RECOGNITION OF BUILDING OCCUPANT BEHAVIORS FROM INDOOR ENVIRONMENT PARAMETERS BY DATA MINING APPROACH

by

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ABSTRACT

Currently, people in North America spend roughly 90% of their time indoors. Therefore, it is important to create comfortable, healthy, and productive indoor environments for the occupants. Unfortunately, our resulting indoor environments are still very poor, especially in multi-occupant rooms. In addition, energy consumption in residential and commercial buildings by HVAC systems and lighting accounts for about 41% of primary energy use in the US. However, the current methods for simulating building energy consumption are often not accurate, and various types of occupant behavior may explain this inaccuracy.

This study first developed artificial neural network models for predicting thermal comfort and occupant behavior in indoor environments. The models were trained by data on indoor environmental parameters, thermal sensations, and occupant 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 °C to 25 °C in winter and from 20.6 °C to 25.6 °C in summer. We also found that the comfortable air temperature in the residences was 1.7 °C lower than that in the offices in winter, and 1.7 °C higher in summer. The reason for this difference may be that the occupants of the houses/apartments were responsible for paying their energy bills. 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 using behaviors was wider.

Then this study used the EnergyPlus program to simulate the energy consumption of HVAC systems in office buildings. Measured energy data were used to validate the simulated results. When using the collected behavior from the offices, the difference between the simulated results and the measured data was less than 13%. When a behavioral ANN model was implemented in the energy simulation, the simulation performed similarly. However, energy simulation using constant thermostat set point without considering occupant behavior was not accurate. Further simulations demonstrated that adjusting the thermostat set point and the clothing could lead to a 25% variation in energy use in interior offices and 15% in exterior offices. Finally, energy consumption could be reduced by 30% with thermostat setback control and 70% with occupancy control.

Because of many contextual factors, most previous studies have built data-driven behavior models with limited scalability and generalization capability. This investigation built a policy-based reinforcement learning (RL) model for the behavior of adjusting the thermostat and clothing level. We used Q-learning to train the model and validated with collected data. After training, the model predicted the behavior with R^2 from 0.75 to 0.80 in an office building. This study also transferred the behavior knowledge of the RL model to other office buildings with different HVAC control systems. The transfer learning model predicted with R^2 from 0.73 to 0.80. Going from office buildings to residential buildings, the transfer learning model also had an R^2 over 0.60. Therefore, the RL model combined with transfer learning was able to predict the building occupant behavior accurately with good scalability, and without the need for data collection.

Unsuitable thermostat settings lead to energy waste and an undesirable indoor environment, especially in multi-occupant rooms. This study aimed to develop an HVAC control strategy in multi-occupant offices using physiological parameters measured by wristbands. We used an ANN model to predict thermal sensation from air temperature, relative humidity, clothing level, wrist skin temperature, skin relative humidity and heart rate. Next, we developed a control strategy to improve the thermal comfort of all the occupants in the room. The control system was smart and could adjust the thermostat set point automatically in real time. We improved the occupants' thermal comfort level that over half of the occupants reported feeling neutral, and fewer than 5% still felt uncomfortable. After coupling with occupancy-based control by means of lighting sensors or wristband Bluetooth, the heating and cooling loads were reduced by 90% and 30%, respectively. Therefore, the smart HVAC control system can effectively control the indoor environment for thermal comfort and energy saving.

As for proposed studies in the future, at first, we will use more advanced sensors to collect more kinds of occupant behavior-related data. We will expand the research on more occupant behavior related to indoor air quality, noise and illuminance level. We can use these data to recognize behavior instead of questionnaire survey now. We will also develop a personalized zonal control system for the multi-occupant office. We can find the number and location of inlet diffusers by using inverse design.

1. INTRODUCTION

1.1 Background

Currently, people in North America spend roughly 90% of their time indoors (Matz, 2014; Klepeis, 2001). 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.

For thermal comfort, unfortunately, 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" in different regions (IFMA, 2003). 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 (Van Craenendonck, 2018). The first category evaluates an indoor environment with the use of models developed from questionnaires under controlled indoor environments (Chow, 1994; Cheong, 2006; Chen, 2016; Yang, 2015; Melikov, 2007). Controlled environments have allowed researchers to study thermal comfort in a uniform and steady-state way. The second category of methods, which is more popular at present, evaluates an indoor environment by mean of questionnaires without varying controlled parameters (De Dear, 1998; Goto, 2007; Cao, 2011). These field studies have typically collected data in operational buildings, with the benefit of larger samples and enhanced ecological validity. However, variation in such thermal environments may be limited. The two types of thermal comfort model do not consider the influence of occupant behavior on thermal comfort. Since occupant behavior is critically related to thermal comfort, the two categories of evaluation method may not be ideal for evaluating the thermal comfort of occupants in indoor environments.

Evaluation of thermal comfort should be based on thermal sensations in natural indoor environments rather than in controlled environments. In a climate chamber, researchers benefit from superior experimental control to validate their models and designs (de Dear, 2013). In an indoor environment such as an office or residence, however, occupants go about their daily activities in surroundings with which they are familiar (Ashkanasy, 2014; Vanus, 2017). If the thermal environment is not satisfactory, the occupants adjust the thermostat set point (Snow, 2017) or their clothing level until they feel comfortable. Such environment-driven actions may reflect the occupants' responses to the indoor environment (Andersen, 2011). Therefore, occupants' interaction with the building systems is a significant determinant of their satisfaction (de Dear, 2013). It is possible to use the occupant behavior to evaluate the indoor environment.

However, there are some negative effects of occupant behavior on building energy use and the HVAC system. First and foremost, Occupants typically use more energy in reality than that predicted by simulations (O'Brien, 2017). The discrepancy may be caused by the various types of occupant behavior in buildings (Zhang, 2018; D'Oca, 2018). 41% of primary energy consumption occurs in buildings in the US, mainly for maintaining a comfortable and healthy indoor environment (US Department of Energy, 2011). Current methods for simulating building energy consumption are often inaccurate, with error ranging from 150% to 250% (De Wilde, 2014; Zou, 2018). Furthermore, changes in occupant behavior have great potential to reduce building energy consumption (Sun, 2017). Therefore, it is important to identify an approach for estimating the impact of occupant behavior on building energy consumption.

Previous studies have tried to predict the energy consumption in commercial and residential buildings with the use of various occupant behavior models. These models can be divided into three categories: data-driven, physics-based and hybrid models. The data-driven models considered different variables that affect occupant behavior in buildings. However, the generalization capabilities of these data-driven models were not good, since the occupant behavior differed from building to building (O'Brien, 2017). Moreover, all the data-driven models require sufficient data for training, but the estimation of building energy and modelling of occupant behavior are done mostly during the early design stages, when collecting occupant behavior data is impossible (O'Brien, 2017). It is hard to build a data-driven occupant behavior model without data or satisfactory generalization capability. But physics-based occupant behavior models with physical meaning have exhibited better generalization capability than data-driven models. Hence, we need to build a physics-based reinforcement learning occupant behavior model to explore the model's scalability.

Moreover, in many buildings, although occupants can actively adjust indoor environment settings, some researches (Peffer, 2011; Karjalainen, 2009) have shown that the occupants know little about the thermostat or the HVAC control system, and thermostats often have unsuitable settings. The resulting overheating and overcooling issues in buildings reportedly waste ten billion dollars per year in the US (Derrible, 2015). We also found that in multi-occupant offices, unawareness of others' feelings and the need to compromise with other people worsened the indoor environment and sometimes made it more extreme (Deng, 2018). To solve these issues, we need to automate HVAC control systems and create "smart" systems that can ascertain occupants' thermal sensation (Dong, 2019). In these ways, the impact of occupant behavior on the built environment, building energy consumption and the HVAC control system could be reduced to the lowest.

1.2 Outline

Chapter 2 presents literature reviews of evaluation methods for thermal comfort, occupant behavior models for building performance simulation and personalized thermal comfort models using various human physiology parameters. Then based on the literature review, we list the tasks that are proposed to do.

Chapter 3 presents artificial neural network models for predicting thermal sensations and occupant behavior. We collected data in offices and apartments/houses, then built and trained the models by using the collected data. Finally, the models were used to predict an acceptable thermal environment.

Chapter 4 presents the impact of occupant behavior on energy use of HVAC systems in offices. We simulated the energy use in the offices and implemented the behavioral ANN model in the simulation program.

Chapter 5 presents the RL model of occupant behavior with logic of pursuit of thermal comfort in Markov decision process. Then we used transfer learning for cross-building transfer for buildings without data and limited information.

Chapter 6 presents a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband. We collected data in seven multi-occupant offices and trained an ANN model using the collected data. Finally, we developed and validated the control strategies for the HVAC systems according to the correlation.

Chapter 7 summarizes the conclusions of this dissertation and potential future works .

2. LITERATURE REVIEW

The layout of this chapter is organized as follows: Section 2.1 reviews the evaluation methods for thermal comfort. Section 2.2 reviews the occupant behavior models for building performance simulation. Section 2.3 reviews the reinforcement learning and transfer learning models. Section 2.4 reviews the personalized thermal comfort using various human physiology parameters. Finally, Section 2.5 draws the conclusions and lists the tasks that are proposed to do.

2.1 Evaluation methods for thermal comfort

Current evaluation methods for thermal comfort can be divided into two categories: with and without the controlled indoor environments categories (Van Craenendonck, 2018). 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 (1970) was developed by testing subjects under different steady-state indoor environments. 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 means of questionnaires without varying controlled parameters (De Dear, 1998; Mishra, 2013; Goto, 2007; Cao, 2011). These field studies have typically collected data in operational buildings, with the benefit of larger samples and enhanced ecological validity. However, variation in such thermal environments may be limited. Some studies (De Dear, 1998; Murakami, 2007; Hwang, 2006) 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 occupant behaviors that influence comfort. 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 (Guerra-Santin, 2016; O'Brien, 2014) may also impact the behaviors. And energy cost (Yu, 2011; Chen, 2017; Cayla, 2011) probably influences the behaviors as well.

Leaman's post-occupancy evaluation (1999) of UK office buildings also found that for occupants, "satisficing" (Simon, 1956) may be a better description of occupant behavior and control than simply thermal comfort optimization. Satisficing means to permit satisfaction at some specified level of all of its needs (Simon, 1956). However, a limitation of some previous thermal comfort studies was that they did not consider occupant behavior in regard to thermal comfort. Numerous studies (Langevin, 2015; Toftum, 2016; Luo, 2014; Zhou, 2014) have found that occupants' control of AC changes their thermal sensations, because the control behavior impacts their expectations of thermal comfort. As Gunay (2013) found that occupants override automation systems indicating their dissatisfaction. Some recent studies have collected data of occupant behaviors to develop some more complex thermal comfort and behavior models in offices and dwellings. For example, D'Oca (2014) developed a logistic regression method for window opening and thermostat set point adjustments in residential buildings. Vellei's model (2016) focused on the effect of real-time feedback on occupants' heating behaviors and thermal adaptation. Lee (2014) and Langevin (2015) developed and validated agent-based behavior models for office buildings. Without the behavioral impact on control, occupants' tolerance for discomfort is significantly reduced (Day, 2017). Therefore, it is necessary to consider occupants' thermal sensations and behavior in indoor environments to develop an evaluation method for indoor thermal comfort.

2.2 Occupant behavior models for building performance simulation

For building environment studies, occupant behavior in buildings refers to occupants' presence, movement and interactions with building systems such as thermostats, windows, lights, blinds and internal equipment (Hong, 2016). 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 (2013), which further impacts predicted energy use as most designers used that standard for building energy estimation (Deng, 2018; Ghahramani, 2018). Similarly, other types of occupant behavior such as occupancy and lighting schedule have been found to vary considerably among buildings (Gunay, 2013). 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 (Paone, 2018). For example, Haldi and Robinson (2011) 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 (2017) collected window-opening data in 76 dormitory rooms in three residential buildings in order to predict window operation. An et al. (2017) 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 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 occupant behavior is impossible (O'Brien, 2017) as Figure 2.1 shows. Therefore, building performance simulation has become a powerful tool for studying the impact of occupant behavior on building energy use.

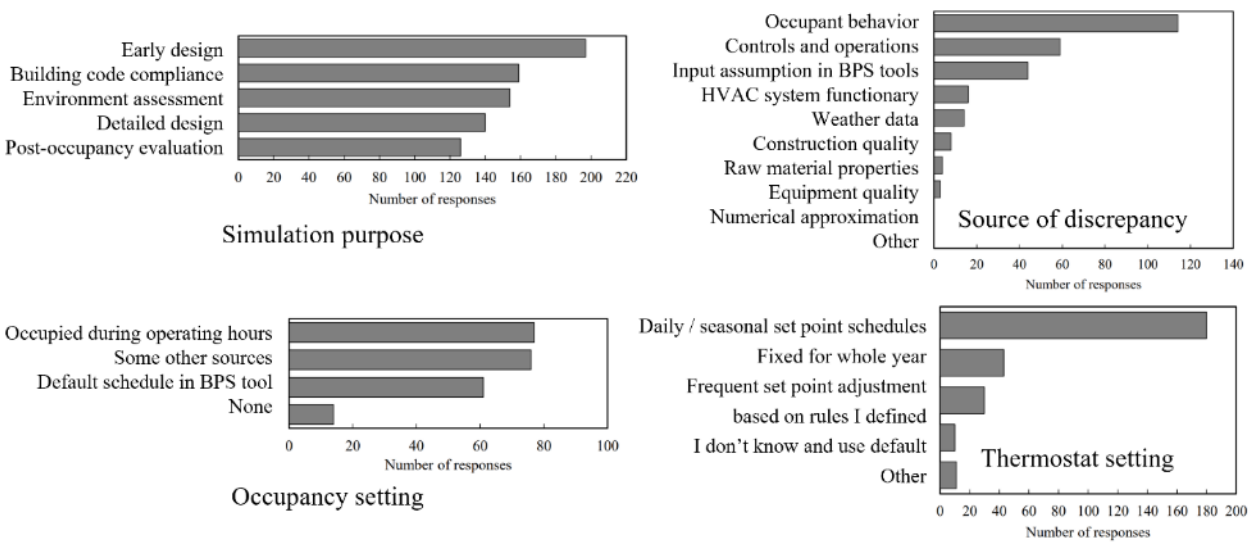
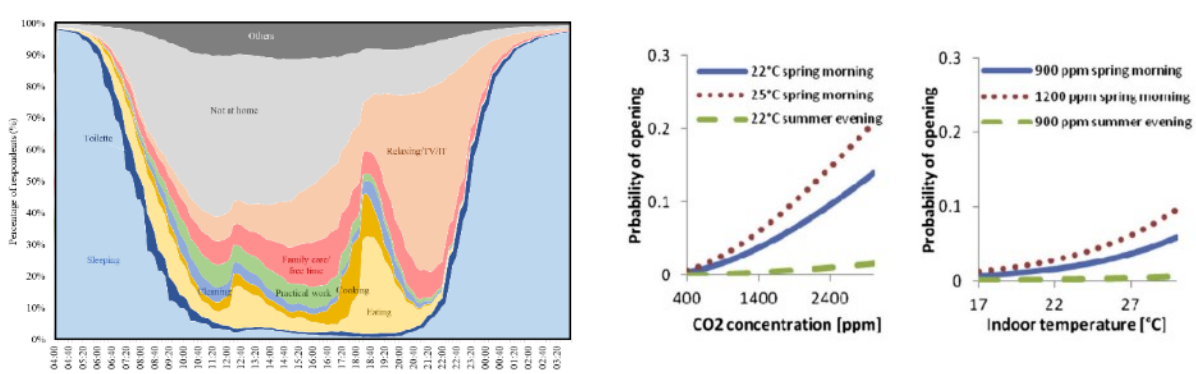


Figure 2.1. International survey results 274 researchers for purpose of building performance simulation, source of discrepancy, occupancy setting and thermostat setting (O'Brien, 2017).

In the building performance simulation, modeling occupant behavior is challenging because of its complexity (Yan, 2015; Hong, 2018). Previous studies have tried to predict the energy consumption in commercial and residential buildings with the use of various occupant behavior models as Figure 2.2 shows, such as linear regression models (Andersen, 2011), logistical regression models (Fabi, 2013; Langevin, 2015) and statistical models (Pfafferott, 2007; Sun, 2017; Jang, 2016). 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 (Feng, 2017; Parys, 2011; Gunay, 2014) represent occupant behavior as a dynamic process in building performance simulations in both spatial and temporal domains. Agent-based models

(Papadopoulos, 2016; Azar, 2011; Lee, 2014) 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 (Dong, 2018) and window-opening behavior (Sun, 2017; Haldi, 2011; Laurent, 2017; Yousefi, 2017; D'Oca, 2014), while neglecting other occupant behavior such as adjusting the thermostat set point.

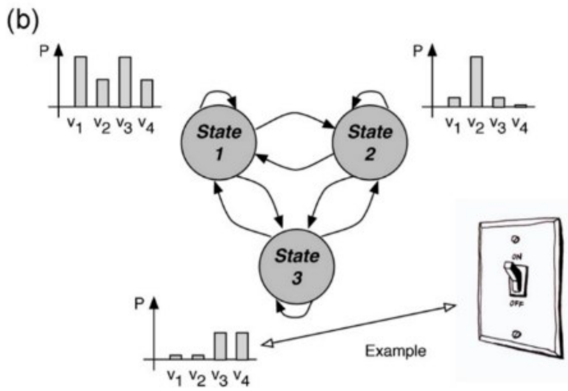
According to a survey of current occupant modeling approaches in building simulations as Figure 2.1 shows (O'Brien, 2017), 66% of the researchers modeled the thermostat set point as a daily schedule, while another 16% used a constant for the entire year. Very few researchers have explicitly acknowledged the occupants' interaction with the thermostats (O'Brien, 2017). For example, Simona et al. studied the effect of thermostat occupant behavior models on energy use in homes according to a probabilistic approach (D'Oca, 2014). Albert and coauthors (2017) 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. Gunay and coauthors (2018) developed and implemented a thermostat learning algorithm in seven private offices to save energy use. However, the US Department of Energy Reference Building Models (Deru, 2011) suggested modelling thermostat set point setback in office buildings. A review paper (Hong, 2016) 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 (Paone, 2018). Table 2.1 lists the comparison of various occupant behavior models.



(a) (b)

Figure 2.2. Various of typical occupant behavior models in literature: (a) schedule model (Barthelmes, 2018); (b) regression model (Andersen, 2013); (c) Markov model (Virote, 2012); (d) decision tree model (Zhou, 2016); (e) agent-based model (Azar, 2012).

Figure 2.2 continued



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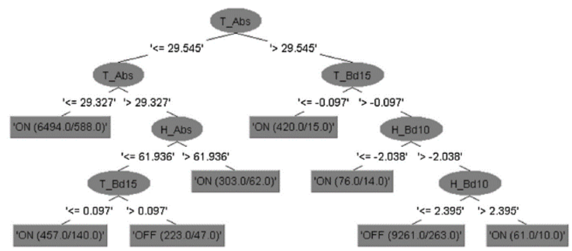

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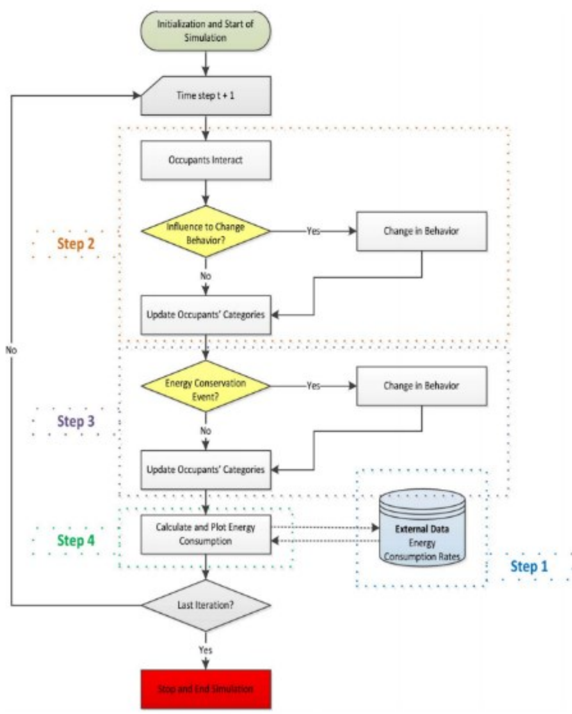


(e)

Table 2.1. Comparison of various occupant behavior models

Models	Non-linearity	Controlled complexity	Flexibility	Scalability	Physical meaning
Schedule	Low	-	-	-	+
Regression	Low	-	-	-	+
Probability	Moderate	-	-	+	+
Decision tree	Moderate	+	+	-	+
Markov	Moderate	+	-	+	+
ANN	High	+	+	+	-
SVM	High	+	+	+	-

These occupant behavior models can be divided into three categories: data-driven, physics-based and hybrid models. In the data-driven category, many researchers have built linear regression models (Andersen, 2011), logistic regression models (Fabi, 2013; Langevin, 2015), statistical models (Pfafferott, 2007; Sun, 2017), and artificial neural network (ANN) models (Deng, 2018). To be specific, regression models by Andersen (2011) and Fabi (2013) collected data on occupants' heating set-points in dwellings and predicted the thermal preference along with indoor environmental quality and heating demand. Langevin's model (2015) used heating set-point data from a one-year field study in an air-conditioned office building. Sun and Hong (2017) used a simulation approach to estimate energy savings for five common types of occupant behavior in a real office building across four typical climates. Deng and Chen (2018) collected data in an office building for one year to predict occupant behavior in regard to thermostat and clothing level by means of an ANN model. In these studies, the models considered different variables that affect occupant behavior in buildings. However, the generalization capabilities of these data-driven models were not good (Wang, 2020), since the occupant behavior differed from building to building. Some review papers (O'Brien, 2014; Stazi, 2017) have discussed contextual factors that cause occupant behavior to vary greatly, such as room occupancy, availability and accessibility of an HVAC system, and interior design. The authors observed that it was difficult to apply an occupant behavior model developed for one building to another building. Hong et al. (2015) also indicated that, because a large number of data-driven behavior models emerged in scattered locations around the world, they lack standardization and consistency and cannot easily be compared one with another. Moreover, all the data-driven models require sufficient data for training, but the estimation of building energy and modelling of occupant behavior are done mostly during the early design stages, when collecting occupant behavior data is impossible (O'Brien, 2017). It is hard to build a data-driven occupant behavior model without data or satisfactory generalization capability.

As for the physics-based models, a review by Jia et al. (2017) pointed out that occupant behavior modelling has progressed from deterministic or static to more detailed and complex. Therefore, many researchers have based their models on the causal relationships of occupant behavior. The driving factors of occupant behavior can be divided into three main types: environmentally related, time related and random factors (Fabi, 2012; Stazi, 2017). Hong et al. (2015) developed a DNAS (drivers, needs, actions, systems) framework that standardized the representation of energy-related occupant behavior in buildings. Many researchers have adopted this framework for their behavior studies. For example, dynamic Bayesian networks by Tijani et al. (2016) simulated the occupant behavior in office buildings as it relates to indoor air quality. The advantage of the Bayesian network model was in its representation of occupant behavior as probabilistic cause-effect relationships based on prior knowledge. D'Oca et al. (2015) built a knowledge discovery database for window-operating behavior in 16 offices. Zhou et al. (2020) used an action-based Markov chain approach to predict window-operating actions in office spaces. They found that the Markov chain reflected the actual behavior accurately in an open-plan office and was therefore a beneficial supplemental module for energy simulation software. The Markov chain model depends on the previous state to predict the probability of an event occurring. This characteristic is useful for representing individuals' actions and motivations (Yan, 2015). In addition, many researchers have built other kinds of models for different building types and scenarios. For instance, hidden Markov models (Jia, 2017; Andrews, 2011) were used to simulate occupant behavior with unobservable hidden states, and thus these models could be employed under very complicated conditions. Survival models (Reinhart, 2004) could feature different occupant types to mimic variations in control behavior. Meanwhile, a decision tree model (Ryu, 2016; Zhou, 2016) regarded occupant decisions and possible behavior as branched graphical classification. This model was straightforward, but complex causal factors in real situations might give rise to too many branches. In recent years, more complex agent-based models (Papadopoulos, 2016; Azar, 2012; Lee, 2014) have yielded good predictions of occupant behavior with individual differences among occupants. In short, physics-based occupant behavior models with physical meaning have exhibited better generalization capability than data-driven models. Hence, the present study used a Markov decision process (MDP) to model occupant behavior and build a logic-based reinforcement learning model to explore the model's scalability.

2.3 Reinforcement learning and transfer learning models

Reinforcement learning (RL) is a machine learning area concerned with the ways in which agents take actions to maximize certain rewards (Sutton, 1998). Off-policy RL can use historical data for training without interacting with the environment. In contrast, policy-based reinforcement learning does not require previous training data because it creates its own experience via random explorations of the environment. As such, this way of learning can obtain rules and knowledge not limited to specific conditions but adaptable to various scenarios. It has been applied successfully to a range of fields, including robot control (Lillicrap, 2015) and playing Go (Silver, 2017). In the built environment, the RL model has been used to improve building energy efficiency and management when the reward is defined as minimizing building energy consumption (Zhang, 2019; Kazmi, 2019; Yu, 2019). For instance, Zhang et al. (2019) used deep reinforcement learning to control a radiant heating system in an existing office building and achieved a 16.7% reduction in heating demand. A multi-agent reinforcement learning framework by Kazmi et al. (2019) achieved a 20% reduction in the energy required for the hot water systems in over 50 houses. Yu (2019) modelled an HVAC scheduling system control as an MDP, and the model did not require prior knowledge of the building thermal dynamics model. Similarly, when the reward is the thermal comfort level of occupants, the RL model can be used to control the thermal comfort and HVAC system in buildings (Han, 2020; Han, 2019). For example, Yoon et al. (2019) built performance-based comfort control for cooling while minimizing the energy consumption. Ruelens and coauthors (2015) used model-free RL for a heat-pump thermostat. Their learning agent reduced the energy consumption by 4–9% during 100 winter days and by 9–11% during 80 summer days. Azuatalam et al. (2020) applied RL to the optimal control of whole-building HVAC systems while harnessing RL's demand response capabilities. Similarly, Chen (2019) and Ding (2020) developed novel deep RL for reducing the training data set and training time. Meanwhile, several previous studies used the RL model for advanced building control (Yoon, 2019; Jia, 2019; Chen, 2018) and lighting control (Park, 2019). In addition, there have been some integrated applications. For example, Valladares et al. (2019) used the RL model with a probability of reward combination to improve both the thermal comfort and indoor air quality in buildings. The RL model developed by Brandi et al. (2020) optimized indoor temperature control and heating energy consumption in buildings. Ding et al. (2019) also employed a novel deep RL framework for optimal control of building subsystems, including HVAC, lighting, blind and window. Hence, RL can be used to model the HVAC system for both thermal comfort and energy management. Physics-based and model-free RL also have the potential to model occupant behavior without data since the logic is very similar. Therefore, this research built an RL model for thermostat set point and clothing level adjustment behavior based on the correlation between thermal sensation and thermally influenced occupant behavior.

For modeling of the occupant behavior in buildings with limited information and no data, transfer learning was a feasible approach (Wang, 2020). The transfer learning method stores knowledge about one problem and then applies it to a related problem. It has been used for cross-building (Li, 2020, Mosaico, 2019), cross-home (Ali, 2019) and even cross-city (Alam, 2017) energy modelling. For instance, Mocanu et al. (2016) transferred a building energy prediction to a new building in a smart grid. Ribeiro et al. (2018) used various machine learning methods to predict school building energy and transfer the prediction to other new schools. Gao et al. (2020) built a transfer learning model for thermal comfort prediction in multiple cities. Xu et al. (2020) conducted transfer learning for HVAC control between buildings with different sizes, numbers of thermal zones, materials, layouts, air conditioner types, and ambient weather conditions. They found that this approach significantly reduced the training time and energy cost. Therefore, based on the potential of transfer learning, we used it to transfer knowledge about occupant behavior from one building to other buildings.

