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Artificial Neural Network Models Using Thermal Sensations and Occupants' Behavior for Predicting Thermal Comfort

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Abstract

It is important to create comfortable indoor environments for building occupants. This study developed artificial neural network (ANN) models for predicting thermal comfort in indoor environments by using thermal sensations and occupants' behavior. The models were trained by data on air temperature, relative humidity, clothing insulation, metabolic rate, thermal sensations, and occupants' behavior collected in ten offices and ten houses/apartments. The models were able to predict similar acceptable air temperature ranges in offices, from 20.6℃ (69℉) to 25℃ (77℉) in winter and from 20.6℃ (69℉) to 25.6℃ (78℉) in summer. The occupants' behavior in multi-occupant offices was more complex, which would lead to a slightly different prediction of thermal comfort. Since the occupants of the houses/apartments were responsible for paying their energy bills, the comfortable air temperature in these residences was 1.7℃ (3.0℉) lower than that in the offices in winter, and 1.7℃ (3.0℉) higher in summer. The comfort zone obtained by the ANN model using thermal sensations in the ten offices was narrower than the comfort zone in ASHRAE Standard 55, but that obtained by the ANN model using behaviors was wider than the ASHRAE comfort zone. This investigation demonstrates alternative approaches to the prediction of thermal comfort.

Keywords

Indoor environment, Model training, Data collection, Air temperature, Relative humidity, Clothing level, Metabolic rate.

1 Introduction

Currently, people in North America spend roughly 90% of their time indoors [1]. Therefore, it is important to create comfortable, healthy, and productive indoor environments for the occupants. Such environments are typically achieved by the use of heating, ventilating, and air-conditioning (HVAC) systems. The energy consumption in residential and commercial buildings by HVAC systems and lighting accounts for about 41% of primary energy use in the United States [2]. Unfortunately, even with such high energy consumption, our resulting indoor environments are still very poor. Survey data from the International

Facility Management Association showed that the predominant complaints by office occupants were that "it is too hot and too cold simultaneously" [3].

To improve an indoor environment for building occupants, one would need a good method for evaluating the environment. Current evaluation methods for thermal comfort can be divided into two categories [4]. The first category evaluates an indoor environment with the use of models developed from questionnaires under controlled indoor environments [5-10]. Controlled environments have allowed researchers to study thermal comfort in a uniform and steady-state way. For example, the predicted mean vote (PMV) model from Fanger [11] was developed by testing subjects under different steady-state indoor environments in the 1970s. The model identifies the relationship between occupants' thermal sensations and six thermal parameters. The second category of methods, which is more popular at present, evaluates an indoor environment by mean of questionnaires without varying controlled parameters [12-15]. These field studies have typically collected data in real buildings, with the benefit of larger samples and enhanced validity. However, variation in such thermal environments may be limited. Some studies [16-18] modelled the occupants' thermal preference by collecting thermal preference votes from occupants by using questionnaires. However, in the thermal preference studies, the common choices in the questionnaires were "want cooler, want warmer or no change", which were different from actual behaviors. Building occupants are often able to adjust the thermostat set point or clothes to make them feel comfortable. But the availability and accessibility to control devices [19, 20] and probably income level [21-23] may also impact the behaviors. Hence, the two types of thermal comfort model do not consider the influence of occupants' behavior on thermal comfort. Therefore, the two categories of evaluation method may not be ideal for evaluating the thermal comfort of occupants in actual environments.

Evaluation of thermal comfort should be based on thermal sensations in actual environments rather than in controlled environments. In a climate chamber, researchers benefit from superior experimental control to validate their models and designs [24]. In an actual environment such as an office or residence, however, occupants go about their daily activities in surroundings with which they are familiar [25, 26]. If the thermal environment is not satisfactory, the occupants adjust the thermostat set point [27] or their clothing level until they feel comfortable. Such environment-driven actions may reflect the occupants' responses to the indoor environment [28]. Therefore, occupants' interaction with the building systems is a significant determinant of their satisfaction [24].

Leaman's post-occupancy evaluation of UK office buildings also found that for occupants, "satisficing" may be a better description of occupants' behavior and control than simply thermal comfort optimization [29]. However, a limitation of some previous thermal comfort studies was that they did not consider occupants' real behavior in regard to thermal comfort. Numerous studies [30-33] have found that occupants' behavior changes their thermal sensations, because the behavior impacts their expectations of thermal comfort. Some recent studies have collected data of occupants' behaviors to develop some more complex thermal comfort and behavior models in offices and dwellings. For example, D'Oca [34] developed a logistic regression method for window opening and thermostat set point adjustments in residential buildings. Vellei's model [35] focused on the effect of real-time feedback on occupants' heating behaviors and thermal adaptation. Lee [36] and Langevin [37] developed and validated agent-based behavior models for office buildings. Without the behavioral impact, occupants' tolerance for discomfort is significantly reduced [38]. Therefore, it is necessary to develop an evaluation method for indoor thermal comfort that considers occupants' thermal sensations and behavior in actual environments.

The purpose of this study is to develop methods for evaluating thermal comfort in actual environments by using thermal sensations and occupants' behavior. Such a method may better reflect the actual satisfaction of building occupants. One then can effectively design, operate and control indoor environment with an appropriate HVAC system in buildings.

2 Methods

To develop a new evaluation method for thermal comfort, this investigation first collected data on the thermal environment, thermal sensations, and occupants' behavior in offices and apartments/houses. Subsequently, we built and trained novel behavior artificial neural network (ANN) models using the collected data. Finally, the ANN models were used to predict an acceptable thermal environment.

2.1 Data collection

This investigation collected data on air temperatures, relative humidity, clothing levels, thermal sensations, thermostat set points, and room occupancy in ten offices in the Ray W. Herrick Laboratories (HLAB) at Purdue University, Indiana, USA as shown in Figure 1 (a). Among the ten offices, half of them were multi-occupant student offices, and the rest were single-occupant faculty offices. The offices were located on the ground floor and second floor of the three-story building as shown in Figure 1 (b) and (c). We chose offices in which the occupants spent a considerable amount of time. Five faculty members and more than fifteen students with different age ranges and genders participated in the data collection. Table 1 lists the occupancy states of the ten offices.

Table 1. Occupancy states of the ten offices

Office No.	*Occupants*	*Age range*	*Gender*
1	1 faculty	50–60	Male
2	1 faculty	40–50	Male
3	3 students	20–30	2 males and 1 female
4	4–5 students*	20–30	1–2 males and 3 females
5	3 students	20–30	2 males and 1 female
6	1 faculty	60–70	Male
7	3–4 students*	30–40	Male
8	2–3 students*	30–50	1–2 males and 1 female
9	1 faculty	30–40	Male
10	1 faculty	50–60	Female

*During the time period of data collection, new students were moving into these offices, and students who had graduated were moving out.

Figure 1. (a) Overview of the HLAB office building. Layout of (b) the ground floor and (c) the second floor of the HLAB building. Red dots mark single-occupant faculty offices. Blue squares mark multi-occupant student offices.

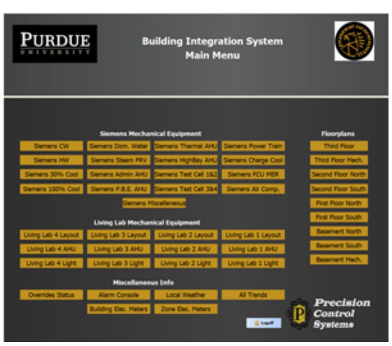
In addition, this study collected data on window/door opening behavior in six apartments and four houses in West Lafayette and Lafayette, Indiana, USA. Half of the residents were students enrolled at Purdue University, and the rest were ordinary families. The apartments/houses had different numbers of occupants with different age ranges and genders. Table 2 provides information about the ten apartments/houses.

Table 2. Information about the ten apartments/houses used for data collection

Building No.	*Building type*	*Occupant type*	*Thermostat type*	*Number of occupants*	*Age range*	*Gender*
1	House	Students	Programmed	4	20–30	Male
2	Apartment	Students	Manual	4	20–30	Male
3	House	Family	Manual	2	50–60	1 male and 1 female
4	Apartment	Students	Manual	5	20–30	Male
5	Apartment	Family	Manual	2	60–70	1 male and 1 female

6	House	Family	Manual	4	Two occupants 0–10, two occupants 30–40	1 male and 3 females
7	House	Family	Programmed	2	40–50	1 male and 1 female
8	Apartment	Students	Manual	3	20–30	Male
9	Apartment	Students	Manual	2	20–30	Male
10	Apartment	Students	Manual	3	20–30	Male

For the offices, this study collected lighting on/off status and thermostat set point data from the online building automation system (BAS) every five minutes. As shown in Figure 2(a), the BAS of this building integrated the monitoring and control system of mechanical equipment inside the building, such as the HVAC system, lighting system, electric meters, etc. By using an online server, the researchers could set up some monitoring and control parameters and also view the current status and download the historical data of the HVAC and lighting systems in the BAS. Inside the building, the lights in the offices had ultrasonic combined with passive infrared sensors (Lutron LOS-CDT 500WH) on the ceiling as shown in Figure 2 (b), so that the lighting on/off status signified that the offices were occupied or unoccupied. Figure 2 (c) shows that each office also had a thermostat (Siemens 544-760A) on the wall which enabled the BAS to control the room air temperature. The occupants could adjust the set point of the thermostat within the range of 18.3℃ (65℉) to 26.7℃ (80℉). We used data loggers (Sper Scientific 800049) as shown in Figure 2 (d) in each office to collect room air temperature and relative humidity every five minutes. Table 3 lists the technical specifications of the data logger. We also used a questionnaire to collect the seven-scale thermal sensation [39] (-3 for cold, -2 for cool, -1 for slightly cool, 0 for neutral, +1 for slightly warm, +2 for warm, and +3 for hot) and clothing level from the occupants when they were inside the offices as well as their behaviors in adjusting the thermostat set point, adjusting their clothing level, arriving at the office, and leaving the office happened. In the early morning, before the occupants' arrival, we adjusted the thermostat set point in each office to a different temperature than that of the previous day. This forced the occupants to adjust the thermostat set point when they arrived at their offices because the air temperature was usually undesirable.



