation (kWh/m^2)	Relative variation
Current control strategy	34,205	128.3	2,718	10.2	8.0%	15,908	59.7	2,128	8.0	13.4%
Thermostat setback	21,980	82.4	2,090	7.8	9.5%	9,751	36.6	1,560	5.9	16.0%
Occupancy control	10,197	38.2	1,430	5.4	14.0%	4,045	15.2	750	2.8	18.5%

4 Discussion

In this study, we used behavioral ANN models to simulate occupant behavior and employed the actual energy use of the HVAC systems in HLAB offices to assess different control strategies. We used questionnaires to record self-reported behavior and clothing level. However, sometimes the occupants may have forgotten to record the data, which would have affected the behavioral modeling and simulated energy results [48]. In addition, we used the assumed occupant load and computer load in the simulations without accounting for individual differences. We only used the simplified metabolic rate values for sitting and walking without accounting for differences in gender and age of occupant. The simplification of these factors may have influenced the behavior occurrence and the energy use of the HVAC system.

For the energy use of HVAC system, we only considered the sensible heating and cooling rate for each room. We did not consider the energy of mixing with fresh air, central heating and cooling, which was almost unaffected by the occupant behavior in the VAV system.

The present study used actual occupant behavior to train the behavioral ANN model, and then utilized this model to evaluate the energy use deviation in the offices. The behavioral ANN model considered various impact factors including indoor environmental parameters, clothing level and metabolic rate. Since these factors also determined the occupants' thermal comfort, this model could be considered a comfort-related behavior model [9]. Since the relationship between the occupant behavior and determining factors can be very complicated, we used ANN models which was a powerful method to deal with highly complex datasets. Although logistic regression [19, 20] can also be used, ANN models are more nonlinear. We could control the number of neurons and layers to adjust the model complexity and avoid overfitting. The limitation was that the complex model was hard to train and use since it had more parameters in the hidden layer to be determined. The ANN model could also be used for simulating other occupant behavior such as opening a window. Since the behavioral ANN model requires training data in order to learn the occupant behavior before it can be used, the application of the model to a newly constructed building or a building in the design stage would require the collection of occupant behavior data in some similar buildings in advance.

Personalized behavior models are more suitable and have a higher prediction accuracy to predict occupant behaviors [49, 50]. However, developing personal model in every individual office would make the simulation too complicated. In this study, we only distinguished the single-occupant and multi-occupant offices. Using personal behavior models is a possible improvement that can be considered in the future.

5 Conclusions

This study validated an energy simulation program and compared the energy use simulated with behavioral ANN models with the energy use measured in the HLAB building and four other buildings on the Purdue University campus. The investigation led to the following conclusions:

1) The simulated energy results were validated by comparing them with data measured in the HLAB building for a one-month period in each season of 2018, and the relative error between the simulated and actual energy use was less than 13%.
2) The simulated energy consumption using the behavioral ANN model exhibited variation as a result of occupant behavior in the HLAB offices. The variation was 25% in interior offices and 15% in exterior offices.
3) The energy consumption data obtained from the other four buildings on the Purdue University campus revealed lower behavior occurrence among the occupants of these buildings. The behavioral ANN model thus calculated a wider comfort zone and a higher variation in energy use for these buildings than for the HLAB building.
4) The data collection in the other four buildings on the campus occurred under a strategy of thermostat setback and occupancy control, whereas the HVAC system operated constantly in the HLAB building and the occupants could adjust the thermostat set point manually. Applying thermostat setback to the HLAB building would reduce the energy consumption by 30%, while occupancy control would provide a 70% reduction.

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Conflict of Interest

None.

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