2.4 Personalized thermal comfort models using various human physiology parameters

Thermal sensation encompasses the physiological and subjective response of occupants to the thermal environment in buildings, in vehicles and outdoors (Arens, 2006). To evaluate thermal sensation, Fanger (1970) developed predictive mean vote (PMV) and predicted percentage dissatisfied (PPD) models in the 1970s. However, the PMV model was developed by conducting a questionnaire with a large group of occupants. The model does not consider individual differences and parameters and thus cannot be used for personalized control. Subsequently, many researchers have developed personalized thermal comfort models (Kim, 2018) that achieve better accuracy with more individualized parameters, and may also be used to control the indoor environment (Ghahramani, 2015; Zhao, 2014; Park, 2018). For example, Lee (2017; 2019) developed a Bayesian classification for personalized thermal preferences in offices. These personalized models (Abouelenien, 2017; Yao, 2008; Choi, 2019; Chaudhuri, 2018) have correlated individual thermal comfort with various parameters of human physiology. The most frequently used physiological parameters for evaluating thermal sensation were local skin temperature (Choi, 2012; Choi, 2017; Wu, 2017), facial temperature (Yi, 2015; Cosma, 2018), heart rate (HR) (Choi, 2012; Nkurikiyeyezu, 2018), blood pressure (Carvalho, 2018; Gilani, 2016), pulse wave (Shin, 2017), brain wave (Yao, 2008; Yao, 2009), and sweat rate (Sim, 2018; Cheng, 2018). These personalized thermal comfort models were able to predict occupants' thermal sensation with high accuracy. Several studies (Sim, 2018; Ji, 2017; Jian, 2017) also found that, when the occupants felt uncomfortable in a transient thermal environment, their skin temperature, HR and sweat rate exhibited a noticeably different pattern from comfortable condition. Hence, a correlation exists between the physiological parameters and occupants' thermal sensation and behavior. It is possible that this correlation can be used to control HVAC systems for thermal comfort.

To measure and monitor human physiological parameters, some studies (Chaudhuri, 2018; Sim, 2018; Liu, 2018; Sim, 2016) used specialized sensors and medical equipment, which were not convenient for occupants' everyday work or for longtime monitoring. In recent years, the development of personal health monitoring devices, such as wristbands and smart watches, have provided the means for nonintrusive monitoring of physiological parameters in real time (Liu, 2018; Li, 2019; Li, 2017). However, only a few studies have used human physiological data for HVAC system control. For example, Li et al. (2017) used the collected data from wristbands and a smart thermostat to build a random forest model for predicting thermal preference, and then used the model to test a smart phone application framework for determining the optimal room conditioning mode and HVAC setting. Yi (2015) and Cosma (2018; 2019) used facial skin temperature from a thermographic camera for a building control system that provided individualized thermal comfort. However, the occupants' clothing level and metabolic rate could not be recorded with the use of the thermographic camera. Li et al. (2018; 2019) used skin temperature and HR to develop an environment optimization algorithm for thermal comfort and energy saving, but the control model was linear, and it could only be used for a single occupant. Currently, there is no smart control algorithm using human physiological data that can be applied to multi-occupant offices.

2.5 Proposed tasks

Based on the literature review conducted in this chapter, the following tasks are proposed to do:

1) To develop methods for evaluating thermal comfort in indoor environments by using thermal sensations and occupant behavior.
2) o investigate the impact of adjusting thermostat set point and occupant's clothing level on the energy use of HVAC systems with measurements and use of an appropriate behavioral model.
3) To build an RL occupant behavior model for thermostat and clothing level adjustment in a particular building, and transfer the model to other buildings with different HVAC control systems.
4) To develop and validate a control strategy for the HVAC systems in multi-occupant offices using wristband.

3. ARTIFICIAL NEURAL NETWORK MODELS FOR PREDICTING THERMAL SENSATIONS AND OCCUPANT BEHAVIOR

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

3.1 Methods

3.1.1 Data collection

Table 3.1. 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.

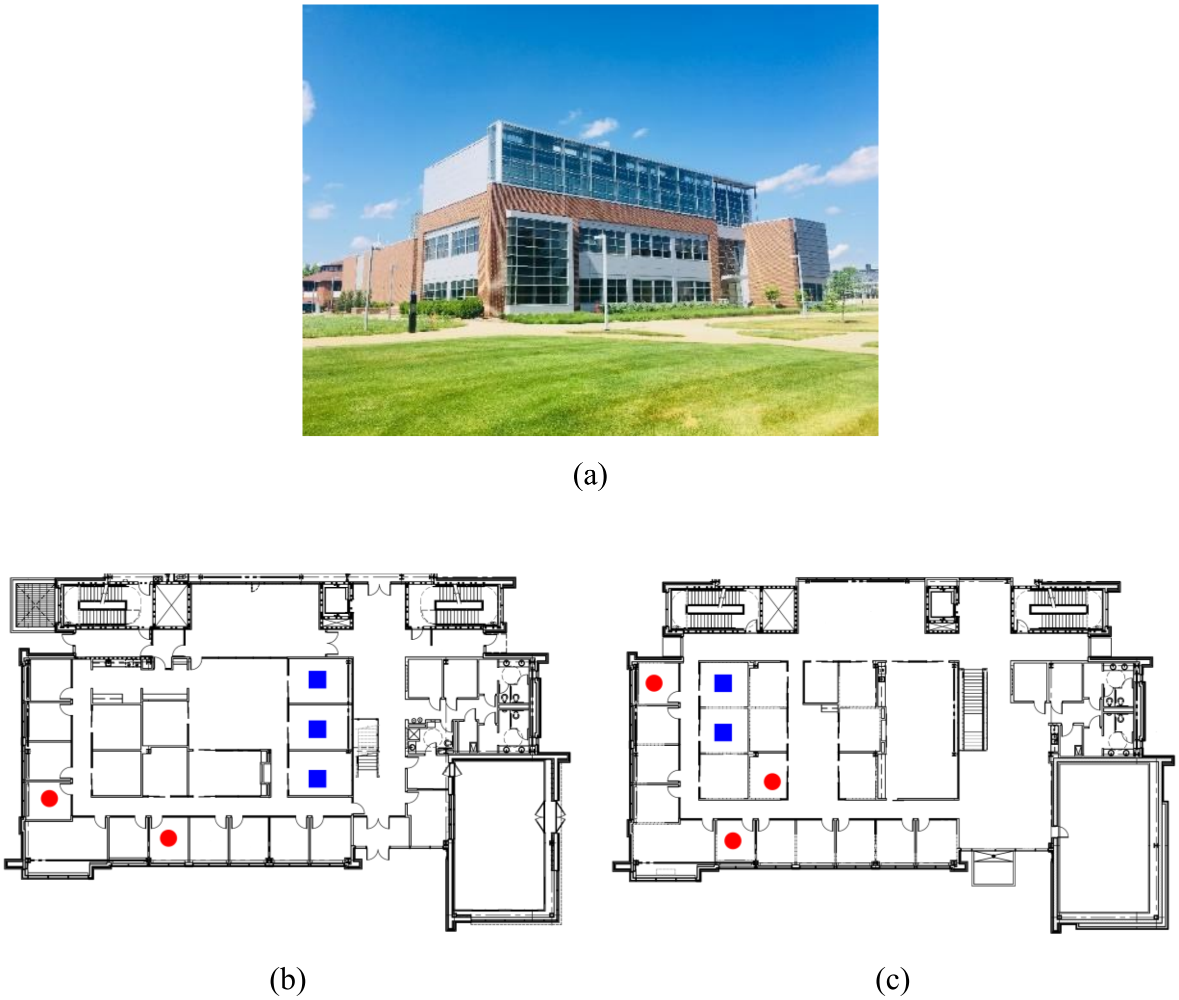


Figure 3.1. (a) Overview of the HLAB office building. Layout of (b) the ground floor and (c) the second floor of the HLAB building. Red dots mark single-occupant faculty offices. Blue squares mark multi-occupant student offices.

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 3.1 (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 3.1. (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 3.1 lists the occupancy states of the ten 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 3.2 provides information about the ten apartments/houses.

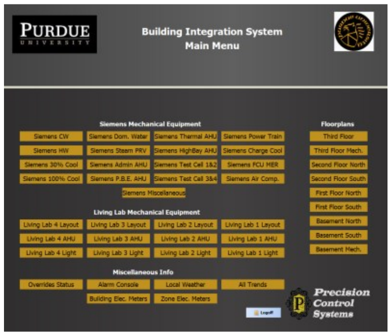
Table 3.2. Information about the ten apartments/houses used for data collection

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 3.2 (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 3.2 (b), so that the lighting on/off status signified that the offices were occupied or unoccupied. Figure 3.2 (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°C (65°F) to 26.7°C (80°F). We used data loggers (Sper Scientific 800049) as shown in Figure 3.2 (d) in each office to collect room air temperature and relative humidity every five minutes. Table 3.3 lists the technical specifications of the data logger. We also used a questionnaire to collect the seven-scale thermal sensation (ASHRAE, 2013) (-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, and also increased the amount of the collected behavior data.

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 purpose of collecting thermal sensation and occupant behavior at the same time was to further compare the model prediction by two kinds of data. The method to answer questionnaire was handwriting.



(a)

(b)

(c)

(d)

Figure 3.2. 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 3.3. 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

The occupant thermal-related behavior of adjusting thermostat set point and clothing level in the indoor environment depend on many different factors (Wei, 2013; Wei, 2014), including thermal comfort level (De Dear, 1998), gender (Karjalainen, 2007), cultural background (Montazami, 2017), outdoor weather (Nicol, 2004; De Carli, 2007), and probably income level (Yu, 2011; Chen, 2017; Cayla, 2011). 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' energy cost 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.

3.1.2 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 (2016) 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 (Ferreira, 2012), residential buildings (Moon, 2012) and office buildings (Marvuglia, 2014). 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 3.3, an ANN model (McCulloch & Pitts, 1943) has a layered structure usually comprised of three layers: an input layer, a hidden layer and an output layer. The number of neurons (Jain, 1996) 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 3.4 shows the mean absolute error (MAE) between predicted and collected thermal sensation with different number of neurons in the hidden layer. The MAE is defined in Eq. (3.1) as follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - x_i\right| \tag{3.1}$$

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 (Jain, 1996) 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.

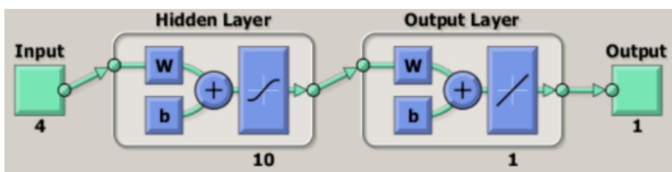


Figure 3.3. Structure of the ANN models, with four input parameters in the input layer, ten neurons in the hidden layer, and one output parameter in the output layer in Matlab (Beale, 2017). The "w" and "b" in the hidden layer and output layer represent weight matrix and bias in Eq. (3.2), respectively, and the transfer functions in the hidden layer and the output layer are a logistic function and a linear function, respectively.

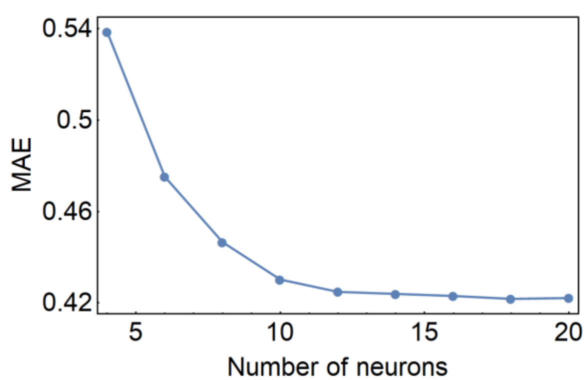


Figure 3.4. Relationship between number of neurons in the hidden layer and the MAE between predicted and collected thermal sensation.

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

$$Y = \mathbf{w}_{output}\{1+\exp[-(\mathbf{w}_{hidden}\mathbf{X}+\mathbf{b}_{hidden})]\}^{-1}+b_{output} \tag{3.2}$$

where $\mathbf{X}$ is an $n \times 1$ 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 (Fanger, 1970), 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 (Hsieh, 1985) and ASHRAE standard 55 (2013), the acceptable comfort zones were within air velocity less than 0.2 m/s, thus the impact of air velocity on thermal comfort could 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. (3.2). 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 (ASHRAE, 2017). Table 3.4 lists the insulation values for different clothing ensembles (ASHRAE, 2017) 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 3.4. Typical insulation values for clothing ensembles (ASHRAE, 2017) 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 3.3 will lead to a mathematical expression of the model for thermal comfort in the following form:

$$\text{Thermal comfort} = f\,(\text{air temperature, relative humidity, clothing insulation, metabolic rate}) \quad (3.3)$$

where f is the ANN model expressed in Eq. (3.2).

This investigation used another ANN model to predict thermal comfort from occupant 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 thermal-related 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

$$\text{Behavior} = g\,(\text{air temperature, relative humidity, clothing insulation, metabolic rate}) \quad (3.4)$$

where g is the ANN model expressed by Eq. (3.2).

3.1.3 Artificial neural network model training

This study used Matlab Neural Network Toolbox (Beale, 2017) in Matlab R2017a to build and train the two ANN models. The training targets were the collected 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 3.5 reveals the least MAE and largest R^2 among the five algorithms. These statistical measures are defined in Eq. (3.1) and (3.5):

$$R^2 = \sqrt{1 - \frac{\sum_{i=1}^{n} (y_i - x_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}} \tag{3.5}$$

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 3.5. 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:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e} \tag{3.6}$$

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. We randomly divided the data into two groups with 70% and 30%. The first one group was for training and the other group was for cross-validation.

Since the occupant behavior in the apartments/houses may be different from that in the offices, the ANN models for offices and apartments/houses were trained separately with the corresponding data.

3.1.4 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 using the following equations:

$$comfort\ zone = \left\{ (air\ temperature, relative\ humidity) \middle| Thermal\ sensation_l \le f \le Thermal\ sensation_u \right\} \tag{3.7}$$

$$comfort\ zone = \left\{ (air\ temperature, relative\ humidity) \middle| g \ge Acceptability \right\} \tag{3.8}$$

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. (3.3), $Thermal\ sensation_l$ and $Thermal\ sensation_u$ 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. (3.4), 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 (Fanger, 1970). The PPD can be calculated by the following expression:

$$PPD = 100 - 95e^{-0.3353PMV^4 - 0.2179PMV^2} \tag{3.9}$$

3.2 Results

The above methods were used to collect the data to train the ANN models for predicting thermal sensations and occupant behavior. The comfort zones predicted by the ANN models were then compared with the comfort zones in ASHRAE Standard 55 (2013).

3.2.1 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 3.5, 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 (spring and fall combined), 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 Figure 3.6, 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 3.6 is exactly the same as that in Figure 3.5. The data contains more than 1000 behavior occurrences in the 10 offices.

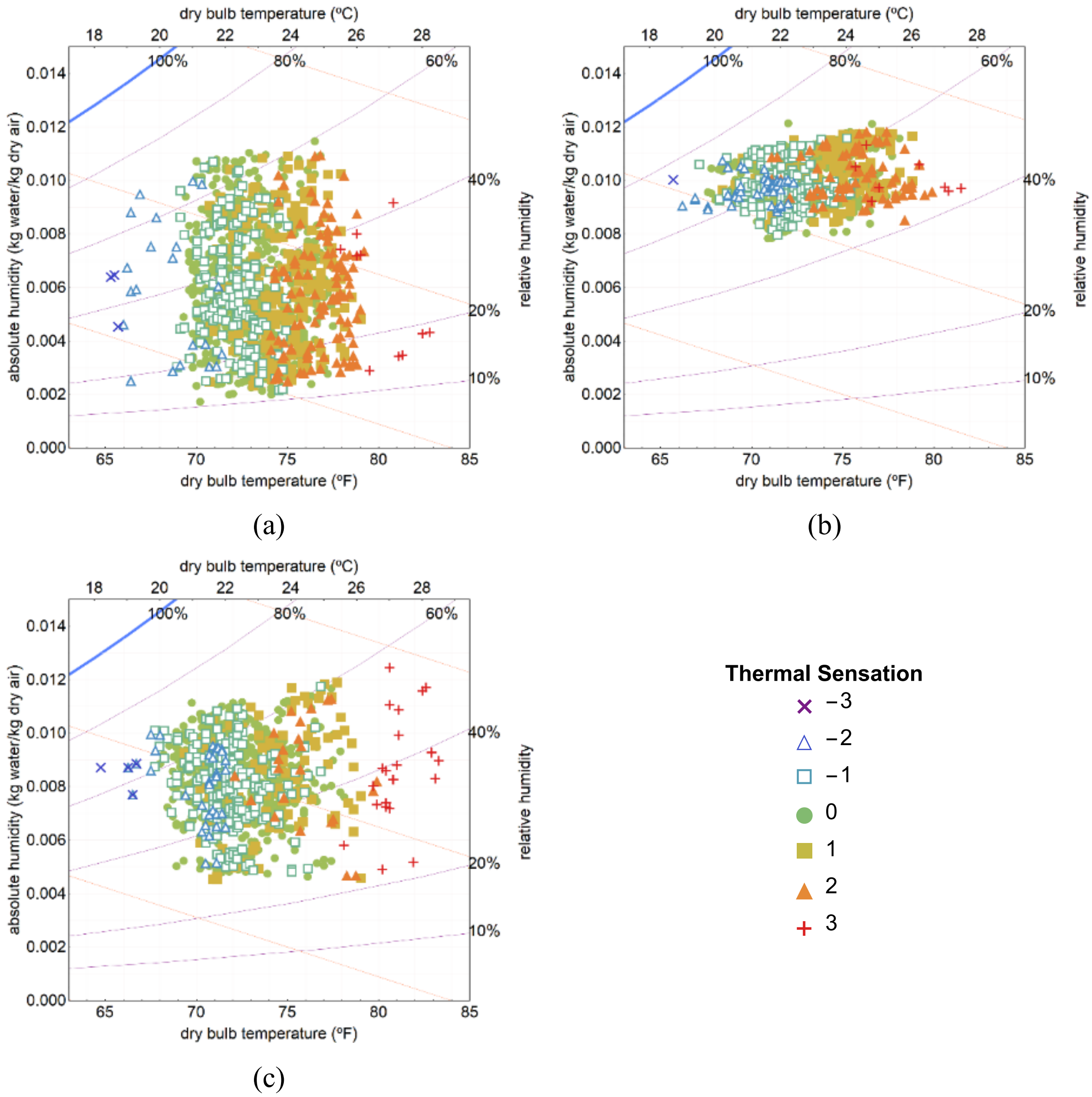


Figure 3.5. Collected thermal sensation data in different thermal environments in (a) winter, (b) summer and (c) shoulder seasons in the offices.

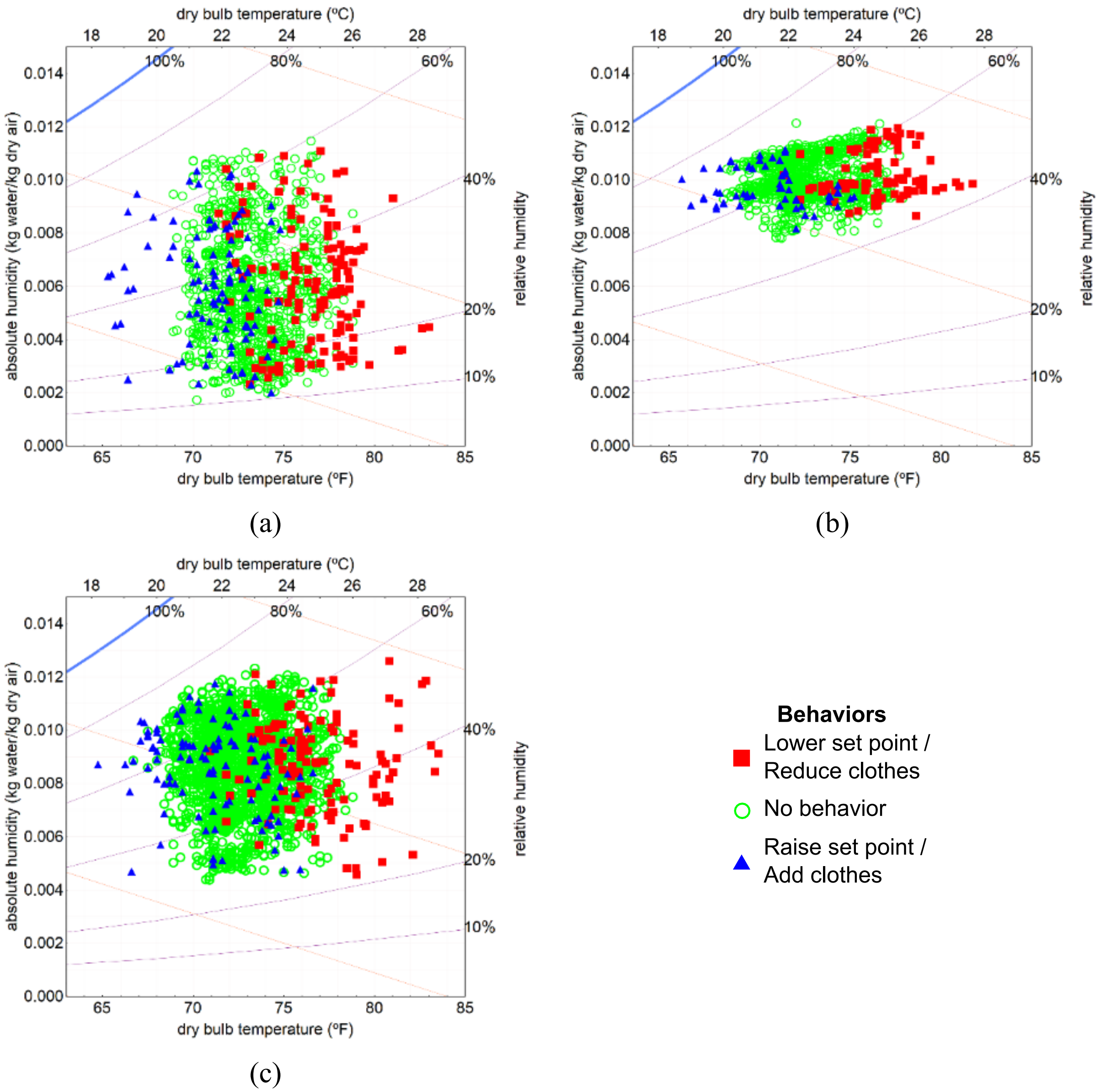


Figure 3.6. Collected behavior data in different thermal environments in (a) winter, (b) summer and (c) shoulder seasons in the 10 offices.

Table 3.6 shows the percentage of occupant 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 thermal-related 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 occupant behavior did not reflect their 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 3.6. Percentages of behavior occurrences under different thermal sensations in the offices. "-1" represents lowering the set point or reducing clothes. "0" represents no behavior. "1" represents raising set point or add clothes.

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 3.7 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°F) to 23.3℃ (74°F) 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°F) 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°F) to 29.4℃ (85°F). 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°F) or lower than 18.9℃ (66°F), 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.

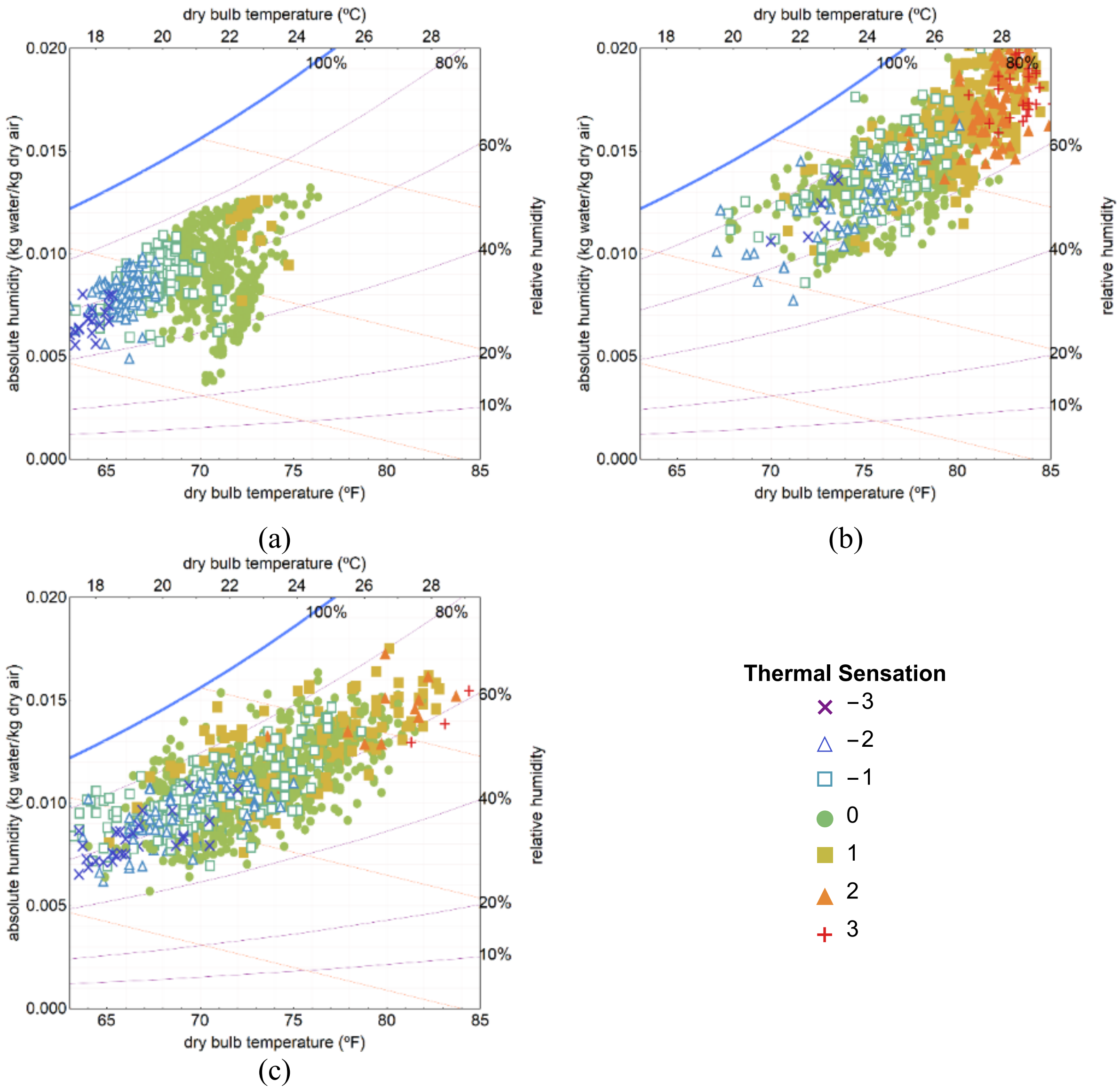
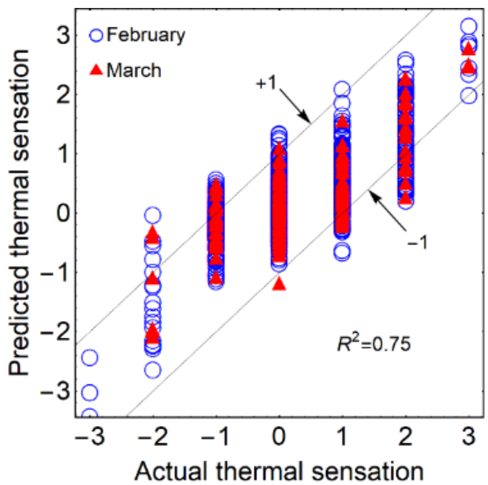


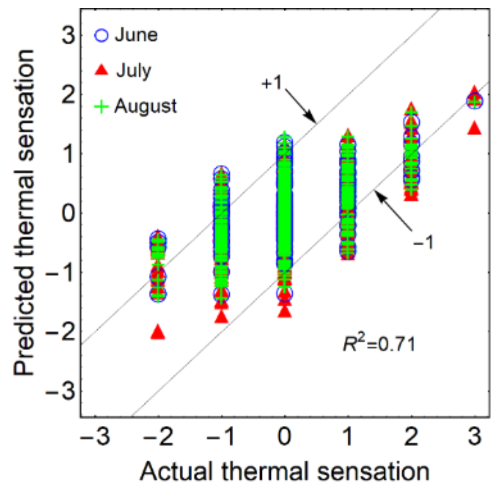
Figure 3.7. Thermal sensation data collected in the 10 apartments/houses in (a) winter, (b) summer, and (c) shoulder seasons.