(a)


(b)

(c)

(d)

Figure 2. Data collection devices used in this study: (a) online building automation system, (b) ultrasonic combined with passive infrared lighting sensor on the ceiling, (c) thermostat on the wall, and (d) data logger.

Table 3. Technical specifications of Sper Scientific 800049 data logger

Parameter	*Range*	*Resolution*	*Accuracy*
Temperature	-10–50□ (-14–122 □)	0.1□ (0.1□)	±1.2□ (± 2.5□)
Relative humidity	0.1%-99.9%	0.1%	± 5%
CO_2 concentration	0-9999 ppm	1 ppm	± 75 ppm + 5% of reading

However, none of the apartments/houses had a BAS, and we could not set the thermostat set point to a different level. This investigation used the same data loggers to record the room temperature, relative humidity, and CO_2 concentration every five minutes. The CO_2 concentration was used for determining building occupancy. The occupants of these buildings used a questionnaire to record the time, thermal sensation, and clothing level whenever they adjusted the thermostat set point, adjusted their clothing level, or opened/closed windows or doors to make themselves more comfortable.

The occupants' behavior in the indoor environment depend on many different factors [40, 41], including thermal comfort level [16], gender [42], cultural background [43], outdoor weather [44, 45], and probably income level [21-23]. This study assumed that occupants of offices actively adjusted the thermostat set point for their comfort, because the cost of maintaining a comfortable environment is typically not on their minds. However, for the apartments/houses, occupants' income level may influence their behavior.

With the above effort, this investigation was able to collect the data. Note that all data collection in this study was approved by Purdue University Institutional Review Board Protocol # 1704019079.

2.2 Artificial neural network models

With the collected data, one can build a model to correlate the indoor environmental data with occupants' thermal sensation and behavior. Since the correlations can be complicated, ANN models have been used as a powerful method to deal with highly complex datasets in thermal comfort. Grabe's study [46] pointed out the potential of ANN model to predict thermal sensation votes. Some researchers also used ANN models as predictive controllers for thermal comfort in public buildings [47], residential buildings [48] and office buildings [49]. Therefore, this study also used ANN models. An ANN model uses machine learning methods to learn a particular relationship between input and output parameters, and it can identify the relationship after being trained with sufficient input and output information. As this investigation sought to correlate occupants' thermal sensation and behavior with indoor environmental parameters, it was necessary to identify two separate ANN models.

As shown in Figure 3, an ANN model [50] has a layered structure usually comprised of three layers: an input layer, a hidden layer and an output layer. The number of neurons [51] in the hidden layer indicates the model's complexity. However, increasing the number of neurons could lead to over-fitting and a long training time. We tried four to twenty neurons in the hidden layer in the ANN model. Figure 4 shows the mean absolute error (MAE) between predicted and actual thermal sensation with different number of neurons in the hidden layer. The MAE is defined in Eq. (1) as follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - x_i\right| \quad (1)$$

where x_i, y_i are two series. Here x_i are all the thermal sensation data collected for the offices, and y_i all the corresponding thermal sensation predicted by the thermal comfort ANN model. We found that ten neurons in the hidden layer could predict thermal sensation with MAE equaling to 0.43. To increase the number of neurons in the hidden layer would not further improve the MAE. By balancing the training time and the model complexity, this study used ten neurons in the hidden layer of the ANN models. The transfer function [51] in the hidden layer is a given function that can provide the corresponding output value for each possible input. In this study, the transfer function in the hidden layer was a logistic function, since it can output the thermal sensation and behavior for any possible input.

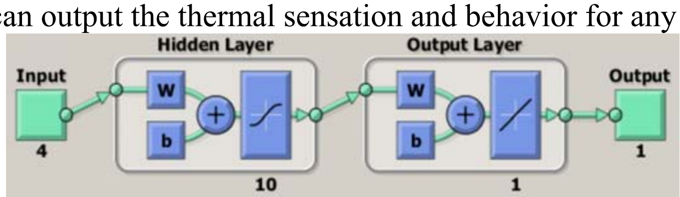


Figure 3. Structure of the ANN models, with four input parameters in the input layer, ten neurons in the hidden layer, and one output parameter in the output layer in Matlab [52]. The "w" and "b" in the hidden layer and output layer represent weight matrix and bias in Eq. (2), respectively, and the transfer functions in the hidden layer and the output layer are a logistic function and a linear function, respectively.

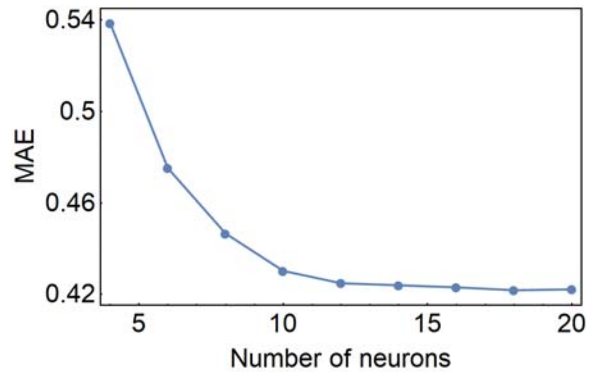


Figure 4. Relationship between number of neurons in the hidden layer and the MAE between predicted and actual thermal sensation.

Hence, the mathematical form of the ANN models in this study can be expressed as

$$Y = \mathbf{w}_{output}\{1+\exp[-(\mathbf{w}_{hidden}\mathbf{X}+\mathbf{b}_{hidden})]\}^{-1}+b_{output} \quad (2)$$

where $\mathbf{X}$ is an $n\times1$ input vector for the n input parameters, $\mathbf{w}_{hidden}$ is a $10\times n$ weight matrix in the hidden layer, $\mathbf{b}_{hidden}$ is a 10×1 vector representing bias in the hidden layer, $\mathbf{w}_{output}$ is a 1×10 weight matrix in the output layer, b_{output} is a number representing bias in the output layer, and Y represents the model output (thermal sensation or behavior).

This investigation used an ANN model to predict thermal comfort. According to the PMV thermal comfort model [11], six parameters have an impact on thermal comfort: air temperature, relative humidity, clothing insulation, air velocity, metabolic rate, and mean radiant temperature. Our measurements showed that the surface temperature of the surrounding walls was almost the same as room air temperature. The offices only had LED lights which did not provide much infrared radiation. In the exterior zone, the offices also have window shades so that the sun light has limited impact. Therefore, our study assumed that the mean radiant temperature was the same as the room air temperature. Our measurements showed that the air velocity in the offices was less than 0.2 m/s. According to previous studies [53] and ASHRAE standard 55 [39], the acceptable comfort zones were within air velocity less than 0.2 m/s, thus the impact of air velocity on thermal comfort can be neglected in this study. To predict thermal comfort, the ANN model requires only four input parameters (air temperature, relative humidity, clothing insulation, and metabolic rate); i.e., n = 4 for Eq. (2). The model output, Y, is the thermal comfort level, which can be expressed as an integer from -3 to 3. The collected data were used to train the model so that the predicted Y would be nearly the same as the thermal sensation collected in the offices and houses/apartments.

The occupants could sit or walk inside their offices, and the corresponding metabolic rates were 60 W/m^2 and 115 W/m^2, respectively, according to the ASHRAE Handbook - Fundamentals [54]. Table 4 lists the insulation values for different clothing ensembles [54] worn by participants in this study. The clothing insulation I_{cl} was expressed in clo unit and 1.0 clo was equal to 0.155 (m^{2}K)/W.

Table 4. Typical insulation values for clothing ensembles [54] in this study

Clothing ensemble description	*I_{cl}(clo)*
Walking shorts, short-sleeved shirt	0.36
Pants, short-sleeved shirt	0.57
Pants, long-sleeved shirt	0.61
Pants, long-sleeved shirt, suit jacket	0.96
Pants, long-sleeved shirt, long-sleeved sweater, T-shirt	1.01
Pants, long-sleeved shirt, long-sleeved sweater, T-shirt, suit jacket, long underwear bottoms	1.3
Knee-length skirt, short-sleeved shirt, panty hose, sandals	0.54
Knee-length skirt, long-sleeved shirt, panty hose, full slip	0.67
Knee-length skirt, long-sleeved shirt, panty hose, half-slip, long-sleeved sweater	1.1

Training the ANN model as shown in Figure 3 will lead to a mathematical expression of the model for thermal comfort in the following form:

Thermal comfort = *f* (air temperature, relative humidity, clothing insulation, metabolic rate) (3)

where *f* is the ANN model expressed in Eq. (2).

This investigation used another ANN model to predict thermal comfort from occupants' behavior. We assumed that the input parameters of this ANN model were again air temperature, relative humidity, metabolic rate, and clothing insulation. The output of the behavioral ANN model is the occupants' behavior, such as adjusting the thermostat set point and/or clothing level. We used "-1" for raising the thermostat set point or adding clothes when occupants feel cool, "0" for no behavior when the occupants feel that the environment is acceptable, and "1" for lowering the thermostat set point or reducing the clothing level when they feel warm. The model can be expressed as

Behavior = *g* (air temperature, relative humidity, clothing insulation, metabolic rate) (4)

where *g* is the ANN model expressed by Eq. (2).

2.3 Artificial neural network model training

This study used Matlab Neural Network Toolbox [52] in Matlab R2017a to build and train the two ANN models. The training targets were the actual thermal sensation and behavior occurrences that had been collected. We tested five popular algorithms available in Matlab to determine which was the best for this study. Table 5 reveals the least MAE and largest R^2 among the five algorithms. These statistical measures are defined in Eq. (1) and (5):

$$R^2 = \sqrt{1 - \frac{\sum_{i=1}^{n} (y_i - x_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}} \quad (5)$$

where x_i, y_i are two series. In this study, x_i are all the thermal sensation data collected for the offices, y_i all the corresponding thermal sensation predicted by the thermal comfort ANN model, and $\overline{y}$ the mean value of y_i. Clearly, the Levenberg-Marquardt (LM) algorithm had the lowest MAE and highest R^2, and thus it was the best option.

Table 5. MAE and R^2 of five training algorithms in Matlab Neural Network Toolbox

Training algorithm	*MAE*	*R^2*
Levenberg-Marquardt	0.430	0.736
Scaled conjugate gradient	0.541	0.576
Bayesian regularization	0.434	0.713
Resilient backpropagation	0.492	0.625
Conjugate gradient with Beale restarts	0.485	0.644

Therefore, we used the LM algorithm to train the two ANN models. Generally, the training process for this algorithm was an iterative procedure. On the basis of an initial guess for parameters $\mathbf{x}$, the LM algorithm used the following approximation to approach the parameters:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{JJ} + \mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e} \quad (6)$$

where $\mathbf{J}$ is the Jacobian matrix that contains first derivatives of the errors with respect to the weights and biases, $\mathbf{I}$ is the identity matrix, and $\mathbf{e}$ is the error vector. The damping factor μ was adjusted at each iteration. If error reduction had been rapid in the previous iteration, then a smaller value was used in the current iteration to bring the algorithm closer to the Gauss–Newton algorithm. Conversely, if an iteration had yielded insufficient reduction in the residual, μ was be increased, taking a step in the gradient-descent direction. Thus, μ was decreased after each successful step, i.e., there had been sufficient reduction in the error, and it was increased only when a tentative step would increase the error. In this way, the error was reduced at every iteration of the algorithm.

Since the occupants' income level may influence their behavior in the apartments/houses, the ANN models for offices and apartments/houses were trained separately with the corresponding data.

2.4 Applications of the ANN models

After training, we used the ANN models to find out the comfort zones for the office and apartment/house environment in winter and summer. The results of comfort zones by ANN models for thermal comfort and behavior were derived by using the following equations:

$$comfort\ zone = \left\{ (air\ temperature, relative\ humidity) \middle| Thermal\ sensation_l \le f \le Thermal\ sensation_u \right\}$$ (7)

$$comfort\ zone = \left\{ (air\ temperature, relative\ humidity) \middle| g \ge Acceptability \right\} \quad (8)$$

where the comfort zone is the set of air temperature range and relative humidity range, f is the expression of the trained ANN model for thermal comfort in Eq. (3), $Thermal\ sensation_l$ and $Thermal\ sensation_l$ are the lower and upper bounds of thermal sensation for the comfort zone, g is the expression of the trained ANN model for behavior in Eq. (4), and $Acceptability$ is the behavior acceptability of the occupants.

We also verified the ANN model results for acceptability of the indoor environment with the predicted percentage of dissatisfied (PPD) model [11]. The PPD can be calculated by the following expression:

$$PPD = 100 - 95e^{-0.3353PMV^4 - 0.2179PMV^2} \quad (9)$$

3 Results

The above methods collected the data to train the ANN models for predicting thermal sensations and occupants' behavior. Then the comfort zones predicted by the ANN models were then compared with the comfort zones in ASHRAE Standard 55 [39].

3.1 Data collection

Data were collected in all four seasons of 2017. In each season, we collected the data for more than one month in every office and apartment/house. We have used psychrometric charts to depict the collected data and comfort zones since this type of chart is typically used to illustrate different air temperatures and humidity levels. In Figure 5, the dots represent the collected air temperature and relative humidity data in the offices in winter, summer, and the shoulder seasons. There were 1254, 1382 and 2303 thermal sensation and behavior data points collected from the ten offices in the winter, summer, and the shoulder seasons, respectively. The colors ranging from purple to red and various shapes of the dots represent the thermal sensations from -3 (cold) to 3 (hot).

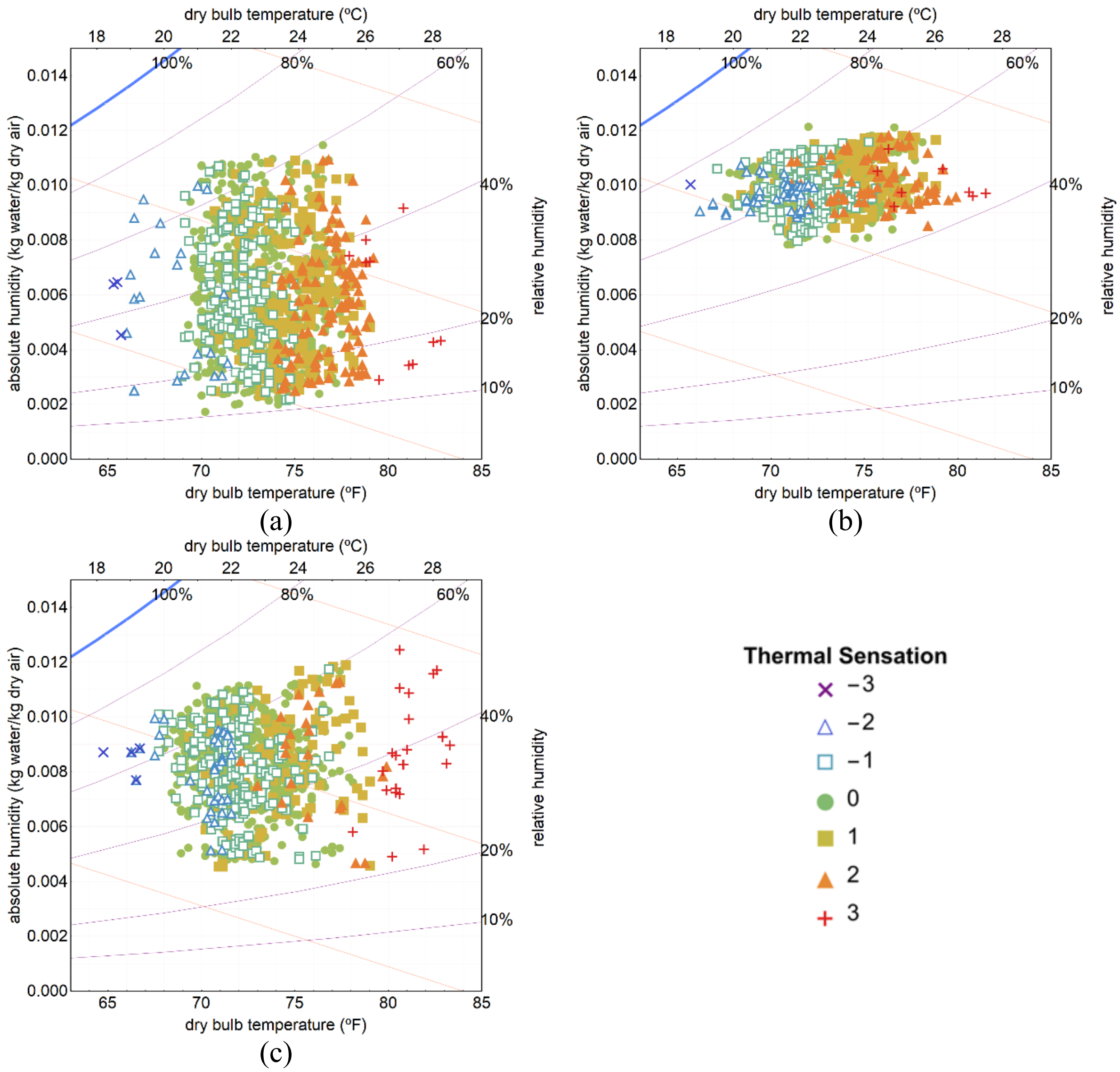


Figure 5. Collected thermal sensation data in different thermal environments in (a) winter, (b) summer and (c) shoulder seasons in the offices.

In Figure 6, the dots represent collected behavior occurrences under different air temperatures and humidity levels in the 10 offices in winter, summer, and the shoulder seasons. The green round dots signify that no behavior occurred; the blue triangle dots represent raising of the thermostat set point or addition of clothing; and the red square dots represent lowering of the thermostat set point or reduction in clothing level. Since the behavior data were collected at the same time as the thermal sensation data, the data distribution in Figure 6 is exactly the same as that in Figure 5. The data contains more than 1000 behavior occurrences in the 10 offices.