3.2.2 Artificial neural network model training

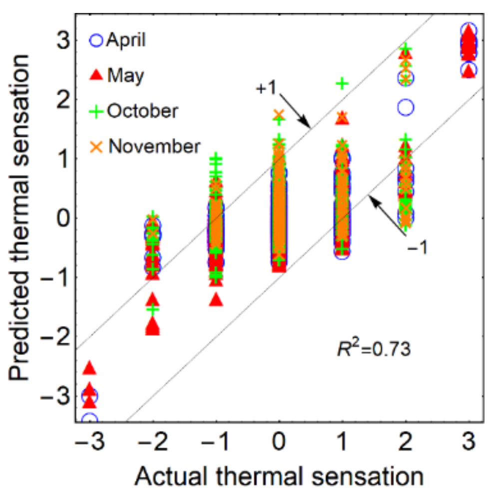
We used the above collected data in all the four seasons to train the ANN models by means of the LM algorithm. Figure 3.8 displays the training results of the ANN model for thermal comfort in winter, summer, and the shoulder seasons in offices. Since the comfort zones in ASHRAE Standard 55 (2013) are 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 3.8, over 85% of the model predictions differed from the collected sensations by less than one unit on the sensation scale. We also used different shapes of the symbols to compare the predicted and collected thermal sensations in different months in each season. Figure 3.8 shows that the comparison between the predicted and collected thermal sensations did not have monthly differences. Figure 3.9 shows the comparison between the predicted and collected thermal sensations for ANN model training and cross validation. The prediction fitted the data with R^2 = 0.74 and 0.71 for training and validation group, respectively. The predicted results were similar for the two groups, which means the good model generalization. In the ASHRAE Handbook (ASHRAE, 2017), previous study (McNall, 1968) 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.



(a)

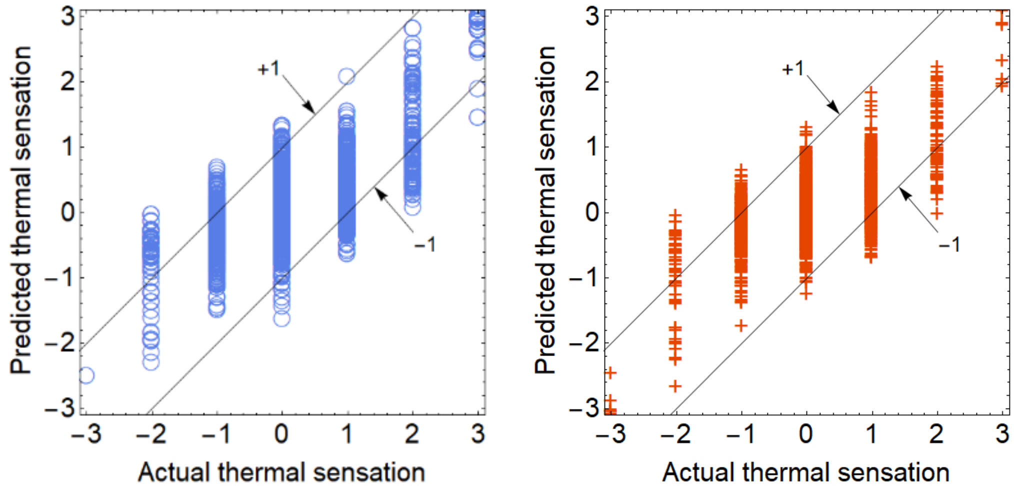


(b)



(c)

Figure 3.8. Comparison between the predicted and collected 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 collected values.



(a) (b)

Figure 3.9. Comparison between the predicted and collected thermal sensations for (a) training group and (b) validation group.

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 on about 17% of all the behaviors, as indicated by the blue and red slices of the pie chart in Figure 3.10. 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 occupant behavior in the offices with the four input parameters.

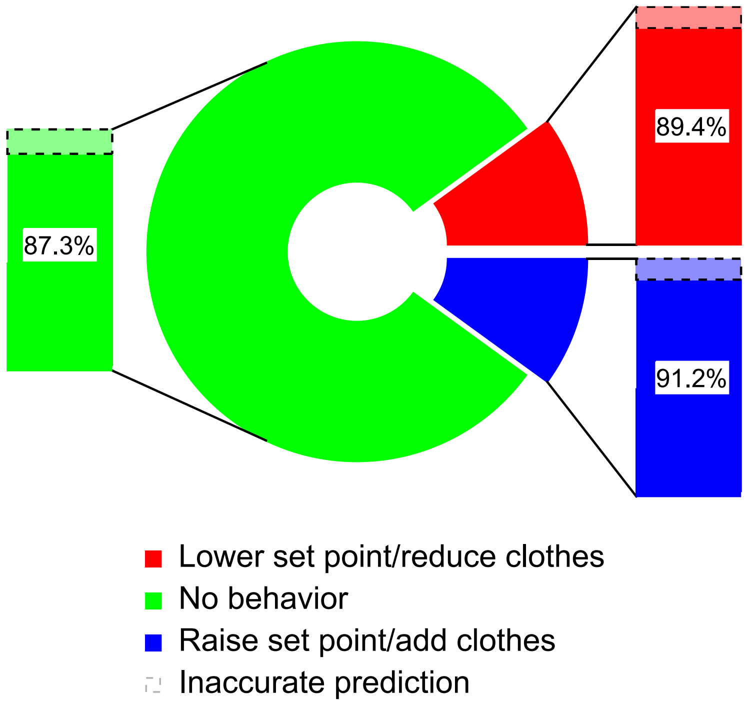


Figure 3.10. Training accuracies of the behavior ANN model for the three kinds of behaviors.

3.2.3 Acceptable indoor environments

3.2.3.1 *Comfort zones predicted by the two ANN models*

After training the ANN models, we used Eq. (3.7) to find the comfort zones by the ANN model for thermal comfort. Figure 3.11 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 (2013) and a short-sleeved shirt and pants in summer (close to 0.5 clo in ASHRAE Standard 55 (2013)). 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°C (69°F) to 25°C (77°F) in winter and from about 20.6°C (69°F) to 25.6°C (78°F) in summer. However, the collected data 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 3.11.

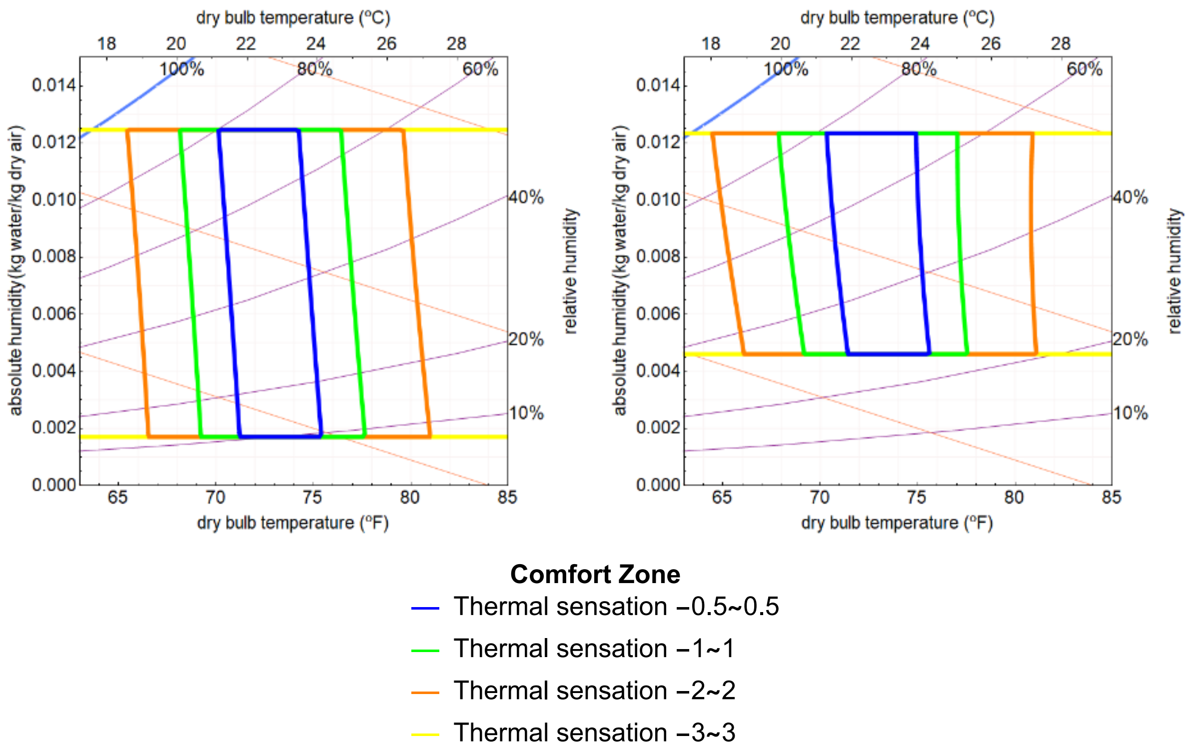


Figure 3.11. Comfort zones for office environments in winter (left) and summer (right) obtained by the ANN model with the use of thermal sensations.

We also used Eq. (3.8) to find out the acceptable zones by the behavioral ANN model. Figure 3.12 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 3.6 correlates occupant 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 3.6 to define the acceptable zones for various percentages of the occupants. The blue zone in Figure 3.11 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°C (70°F) to 25.6°C (78°F) in winter and 20.6°C (69°F) to 25°C (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.

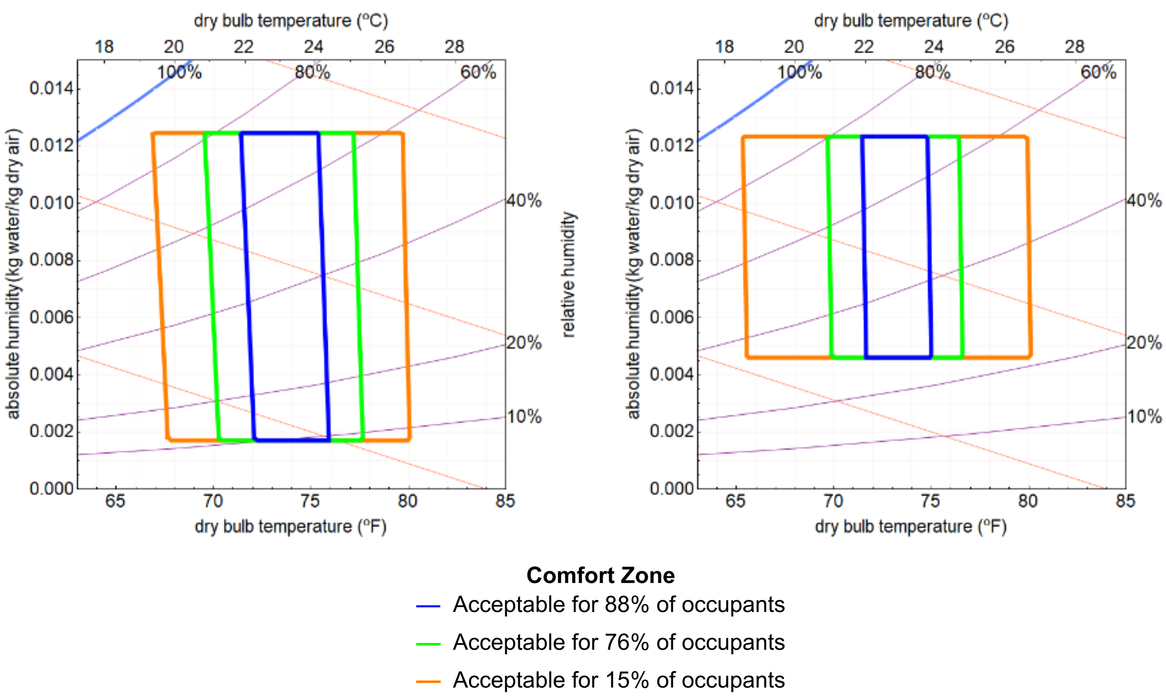


Figure 3.12. Acceptable zones for office environments in winter (left) and summer (right) obtained by the ANN model using behavior.

The acceptable zones obtained by the ANN model with the use of behavior, shown in Figure 3.12, are similar to the comfort zones obtained by the ANN model using thermal sensations, displayed in Figure 3.11. 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 3.7 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, occupant behavior can be used to evaluate the acceptability of an indoor environment in a similar way to can thermal sensations.

In Table 3.7, we also compare the ANN model results for acceptability of the indoor environment with the PPD model. The PPD was calculated by using Eq. (3.9) 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 occupant behavior on thermal comfort. However, our results show that occupant behavior in indoor environments could lower their expectations of comfort and their tolerance for discomfort, which is similar with findings in several previous studies (Langevin, 2015; Toftum, 2016; Luo, 2014; Zhou, 2014).

Table 3.7. 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%

3.2.3.2 *Comparison of comfort zones between multi-occupant and single-occupant offices*

Figure 3.13 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 likely because most of the single-occupant offices located in the exterior zone of the building as shown in Figure 3.1 (b) and (c). These offices had huge glass windows as shown in Figure 3.1 (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°F) to 25℃ (77°F) in winter. The comfortable air temperature for the single-occupant faculty offices in summer was about 1.1℃ (2°F) higher than that in winter. For the multi-occupant student offices, however, the comfortable air temperature in summer was 1.1℃ (2°F) lower than that in winter, as shown in Figure 3.13 (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 3.8 compares the percentage of occupant 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.

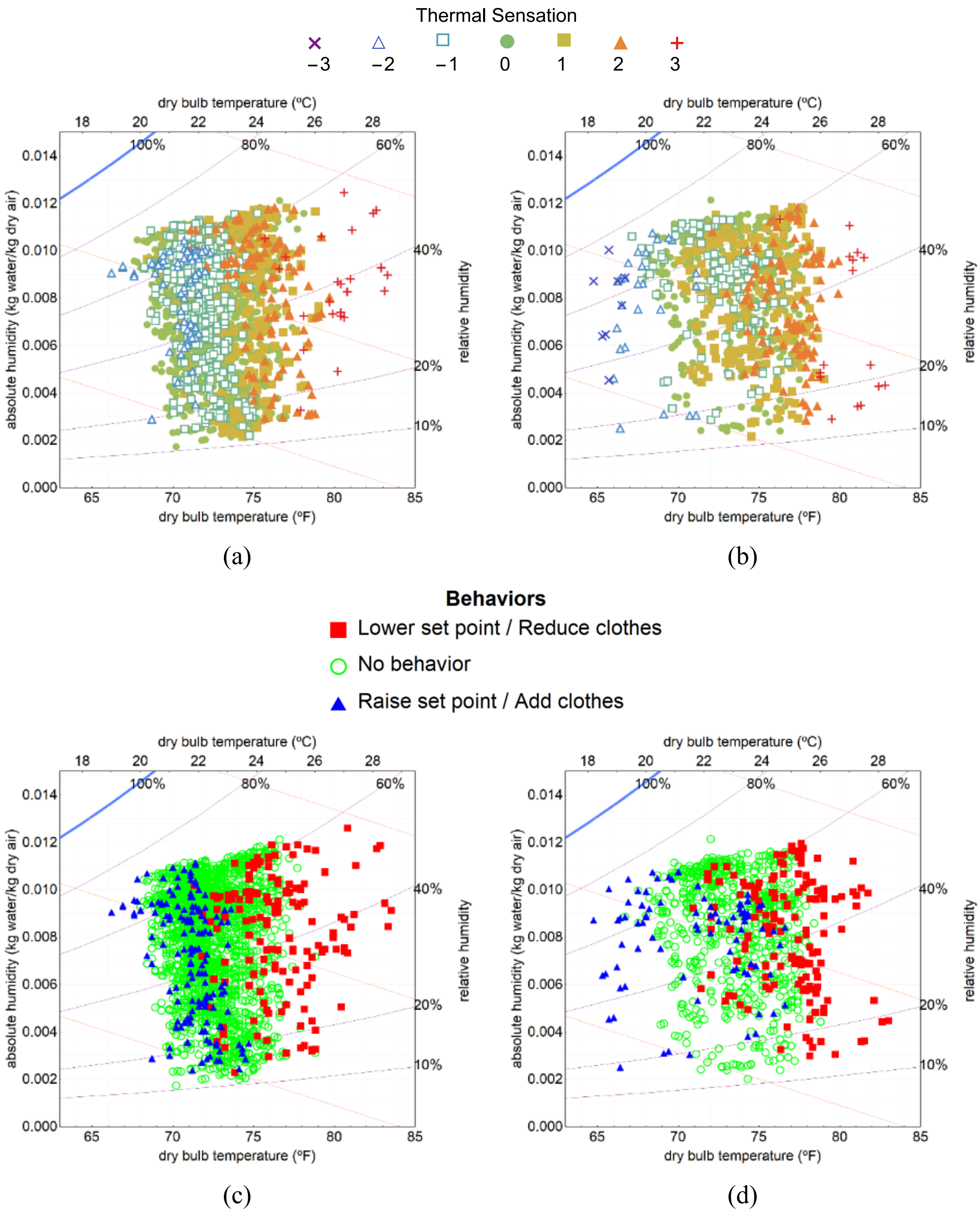
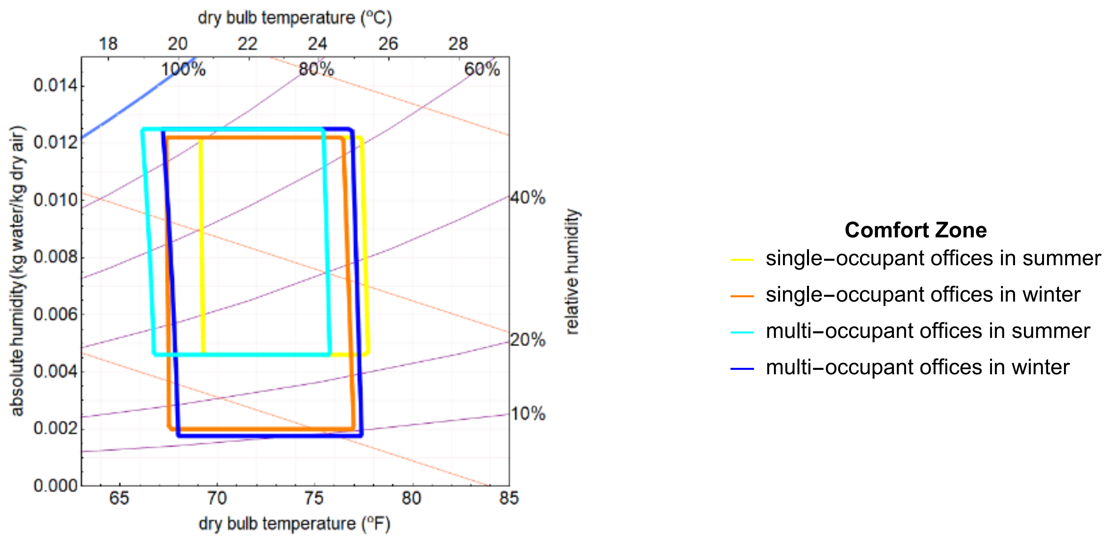


Figure 3.13. (a) Thermal sensation data collected from the multi-occupant student offices, (b) thermal sensation data collected from the single-occupant faculty offices, (c) behavior data collected from the multi-occupant student offices, (d) behavior data collected from the single-occupant faculty offices, and (e) comparison of comfort zones between single-occupant and multi-occupant offices.

Figure 3.13 continued



(e)

Table 3.8. 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%

3.2.3.3 ***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 3.14 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°C (3°F) lower than that in the offices. In summer, the comfortable air temperature in the apartments/houses was 1.7°C (3°F) 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 occupant behavior.

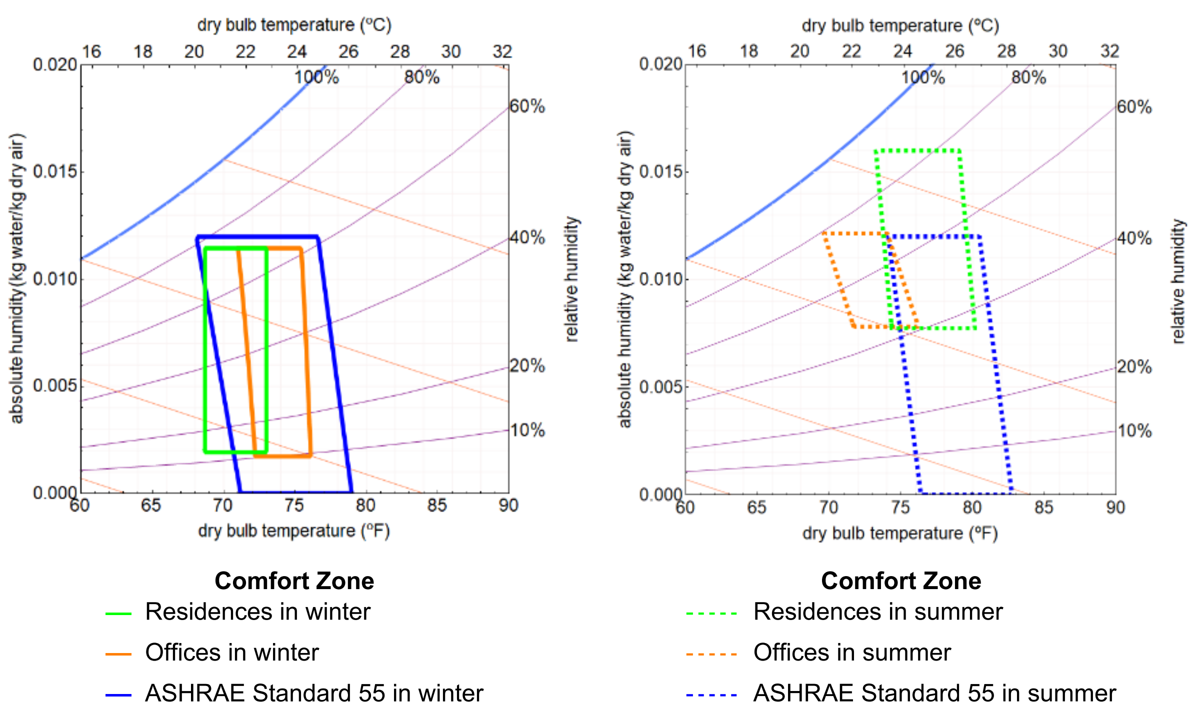


Figure 3.14. Comparison of the comfort zones for the offices, the zones for the apartments/houses, and the ASHRAE comfort zone in (a) winter and (b) summer.

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

Figure 3.15 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 who 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, this assumption can be questioned as stated in Section 3.1.1, 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°F) 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, since the comfort temperature for male may be different from female (Chang, 2019). 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.

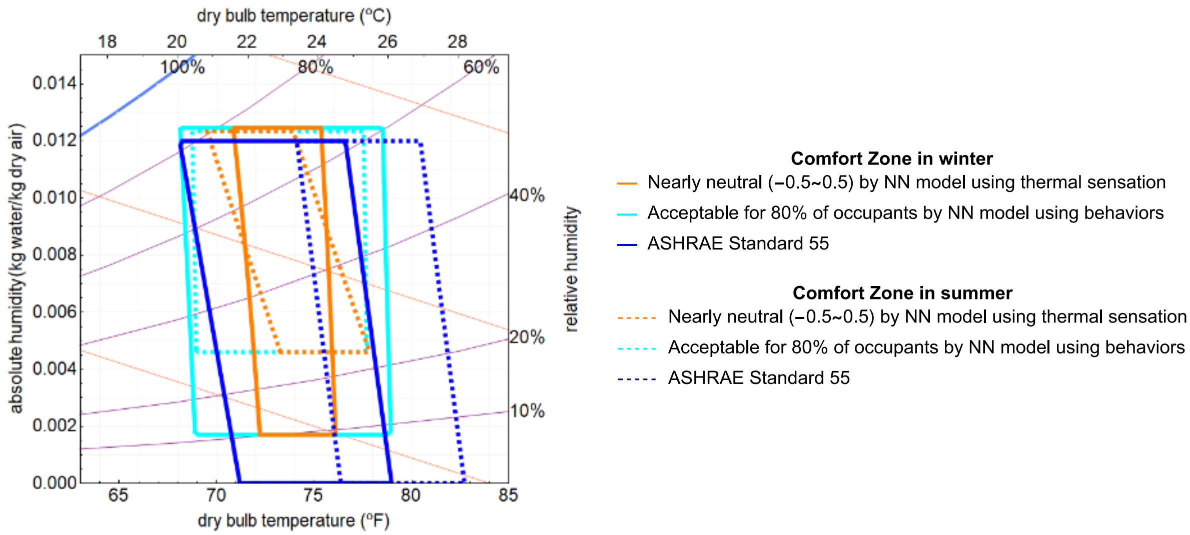


Figure 3.15. Comparison of the comfort zones obtained by the two ANN models and the ASHRAE comfort zones in winter and summer.

3.3 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 3.4, the choices on the questionnaire were limited, but an overly long list might have confused the participants. In addition, we used metabolic rates of $60 W/m^2$ for sitting and $115 W/m^2$ for walking, without accounting for differences in gender or age. Furthermore, the 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' energy cost may have influenced their behavior. A study by Kwon et al. (2007) 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 likely 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 occupant 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 indoor 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.

3.4 Conclusions

In this chapter, 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℃ (2°F) lower than that in the single-occupant offices.

3) Responsibility for paying the energy bill could have an impact on occupant behavior in apartments/houses. The results showed that the comfortable air temperature in the apartments/houses was 1.7℃ (3°F) lower than that in the offices in winter, and 1.7℃ (3°F) 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.

4. SIMULATING THE IMPACT OF OCCUPANT BEHAVIOR ON ENERGY USE OF HVAC SYSTEMS

The layout of this chapter is organized as follows: Section 4.1 presents the methods for collecting data, simulating energy use in the offices and implementing the behavioral ANN model in the simulation program. Section 4.2 presents the comparison between the measured energy use and simulated results. Section 4.3 and 4.4 contain a discussion and conclusions of this chapter, respectively.

4.1 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 (Deng, 2018) to simulate the energy consumption of the HVAC systems in the buildings. What is more, the occupant behavior in some other Purdue buildings was explored. Finally, we quantified the energy saving potential and impact of occupant behavior for other control strategies.

4.1.1 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. Half of the offices were multi-occupant student offices, and the rest were single-occupant faculty offices. Figure 4.2 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. 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.

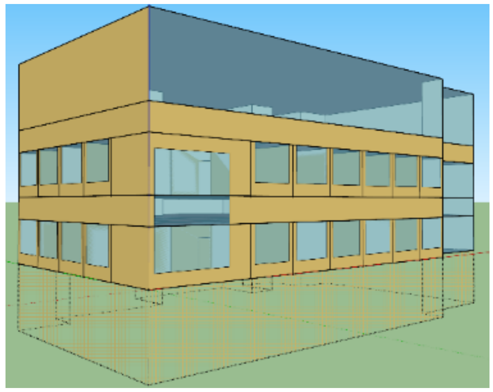


Figure 4.1. Geometric model of the HLAB building for EnergyPlus simulation

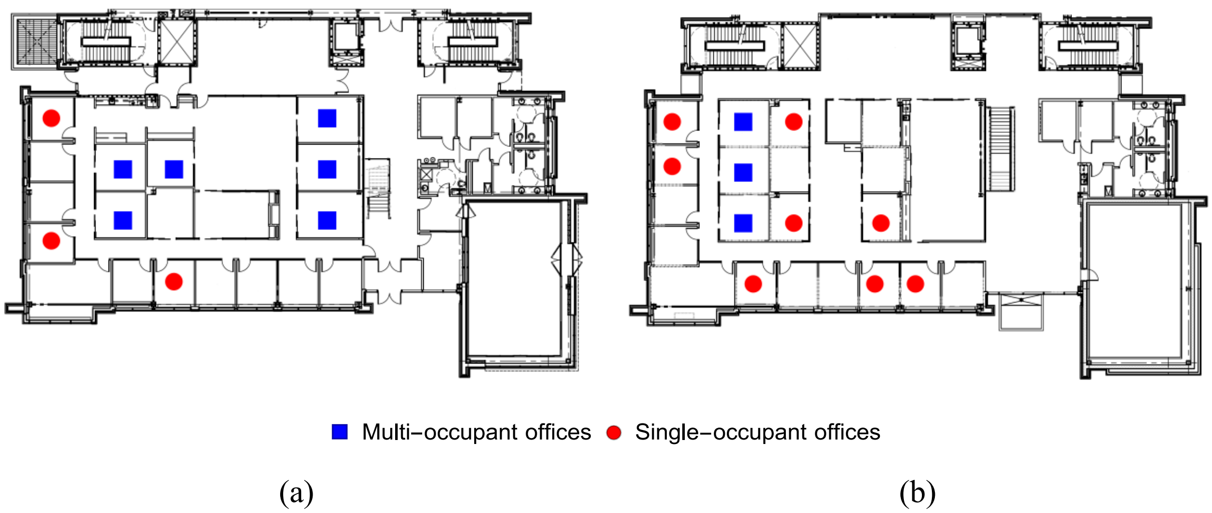


Figure 4.2. Layout of (a) the first floor and (b) the second floor of the HLAB building. The dots and squares indicate the single-occupant and multi-occupant offices used for data collection.

Most data collection methods for indoor environment parameters, occupant behavior and TSV were the same in Chapter 3. What is more, 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°C for heating and 15.5±2.8°C for cooling.

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.

4.1.2 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:

$$V \frac{dC_i}{dt} = \left(C_0 - C_i\right) Q \tag{4.1}$$

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. (4.1), we obtained

$$Q\, t = -V \ln \frac{C_i - C_0}{C_{i,initial} - C_0} \tag{4.2}$$

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. (4.2). 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 (ASHRAE, 2017), *E*, in the offices is

$$E = C_p \rho Q (T_{supply} - T_{room}) \tag{4.3}$$

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 do 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 4.1. 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 4.1 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 (ASHRAE, 2017). 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.

To enable comparison of the simulated results with the measured data, our simulations used 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 collected thermostat set point from the BAS at each moment when validating the simulation program. We then implemented the behavioral ANN model (Deng, 2018) for simulating the occupant behavior of adjusting the thermostat set point and clothing level.

Table 4.1. 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

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 (Tian, 2018). When validating the simulation program, we used the collected thermostat set points, occupancy schedules and clothing level information. For prediction of energy use, we used the behavioral ANN model (Deng, 2018), which is expressed as:

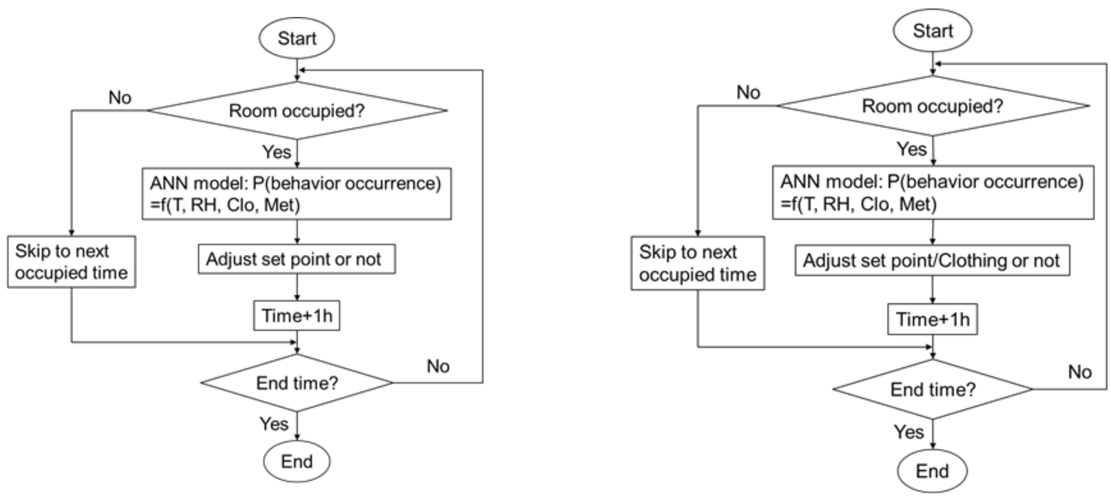
$$\text{Behavior occurrence} = f\,(\text{air temperature, relative humidity, clothing insulation, metabolic rate}) \tag{4.4}$$

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 (ASHRAE, 2017). 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 were 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 Chapter 3.

Figure 4.3 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 (Deng, 2018; Barakat, 2016) 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 occupants in single-occupant offices only took off clothes (e.g., sweaters or coat) when entering the offices. When they stayed in the office and felt uncomfortable, they usually adjusted the thermostat set point to make them 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.



(a) (b)

Figure 4.3. Energy simulation process with the behavioral ANN model for (a) single-occupant office and (b) multi-occupant office.

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 (Deng, 2018), 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 for a short time, no occupant behavior occurred.

With the above methods of data collection, we collected the energy-related data and occupant behavior data from the HLAB building to learn the 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, 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 obtain the simulated energy and their variations in various conditions.

4.2 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 collected occupant behavior, with the behavioral ANN model, and with constant thermostat setting. The measured data are also used for comparison.

4.2.1 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 (Parys, 2011). 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 4.4 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.

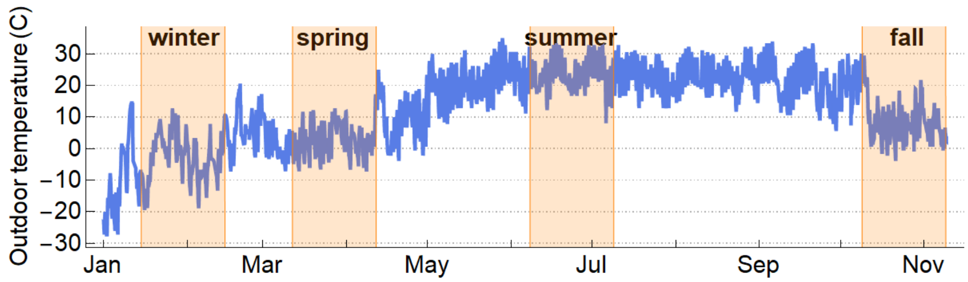


Figure 4.4. Outdoor temperature from January to November of 2018. The shaded regions represent the simulated time windows.

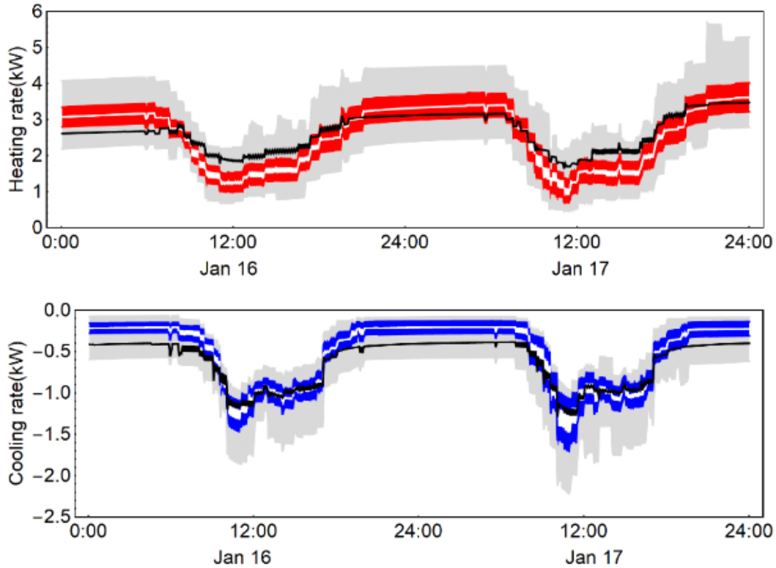
Table 4.2. Comparison between simulated and measured energy use in all the HLAB offices for a one-month period in each of the four seasons.

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
Winter	5,314	19.9	5,156	19.3	3%
Spring	2,833	10.6	2,719	10.2	4%
Summer	2,102	7.9	1,945	7.3	7%
Fall	3,183	11.9	3,083	11.6	3%
	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	998	3.7	870	3.3	13%
Spring	2,261	8.5	2,041	7.7	10%
Summer	2,726	10.2	2,565	9.6	6%
Fall	1,205	4.5	1,315	4.9	9%

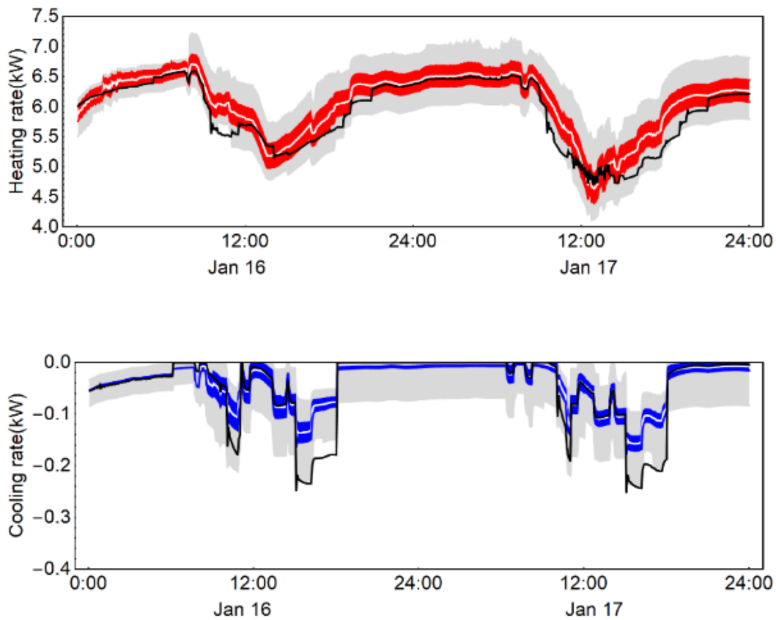
To validate the simulation program, we used the collected behavior data from BAS and questionnaire and fed the behavior data in each time step into EnergyPlus. We compared the simulated and measured energy use in all the offices in the four seasons. On January 30 and October 29, the HVAC system was shut 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 collected data was less than 13%, as shown in Table 4.2. 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 doors were not totally air tight, which added uncertainty to the measured heating and cooling rate.

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.

Figure 4.5 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 4.5 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 4.5 and 4.6. 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.



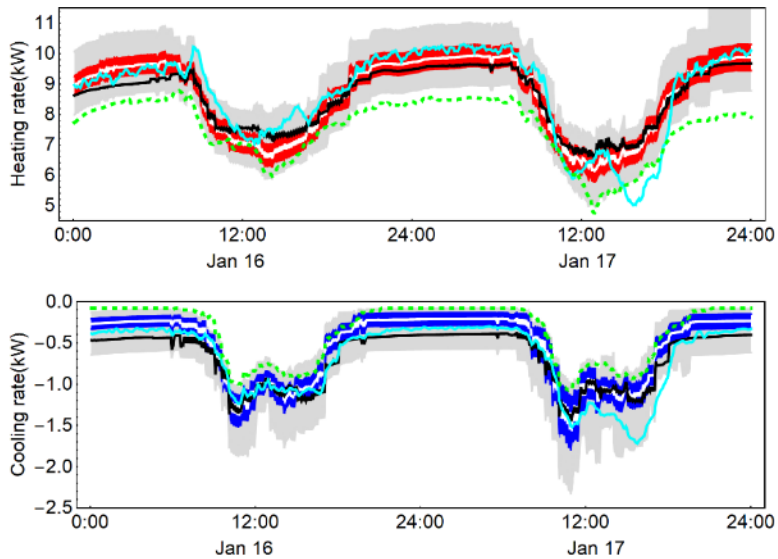
(a)



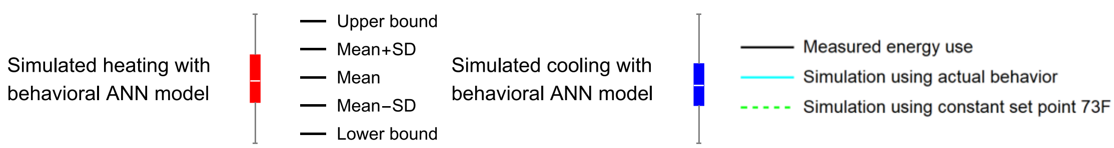
(b)

Figure 4.5. 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.

Figure 4.5 continued



(c)



Figures 4.5 (c) and 4.6 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 collected behavior. The results that were simulated with the use of collected 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°C (73°F) 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 (O'Brien, 2017).

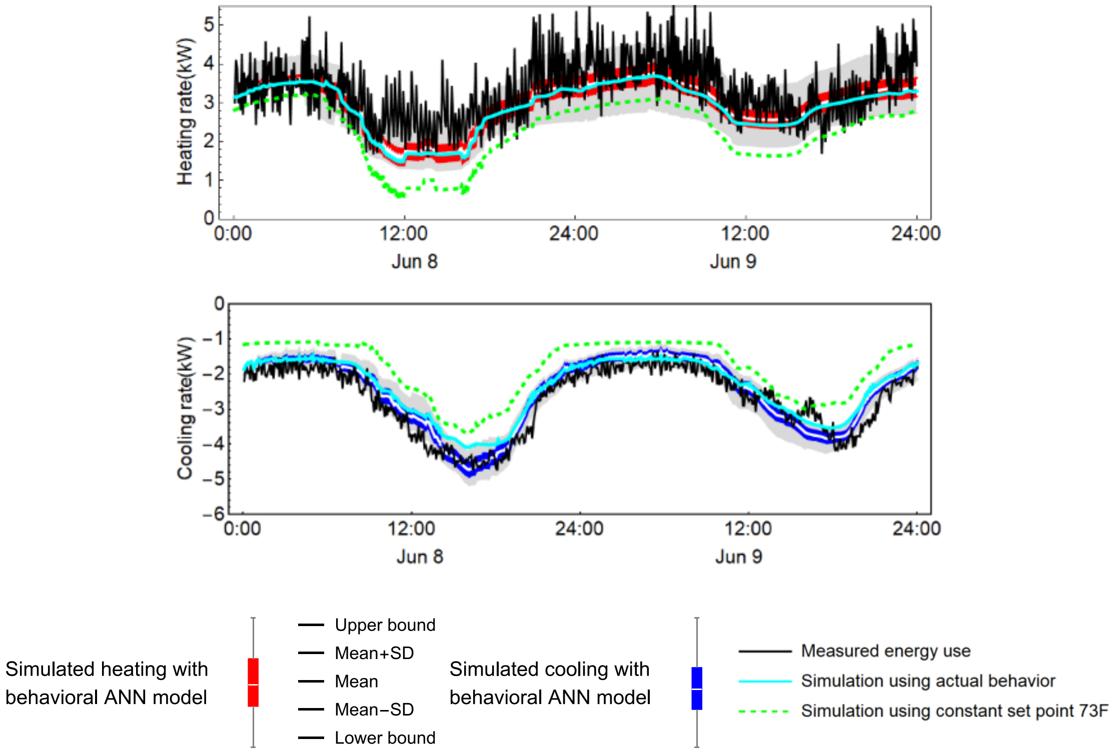


Figure 4.6. Comparison of heating and cooling rate in all the 20 offices for the two selected days in summer

Note that Figure 4.6 portrays a large fluctuation in the collected 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°C, the supply water temperature fluctuated greatly and could sometimes be as high as 76.7°C. This water-temperature control issue caused the fluctuation in the heating energy use in the HLAB building.

Figure 4.7 summarizes the measured energy use and the results of the simulations using collected 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.

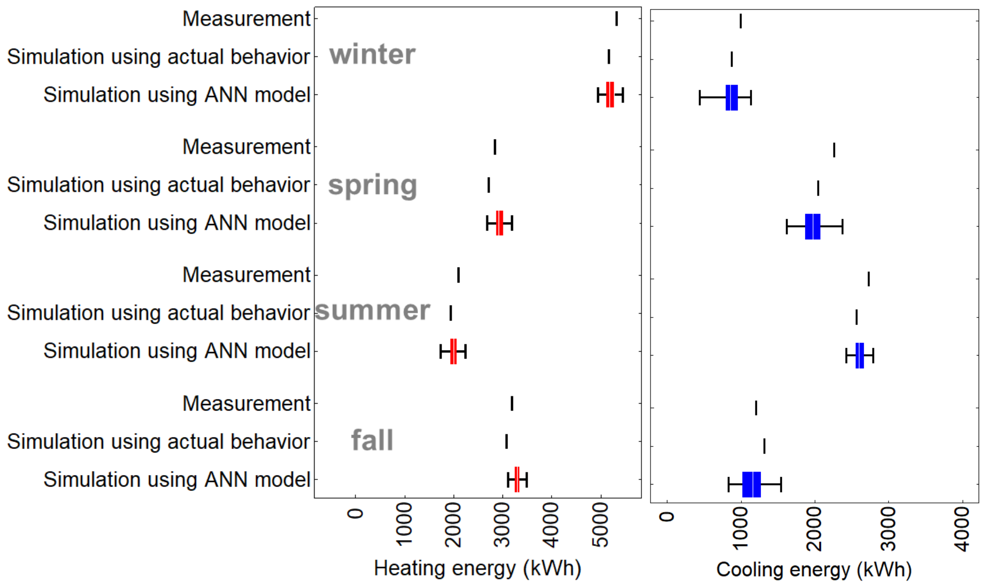


Figure 4.7. Comparison of measured and simulated total energy use in the HLAB offices for a one-month period in each of the four seasons.

4.2.2 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 4.8 (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 for the four buildings. Figures 4.8 (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 reveals that the comfortable temperature range was larger in the four buildings. For an 80% comfortable rate, the temperature ranged from 20°C to 25.6°C in the four buildings in summer, whereas the range for the HLAB building was from 21.1°C to 24.4°C. 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.

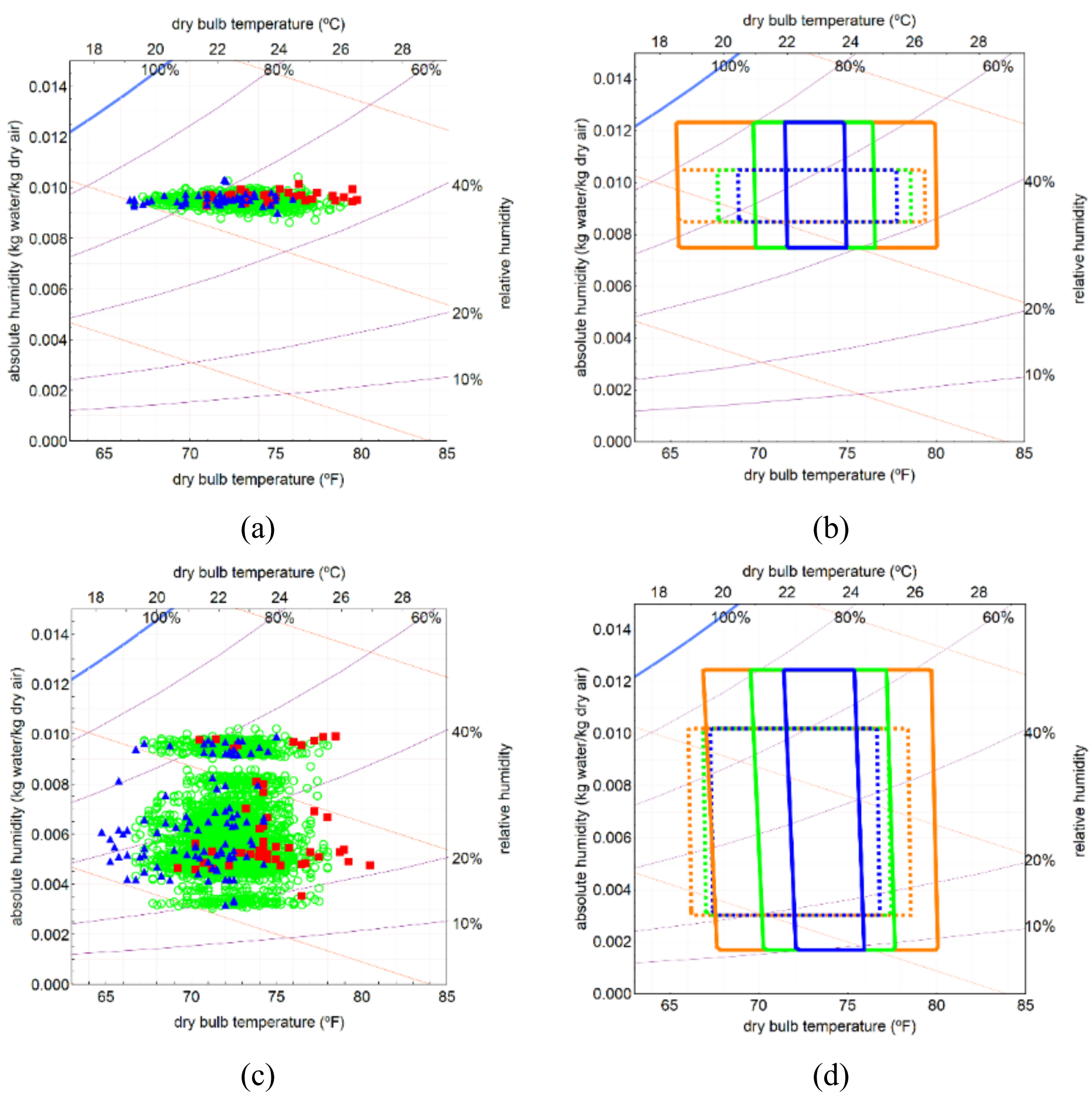
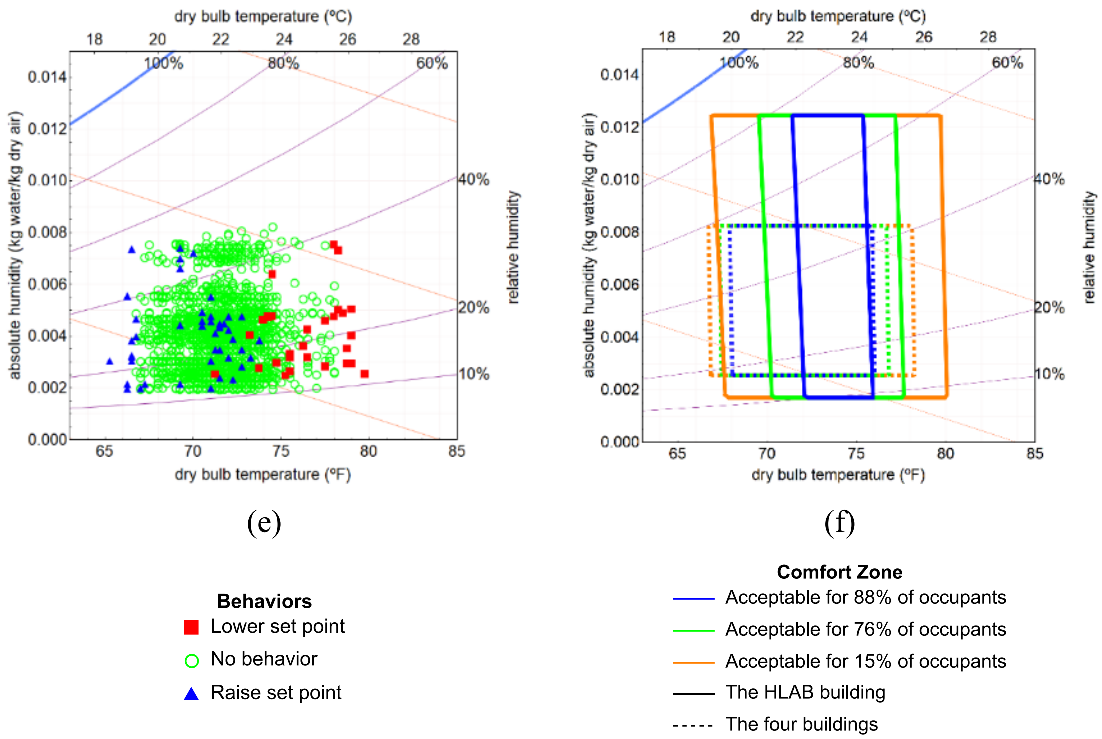


Figure 4.8. Collected behavior data (left) and comfort zone (right) obtained with the behavioral ANN model: (a) and (b) summer, (c) and (d) fall, and (e) and (f) winter.

Figure 4.8 continued



(e) (f)

We found that the comfort zone in the four buildings was different from that in the HLAB building. Previous studies (Albatayneh, 2018; Bonte, 2014) 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 4.1.1. Table 4.3 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 4.8. 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 4.3. Comparison of simulated total energy use with different behavioral ANN models in the HLAB offices for a one-year period.

Model used in simulation	Simulated heating energy use				Simulated cooling energy use			
	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%

4.2.3 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 4.1.1 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 collected 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 4.9 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.