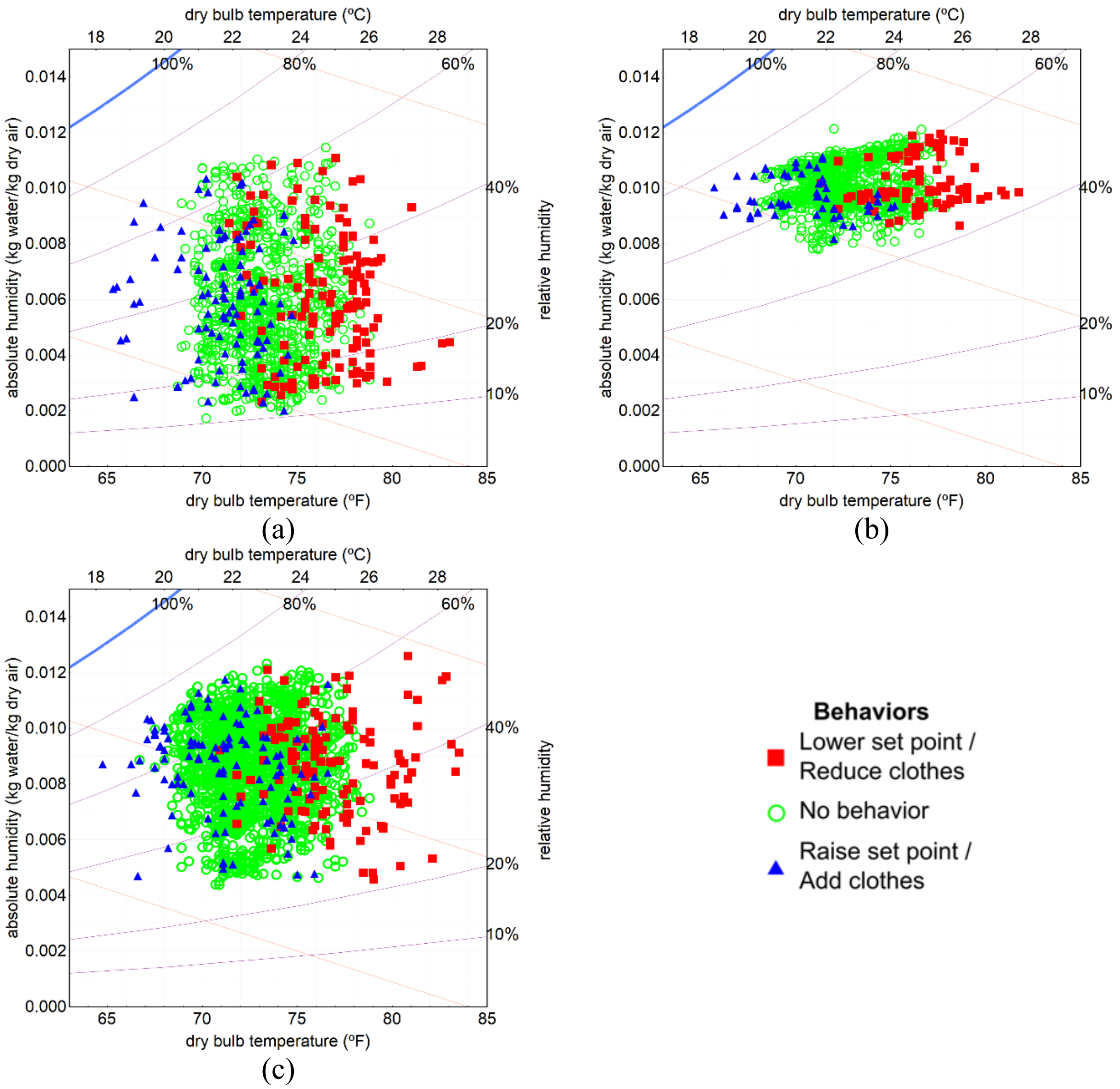


Figure 6. Collected behavior data in different thermal environments in (a) winter, (b) summer and (c) shoulder seasons in the 10 offices.

Table 6 shows the percentage of occupants' behavior occurrences at different thermal sensations in the offices according to the collected data. When the occupants felt hot (+3) or cold (-3), they always adjusted the thermostat set point or their clothing level. However, if the occupants felt warm (+2) or cool (-2), the percentages of behavior occurrences were only 72.2% and 53.3%, respectively. When they felt slightly warm (+1) or slightly cool (-1), the percentages of behavior occurrences dropped further to 17.6% and 26.4%, respectively. According to the collected data, there were several cases in which occupants felt uncomfortable, but no behavior occurred. For example, when feeling uncomfortable immediately after entering the office, some occupants preferred to adjust the thermostat set point after some time had passed. In other cases, the HVAC system may not have responded quickly to the latest adjustment, yet the occupant waited for a while even though he/she may have felt uncomfortable. In these cases, the occupants' behavior did not reflect their true desires in regard to controlling the indoor environment. For multi-occupant offices, meanwhile, an acceptable indoor environment may have been a compromise among several occupants. Some occupants may have felt uncomfortable, but they did not adjust the thermostat set point because the other occupants were not complaining about the comfort level, or they were unsure whether others would feel the same way.

Table 6. Percentages of behavior occurrences under different thermal sensations in the offices

Thermal sensation	*Behavior occurrences*		
	-1	0	1
-3	0%	0%	100%
-2	0%	46.7%	53.3%
-1	0%	73.6%	26.4%
0	0%	100%	0%
1	17.6%	82.4%	0%
2	72.2%	27.8%	0%
3	100%	0%	0%

Similarly, Figure 7 displays the collected thermal sensation data from the apartments/houses in all four seasons on psychrometric charts. There were 922, 1152 and 1391 thermal sensation data points collected from the ten apartments/houses in winter, summer, and the shoulder seasons, respectively. The colors ranging from purple to red and various shapes of the dots represent the thermal sensations from -3 (cold) to 3 (hot) in the apartments/houses. In the winter, the room air temperature ranged from 19.4□ (67□) to 23.3□ (74□) and occupants usually reported a neutral thermal sensation. Slightly cool and slightly warm thermal sensations made up only a small part of the data. No warm or hot thermal sensations were recorded in the winter. Sometimes the room air temperature was quite low during this season, and it was because the occupants had opened a window or door. In the summer, the room air temperature was maintained below 28.3□ (83□) at most times, and the relative humidity was higher than in the winter. In the shoulder seasons, the occupants used the HVAC system occasionally, and thus the room air temperature varied within a large range, from 17.2□ (63□) to 29.4□ (85□). The relative humidity was between the levels in the winter and summer seasons. The hot or cold thermal sensation appeared only when the air temperature was higher than 27.8□ (82□) or lower than 18.9□ (66□), respectively. However, most of the behavior occurrences collected in the ten apartments/houses were cooking and opening of windows or doors. Adjustment of the thermostat set point occurred rarely in these residences.

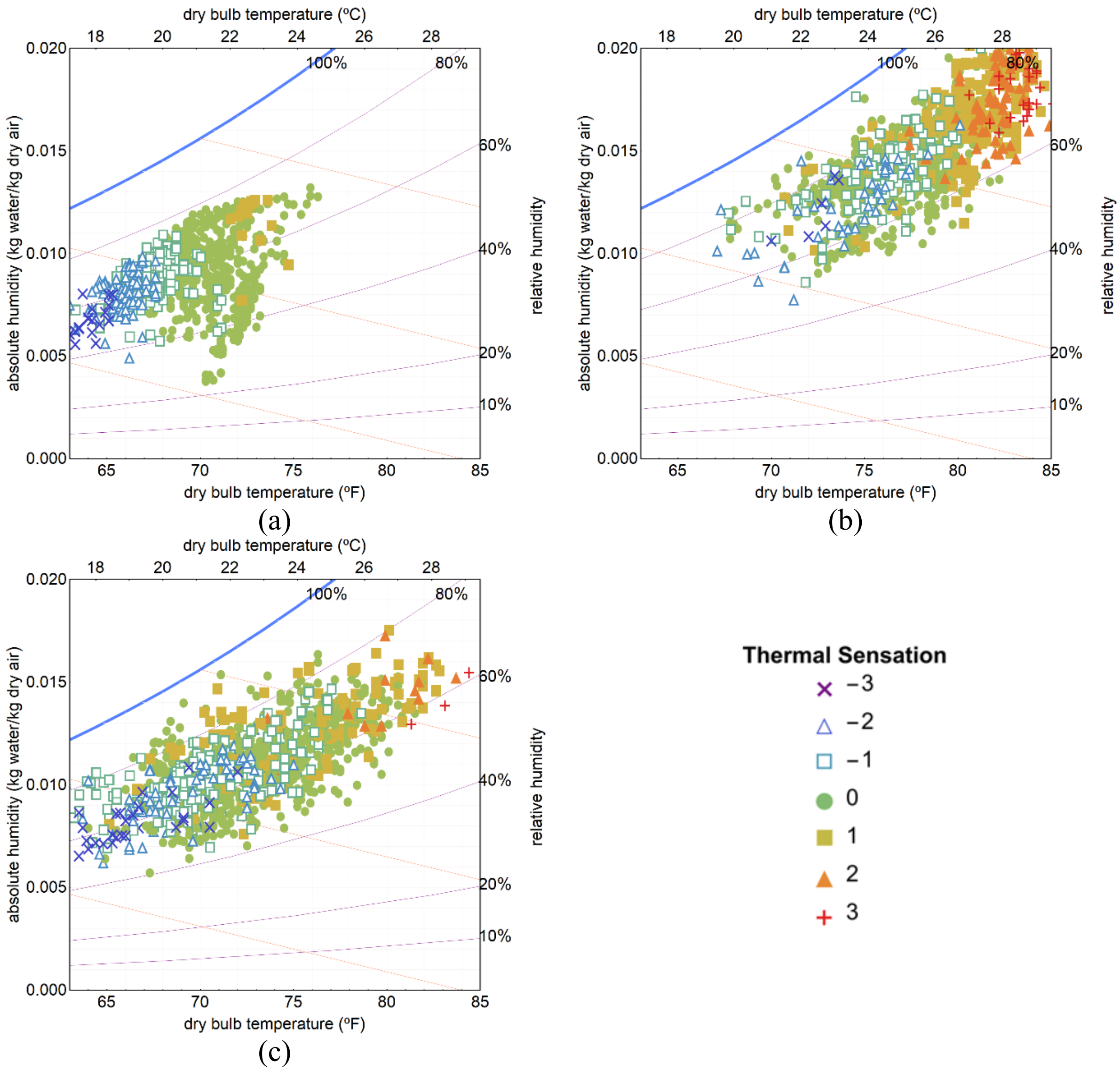


Figure 7. Thermal sensation data collected in the 10 apartments/houses in (a) winter, (b) summer, and (c) shoulder seasons.

3.2 Artificial neural network model training

We used the above collected data in all the four seasons to train the ANN models by means of the LM algorithm. Figure 8 displays the training results of the ANN model for thermal comfort in winter, summer, and the shoulder seasons in offices. Since the comfort zones in ASHRAE Standard 55 [39] are for winter and summer, we trained the ANN model for these two seasons. The ANN model was able to predict occupants' thermal sensations, and the prediction fitted the collected data with R^2 = 0.75, 0.71 and 0.73 in winter, summer, and the shoulder seasons, respectively. As shown in Figure 8, over 85% of the model predictions differed from the actual sensations by less than one unit on the sensation scale. We also used different shapes of the symbols to compare the predicted and actual thermal sensations in different months in each season. Figure 8 shows that the comparison between the predicted and actual thermal sensations did not have monthly differences. In the

ASHRAE Handbook [54], previous study [55] pointed out that there was no difference between the comfortable conditions in winter and summer because people cannot adapt to prefer warmer or cooler environment in different seasons. Therefore, the trained model performed reasonably well in predicting thermal sensations for the offices with the four input parameters.

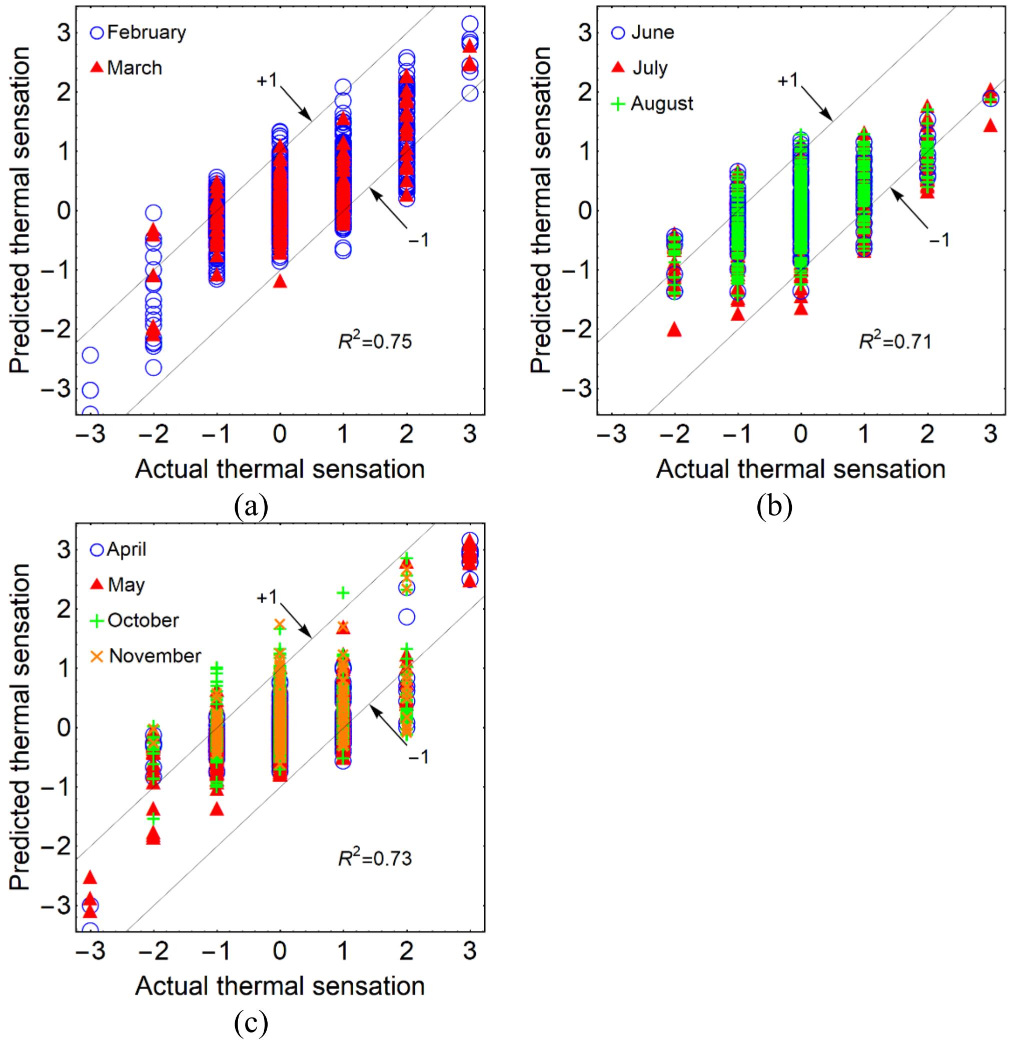


Figure 8. Comparison between the predicted and actual thermal sensations in (a) winter, (b) summer and (c) shoulder seasons for the offices, where "+1" and "−1" are the lines at which predicted thermal sensations are one unit higher or lower than the actual values.

We also trained the ANN model for behavior with the collected behavior data from the offices. Among the collected data, the actions of adjusting the thermostat set point or clothing level occurred about 17% of all the behaviors, as indicated by the blue and red slices of the pie chart in Figure 9. The figure also shows that the training accuracies of the behavior ANN model for the three kinds of behavior (lowering the set point or reducing the clothing level, no behavior, and raising the set point or adding clothing) were 89.4%, 87.3% and 91.2%, respectively. The overall training accuracy of the ANN model in predicting all three kinds of behavior was 87.5%. Therefore, the trained ANN model performed well in predicting occupants' behavior in the offices with the four input parameters.

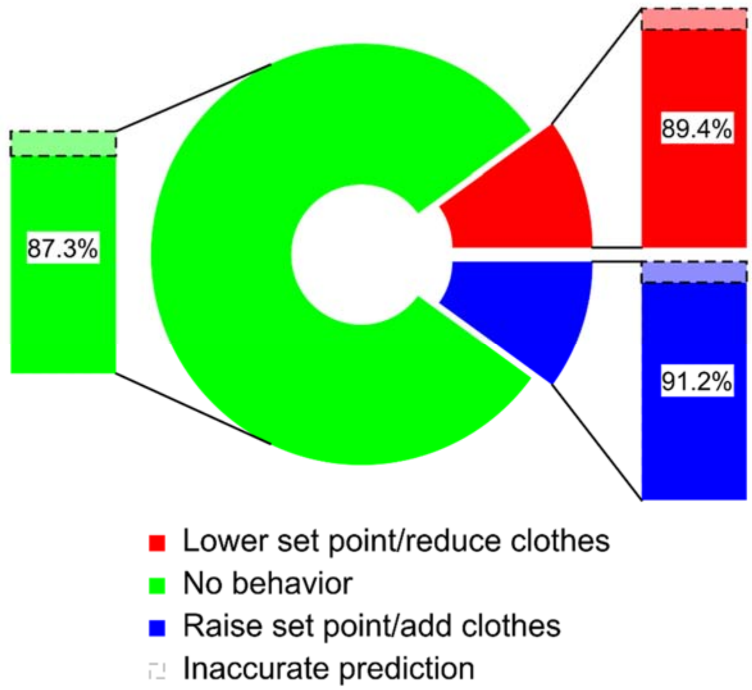


Figure 9. Training accuracies of the behavior ANN model for the three kinds of behaviors.

3.3 Acceptable indoor environments

<u>3.3.1 Comfort zones predicted by the two ANN models</u>

After training the ANN models, we used Eq. (7) to find out the comfort zones by the ANN model for thermal comfort. Figure 10 illustrates the comfort zones for the office environment in winter and summer obtained by the ANN model using thermal sensations. The default clothing level was a long-sleeved shirt, sweater and pants in winter (close to 1.0 clo in ASHRAE Standard 55 [39] and a short-sleeved shirt and pants in summer (close to 0.5 clo in ASHRAE Standard 55 [39]). We assumed that the office occupants were sitting, and thus their metabolic rate was 1.0 MET. The zone outlined in blue in the figure represents a nearly neutral thermal sensation (from -0.5 to 0.5), the green zone a sensation between slightly cool and slightly warm (from -1 to 1), and the orange zone a sensation between cool and warm (from -2 to 2). For the comfort zone from slightly cool to slightly warm, the air temperature ranged from about 20.6□ (69□) to 25□ (77□) in winter and from about 20.6□ (69□) to 25.6□ (78□) in summer. However, the data we have collected had limited range in relative humidity. Therefore, 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, which may not be equivalent to the comfort boundaries. Within the range of the data, humidity does not seem to have been a key thermal comfort parameter in the offices. Further study of the impact of humidity on thermal comfort would require more data outside the range shown in Figure 10.