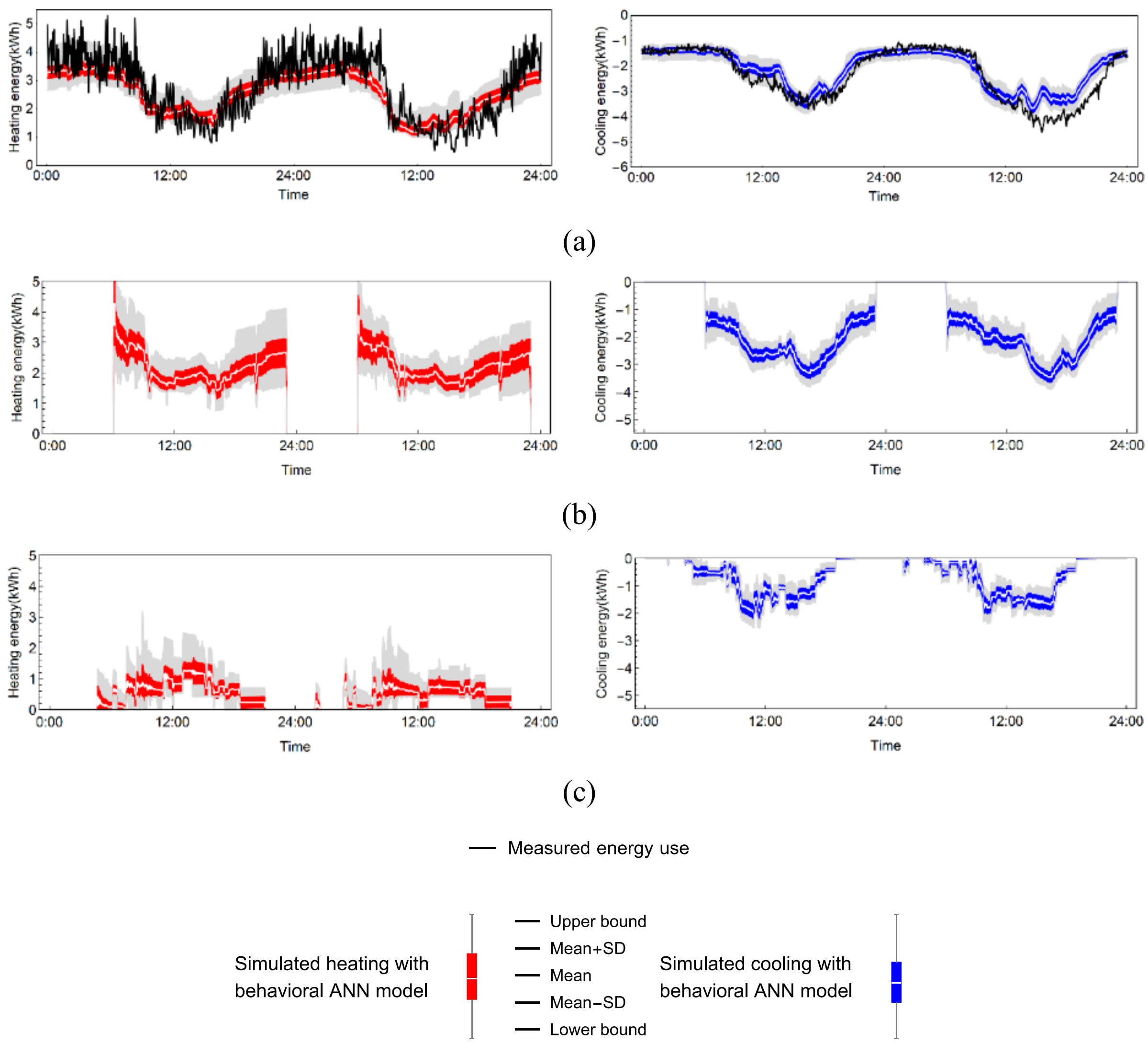


Figure 4.9. Comparison of measured and simulated heating (left) and cooling (right) energy use under different control strategies in the HLAB offices for two selected days in summer: (a) existing 24-hour constant-temperature control strategy; (b) thermostat setback; and (c) occupancy control

Table 4.4 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 18.3°C to 26.7°C 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% (Moon, 2011; Ingersoll, 1985; Nelson, 1978), and the occupancy control could save 20% to 70% (Erickson, 2010; Goyal, 2015; Erickson, 2011; Bengea, 2014). The energy saving was also related to the building type, HVAC system type and outdoor climate. Table 4.4 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 4.4. Comparison of simulated total energy use under different control strategies in the 20 HLAB offices for a one-year period.

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

4.3 Discussion

In this study, we used behavioral ANN models to simulate the occupant behavior and employed the 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 (Gilani, 2017). 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 collected 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 (Paone, 2018). 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 (Fabi, 2013; Langevin, 2015) 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 (Li, 2017; Jung, 2019). 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.

4.4 Conclusions

This chapter 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 collected 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.

5. REINFORCEMENT LEARNING OF OCCUPANT BEHAVIOR MODEL FOR CROSS-BUILDING TRANSFER LEARNING TO VARIOUS HVAC CONTROL SYSTEMS

In this chapter, we first built an MDP of the occupant behavior and used a thermal sensation model to build the rewards. We then trained the RL model with the use of Q-learning. Next, we used transfer learning to explore the occupant behavior in several other buildings. We also validated the RL occupant behavior model and the transferred model with data collected from various buildings. Finally, we analyzed the simulated building energy performance with the use of the RL model and the transferred model.

5.1 Methods

To develop an occupant behavior model, we first modeled the occupant behavior as an MDP and developed the RL model on the basis of this process. Subsequently, we trained the model with the use of a Q-learning algorithm. Next, we transferred the knowledge of the occupant behavior model from one building with manual control to other buildings with thermostat setback and occupancy control systems. Finally, we validated the transfer learning model with collected data. Figure 5.1 summarizes the methods and models in this study.

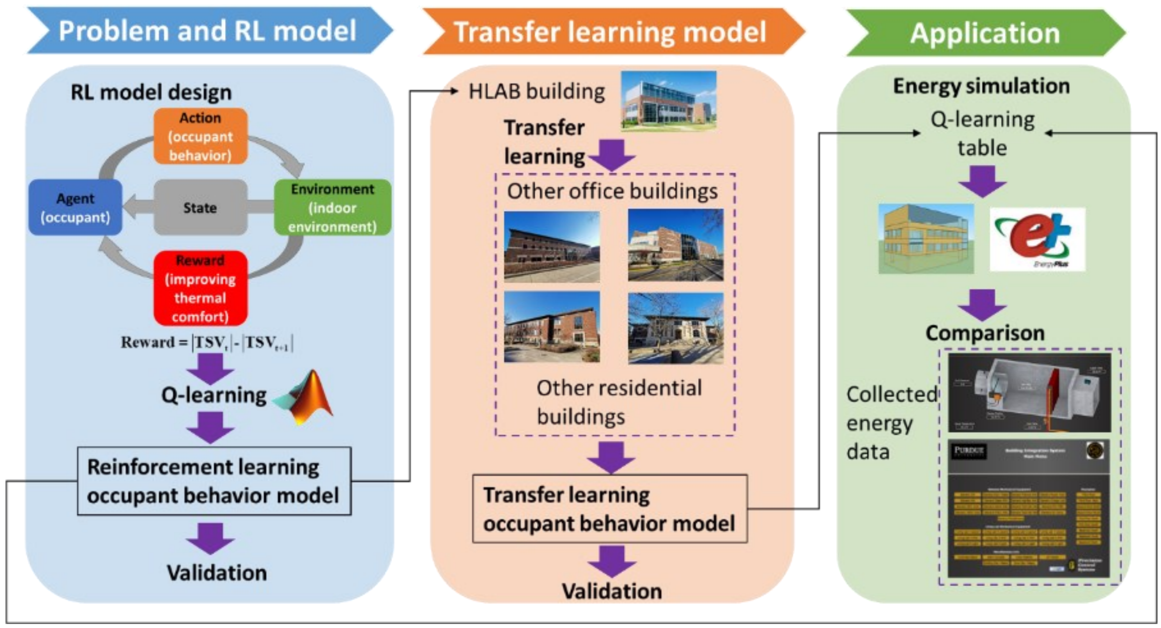


Figure 5.1. Flow chart of methods in this study, including the reinforcement learning occupant behavior model, transfer learning model and energy simulation

5.1.1 Framework of reinforcement learning model

As shown in Figure 5.2, in the RL model, an agent can gather information directly from the environment of different states, and then take actions inside and compare the results of these actions via the reward function. This cycle is repeated over time, until the agent has enough experience to correctly choose the actions that yield the maximum reward. Thus, through interaction with an environment and repeated actions, the RL model can evaluate the consequences of actions by learning from past experience. As for the building occupants, the decision to take an action in a specific indoor environment is a similar process to that of the RL model. The MDP is used to describe an environment for reinforcement learning, because the indoor environment and thermal comfort are fully observable. In this study, the occupant behavior was modelled as a decision-making process in which the policy-based RL was used. The building occupant, the occupant behavior, the indoor environment and the improving thermal comfort level are the agent, action, state and reward, respectively, in the model. In each state, the logic of occupant behavior is to proactively seek more comfortable conditions in the indoor environment (Hong, 2017). Numerous factors are related to the occupant behavior, and we will introduce them in detail in the following sections.

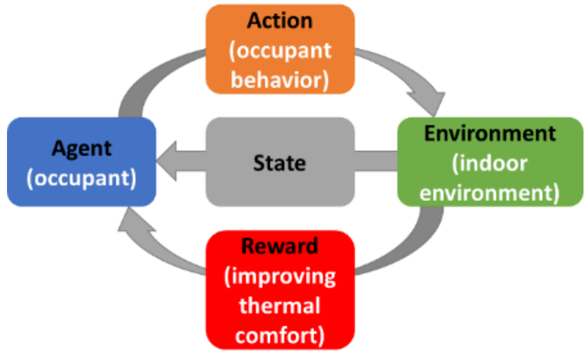


Figure 5.2. Illustration of the RL model with agent, action space, environment space and rewards.

We modeled the occupant behavior in offices as an MDP, as shown in Figure 5.3. In the initial state, the agent had many possible choices of behavior, such as adjusting the thermostat set point by various degrees or adjusting the clothing level. For every action, there was a corresponding feedback reward, such as improvement or deterioration of thermal comfort. The agent took an action to enter a follow-up environment, and this process kept going. The time step size for action prediction was 15 minutes. We took the actual occupant behavior occurrence into consideration, because there was a certain delay in the occurrence of the behavior, and the occupant did not act immediately when feeling uncomfortable. We also assumed that the action could take effect in the subsequent time step if the HVAC system was in normal operation. Note that in Fig. 3 we have listed only some possible actions. There may be others, such as reducing the clothing level and making a more extreme adjustment to the thermostat set point. These additional actions are represented by an ellipsis.

The MDP in this study entailed the following specifications:

Environment space: The state contains information about the indoor environment that occupants use in deciding on the proper action. In this research, the state space included room air temperature, room air relative humidity, thermostat set point, clothing level of occupants, metabolic rate, room occupancy and time of day. Although there are many other factors (Stazi, 2017; Fabi, 2012) that impact occupant behavior, we neglected them in order to simplify the structure of the RL model. Here we assumed that the thermal sensation of occupants was not impacted by the time of day. Therefore, time was not included in the TSV and reward calculation.

An exception was the transfer learning model for setback and occupancy control in Section 5.1.3, which moved to a nighttime state at certain times. Generally, time functioned as a label, and it did not contain a numerical value that might influence the RL model and training. In summary, the state space can be expressed as

$$S = \left\{ T_{air}, RH_{air}, T_{setpoint}, Clo, Met, occupancy, time \right\} \tag{5.1}$$

Action space: The action is the occupant behavior that is performed with the goal of more comfortable conditions. In this research, the action space included raising or lowering the thermostat set point by different degrees, or maintaining the same set point; putting on, keeping the same, or taking off clothes; and arriving. The action space can be expressed as

$$A = \left\{ A_{raise}, A_{keep}, A_{lower}, A_{put\ on}, A_{keep}, A_{take\ off} \right\} \tag{5.2}$$

where the first three actions $A_{raise}, A_{keep}, A_{lower}$ represent adjustments to the thermostat set point, and the last three actions $A_{put\ on}, A_{keep}, A_{take\ off}$ represent adjustments to the clothing level.

Reward function: The goal of the action is a higher thermal comfort level for the occupants. Therefore, in this research, the reward was modelled as the absolute difference between the initial thermal sensation vote (TSV) before the action and the final TSV after the action, which can be expressed as

$$R = \left| TSV_t \right| - \left| TSV_{t+1} \right| \tag{5.3}$$

where subscripts *t* and *t+1* represent the current and next time steps, respectively. It is clear that in order to maximize the reward *R*, $TSV_{t+1} = 0$, which means that the desired thermal sensation is neutral after the occupant behavior occurs.

In this research, we predicted the TSV in offices with the use of an ANN model (Deng, 2017; Deng, 2020) that expresses TSV as a function of four input parameters as:

$$\text{TSV} = f\,(\text{air temperature, relative humidity, clothing insulation, metabolic rate}) \tag{5.4}$$

where *f* represents the function of the ANN model. We assumed that the mean radiation temperature was the same as the air temperature, and the air velocity was less than 0.2 m/s. To develop the ANN model, we collected data from over 25 occupants in an office building during the four seasons of 2017. The number of collected data points for training the model was about

5,000. The model had three layers, and there were ten neurons in the hidden layer. We used the Levenberg-Marquardt algorithm to train the model, and it predicted the TSV with a mean absolute error (MAE) of 0.43 after training.

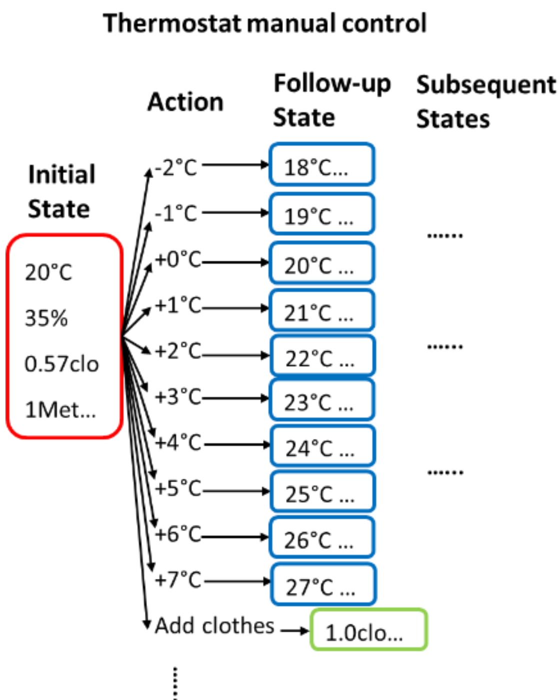


Figure 5.3. MDP for the occupant behavior of thermostat set point manual control and clothing level adjustment. Each state space includes numerous parameters, as expressed by Eq. (5.1), and the figure displays only the key parameters. The initial state is followed by many actions, follow-up states and possible subsequent states. In addition to what is shown in the figure, further possibilities are indicated by an ellipsis.

For buildings without a thermal comfort model, predicted mean vote (PMV) (ASHRAE, 2017) can also be used to model the reward, which is expressed as

$$R = |PMV_t| - |PMV_{t+1}| \tag{5.5}$$

As above, maximizing the reward R requires that $PMV_{t+1} = 0$.

Reward modelling in the RL model for multi-occupant offices with multiple agents [64] was different from that for single-occupant offices. For multi-occupant offices, the modelling was divided into two categories. In one category, the reward of a dominant occupant was maximized.

Here, one occupant near the thermostat would adjust the thermostat dominantly, and the others in the room would compromise with this occupant's preference, as is the case in some workplaces (Deng, 2018; Klein, 2012). Thus, the reward was for the dominant individual and can be expressed as

$$R = \left|TSV_{t,dominant}\right| - \left|TSV_{t+1,dominant}\right| \tag{5.6}$$

During data collection, we also found that in some offices all the occupants had equal control of the thermostat (Deng, 2018). Therefore, in our other multi-occupant office category, the average reward for all occupants was maximized. The reward was averaged as

$$R = \frac{1}{n}\sum_i \left(\left|TSV_{t,i}\right| - \left|TSV_{t+1,i}\right|\right) \tag{5.7}$$

where *n* is the number of occupants in the room, and *i* represents different occupants.

For a single-occupant office where only the dominant occupant was in the room, the two categories of reward modelling were the same as Eq. (5.6) and (5.7).

5.1.2 Q-learning

After designing the model framework, we needed to train the RL model. One of the available training methods is Q-learning. Here "Q" means "quality," a policy function of an action taken in a given state. It can be expressed as the following mapping:

$$Q : S \times A \rightarrow R \tag{5.8}$$

Q-learning is a model-free RL algorithm for learning a policy that tells an agent which actions to take under various circumstances (Melo, 2001). This learning method has been widely used for training RL models (Yoon, 2019; Chen, 2018; Valladares, 2019; Yang, 2015; Cheng, 2016). With the state space, action space and reward modelling described in Section 5.1.1, we used the Q-learning algorithm to update the quality. The updating equation for Q-learning can be expressed as

$$Q_{new}\left(s_t, a_t\right) = Q_{old}\left(s_t, a_t\right) + \alpha \cdot \left[r_t + \gamma \cdot \max_a Q\left(s_{t+1}, a\right) - Q_{old}\left(s_t, a_t\right)\right] \tag{5.9}$$

where Q is the quality, s the state, a the action, α the learning rate, r the reward, γ the discount factor, and $\max_a Q\left(s_{t+1}, a\right)$ the estimation of optimal future value. According to this equation, as the training begins, the quality is initialized to arbitrary or uniform values. Then, at each episode t of the training process, the agent in state s_t selects an action a_t with a reward r_t and an estimated future reward for future actions. After the action, the agent enters a new state s_{t+1}. When the maximized reward is confirmed, the optimal action is learned and the quality Q is updated. In this process, the RL model gradually learns to take actions in a certain environment, and we can obtain a Q-learning table of states by various actions. Q-learning is similar to the actual decision process for occupant behavior in buildings.

The learning rate and discount factor could impact the learning process. In this study, we selected a learning rate of 0.3 and discount factor of 1. We used a table of states by various actions because the choices of actions in the MDP were discrete for adjusting the thermostat by different degrees or clothing insulation to certain values. Thus, the discount factor had little impact on the Q-learning result. As for the learning rate, we will provide training results for learning rate variations in Section 5.2. We used the MATLAB 2020a Reinforcement Learning Toolbox to build and train the RL model.

5.1.3 Transfer learning

After designing and training the RL occupant behavior model, we sought to transfer the model to other buildings with limited information and even with no data. As shown in Figure 5.4(a), an ANN model, one of the data-driven models, has a layered structure with input, hidden and output layers. The training process for the ANN model uses data to update the values of coefficients in the hidden layer. Therefore, the model can only be used for similar buildings with available data. In previous attempts to apply the model directly to other buildings, the performance was usually not good (Wang, 2020; Hong, 2015). In those studies, transfer learning of the ANN model grabbed layers of neural network weights and trained the model again with new data. Prediction for different buildings with transferring data-driven models requires the data to retrain. Additionally, the meanings of the coefficients inside the models are still unclear to researchers. Therefore, the information in the hidden layer cannot be transferred or used for other buildings. However, as shown in Figure 5.4(b), the policy-based RL occupant behavior model is a logical model with physical meaning, and thus it can be partially transferred to other buildings. We transferred the higher-level rules of the RL model, i.e., the logic of thermal actions, the pursuit of thermal comfort from one building to another building. We could do this because even for different buildings and HVAC control systems, the logic of occupant behavior that seeks more comfortable conditions remained the same. Therefore, the feasible actions and rewards of the RL model were similar for different buildings. For example, we built an RL occupant behavior model for a building with manual thermostat control. In other buildings with thermostat setback or occupancy control, occupants might adjust the thermostat set point in different ways. When they left the room or during the night, the building automation system could reset the thermostat set point to save energy. When the occupants reentered the room, they could adjust the set point and override the system operation. The occupants' overriding of the automation systems might indicate their dissatisfaction (Gunay, 2013). As such, there was a "night state" before the occupants' arrival in the morning, when the set point and air temperature were different, as depicted in Figure 5.4(b). After the occupants' arrival or in the morning, the state space entered the normal initial state. Thus, the transfer learning model structure was similar to original model with possible actions and rewards in the daytime. We could therefore transfer a portion of the parameters in the action space and the rewards to other buildings. Even without data for these buildings, we could still model and predict the occupant behavior.

For residential buildings, large-scale collection of occupant behavior data has usually been more difficult, because such buildings are generally not equipped with building automation system (BAS). The use of questionnaire surveys to gather data has been reported as time-consuming and limited in accuracy (Jia, 2017). Under this circumstance, building a model by transfer learning was a feasible approach. Similarly, we also transferred the RL occupant behavior model for office buildings to residential buildings. The occupant behavior of manual thermostat control was the same in both types of buildings, but the improved thermal comfort level and reward for actions were different. Moreover, there were other factors that distinguished the occupant behavior in office buildings from that in residential buildings (Wei, 2014; Yu, 2011). Therefore, we needed to modify the state space and reward in the transfer learning model for residential buildings.

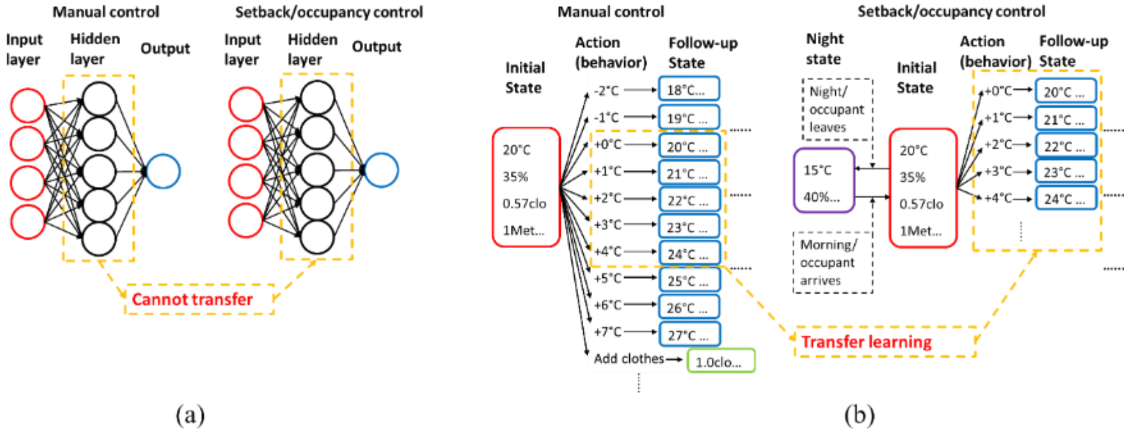


Figure 5.4. Transfer of the occupant behavior model for manual control to other buildings with thermostat setback or occupancy control: (a) the data-driven ANN model cannot be transferred because of the coefficient values in the hidden layer; (b) the policy-based RL model can be transferred, and portions of the action and state space are the same.

For residential buildings, our previous study found that the comfort zone of a building was 1.7 °C (3 °F) higher in summer, and 1.7 °C (3 °F) lower in winter, than the ASHRAE comfort zone. Therefore, we were able to use this information to transfer the thermal sensation and occupant behavior model from the office building to residential buildings. Since the shape of the thermal comfort zone was similar, whereas the impact of air temperature on thermal comfort and occupant behavior was different, the logical RL behavior model could be partially transferred. The MDP for manual control of the thermostat was the same in the office building and residential buildings. We transferred the RL occupant behavior model with the use of PMV to calculate the reward as

$$R = \left|PMV_{Residence\_i}\right| - \left|PMV_{Residence\_f}\right| \tag{5.10}$$

Here, the PMV in the residence was defined differently from the traditional PMV model because of the different comfort zone. With the 3 °F difference in winter and summer, it was calculated as

$$PMV_{Residence\_winter} = PMV(T_{air} + 3, RH, T_r, V, Clo, Met) \tag{5.11}$$

$$PMV_{Residence\_summer} = PMV(T_{air} - 3, RH, T_r, V, Clo, Met) \tag{5.12}$$

where the *PMV* function represents the traditional way of calculating PMV with six parameters.

5.1.4 Data collection for model validation

In order to validate the RL model, this study collected indoor air temperature, relative humidity, thermostat set point, lighting occupancy, clothing level of occupants, and data on the occupant behavior of adjusting the thermostat, from the BAS in 20 offices in the Ray W. Herrick Laboratories (HLAB) building at Purdue University in 2018, as shown in Figure 5.5 (a). Half of the offices were multi-occupant student offices, and the rest were single-occupant faculty offices. The 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 BAS to control the air temperature in the room. We downloaded the indoor environment data of room air temperature and thermostat set point from the BAS. In addition, we used a questionnaire to record the clothing level of the occupants and their clothing-adjustment behavior in the HLAB building.

We also gathered room air temperature, relative humidity, thermostat set point and lighting occupancy data in four other office buildings on the Purdue University campus in three seasons of 2018, as shown in Figure 5.5(b)-(e). Table 5.1 provides the data collection information for each building, including the number of offices in which data was collected, the HVAC control type, the data collection interval, and the types of data that were collected.

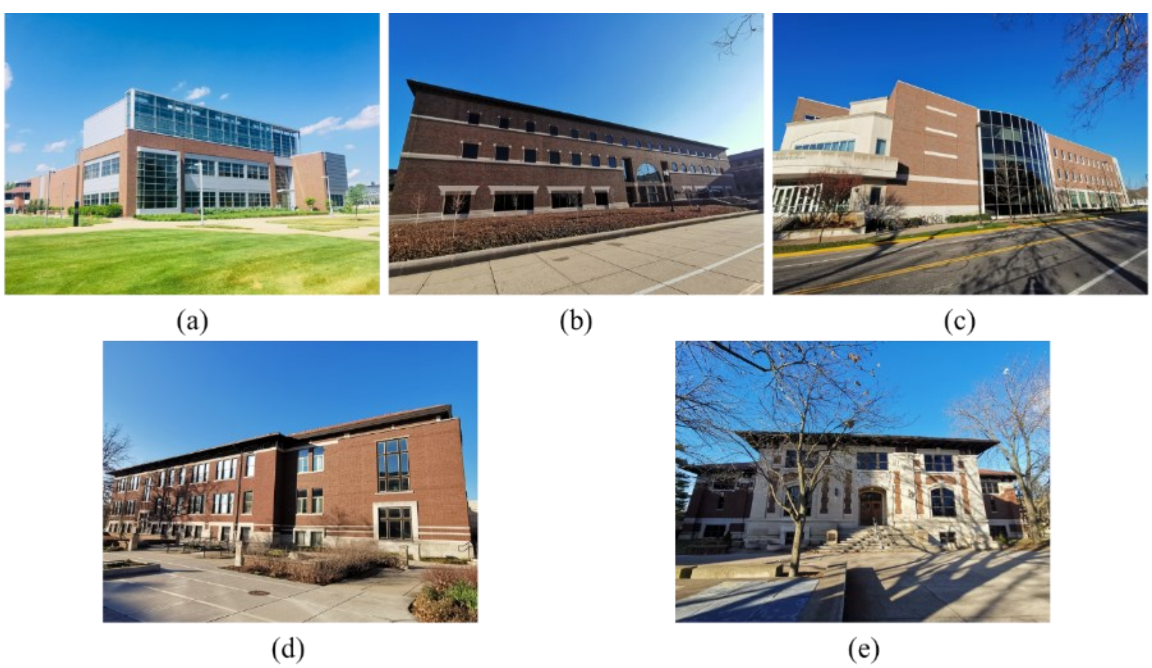


Figure 5.5. Photographs of the buildings used for data collection: (a) HLAB building, (b) MSEE building, (c) LWSN building, (d) STAN building and (e) HAAS building

Table 5.1. Data collection information for each building

Building	Offices for data collection	HVAC control type	Data collection interval	Collected data
HLAB	20	Manual control	5 min	Room lighting status Number of room occupants Room air temperature and RH Thermostat set point Room CO_2 concentration Clothing level Room supply-air flow rate Room supply-air temperature
LWSN	106	Manual control +thermostat setback	10 min	Room lighting status Number of room occupants Room air temperature and RH Thermostat set point Clothing level
MSEE	99	Manual control +occupancy control	15 min	
STAN	122	Manual control +occupancy control	15 min	
HAAS	48	Manual control +occupancy control	15 min	

5.1.5 Building energy simulation with RL model

The purpose of constructing the RL occupant behavior model was to evaluate the impact of occupant behavior on building energy performance. Therefore, we also implemented the RL occupant behavior model in EnergyPlus.

Figure 5.6 depicts the simulation process with the RL occupant behavior model. When the simulation starts, the program first checks whether or not the office is occupied, since the behavior occurs only when there is an occupant inside the office. If so, the agent decides on the action to the next time step based on the Q-learning table. Next, the energy simulation program decides whether or not to adjust the thermostat set point or the clothing level of the occupants. The building energy use will correspond to this decision. Moving to the next time step, the program checks whether or not the simulation time has ended; if not, it again checks if the room is occupied. To obtain a reasonable variation range, we performed the simulation 200 times and analyzed the results (Deng, 2019).

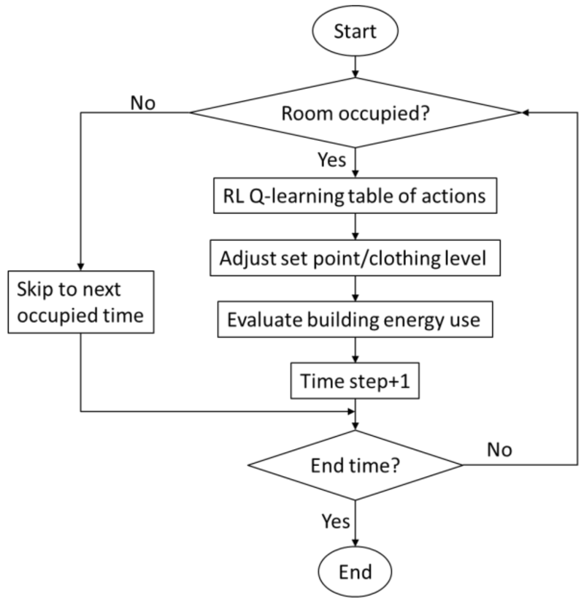


Figure 5.6. Building energy simulation process incorporating the RL occupant behavior model and Q-learning table of actions

5.2 Results

5.2.1 Results of modelling the reward for action

Figure 5.7 shows the result of reward modelling when the PMV model and the thermal comfort ANN model were used with Eqs. (5.3)–(5.5). The figure depicts the relationship between occupant behavior and the corresponding rewards in various air temperatures when other parameters were the same. For example, when the air temperature was 19.4 °C (67 °F), the occupant might feel cool in winter. Thus, the reward for raising the thermostat set point was positive most of the time, until the occurrence of overheating caused by an excessive adjustment. For each state, there was one occupant behavior of set point adjustment that led to the maximum reward. The reward situation was similar when the air temperature was high and the occupant lowered the set point. When the air temperature was about 22.8 °C (73 °F), the occupant already felt nearly neutral. In this case, either raising or lowering the set point would lead to a negative reward, and the optimal occupant behavior was to make no adjustment. We used this quantified logic to build the RL model.

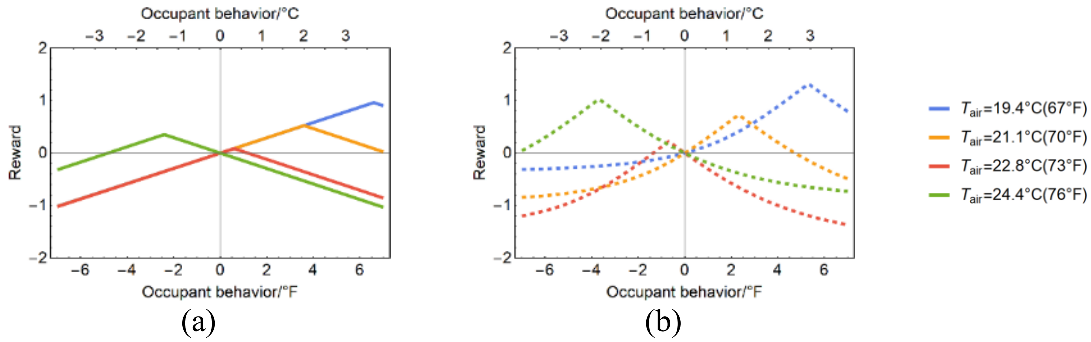


Figure 5.7. Reward value modelled for different air temperatures in winter by using (a) the PMV model and (b) the thermal comfort ANN model.

5.2.2 Results of the RL occupant behavior model

Figure 5.9 depicts the training process for the RL model with the use of Q-learning. The blue, red, and orange curves represent the episode reward, the average reward in nearby episodes, and the quality, respectively. Initially, at the beginning of the training process, the RL model knew nothing about the relationship between the environment, states and actions. Thus, it could only take random actions to explore the relationship, and it received varying rewards. As a result, the episode reward was very low. As the learning process went on, the RL model tried various actions to find a way of maximizing the reward. The quality was updated with the use of Eq. (5.9). In the examples shown in Figure 5.8, the thermostat set point and air temperature were 22.8 °C (73 °F), and the occupant was wearing summer clothing. After training over 300 episodes, the RL model learned to take the action at this state that maximized the reward at 0.61. Figure 5.8 also shows that an overly high learning rate made the learning process very unstable, and the quality fluctuated during the training. Meanwhile, a low learning rate would slow down the training process.

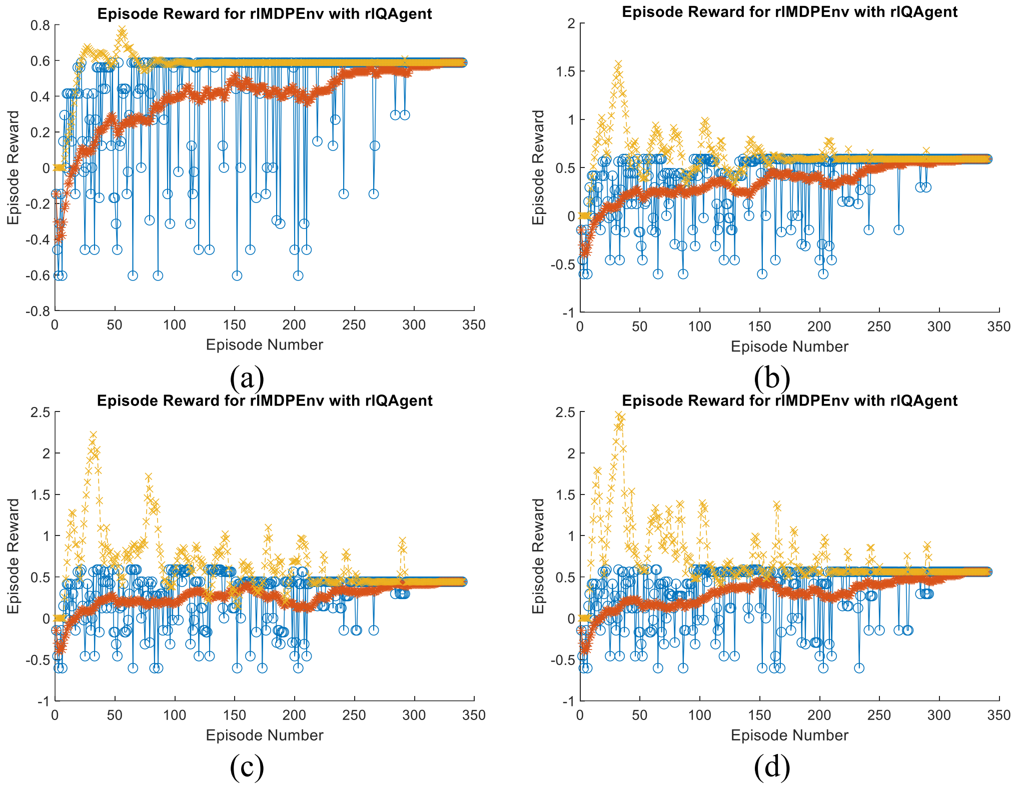


Figure 5.8. Training of the RL model with the use of Q-learning as the number of episodes increases. The blue, orange, and yellow curves represent the episode reward, the average reward in nearby episodes, and the quality, respectively. (a) learning rate = 0.1; (b) learning rate = 0.3; (c) learning rate = 0.5; (d) learning rate = 0.7.

The trained RL model would always predict the same occupant behavior in the same state and environment, which was unrealistic. Actual office occupant behavior is influenced by many other factors that we did not build into the RL model (Fabi, 2012; Andrews, 2011). Considering all these factors would have led to an overly complex behavior model. A previous study (Hong, 2017) pointed out that behavior models should not only represent deterministic events but also be described by stochastic laws. Additionally, different thermal preferences on the part of occupants would cause their behavior to differ. Figure 5.9 displays the distribution of collected thermostat set point adjustment behavior at different air temperatures in the HLAB offices. In the box-and-whisker charts, the boxes, whiskers and dots represent the standard deviation, upper and lower bounds, and outliers of the occupant behavior, respectively. The air temperature and occupant behavior had a clear negative correlation. The figure indicates that even at the same air temperature and similar states, the variation range of collected occupant behavior was over ±1.1 °C (2°F) in both single- and multi-occupant offices in different seasons. Under these conditions, the rewards of different actions did not differ greatly, but the RL model always pursued the action that absolutely maximized the reward. For example, the RL model might predict the occupant behavior of raising the set point by 5 °F, while raising it by 4 °F or 6 °F would also be reasonable behavior in a real scenario. Therefore, based on the results in Figure 5.9, we added a randomness of -2 °F to +2 °F into the RL model for the final decision to make it more reasonable.

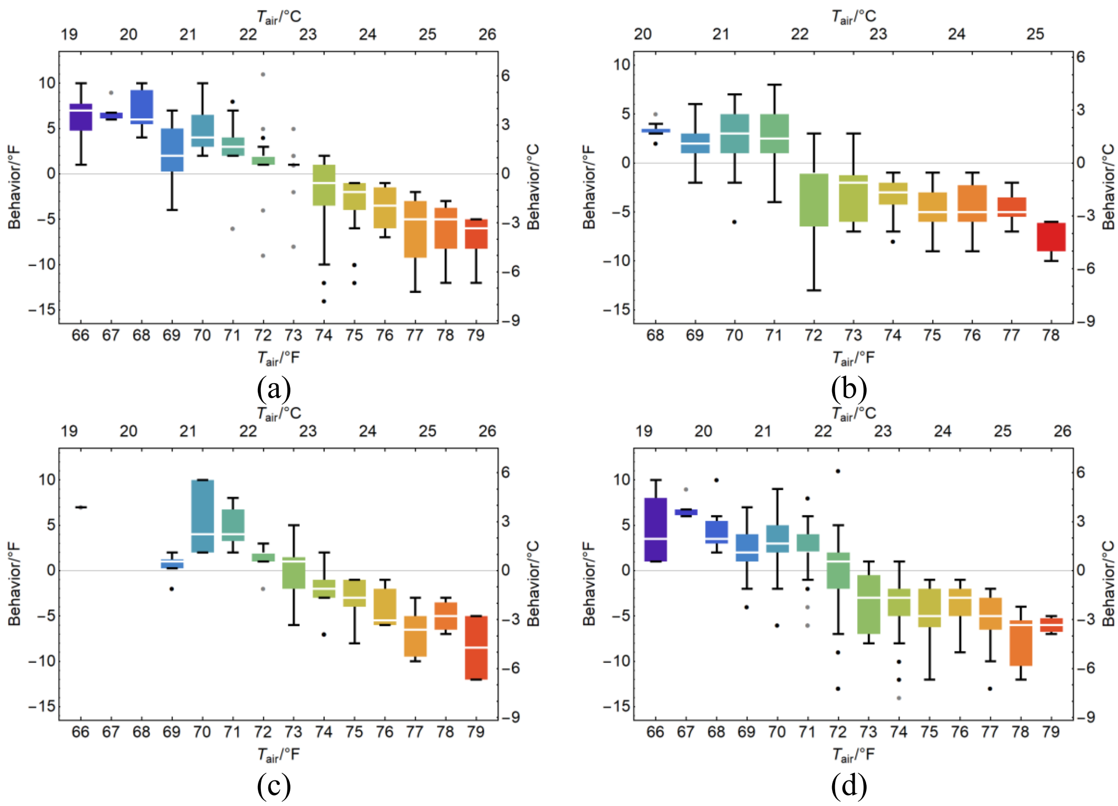


Figure 5.9. The distribution of thermostat set point adjustment by occupants in: (a) single-occupant offices, (b) multi-occupant offices, (c) winter with Clo = 1, and (d) summer with Clo = 0.57.

5.2.3 Validation of the RL model

We validated the RL model with the use of data collected in 2018 after adding the randomness for the final decision. Figure 5.10 compares the collected occupant behavior with the RL model prediction for HLAB offices in four seasons in 2018. For most of the time, the RL prediction results matched the collected data. Table 5.2 lists all the prediction results for R^2 and MAE. The R^2 was around 0.7–0.8, and the mean absolute error (MAE) was around 1.5–1.9 °F. The overall R^2 and MAE were 0.79 and 1.68 °F, respectively. We removed some data as outliers when the HVAC system was under maintenance and the occupant lost control. We also compared the performance of the RL model for single- and multi-occupant offices. For single-occupant offices, the R^2 was 0.8 and the MAE was 1.5 °F. For multi-occupant offices, the R^2 was 0.78 and the MAE was 1.8 °F. The prediction results for multi-occupant offices were not as good as for single-occupant offices. In previous studies, a prediction R^2 of 0.8 was deemed acceptable for an occupant behavior model (Deng, 2019). What is more, Figure 5.11 shows that the prediction error of the RL model follows a normal distribution with mean value around -0.4. So the bias of model training was little. Hence, the model performance of the RL model was reasonable.

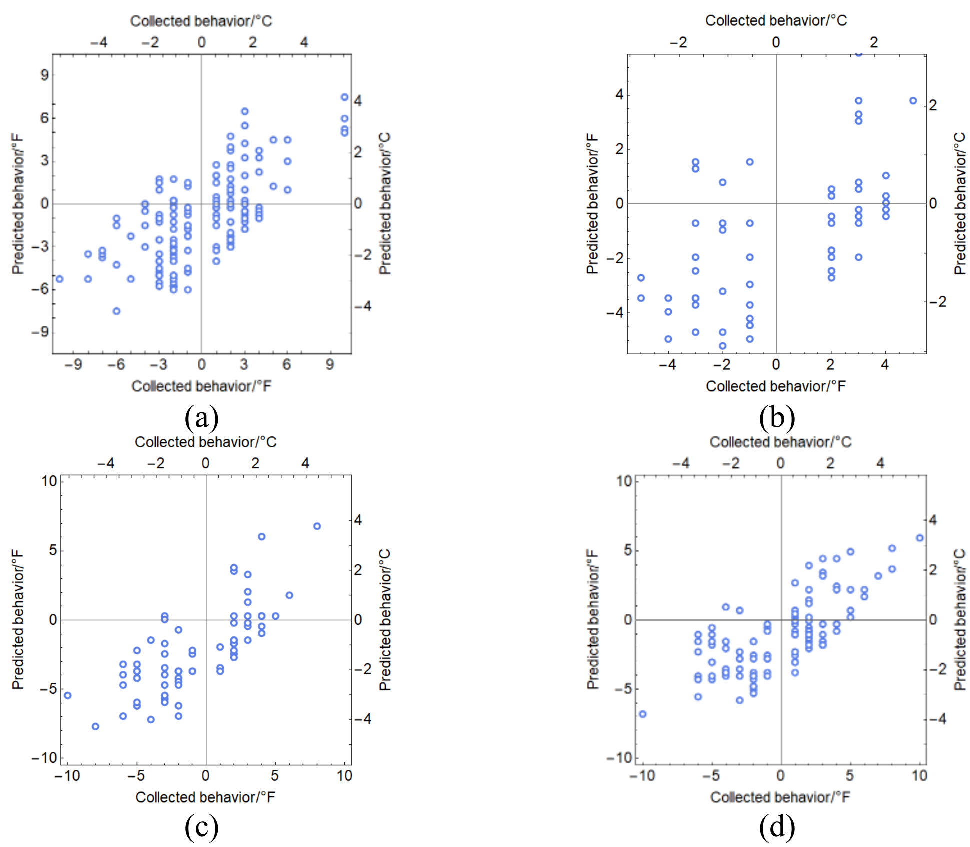


Figure 5.10. Comparison of collected data on the occupant behavior of adjusting the thermostat set point and the RL model prediction for HLAB offices in 2018: (a) winter, (b) spring, (c) summer, and (d) fall.

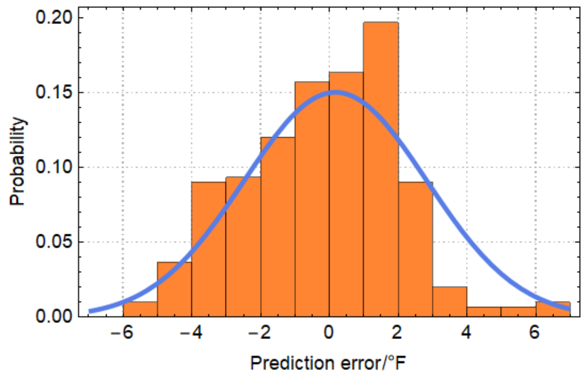


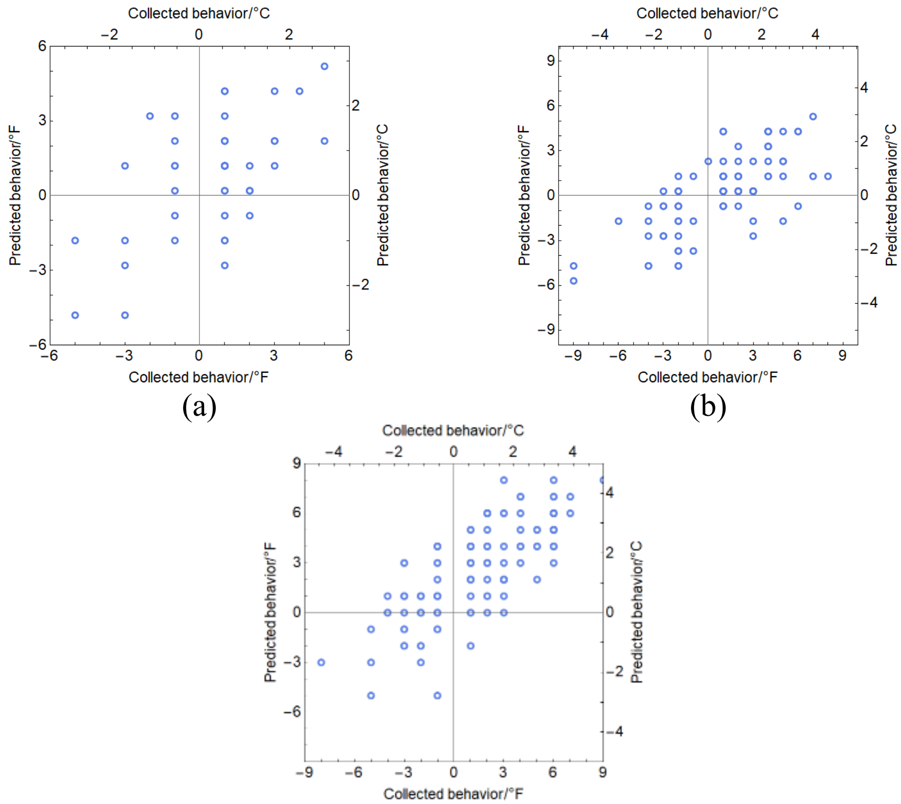
Figure 5.11. Prediction error distribution of the RL model for HLAB offices in 2018.

Table 5.2. Prediction performance of the RL model for the HLAB offices

	R^2	MAE
Winter 2018	0.75	1.6
Spring 2018	0.79	1.9
Summer 2018	0.79	1.5
Fall 2018	0.81	1.7
Overall	0.79	1.68

5.2.4 Results of transfer learning model

After validating the RL model for the HLAB offices, we used the transfer learning model to predict occupant behavior in four other office buildings on the Purdue University campus. Figure 5.12 shows the collected occupant behavior data and the transfer learning model prediction in three seasons. The overall R^2 was 0.7, and the MAE was 1.7 °F. Figure 5.13 also shows that the prediction error of the transfer learning model follows a normal distribution with mean value around 0. But the standard deviation was larger than RL model prediction error. Therefore, the transfer learning results were not as good as the model validation results for the same building, but it was a feasible method for predicting occupant behavior for the different buildings without data.



(a) (b)

(c)

Figure 5.12. Comparison between collected behavior data and behavior predicted by the transfer learning model in four other Purdue University office buildings in 2018 in (a) summer, (b) fall, and (c) winter.

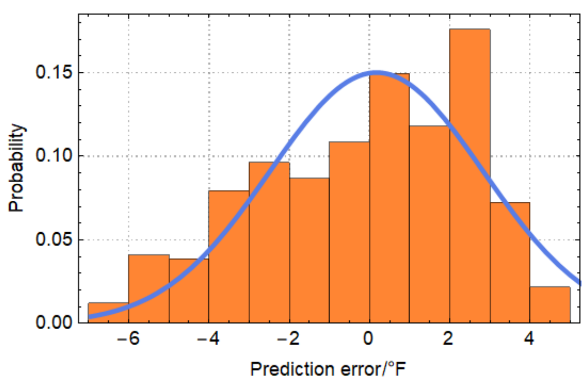


Figure 5.13. Prediction error distribution of the transfer learning model for HLAB offices in 2018.

We also used the defined reward in Eqs. (5.10)–(5.12) to train the RL model again for residential buildings. Table 5.3 shows the prediction performance of the transfer learning model. In the residential buildings, the R^2 was between 0.6 and 0.7 in the four seasons, and the MAE varied from 2.1 °F to 2.9 °F. The results were worse than for the transfer learning in the other four office buildings. The reason was that the cross-type prediction was more difficult than cross-building prediction. In the residential buildings, there were many factors that impacted the occupant behavior differently than in the office buildings (Wei, 2014; Yu, 2011) but were not considered in the current RL model. One feasible way to further improve the transfer learning model would be to introduce more impact factors in the state space, in addition to re-modeling the reward function. Furthermore, the quality and quantity of collected data in the residential buildings were not as good as in the office buildings because we used questionnaire surveys in the former. Recording accurate occupant behavior data with corresponding environmental parameters and incorporating the impact factors are directions for improvement in further studies of residential buildings.

Table 5.3. Prediction performance of the transfer learning model from the HLAB building to residential buildings

Season	R^2	MAE
Winter	0.67	2.1
Spring	0.61	2.9
Summer	0.69	2.3
Fall	0.67	2.7

5.2.5 Energy analysis with the RL occupant behavior model

After using the transfer learning model to predict occupant behavior in different buildings, we compared the collected heating and cooling energy use data and the simulation with the RL model in the HLAB building, for two days in winter. In Figure 5.14, the box-and-whisker charts represent the simulation results with the use of the RL model and the ANN model. The black curve represents the measured data. For most of the time, the measured energy fluctuated within the lower and upper bounds predicted by the RL model. However, the variation range predicted by the

RL model was narrower than that predicted by the ANN model. Table 5.4 lists the average heating and cooling loads and standard deviations for different seasons in one year. The reason for the difference between models was that the logic of the RL model was to improve the thermal comfort level of occupants. Therefore, the predicted occupant behavior was mostly reasonable. The model could not simulate illogical and extreme behavior such as adjusting the thermostat set point to the highest or lowest value for quick heating or cooling. Such behavior can waste a lot of energy.

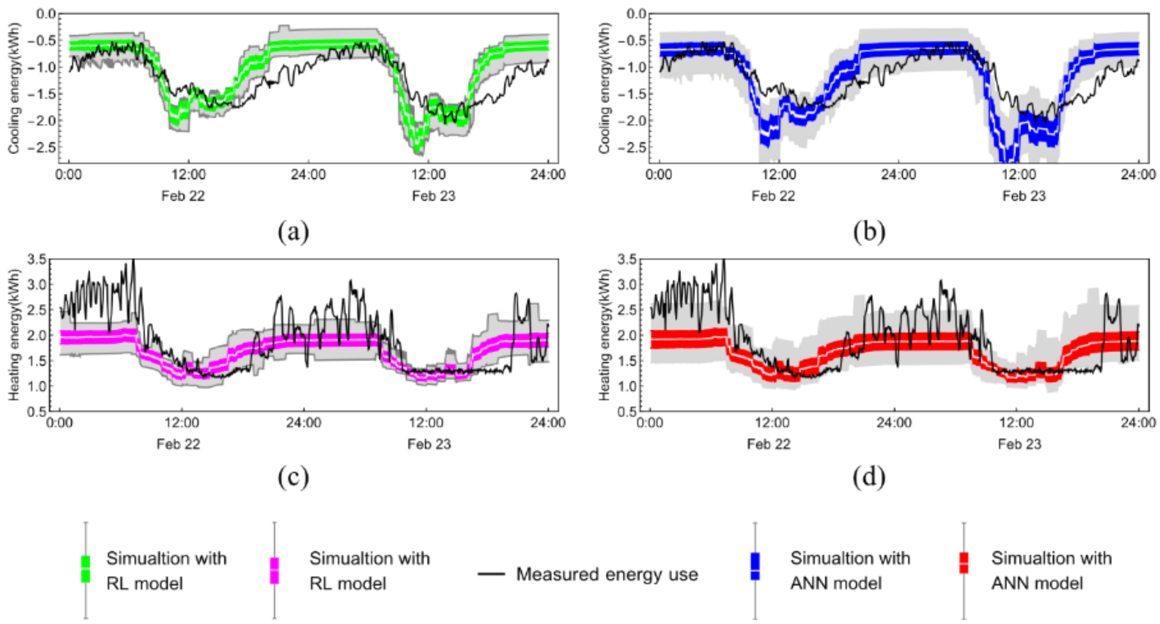


Figure 5.14. Comparison of the collected heating and cooling energy use data and the simulation of manual thermostat control with the RL model in the HLAB building for two days in winter.

Table 5.4. Comparison of measured data with the heating and cooling loads (kWh) simulated by the ANN and RL models in four seasons.

Load		Winter	Spring	Summer	Fall
	Measurement	3396	2833	2102	3183
Heating	Simulation using ANN model	3526±108	2925±110	2275±35	3298±68
	Simulation using RL model	3084±67	2948±41	2239±27	3067±24
	Measurement	857	2261	2725	1205
Cooling	Simulation using ANN model	902±170	2006±115	2597±42	1136±90
	Simulation using RL model	863±72	1812±56	2570±30	974±30

We also used the transfer learning RL model to predict the energy use with thermostat setback and occupancy control. Figure 5.15 shows all the energy simulation results in summer. The measurement and simulation using actual behavior exhibited little divergence. Thermostat setback and occupancy control could reduce energy use by about 30% and 70%, respectively. The average energy simulation results using the RL model were almost the same as with the ANN model, but the variation was less with the former model; this finding was similar to the results in Table 5.3. Hence, it is feasible to use the transfer learning RL model to predict the energy use in other buildings with various HVAC control systems.

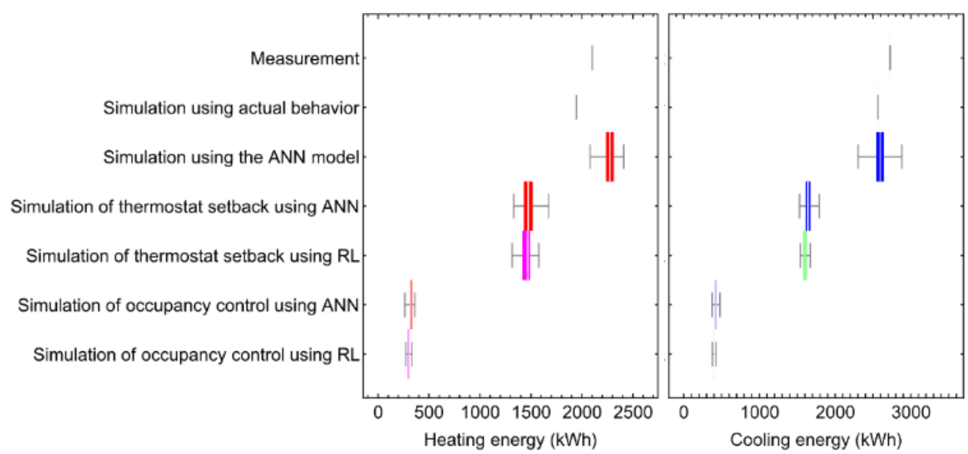


Figure 5.15. Comparison of the measured heating and cooling loads and the results simulated by different models with thermostat setback and occupancy control in summer.