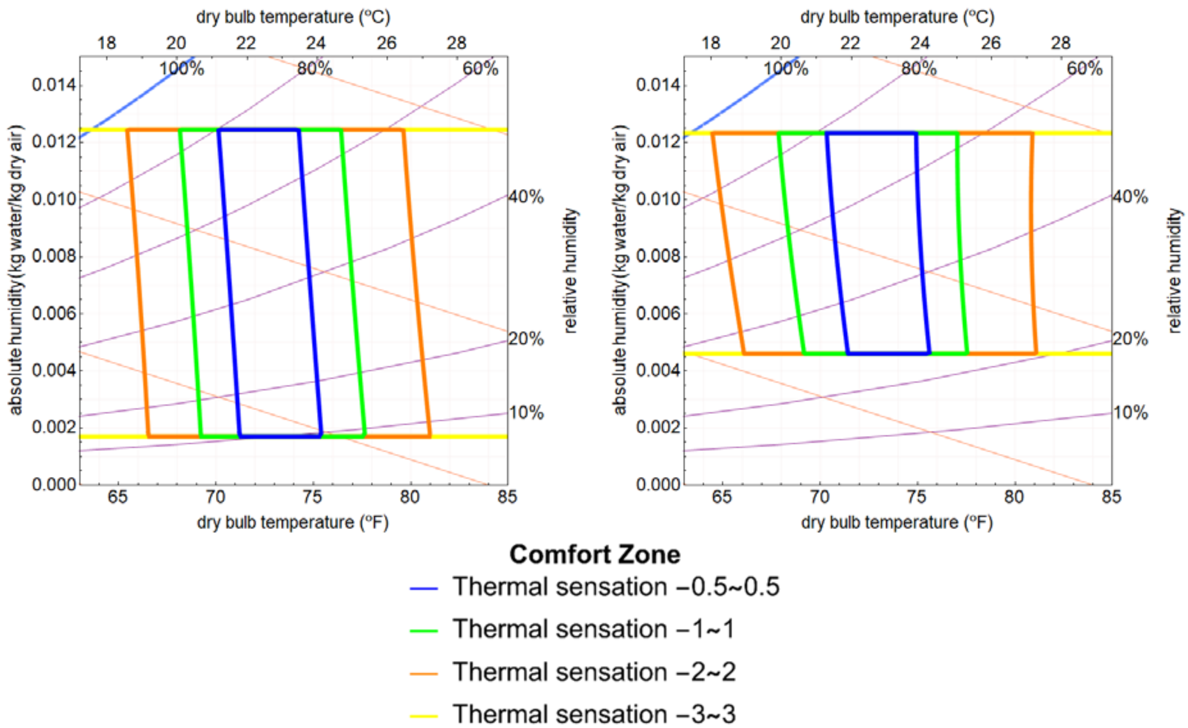


Figure 10. Comfort zones for office environments in winter (left) and summer (right) obtained by the ANN model with the use of thermal sensations.

We also used Eq. (8) to find out the acceptable zones by the behavioral ANN model. Figure 11 illustrates the acceptable zones for an office environment in the winter and summer seasons obtained by the ANN model using behavior. As mentioned previously, Table 6 correlates occupants' behavior occurrences with their thermal sensations. An acceptable environment is one in which occupants can work without adjusting their behavior, although they may feel slightly uncomfortable. An unacceptable environment is one in which occupants have to adjust the thermostat set point or their clothing level. This study used the information in Table 6 to define the acceptable zones for various percentages of the occupants. The blue zone in Figure 11 represents the humidity and temperature ranges within which 88% of the occupants did not adjust the thermostat set point or their clothing level; the green zone represents the conditions under which 76% of the occupants made no adjustments; and the orange zone represents the conditions under which 15% of the occupants made no adjustments. Under the assumption that "no behavior" signifies an acceptable environment, the acceptable indoor air temperature for 76% of the occupants ranged from 21.1℃ (70°F) to 25.6℃ (78°F) in winter and 20.6℃ (69°F) to 25℃ (77°F) in summer. The results of the behavior ANN model also indicate that the humidity had little impact on behavior in the offices in different seasons. This was because our data were collected within a narrow humidity range. Furthermore, office occupants could not signify their humidity preferences by any of the adjustment actions that were recorded.

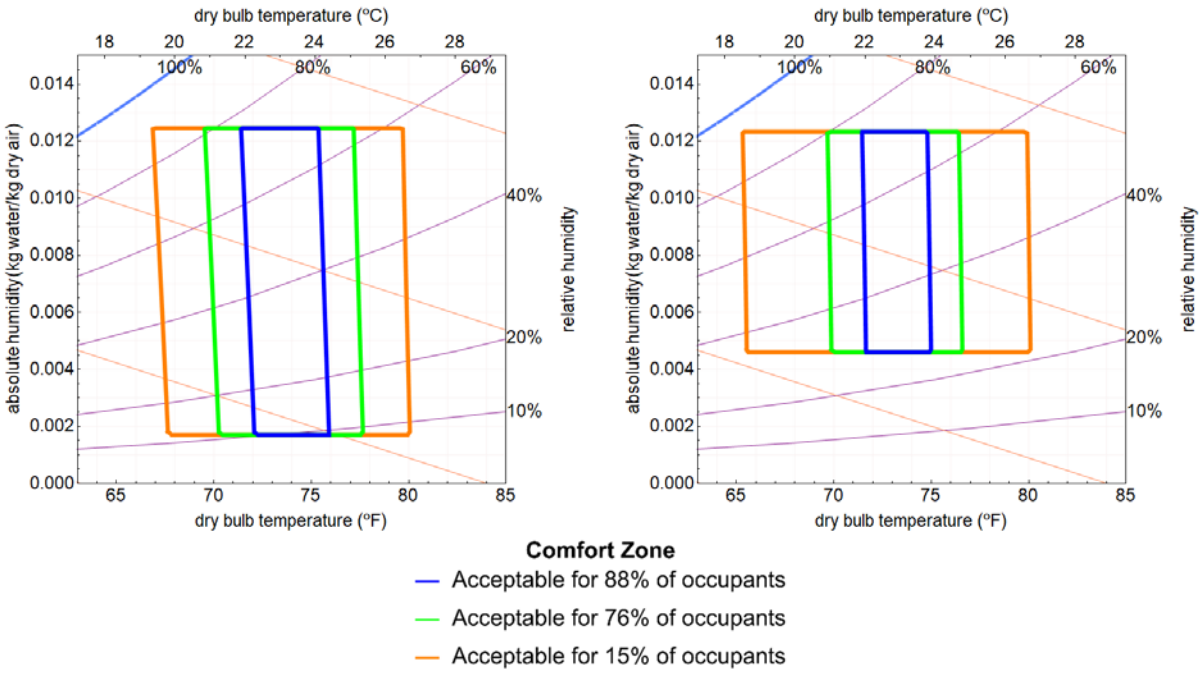


Figure 11. Acceptable zones for office environments in winter (left) and summer (right) obtained by the ANN model using behavior.

The acceptable zones obtained by the ANN model with the use of behavior, shown in Figure 11, are similar to the comfort zones obtained by the ANN model using thermal sensations, displayed in Figure 10. The good correlation between the two sets of results implies that one may evaluate the indoor environment in offices by using either of the ANN models. To verify this finding, Table 7 shows the acceptability of the indoor environment for different thermal sensations in the offices. Using the two ANN models, we found that when the occupants' thermal sensation was nearly neutral (from -0.5 to 0.5), the acceptance rate of the occupants was 88%. When the thermal sensation was between slightly cool and slightly warm (from -1 to 1), the acceptance rate was 76%. When the thermal sensation was between cool and warm (from -2 to 2), only 15% of the occupants found the indoor environment acceptable. Hence, occupants' behavior can be used to evaluate the acceptability of an indoor environment in the same way as can thermal sensations.

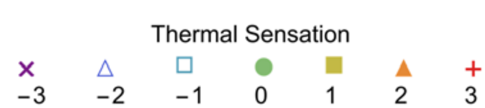
In Table 7, we also compare the ANN model results for acceptability of the indoor environment with the PPD model. The PPD was calculated by using Eq. (9) and we used the occupants' thermal sensations to represent PMV. We found that when the occupants felt uncomfortable, where the thermal sensation was between cool and warm (from -2 to 2) or between slightly cool and slightly warm (from -1 to 1), the rate at which they considered the indoor environment unacceptable was 15-20% lower than the PPD. Since the PPD model was developed in a controlled environment, it does not consider the impact of occupants' behavior on thermal comfort. However, our results show that occupants' behavior in real environments could lower their expectations of comfort and their tolerance for discomfort, which is similar with findings in several previous studies [30-33].

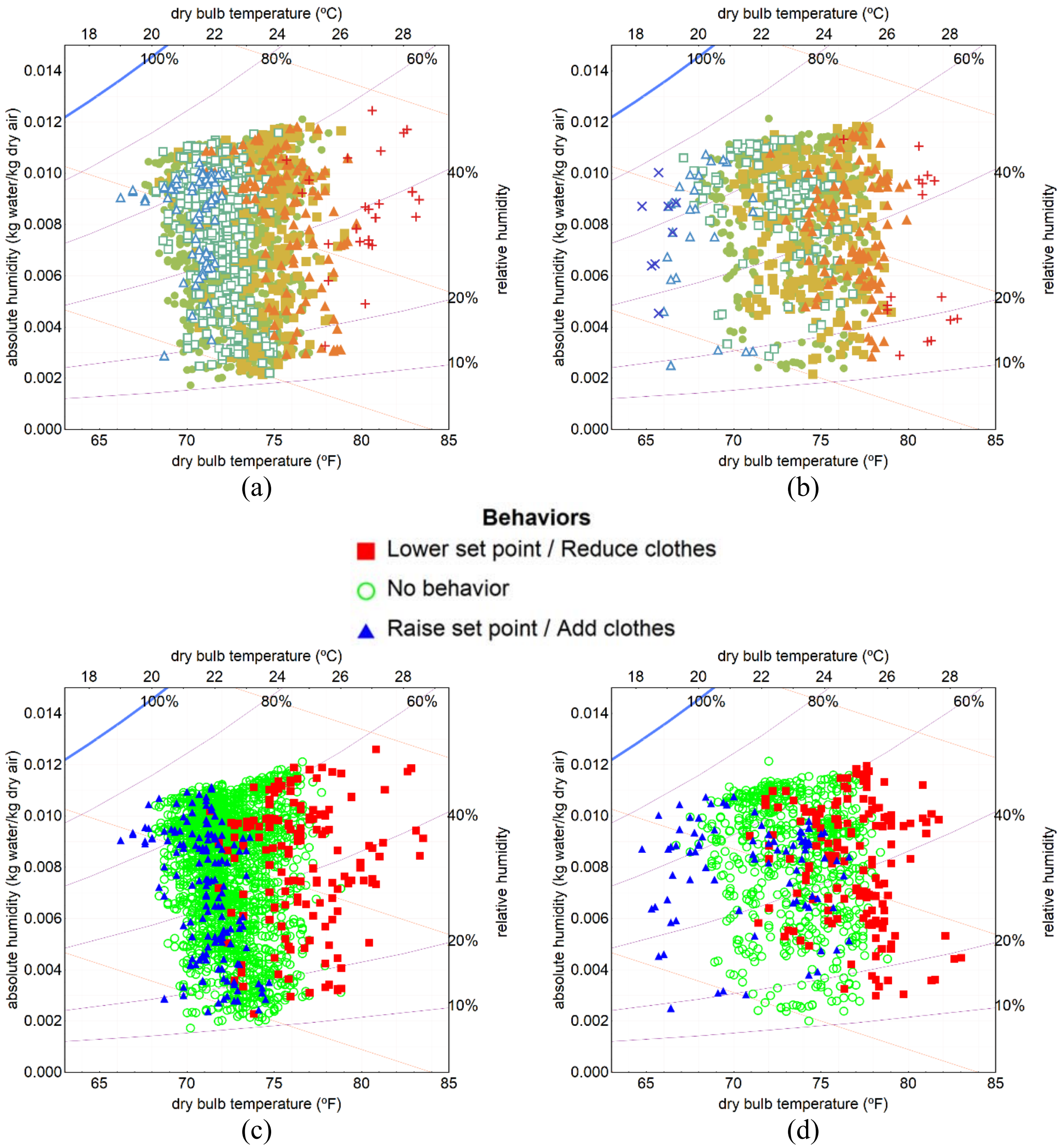
Table 7. Acceptability and unacceptability of the indoor environment for different thermal sensations in the 10 offices with the use of behavior