5.3 Discussion

In this study, we built an RL model to predict comfort-related occupant behavior in office buildings, and validated the model with collected data. We also used transfer learning for cross-building occupant behavior modelling. Although various impact factors were modelled in state space, including indoor air temperature and relative humidity, room occupancy and time, we neglected factors such as gender (Karjalainen, 2007), cultural background (Montazami, 2017), and age (Zhang, 2018). To improve the model's performance and widen its applicability, we need to determine the quantitative relationship between these factors and the occupant behavior for reward modelling in future studies. In the MDP, the time step size for occupant behavior prediction was 15 minutes. Thus, the impact of occupant behavior on the HVAC system and indoor environment was not immediate; rather, it was somewhat delayed. We assumed that the action could take effect in the subsequent time step if the HVAC system was in normal operation. Actually, based on the collected data and observation, after adjusting their behavior, the occupants tended to wait for a while, being aware of the HVAC response time. Even though the neutral TSV had not been reached, no occupant behavior occurred during this waiting time. If an occupant waited for a long time, such as 3–4 time steps, and still did not feel neutral, then there may have been issues with the HVAC control system or air handing units. In this case, the occupant behavior would be very complicated and personalized, including complaining and making another adjustment, this time to an extreme high or low set point. To improve the learning process and model performance, possible rewards could account for abnormal HVAC operations with longer response time and more time steps. Improving thermal comfort and energy efficiency behavior modelling is a potential direction for our future research.

In this study, we assumed that the occupant behavior and TSV decisions were based on the current indoor environment. This assumption was similar to those in the most recognized PMV thermal comfort model. According to the adaptive thermal comfort model, the outdoor climate and past thermal history may influence occupants' thermal preference and behavior. This could explain some of the prediction discrepancy exhibited by the current RL occupant behavior model, which was a limitation in the current study. Furthermore, the adaptive thermal comfort model has usually been applied to naturally ventilated rooms. In this study, the buildings were all mechanically ventilated. If we assumed adaptive thermal comfort and considered the outdoor climate and past thermal history, we could still build the MDP and introduce these factors in the state and reward. In this case, the model would be more complex. We could apply the adaptive thermal comfort theory and use historical states in the RL model to improve the prediction result as a future research direction. In the present study, we defined the reward as the difference between initial and final TSV as shown in Eqs. (5.5)–(5.7). Such definition was result-oriented and path-independent, because the middle terms could be canceled if there were many adjustment behaviors. Thus, the occupants could find the set point that maximized the cumulative reward in different ways, which increased the variation in occupant behavior. However, this study considered only comfort-related occupant behavior and not energy-related behavior in offices. This was because the cost of maintaining a comfortable environment in an office is typically not on the minds of occupants. For simulation of energy-saving occupant behavior in other kinds of buildings, the RL model would also require energy parameters for the state space and reward modelling, such as heating and cooling rates and air change rate. Finally, the RL model and transfer learning in this study exhibited good generalization capability and scalability. These models also have potential for other kinds of occupant behavior, such as interactions with windows (Fabi, 2012), shades (O'Brien, 2014), lighting (Yan, 2018) and other indoor appliances.

With the RL model, we tried to model and predict the occupant behavior without collecting data but rather by building a policy-based MDP. We also used transfer learning to obtain the occupant behavior in other office buildings and in residential buildings with different HVAC systems and very limited information. This cross-building occupant behavior transfer was extremely difficult in the data-driven models. Therefore, the generalization capability of the RL and transfer learning models was better than that of the regression models. Meanwhile, the better generalization capability of the RL model may indicate a lesser ability to make predictions for specific buildings. As a result, the prediction accuracy of the RL model may not be as good as that of the data-driven models.

5.4 Conclusion

This study built and validated an RL occupant behavior model for an office building and transferred it to other buildings with thermostat setback and occupancy control. We also compared the energy use simulated by the RL model with measured data and predictions by the ANN model for the HLAB offices and four other office buildings on the Purdue University campus. This investigation led to the following conclusions:

1) The policy-based RL occupant behavior model trained by Q-learning was able to learn the logic of occupant behavior and predict the behavior accurately. The results for prediction of set point adjustment exhibited an R^2 around 0.8 and MAE less than 2 °F.
2) Transfer learning successfully transferred the logic and part of the occupant behavior model structure to other buildings with different HVAC control systems, such as thermostat setback and occupancy control. We also transferred the RL model from office buildings to residential buildings with a modification to the impact of air temperature on occupant behavior. The prediction performance was good, with R^2 above 0.6 and MSE less than 2 °F.

These transfer learning models did not require data collection. Unlike data-driven models, the transfer learning RL model had physical meaning and strong generalization capability.

3) The results of energy simulation for thermostat manual control, setback and occupancy control with the use of the RL model were similar to the results with the ANN model. The RL simulation accurately reflected the impact of occupant behavior on building energy use, but the variation predicted by the RL model was less than that predicted by the ANN model.

6. DEVELOPMENT AND VALIDATION OF A SMART HVAC CONTROL SYSTEM FOR MULTI-OCCUPANT OFFICES USING OCCUPANTS' PHYSIOLOGICAL SIGNALS FROM WRISTBAND

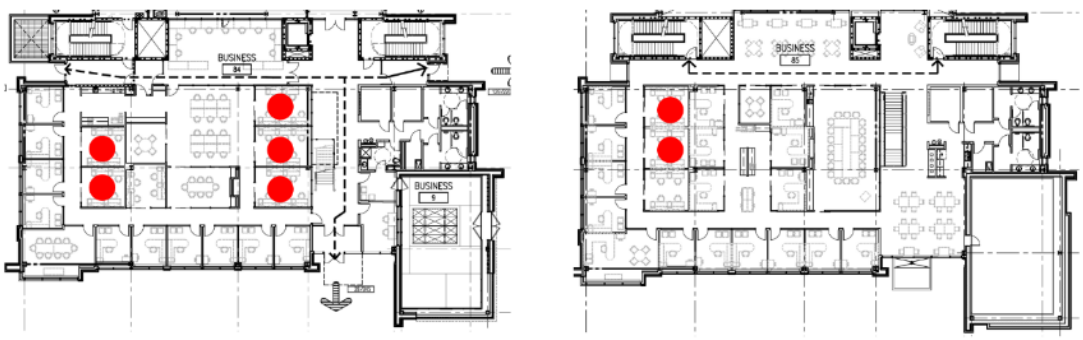
The layout of this chapter is organized as follows: Section 6.1 describes the methods for collecting data, predicting thermal sensation, and developing and validating HVAC control strategies. Section 6.2 provides the results of data collection and comfort control system analysis. Sections 6.3 and 6.4 discuss the results and summarize conclusions of this study, respectively.

6.1 Methods

To develop an HVAC control system for overall thermal comfort that uses occupants' physiological parameters, we first collected data on the indoor environment, thermal sensation, and physiological parameters in seven multi-occupant offices. Subsequently, we built and trained an ANN model using the collected data. Finally, we developed and validated the control strategies for the HVAC systems according to the correlation between the physiological parameters and occupants' thermal sensation.

6.1.1 Data collection

This study collected data on air temperature, relative humidity (RH), clothing level, thermal sensation, wrist skin temperature, wrist skin RH, and HR in seven multi-occupant offices at Purdue University, US. The offices were located on the first and second floors of a three-story building as shown in Figure 6.1. We chose offices in which the occupants spent a considerable amount of time. A total of 24 students (16 males and eight females) of different ages participated in the data collection.



(a) (b)

Figure 6.1. Layout of (a) the first floor and (b) the second floor of the building used for the data collection. The red dots indicate the multi-occupant offices used.

Most data collection methods for indoor environment parameters, occupant behavior and TSV were the same in Chapter 3. Additionally, we used wristbands (Hesvit S3) as shown in Figure 6.2 to record the occupants' physiological data in the HLAB offices, including wrist skin temperature, wrist skin RH and HR, every ten minutes. Each wristband had a unique serial number and could communicate with a cellphone via Bluetooth. The working distance of the Bluetooth connection was 5 m, and thus we could use it to detect the presence of each occupant in the offices.

Figure 6.2. Data collection device - wristband used in this study.

With the above effort, we were able to collect the necessary data. Note that all data collection in this study was approved by the Purdue University Institutional Review Board Protocol # 1902021796.

6.1.2 Artificial neural network model for thermal comfort

With the collected data, we built a model to correlate the indoor environmental and physiological data with occupants' TSV. This study began with the following hypothesis:

- The impact of the outdoor weather and solar radiation on the indoor environment and TSV was neglected, since all the data were collected in interior offices as shown in Figure 6.1.
- Based on the collected data and published literature (Yi, 2015; Liu, 2013), the wrist skin temperature difference in each time step was linearly related to the air temperature difference. Therefore, we used linear regression to determine the correlation coefficient with the collected data, as the following equation shows:

$$T_{skin,f} - T_{skin,i} = C(T_{air,f} - T_{air,i}) \tag{6.1}$$

where T_{skin} is the skin temperature, T_{air} the air temperature, C the coefficient, and the subscripts i and f represent the initial values before the control system adjusted the thermostat set point and the final values after control, respectively.

- Room air RH changed when the thermostat set point was adjusted. Based on the collected data, we assumed that the air pressure and humidity ratio remained constant, and the skin RH variation was the same as the air RH variation to simplify the variation of RH when the control system works. Thus, we have

$$AH(T_{air,i}, RH_{air,i}) = AH(T_{air,f}, RH_{air,f}) \tag{6.2}$$

$$RH_{skin,f} - RH_{skin,i} = RH_{air,f} - RH_{air,i} \tag{6.3}$$

where $AH(T_{air}, RH_{air})$ is the absolute humidity at a specific air temperature *T* and air *RH*, and RH_{skin} the wrist skin relative humidity.

- Metabolic rate was related to HR, according to the literature (Green, 2011) and ISO8996 (ISO, 2004). Occupants' clothing level and HR remained the same in the offices before and after the control system adjusted the thermostat set point. Thus,

$$HR_i = HR_f \tag{6.4}$$

$$Clo_i = Clo_f \tag{6.5}$$

With the above hypothesis, this study could predict the occupants' TSV. In many previous studies (Deng, 2018; von Grabe, 2016; Liang, 2005; Liu, 2007), ANN models have been very effective in dealing with the highly complex correlations between input parameters and TSV. Therefore, the present study also employed this type of model. An ANN model uses machine learning methods to learn a particular relationship between input and output, and it can identify the relationship after being trained with sufficient data. This study sought to correlate occupants' thermal sensation with indoor environmental parameters and physiological parameters.

As shown in Figure 6.3, an ANN model has a layered structure, typically comprised of an input layer, a hidden layer and an output layer. The number of neurons in the hidden layer indicates the model's complexity, and adjusting this number allows one to control the complexity. However, increasing the number of neurons could result in overfitting and a longer training time. In this study, we found that six neurons in the hidden layer could predict the TSV accurately without overfitting. The transfer function in the hidden layer is a given function that can provide the corresponding output value for each possible input. In this study, we used the logistic function as the transfer function because it can provide the TSV for any possible input.

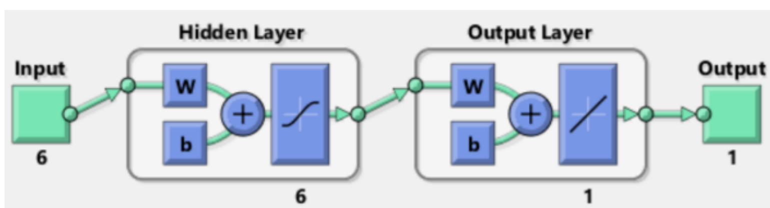


Figure 6.3. Structure of the ANN model in this study. There are six input parameters, six neutrons in the hidden layer and one output parameters.

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

$$TSV = \mathbf{w}_{output}\{1+\exp[-(\mathbf{w}_{hidden}\mathbf{X}+\mathbf{b}_{hidden})]\}^{-1}+b_{output} \tag{6.6}$$

where $\mathbf{X}$ is an $n\times 1$ input vector for the n input parameters, $\mathbf{w}_{hidden}$ is a $6\times n$ weight matrix in the hidden layer, $\mathbf{b}_{hidden}$ is a 6×1 vector representing bias in the hidden layer, $\mathbf{w}_{output}$ is a 1×6 weight matrix in the output layer, b_{output} is a number representing bias in the output layer, and TSV represents the output thermal sensation vote.

We used the ANN model to predict the TSV of the occupants, which was similar with the ANN model used in Chapter 3. For the input parameter like metabolic rate, a review paper (Green, 2011) and ISO 8996 (ISO, 2004) have identified a correlation between HR and metabolic rate. High HR typically indicates high metabolic rate. Choi (2012) and Kizito (2018) also showed that HR was an important factor for predicting individual TSV. Therefore, the HR could be used to predict TSV, replacing metabolic rate in this study. Meanwhile, skin temperature is related to radiative, convective and evaporative heat loss from human skin (Katić, 2016) and is therefore a crucial factor in individual thermal comfort (Davoodi, 2018). In addition, previous studies have found a correlation between thermal sensation and sweat rate or skin wetness (Sim, 2018; Cheng, 2018).

To predict individual TSV, then, the ANN model in this study required six input parameters: two indoor environmental parameters (air temperature and air RH) and four individual parameters (wrist skin temperature, wrist skin RH, HR and clothing insulation). Therefore, n = 6 in Eq. (6.6) and the input vector **X** of the six input parameters is

$$\mathbf{X} = [T_{air}, RH_{air}, T_{skin}, RH_{skin}, HR, Clo]^T \tag{6.7}$$

The model output TSV can be expressed as a number from −3 to 3. The collected data were used to train the ANN model so that the predicted TSV would be nearly the same as the collected data in the offices.

This study used Matlab Neural Network Toolbox (Beale, 2017) in Matlab R2018a to build and train the ANN model. The training targets were the mean absolute error between the TSV that had been collected and the predicted TSV. All the data were randomly split so that 70% for training and 30% for cross validation. We used the min-max normalization to rescale the values of each input parameter. For the training process, the Levenberg-Marquardt (LM) algorithm (Lourakis, 2005) was used to approach the unknown weight coefficients as shown in Eq. (3.6).

6.1.3 HVAC control algorithm for thermal comfort

After training the ANN model, we developed a control strategy for the HVAC system by using the correlation between the physiological data and occupants' TSV. Figure 6.4 shows the working principle of the control strategy for the HVAC system. The lighting occupancy sensor on the ceiling and the Bluetooth receiver in the wristband can sense the occupant's arrival and departure in the offices. Thus, the BAS can control the on/off status of the HVAC system automatically. The wristband measures the physiological data, including skin temperature, skin RH and HR, every ten minutes. The ANN model then uses the correlation to predict the TSV, and the control system determines whether or not the occupants feel comfortable and the indoor environmental parameters need to be adjusted. If the occupants feel cold, the thermostat set point needs to be raised, and vice versa. If the occupants feel comfortable, the thermostat set point remains unchanged. The process updates every ten minutes, or whenever a new occupant enters or an occupant leaves the room. When the room is unoccupied, the HVAC system is shut down.

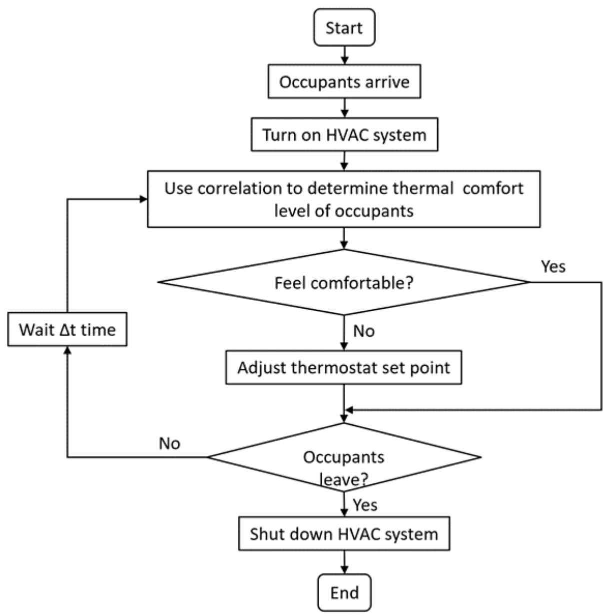


Figure 6.4. The working principle of the control algorithm of using the physiology parameters from the wristband

With the above working principle, the control system was able to calculate comfortable indoor environmental parameters. In a single-occupant office, "comfort" means a neutral feeling and $TSV = 0$ on the part of the occupant. To enable this neutral feeling, we can solve the air temperature in the input vector with the following equation based on Eq. (6.6):

$$\mathbf{w}_{hidden}\mathbf{X} = -\mathbf{b}_{hidden} - \ln\left(-1 - \frac{\mathbf{w}_{output}}{b_{output}}\right) \tag{6.8}$$

However, in multi-occupant offices, it is typically impossible for every occupant to feel neutral simultaneously, which means that all $TSV = 0$ is impossible. Rather, thermal comfort in a multi-occupant office implies that all TSV values are close to 0 (Lourakis, 2005), which means

$$\min_{T_{air}} \sum (TSV - 0)^2$$

where the summation symbol represents the adding of the TSV^2 for all occupants of the room. According to the study's hypothesis and Eqs. (6.1) through (6.5), the room air temperature is the variable. Thus, at the minimum we have

$$\frac{\partial(\sum TSV^2)}{\partial T_{air}} = \sum 2TSV \frac{\partial TSV}{\partial T_{air}} = 0 \tag{6.9}$$

With Eq. (6.9), it is clear that for single-occupant offices.

$$\frac{\partial(\sum TSV^2)}{\partial T_{air}} = 0 \Leftrightarrow TSV = 0$$

For multi-occupant offices, by using the chain rule and Eq. (6.6) for Eq. (6.9), we obtain

$$\frac{\partial(\sum TSV^2)}{\partial T} = \sum 2TSV \cdot \left(- \frac{w_{output}}{[1+\exp(-\mathbf{w}_{hidden}\mathbf{X} - \mathbf{b}_{hidden})]^2} \right) \cdot \exp(-\mathbf{w}_{hidden}\mathbf{X} - \mathbf{b}_{hidden}) \cdot \left(-\mathbf{w}_{hidden}[1, \frac{\partial RH_{air}}{\partial T_{air}}, \frac{\partial T_{skin}}{\partial T_{air}}, \frac{\partial RH_{skin}}{\partial T_{air}}, 0, 0]^T \right) \tag{6.10}$$

Where $\frac{\partial RH_{air}}{\partial T_{air}}$ can be calculated directly by psychrometric relationship; $\frac{\partial T_{skin}}{\partial T_{air}}$ and $\frac{\partial RH_{skin}}{\partial T_{air}}$ can be calculated by Eqs. (6.2) and (6.3).

Hence, the control system can solve the above equations to find the comfortable air temperature for the offices. Because the current thermostats and control system only accept integers for the set point, the system identifies the closest integer as the thermostat set point with the optimal air temperature.

As a previous study (Deng, 2018) observed the occupants of multi-occupant offices may compromise according to others' thermal preferences. When occupants do not know the thermal needs of others, they often choose not to adjust the HVAC system. As a result, thermal comfort for all occupants is hard to achieve, and the room air temperature may become extremely hot or cold. However, because it receives physiological signals from all the occupants in the room, the smart control system knows if some occupants feel uncomfortable and the indoor environment needs to be adjusted. Even if the occupants do not communicate with one another, the smart control system is able to determine the indoor environmental parameters. Therefore, the problem of thermal comfort in multi-occupant offices can be solved.

6.1.4 Validation of HVAC control algorithm

After designing this smart HVAC control system, we needed to experimentally validate its ability to improve thermal comfort in the offices. To do so, we applied the control strategy for the HVAC system in several multi-occupant offices. We used the collected indoor air temperature and RH measured by the data loggers, and physiological parameters measured by the wristbands, as input to the control system. The system adjusted the thermostat set point in response to the measured data. We used a questionnaire to record the occupants' TSV before and after the adjustment. The methods of conducting questionnaire survey was the same as Chapter 3. We validated the system in summer, fall and winter, since the clothing levels of the occupants and the indoor RH pattern varied from season to season. However, the experimental validation was time-consuming. The limited number of validation cases covered only a small group of occupants and limited ranges of the control parameters. The control parameters, such as air temperature, skin temperature, skin RH and HR, were hard to go to extremes, so validating these extreme cases was hard. Therefore, we also used numerical simulations to validate the control system. We used Monte Carlo method to generate different combinations of the input parameters. We simulated the number of occupants in the office, from one to five. Next, we randomly generated the air temperature, air RH, clothing insulation, skin temperature, skin RH and HR as the inputs to the control system. With these inputs, we calculated the TSV with the ANN model in the control system and compared the TSV before and after the control of the indoor environment. Therefore, we could evaluate the performance of the developed control system by using numerical methods with a large amount of data in different scenarios of larger range.

6.1.5 Energy analysis

We also analyzed the energy use of the HVAC system in the offices with the developed control strategy by using an energy simulation program. We simulated the heating and cooling loads in the offices with EnergyPlus. We constructed a building geometry model based on the HLAB building as shown in Figure 4.1, and used the actual properties of the HLAB building and the HVAC system in the energy simulation. This model had been validated previously, and detailed information can be found in Chapter 4. The weather data used in the simulation was that for a typical meteorological year (TMY3). The developed control system with wristbands was able to adjust the thermostat settings based on the indoor environmental and human physiological parameters. We simulated these parameters numerically for the control system and generated the schedule and settings of the HVAC system for the energy simulation.

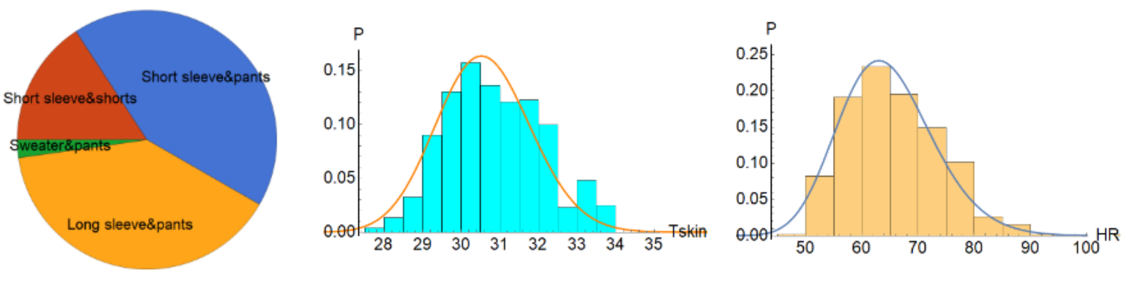
6.2 Results

The above methods collected the data to train the ANN models for predicting TSV. The correlations between the physiological parameters and occupants' TSV were then used to improve the overall thermal comfort in multi-occupant offices. Finally, we analyzed the HVAC control system experimentally and though simulations.

6.2.1 Data collection

Data were collected during three seasons of 2019. In each season, we collected the data for more than three weeks in every multi-occupant office. We obtained over 500 data points from the 24 occupants to train the ANN model. The average data collection duration for each occupant exceeded 5 h.

Figure 6.5 shows the distributions of clothing level, wrist skin temperature and HR in the collected data. In winter, shoulder seasons and summer, the typical clothing level was a sweater with thick pants, a long/short sleeve shirt with pants, and a short sleeve shirt with pants/shorts, respectively. However, some occupants kept almost the same clothing level indoors all year around. As for the skin temperature and HR, the obtained distributions were very similar to those in previous studies (Inoue, 2001; Inoue, 2009) from over 2000 people. Therefore, the bias of the data collection was small.



(a) (b) (c)

Figure 6.5. Distribution of the collected data: (a) clothing level; (b) wrist skin temperature; (c) heart rate. The probability density curves of the collected data were lognormal distribution.

6.2.2 ANN model training

We used the above collected data from the four seasons to train the ANN model by means of the LM algorithm. Figure 6.6 displays the training results for TSV. The ANN model was able to predict occupants' TSV with six input parameters. After training, the prediction fitted the collected data with R^2=0.86. Compared with the R^2=0.75 (Deng, 2018) when physiological parameters were not used, the ANN model in this study was more accurate.

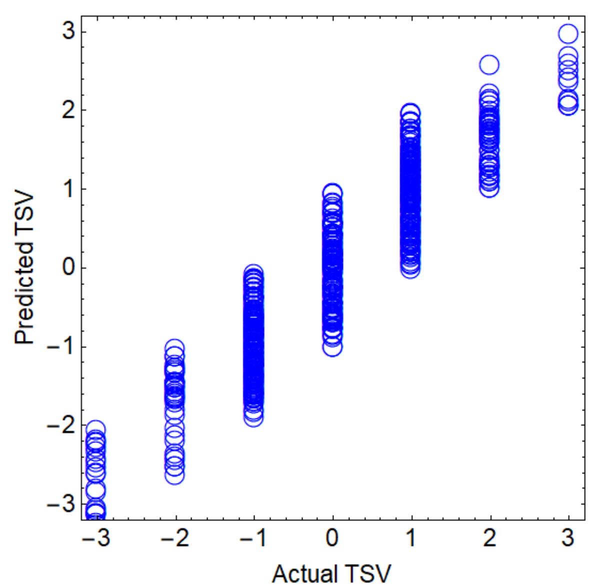


Figure 6.6. The training results of the ANN model.

6.2.3 Control system for multi-occupant office

6.2.3.1 *GUI of the control system*

After training the ANN model, we developed an HVAC control system for the offices. Figure 6.7 shows the graphical user interface (GUI) of the control system that incorporates wristband data. It is a dynamic GUI and can update the input and control information automatically. The left and right halves of the panel are the input and output fields, respectively. As shown at the top of the input field, we need the indoor air temperature and RH data from the data logger in the office. The small thermometer next to is updated automatically with the input data. Next, in the middle of the GUI, we must select checkboxes to indicate the presence of occupants in the office based on the Bluetooth transmissions from their wristbands. The current system supports a maximum of five occupants. The greater the number of occupants, the more input fields are available for the physiological data. We then need the physiological data from the occupants' wristbands and their clothing insulation values for the input fields. With these data, the program uses the algorithm presented in Section 6.1.3 to calculate the optimal air temperature set point and the control behavior. It also uses the ANN model to predict the occupants' TSV before and after the control behavior. Finally, the GUI displays the TSV, control behavior and thermostat diagram in the output field, on the right side of Figure 6.7. The light red arrow and the red arrow in the thermostat diagram point to the current and optimal set points, respectively. For example, Figure 6.7 portrays a case with three occupants. The current air temperature is 22.3°C, and the control behavior is raising of the set point by 2°C. Occupants No. 1 and 2 feel slightly cool before the control behavior. After control, they feel almost neutral. However, occupant No. 3 feels neutral before control, but slightly warm after control. The overall thermal comfort in this three-occupant office is improved, but not for all the occupants. If the TSV of some occupants contradicts that of others, the current system can satisfy most but not all of the occupants. This occurs because the goal of the control algorithm is to minimize the summation of TSV^2. The system can control only the room air temperature. Hence, further study is needed to provide personalized environmental control and satisfy all occupants.

To avoid the impact of incorrect measurements by the wristband and data logger on the control system, and to enhance the system's robustness, the input fields accept only reasonable inputs. The acceptable range of the air temperature is from 15°C to 35°C, wrist skin temperature from 28°C to 36°C, and HR from 50 to 160 bpm. If any input data are outside the acceptable range, the system will display an error message and will not adjust the set point.

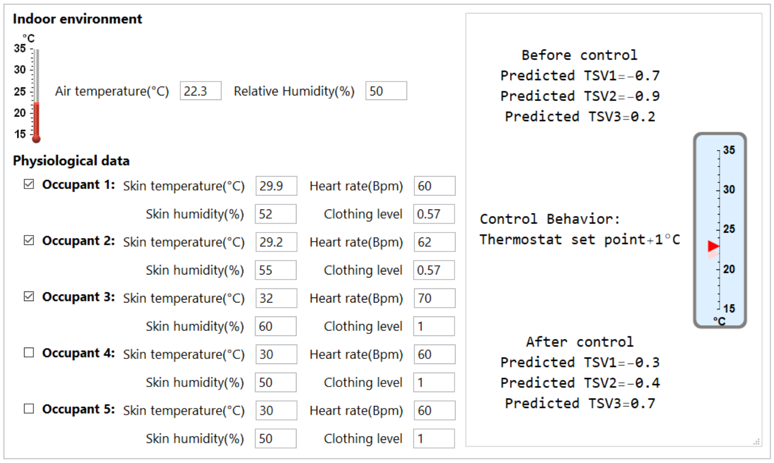


Figure 6.7. The GUI of the developed control system using wristbands with three occupants.