Thermal sensation	Acceptability	Unacceptability	PPD
-3–3	0%	100%	100%
-2–2	15%	85%	99.8%
-1–1	76%	24%	45.4%
-0.5–0.5	88%	12%	11.9%

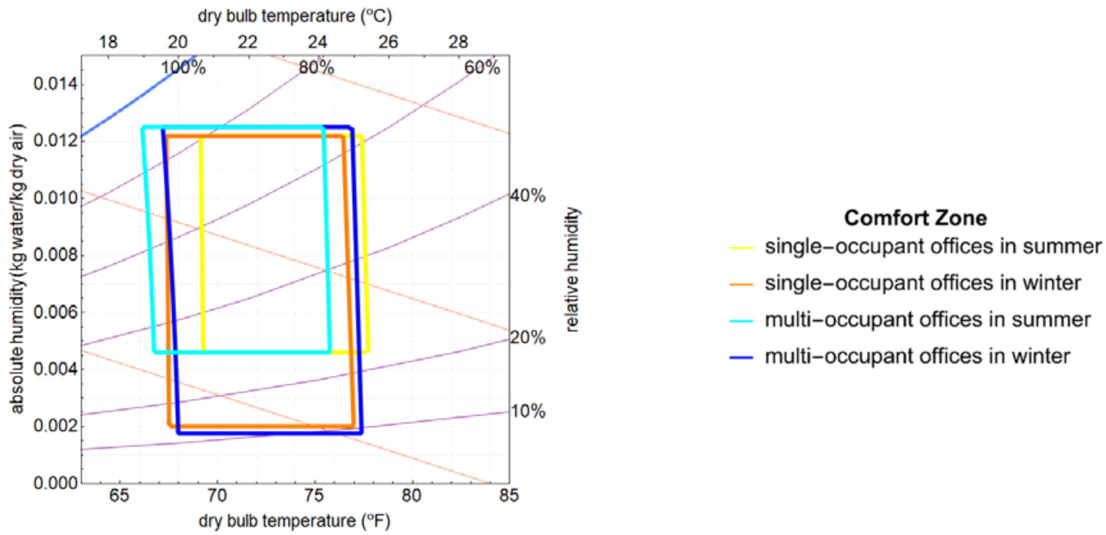
3.3.2 Comparison of comfort zones between multi-occupant and single-occupant offices

Figure 12 compares the collected thermal sensation and behavior data and comfort zones in multi-occupant student offices and single-occupant faculty offices. Data from the multi-occupant student offices made up about 80% of the total data that were collected. The two sets of data appear to have the same center of gravity, but the data set for single-occupant offices is more divergent. This is because most of the single-occupant offices located in the exterior zone of the building as shown in Figure 1 (b) and (c). These offices had huge glass windows as shown in Figure 1(a) and the room air temperature was impacted very much by the outdoor weather. We obtained the comfort zones for the two types of offices with the ANN model using thermal sensations. In winter, the comfort zones were almost the same for single-occupant and multi-occupant offices. The comfortable air temperature range, between slightly cool and slightly warm, was from 20℃ (68℉) to 25℃ (77℉) in winter. The comfortable air temperature for the single-occupant faculty offices in summer was about 1.1℃ (2℉) higher than that in winter. For the multi-occupant student offices, however, the comfortable air temperature in summer was 1.1℃ (2℉) lower than that in winter, as shown in Figure 12 (e). Normally, the comfortable air temperature is higher in summer than in winter, since occupants tend to wear less clothing in summer, but the situation in the multi-occupant student offices was exactly the opposite. The difference may have been due to the presence of multiple occupants. Table 8 compares the percentage of occupants' behavior occurrences at different thermal sensations between single-occupant and multi-occupant offices according to the collected data. When the occupants felt warm (+2), the percentages of behavior occurrences were 82.3% and 59.8% in multi-occupant and single-occupant offices, respectively. Similarly, when the occupants felt cool (-2), slightly cool (-1) or slightly warm (1), the behavior occurrences in multi-occupant offices was 53.6%, 29.4% and 22.5% higher than single-occupant offices, respectively. In the single-occupant offices, each occupant could adjust the thermostat set point according to his or her preference without considering others. By contrast, in the multi-occupant offices, a few students preferred a low air temperature in summer, and they set a low thermostat set point. Although other students in the same office felt uncomfortable, they were unsure whether others felt the same. Therefore, they compromised and did not adjust the thermostat set point. This phenomenon would make the indoor environment extreme to some degree, such as a lower air temperature in summer.





dry bulb temperature (ºC)
18
20
22
24
26
28
100%
80%
60%
40%
20%
10%
absolute humidity (kg water/kg dry air)
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
relative humidity
65
70
75
80
85
dry bulb temperature (ºF)
(a)
(b)
Behaviors
Lower set point / Reduce clothes
No behavior
Raise set point / Add clothes
(c)
(d)



(e)

Figure 12. (a) Thermal sensation data collected from the multi-occupant student offices, (b) thermal sensation data collected from the single-occupant faculty offices, (c) behavior data collected from the multi-occupant student offices, (d) behavior data collected from the single-occupant faculty offices, and (e) comparison of comfort zones between single-occupant and multi-occupant offices.

Table 8. Comparison between the percentages of behavior occurrences under different thermal sensations in single-occupant and multi-occupant offices

Thermal sensation	*Behavior occurrences*					
	Single-occupant offices			*Multi-occupant offices*		
	-1	*0*	*1*	*-1*	*0*	*1*
-3	0%	0%	100%	0%	0%	100%
-2	0%	10.7%	89.3%	0%	64.2%	35.7%
-1	0%	48.1%	51.9%	0%	77.5%	22.5%
0	0%	100%	0%	0%	100%	0%
1	24.3%	75.7%	0%	14.4%	85.6%	0%
2	82.3%	17.7%	0%	59.8%	40.2%	0%
3	100%	0%	0%	100%	0%	0%

3.3.3 Comparison of comfort zones between offices and apartments/houses

After analyzing the occupants' thermal sensations and behavior in the offices, this study employed the same method to evaluate residential indoor environments. We used the thermal sensation data collected in the ten apartments/houses to train the ANN model and then obtained the comfort zone for these residences. Figure 13 compares the comfort zones in which the thermal sensation was nearly neutral (from -0.5 to 0.5) between the offices and the apartments/houses. The comparison indicates that in winter, a large portion of the comfort zone for the apartments/houses and the entire zone for the offices were within the ASHRAE comfort zone. However, the comfortable air temperature in the apartments/houses was 1.7□ (3□) lower than that in the offices. In summer, the comfortable air temperature in the apartments/houses was 1.7□ (3□) higher than that in the offices. The comfort zone in the offices in summer was outside the ASHRAE comfort zone. Since the office occupants did not pay the electricity bill for cooling, they consistently turned on the HVAC system and set the thermostat to the lowest temperature to quickly create a comfortable environment. This behavior often led to over cooling. Generally, the air temperature in the offices was higher in winter and lower in summer than that in the apartments/houses. This kind of behavior led to using more energy and money on the HVAC system in offices than apartments/houses. Therefore, the office buildings had more potential for energy saving of HVAC system by improving occupants' behavior.

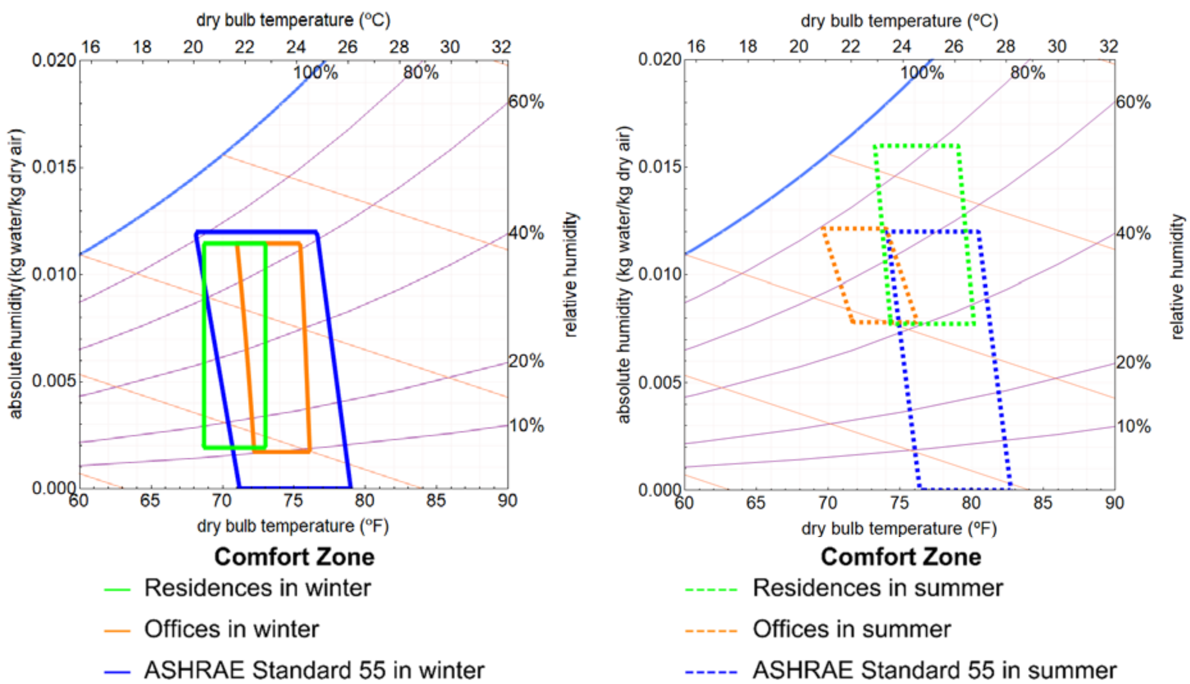


Figure 13. Comparison of the comfort zones for the offices, the zones for the apartments/houses, and the ASHRAE comfort zone in (a) winter and (b) summer.

3.3.4 Comparison of the comfort zones obtained by the two *ANN* models with the ASHRAE comfort zones

Figure 14 compares the comfort zones obtained by the two ANN models with the ASHRAE comfort zones. The blue outlines indicate the ASHRAE comfort zones, which uses a PMV range from -0.5 to 0.5 and an acceptability of 80% for the occupants. The orange zones represent the ANN model using thermal sensations and a range of -0.5 to 0.5 for thermal comfort. The cyan zones represent the ANN model using behavior and an acceptability of 80%. The solid and dashed lines represent the comfort zones in winter and summer, respectively. The comfort zones obtained by the ANN model using thermal sensations are narrower than the ASHRAE comfort zone. This implies that the office occupants were pickier than the occupants participated in the study of obtaining ASHRAE comfort zone. However, the comfort zone obtained by the ANN model using behaviors was wider than the ASHRAE comfort zone, especially in summer. This is because we assumed that the absence of behavior signified an acceptable environment. However, in some situations, as stated in Section 3.1, the occupants may have felt that the environment was unacceptable, yet they exhibited no behavior. Thus, these situations led to a higher acceptability of the indoor environment in the offices.

In addition, the comfortable room air temperature predicted by the two ANN models in summer was about 2.2□ (4□) lower than the temperature of the ASHRAE comfort zone. One possible reason is that the data in this study were gathered primarily from students, who were young and of whom 75% were male; the age and gender of the participants may have caused biases in the results. Another possible reason is that the office occupants were not responsible for the electricity bill and often set the temperature lower than would be desirable in the comfort zone in order to cool the room more quickly. Actually, setting a lower temperature does not cause faster cooling but over cooling.

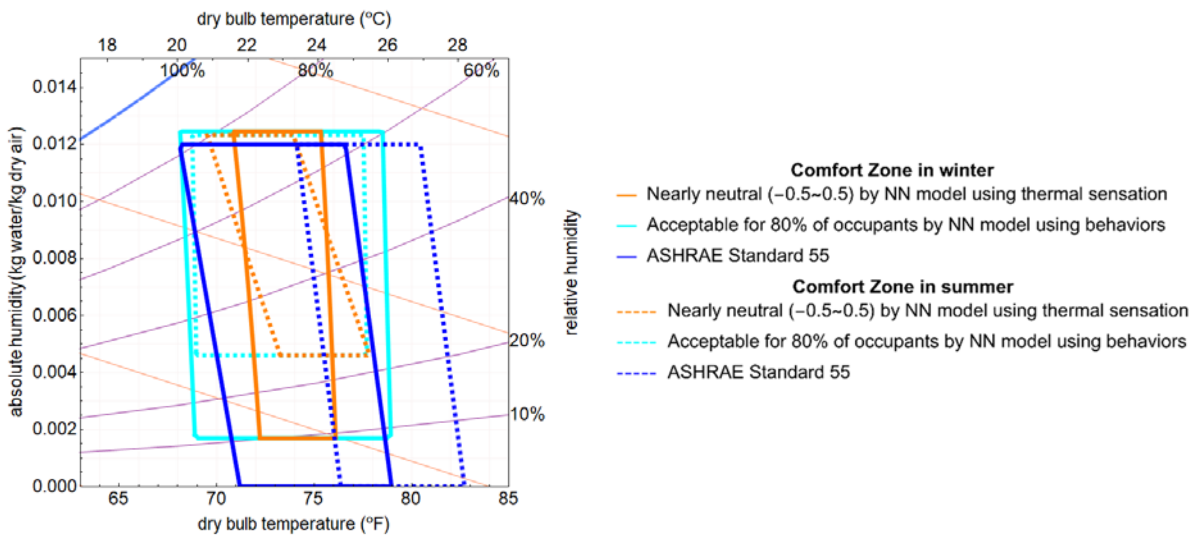


Figure 14. Comparison of the comfort zones obtained by the two ANN models and the ASHRAE comfort zones in winter and summer.

4 Discussion

The ANN models have been developed to determine the relationship between the adjustment of thermostat set point and clothing level or thermal sensations, and air temperature and relative humidity. High-quality data were necessary for training the models. However, we used a questionnaire to collect clothing level data. As shown in Table 4, the choices on the questionnaire were limited, but an overly long list might have confused the participants. In addition, we used metabolic rates of 60W/m^2 for sitting and 115W/m^2 for walking, without accounting for differences in gender or age. Furthermore, the actual activities of the office occupants were not limited to sitting and walking. Sometimes the occupants may forget to record some information although their behavior happened. The reliability of collected data depended on the occupants since they provided all the data. In this study, we assumed that the mean radiant temperature was the same as the room air temperature. However, the very high or low outdoor temperature and the intense solar radiation could make the radiant temperature different from the air temperature for exterior rooms. In addition, the radiation from human bodies and computers cannot be avoided in this study. Any discrepancies may have significantly impacted the robustness of the training process and thus the prediction accuracy of the ANN models. In addition, since humidity was not controlled in the offices and apartments/houses in this investigation, the models may not be appropriate when the humidity level exceeds the range of the study.

Our study of apartment/houses revealed that the occupants' income level may have influenced their behavior. A study by Kwon et al. [56] compared the indoor temperature in a university student dormitory and in their family apartments when air conditioners were on. The researchers found that the room air temperature in the dormitory was lower in summer and higher in winter than that in the family apartments. That difference arose because the students did not pay the electricity bill in the university dormitory. This finding is similar to our results for offices in comparison to apartments/houses.

The present study made full use of the occupants' behavior to evaluate the indoor environment in offices. The ANN models may be more objective than those available in the previous literature, because the occupants in our case communicated their preferences in terms of adjustment behavior in actual environments rather than through more subjective surveys in controlled or uncontrolled environments. The behavior of occupants could be a significant parameter for evaluating indoor environments in buildings.

5 Conclusions

In this study, we collected data on the air temperature, relative humidity, clothing level, metabolic rate, thermal sensation, and behavior in ten offices and ten apartments/houses in Indiana, USA. We built and trained two ANN models to determine the relationship between air temperature and relative humidity, and occupants' thermal sensations and behavior. This investigation led to the following conclusions:

(1) Under the assumption that a slightly cool to slightly warm environment is comfortable for occupants, the air temperature should be between 20.6°C (69°F) and 25°C (77°F) in winter and between 20.6°C (69°F) and 25.6°C (78°F) in summer. For a 76% acceptance rate, the corresponding indoor air temperature should be between 21.1°C (70°F) and 25.6°C (78°F) in winter and between 20.6°C (69°F) and 25°C (77°F) in summer. The two ANN models provided similar results. Hence, we can use the behavior of occupants to evaluate the acceptability of an indoor environment in the same way that we use thermal sensations.

(2) A comparison of the comfort zones in single-occupant and multi-occupant offices revealed that the occupants' actions in these two types of office were different. In the multi-occupant offices, some occupants may have compromised with other occupants' thermostat set point preferences, such as lower temperature in summer. As a result, the acceptable temperature in the multi-occupant offices in summer was 1.1°C (2°F) lower than that in the single-occupant offices.

(3) Responsibility for paying the energy bill could have an impact on occupants' behavior in apartments/houses. The results showed that the comfortable air temperature in the

apartments/houses was 1.7□ (3□) lower than that in the offices in winter, and 1.7□ (3□) higher in summer.

(4) The comfort zone obtained by the ANN model using thermal sensations in the ten offices was narrower than the comfort zone in ASHRAE Standard 55, but the comfort zone obtained by the ANN model using behavior was wider than the ASHRAE comfort zone.

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Highlights

- Occupants' behaviors and thermal sensations were used in artificial neural network models for predicting thermal comfort.
- A comparison between single-occupant and multi-occupant offices revealed the occupants' compromised behavior with other occupants' thermal preferences.

- The comfortable air temperature in apartments/houses was 1.7□ (3□) lower than that in the offices in winter, and 1.7□ (3□) higher in summer.