6.2.3.2 *Experimental validation of the control system*

After designing this control system, we validated it in summer, shoulder and winter seasons as described in 6.1.4. Most of the validation cases were conducted in offices with two or three occupants. Only 10% of the cases had one occupant, and 15% had four occupants. As for the clothing level, most occupants wore short sleeve shirts and pants in summer, and long sleeve shirts and pants in shoulder seasons, and adding sweaters in winter. In summer some wore short sleeve shirts and shorts, and only a few wore long sleeve shirts with pants. Some occupants wore short sleeve shirts and pants all year around.

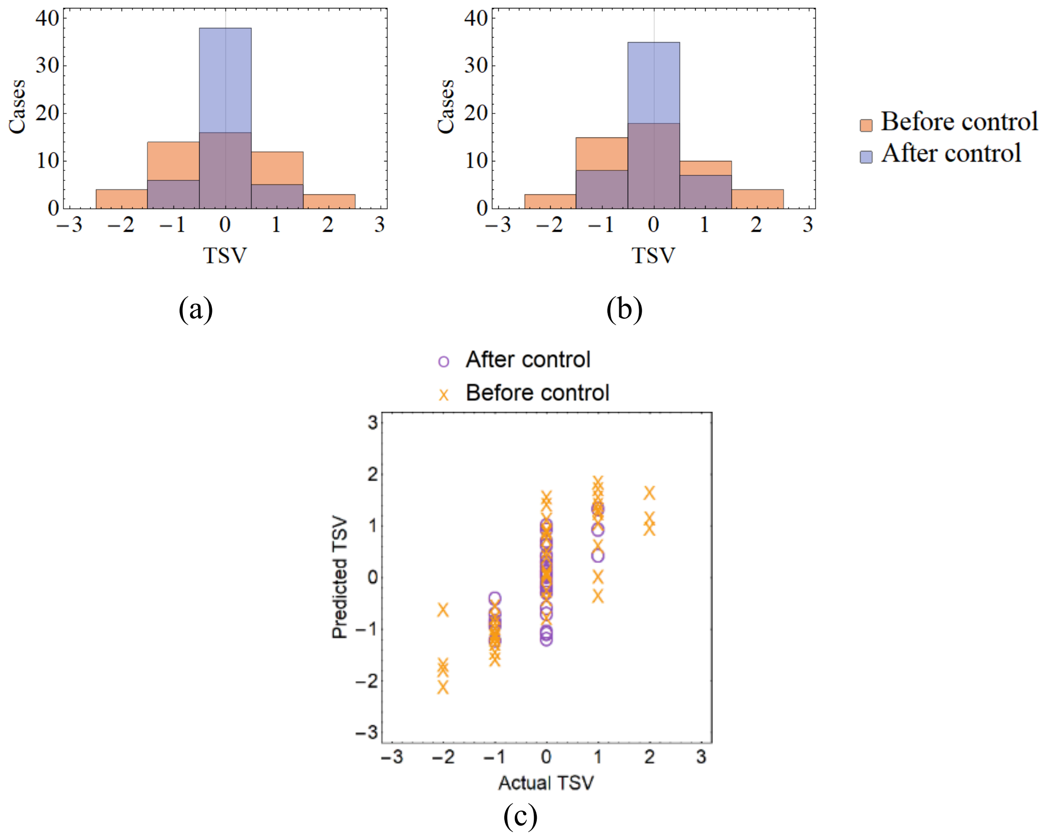


Figure 6.8. Results for the experimental validation cases before and after using the developed control system: (a) collected TSV; (b) predicted TSV by ANN model; (c) comparison of the ANN results with collected TSV data.

Figure 6.8 (a) displays the collected TSV of the occupants, as recorded on a questionnaire before and after the control behavior. Figure 6.8 (b) shows the TSV predicted by the ANN model that was used in the control system. Figure 6.8 (c) to shows the comparison of each ANN results with the collected TSV data. The predicted TSV exhibited a similar pattern to that of the collected TSV, and this finding further validated the accuracy of the ANN model. The figure also demonstrates that the control system was able to improve the thermal comfort in the office. Before using the control system, over half of the occupants felt uncomfortable, ranging from cool (TSV=-2) to warm (TSV=2). After using the system, almost all the occupants reported a neutral feeling. Fewer than 10% of the occupants still felt slightly cool or slightly warm, while none of the occupants felt cool or warm. Because the control system optimized the overall thermal comfort for all the occupants, some occupants still compromised for the sake of others' thermal preferences, as in the example shown in Figure 6.7. Thus, we experimentally validated the developed control system that uses wristbands and the ANN model.

6.2.3.3 *Numerical validation of the control system*

Since the validation tests were very time-consuming, we also performed numerical simulations. The purpose of these simulations was to increase the test size and explore more cases, especially extreme cases. For numbers of office occupants ranging from 1 to 5, we ran 1000 numerical cases each. We used a uniform distribution to randomly generate air temperatures from 18°C to 25°C, clothing insulation values from 0.36 to 1.3, and RH from 0% to 100% as the input parameters of the control system. As for generating the human skin temperature and HR data, previous studies (Huxley, 1932; Kuikka, 2003) had found that a lognormal distribution was suitable for describing biological and medical phenomena such as growth and metabolic rate. The probability density function of the lognormal distribution was

$$P = \frac{1}{x\sigma\sqrt{2\pi}} e^{-(\ln x-\mu)^2/2\sigma^2} \tag{5.11}$$

where μ and σ were mean and standard deviation of the collected data, respectively.

Thus, we randomly generated the skin temperature and HR by using the lognormal distribution, and the probability density curves are shown in Figure 6.5. These curves fitted the collected data well.

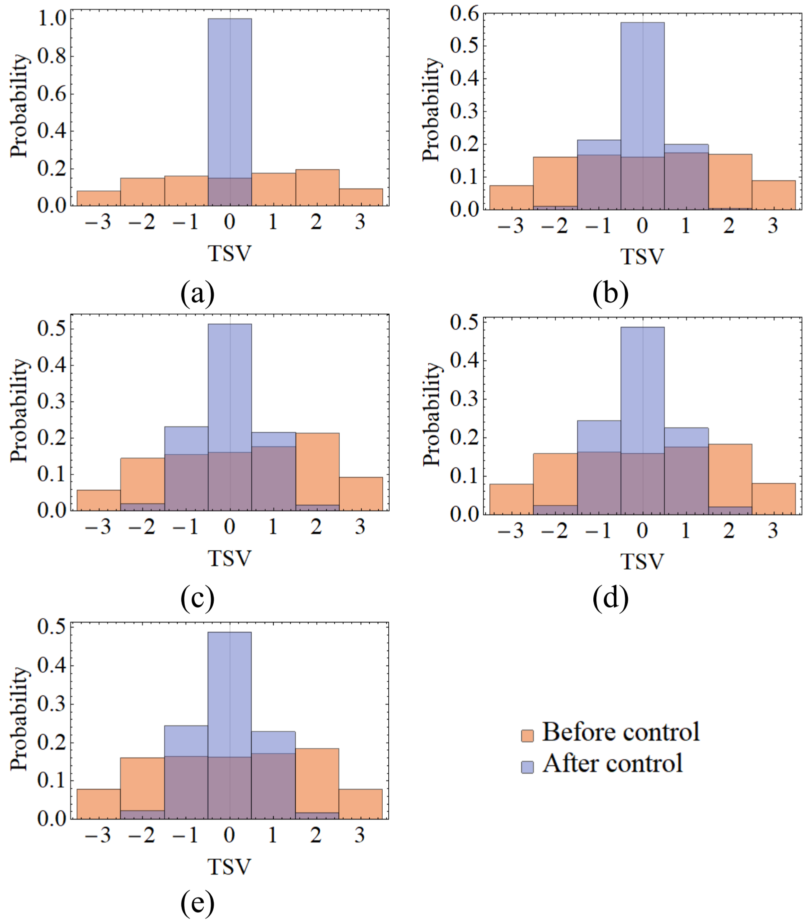


Figure 6.9. The distribution of TSV before and after using the developed wristband control system in the numerical validations. The number of the occupants was from one to five in (a) to (e).

Figure 6.9 shows the TSV distribution in the numerical validations before and after the developed wristband control system was used. Since we generated the parameters randomly within a large range, the simulated TSV before control was distributed from cold to hot almost evenly. In a single-occupant room, the wristband control system would always find the neutral temperature at which TSV = 0, as shown in Figure 6.9 (a). However, if the number of occupants in the room was greater than one, the TSVs of most occupants would still not be optimized after control. Some occupants might still feel slightly cool or warm because of the necessary compromise among different occupants, as in the example shown in Figure 6.8 (b). A similar phenomenon occurred more often in the offices with greater numbers of occupants, as shown in Figure 6.9 (b) through (e).

Table 6.1 lists the improved TSV results in the simulated validation cases. "Improved" TSV means that the absolute value of TSV was reduced after control. In single-occupant offices, TSV would certainly be improved, while in multi-occupant offices most TSVs would be improved. The greater the number of occupants in an office, the harder it would be to improve the overall thermal comfort. This would occur because of the various thermal preferences among the occupants, especially when some occupants have opposing preferences. Therefore, the TSVs of most occupants were between -1 and 1 after control. Feeling cool and feeling warm still existed, but only for a very small number of occupants in extreme cases.

Table 6.1. Improved TSV results in the simulated cases

	Percentage of improved TSV	TSV_f around 0	TSV_f around 1 or -1	TSV_f around 2 or -2
1 occupant	100%	100%	0%	0%
2 occupants	97%	57%	41%	2%
3 occupants	93%	52%	45%	3%
4 occupants	89%	49%	47%	4%
5 occupants	85%	47%	48%	5%

6.2.3.4 *Energy analysis of the control system*

After analyzing the thermal comfort in the offices with the wristband control system, we simulated the office heating/cooling load with the number of occupants ranging from 1 to 5. For each number of occupants, we simulated 1000 cases and obtained the average heating/cooling load. We still generated the parameters randomly as in Section 6.2.3.2. The wristband control system was able to calculate and adjust different set points for different input values of air temperature, skin temperature, clothing level, etc. Note that every ten minutes the set point was recalculated as shown in Figure 6.4. We used the resulting set point schedules in the energy simulation program. We compared the energy use per area in order to eliminate the impact of room size, because the areas of these multi-occupant offices were different. Since all the multi-occupant offices were in the interior zone as shown in Figure 6.1, the cooling load dominated. We compared the developed wristband control system with the use of constant set points. On the basis of ASHRAE comfort zone specifications (2013), the set points for winter, shoulder and summer seasons were 27°C, 25°C and 21°C, respectively.

Table 6.2 compares the average heating and cooling loads per area between the control system using wristbands and the constant set point for a one-year period. The simulated heating load was almost the same as that with the constant set point, but the cooling load was slightly higher. The difference was less than 7%. We also compared the control systems when coupled with occupancy-based control. There were lighting sensors in the offices that could detect the room occupancy and shut down the HVAC system to save energy. The developed control system could also use the Bluetooth connection with the wristbands to detect the number of room occupants. We found that coupling with occupancy-based control yielded an energy saving of about 90% for heating load and 30% for cooling load, when either the constant set point or wristband control system was used. The reason for the huge energy saving was that the largest heating load occurred when the room was unoccupied. Shutting down the HVAC system could save energy during this period. The energy saving of the wristband control system when the room was occupied was close to that of a similar control system in a previous study (Li, 2019).

Table 6.2. Comparison of average heating and cooling load per area between the control systems using wristband and constant set point in one year

Load per area (W/m^2)	Constant set point	Constant set point with occupancy control	Wristband control	Wristband control with occupancy control
Heating	53.4	7	53.2	6.3
Cooling	98.8	72.7	106.4	72

6.3 Discussion

In this study, we used the ANN model to predict the occupants' TSV by using human physiological data such as wrist skin temperature and HR from wristbands. Because the ANN model developed here was personalized, the accuracy was good. Heart rate was used instead of metabolic rate because the actual metabolic rate was hard to measure under naturalistic conditions (Na, 2019). However, the heart rate may be influenced by other individualized factors, such as physical fitness, health, mood and age (Dishman, 1996; Hughes, 2000). Furthermore, the sensors in the wristbands may sometimes have measured the data inaccurately, for example, if the occupants did not wear the wristbands properly (too tight or too loose). Although we limited the input field, failed measurements would have interfered with and delayed the control system. In addition, the developed control system required a large number of parameters as input in order to control the HVAC system. All the indoor environmental parameters and physiological parameters could be measured automatically, but the clothing insulation level could not. Developing a smart system that detects occupants' clothing level automatically is a possible improvement for consideration in the future.

This research focused on improving the thermal comfort of occupants in multi-occupant offices by using wristband. Therefore, for developing the HVAC control system, we would like to find the best thermostat set point for multiple occupants. We did not consider compromising the thermal comfort for energy saving. Based on the results, the wristband control could provide a better thermal comfort level. It used almost the same energy consumption as using constant set point. The reason was that the wristband control only adjust the thermostat set point but did not change the architecture of the HVAC system. To further save energy, we could use occupancy control to save energy when the room was unoccupied. Currently, the lighting occupancy sensors, such as motion sensors and infrared sensors, are more friendly to occupant's privacy and application convenience. However, the lighting occupancy sensors can only determine whether the room is occupied or not. They cannot determine the number of occupants in the room, or identify which occupants are in the room. The wearable devices, such as the wristband can communicate with the BAS through Bluetooth. As a result, the BAS could identify exactly which occupants are in the room, and even their locations (Feng 2015). Therefore, the wristband has more potential for developing a personalized ventilation system for every occupant's thermal comfort and energy saving in the future. In the meanwhile, privacy and security issue of data communication for smart buildings are also the future directions for further studies (Jia 2017, Dong 2019).

We collected the data in multi-occupant offices and simulated the energy use in these offices. All the offices were in the interior zone, and we neglected the impact of solar radiation and outdoor weather on the occupants' thermal sensation and the energy use. The developed control system was able to find one optimal set point for all the occupants in a given office. However, it could not satisfy all the occupants if their thermal preferences were in conflict. Therefore, in the future it is necessary to develop a smart HVAC system with zonal control that can satisfy all the occupants.

6.4 Conclusions

In this study, we collected data on skin temperature, skin RH and HR from wristbands worn by occupants in multi-occupant offices. We developed an HVAC control system and validated it by means of experiments and numerical simulations. We also compared the energy use of the wristband control system with constant set point control. This study led to the following conclusions:

1) The ANN model predicted the occupants' TSV accurately with physiological input parameters such as skin temperature, HR and skin RH. This correlation between the physiological parameters and occupants' TSV could be used for the HVAC control system.
2) The wristband control system was capable of improving the overall thermal comfort in multi-occupant offices. The control system was smart and could adjust the thermostat set point automatically in real time. We validated the system by means of both experiments and numerical simulations. In most cases, we improved the occupants' thermal comfort level. Over half of the occupants reported a neutral feeling, and fewer than 5% of the occupants still felt uncomfortable, after using the control system.
3) The energy use by the HVAC system with the wristband control was almost the same as that with the constant set point. Coupling with occupancy-based control, by means of lighting occupancy sensors or Bluetooth, reduced the heating and cooling loads by 90% and 30%, respectively, in the interior offices.

7. CONCLUSION AND FUTURE WORK

The layout of this chapter is organized as follows: Section 7.1 summarizes the work and conclusions of this dissertation. Section 7.2 provides the potential future works.

7.1 Conclusion

First of all, in Chapter 3, we collected data on the air temperature, relative humidity, clothing level, metabolic rate, thermal sensation, and behavior in ten offices and ten apartments/houses. We 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. 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 occupant behavior in apartments/houses. The results showed that the comfortable air temperature in the apartments/houses was 1.7°C (3°F) lower than that in the offices in winter, and 1.7°C (3°F) 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.

Then, in Chapter 4, we 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. This 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 collected 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.

Next, in Chapter 5, we built and validated an RL occupant behavior model for an office building and transferred it to other buildings with thermostat setback and occupancy control. We also compared the energy use simulated by the RL model with measured data and predictions by the ANN model for the HLAB offices and four other office buildings on the Purdue University campus. This investigation led to the following conclusions:

1) The policy-based RL occupant behavior model trained by Q-learning was able to learn the logic of occupant behavior and predict the behavior accurately. The results for prediction of set point adjustment exhibited an R^2 around 0.8 and MAE less than 2 °F.
2) Transfer learning successfully transferred the logic and part of the occupant behavior model structure to other buildings with different HVAC control systems, such as

thermostat setback and occupancy control. We also transferred the RL model from office buildings to residential buildings with a modification to the impact of air temperature on occupant behavior. The prediction performance was good, with R^2 above 0.6 and MSE less than 2 °F. These transfer learning models did not require data collection. Unlike data-driven models, the transfer learning RL model had physical meaning and strong generalization capability.

3) The results of energy simulation for thermostat manual control, setback and occupancy control with the use of the RL model were similar to the results with the ANN model. The RL simulation accurately reflected the impact of occupant behavior on building energy use, but the variation predicted by the RL model was less than that predicted by the ANN model.

Finally, in Chapter 6, we collected data on skin temperature, skin RH and HR from wristbands worn by occupants in multi-occupant offices. We developed an HVAC control system and validated it by means of experiments and numerical simulations. We also compared the energy use of the wristband control system with constant set point control. This study led to the following conclusions:

1) The ANN model predicted the occupants' TSV accurately with physiological input parameters such as skin temperature, HR and skin RH. This correlation between the physiological parameters and occupants' TSV could be used for the HVAC control system.
2) The wristband control system was capable of improving the overall thermal comfort in multi-occupant offices. The control system was smart and could adjust the thermostat set point automatically in real time. We validated the system by means of both experiments and numerical simulations. In most cases, we improved the occupants' thermal comfort level. Over half of the occupants reported a neutral feeling, and fewer than 5% of the occupants still felt uncomfortable, after using the control system.
3) The energy use by the HVAC system with the wristband control was almost the same as that with the constant set point. Coupling with occupancy-based control, by means of lighting occupancy sensors or Bluetooth, reduced the heating and cooling loads by 90% and 30%, respectively, in the interior offices.

This dissertation has the following innovations and implementations:

- The ANN models built in Chapter 3 were a pioneer of using implicit occupant behavior for evaluating thermal comfort. This model could be used when the questionnaire survey was not convenient to conduct.
- The EnergyPlus simulation program in Chapter 4 was implemented by ANN occupant behavior model and could evaluate the impact on building energy use quantitatively. The energy simulation was also validated by the operational office building.
- Transfer learning was used for the first time to achieve cross-building behavior model without data collection in Chapter 5. It had the potential to be expanded to more kinds of behavior with satisfactory generalization.
- The smart HVAC control system in Chapter 6 was a cutting-edge method to control indoor environment for multiple occupants non-invasively by using physiological signals.

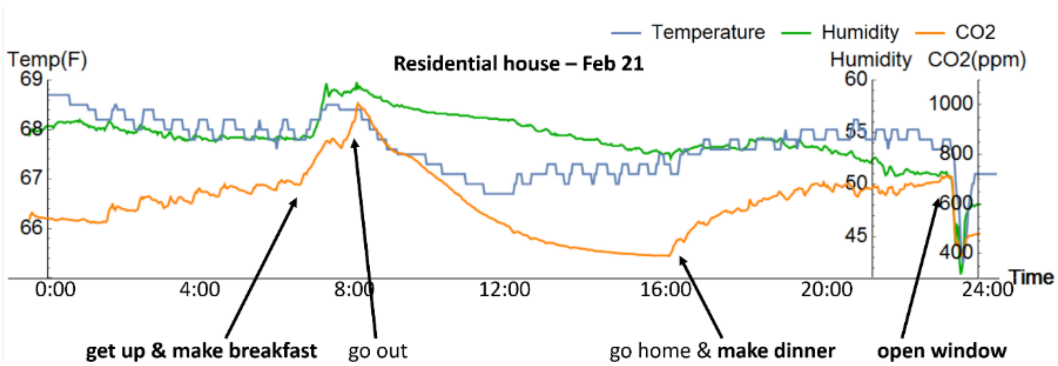
7.2 Future works

I plan to expand the PhD work and further enhance the modelling of occupant behavior and thermal comfort. With the development of more advanced sensor technology, artificial intelligence, and computational tools, the occupant behavior can be recognized and recorded by advanced sensors and AI automatically. We can also integrate a complex occupant behavior model related to indoor air quality, noise and illuminance. Finally, we can use inverse design method for personal zonal HVAC system in multi-occupant offices.

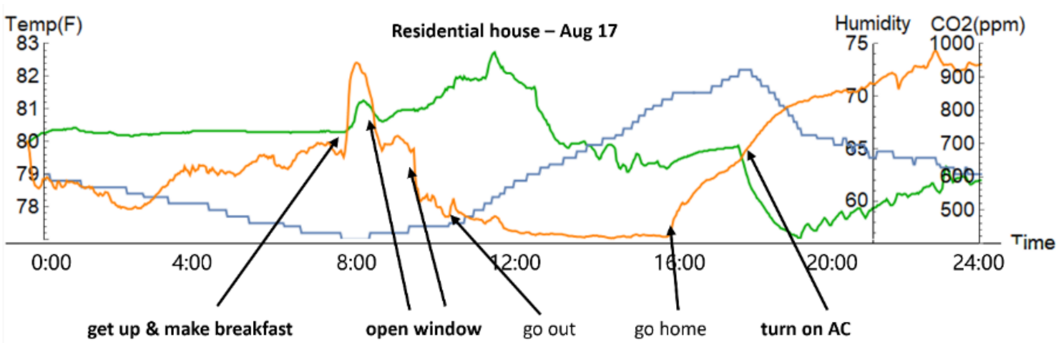
7.2.1 Recognition of occupant behavior by using advanced sensors and AI

Building energy simulation could have error with 250%, and one possible reason is occupant behavior. Therefore, collecting data on occupant behavior accurately is necessary. Previous studies collected occupant behavior and tried to make the profile and classify behaviors in residential buildings, as Figure 2.2(a) shows. The behavior profile was in very detailed way so that the simulation could be accurate. However, to obtain such results, they collected data for more than two years from thousands of residential buildings.

The measurement and record of occupant behavior was challenging, which can be divided into two categories. First one was using smart meters and sensors, such as data logger, video camera or infrared sensor. Some studies used these sensors for recording window opening and room occupancy. The limitation for this method was the high cost for installation and hard to operate sensors, especially for the residential buildings. Typically, each kind of sensor can only record one behavior. If studying different kinds of behaviors, we need to install many sensors. Another method was subjective measurement, which used survey and questionnaires to collect data. The limitations of survey were time-consuming and low accuracy. The actual behavior was often inconsistency of self-reported record since occupants may forget to record many things. There are a lot of criticism for long-term survey. For behavior study, collecting data for a long time is necessary. But the data quality always became worse and worse. The last the limitation is the "observer effect" (Rosenthal, 1976), since the occupants knew they were recorded, their behavior may change.



(a)



(b)

Figure 7.1. The relationship between air temperature, RH and CO_2 concentration and various occupant behavior in a residential building in (a) winter and (b) summer.

As the data collection in Chapter 3, we found that different kinds of behavior can impact the indoor environment differently. Figure 7.1 shows that opening window could make the room air temperature and relative humidity drop quickly in winter, but not in summer. Therefore, it is possible to recognize the occupant behavior from these parameters.

There are some studies that have used different kinds of method to detect the behavior form the indoor environment parameters, such as decision tree, curve description algorithm, change point analysis. But most only studied a few rooms, and their model worked only for one room but no validation for other rooms. We will use convolutional neural network, which was a powerful tool for curve pattern and time series. It was also used for image recognition, language processing and voice recognition. The strength of this method was that it could handle long and ordered input data series. Hence, we could use only a few weights to learn the features of occupant behavior and gain high accuracy.

7.2.2 Integrated complex occupant behavior model related to overall indoor environment

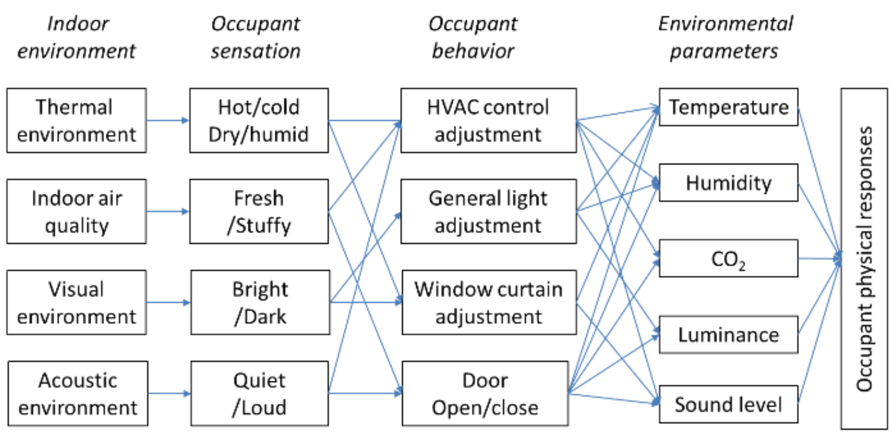


Figure 7.2. The relationship between indoor environment, occupant sensations, occupant behaviors, changes of environmental parameters, and occupant physical responses

In Chapter 3 and 4, we developed ANN models to correlate thermal comfort-related occupant behavior with indoor environment parameters. But occupant behavior in buildings refers to many other interactions with building systems such as windows, lights, blinds and internal equipment. Figure 7.2 shows the complex relationship between the occupants and indoor environments. The behavior models available from the literature for single indoor environmental aspect may not be directly used for multiple indoor environmental aspects. Thus, it is important to identify the correlations between different indoor environmental parameters and occupant behaviors.

We will use different kinds of sensors to collect occupant behavior on windows, blinds, lights hot water and different equipment. Then we will use the similar method in Chapter 3 to 5 to correlate the occupant behavior with indoor air quality, noise and illuminance. For example, opening window may be related to thermal comfort, but also indoor air quality. Closing window could also because of the noise or wind speed outside. Therefore, we can build data-driven models and physics-based models with the collected data. The models can be used to evaluate the overall indoor environmental quality with thermal comfort, air quality, lighting and acoustics. As a result, we can identify the satisfied overall indoor environmental quality for building occupants.

7.2.3 Prediction of clothing level and metabolic rate by advanced cameras

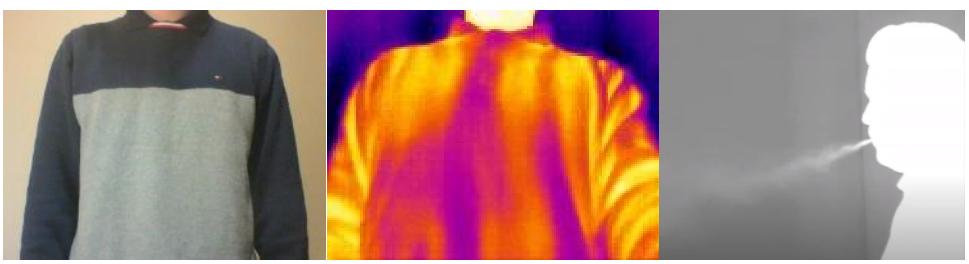


Figure 7.3. Images captured by normal camera (left), infrared camera (middle) and gas detection camera (right).

Clothing level and metabolic rate are important factors for predicting thermal comfort. Traditional method of collecting clothing level information from occupants was using questionnaire survey (ASHRAE, 2017). We also used this method to collect clothing insulation in Chapter 3. However, this method was very time-consuming as number of occupants was large. To collect the clothing level accurately and automatically, we could use normal camera and infrared camera. The normal camera could capture the image so that we could use image classification algorithm to detect the clothing level as Figure 7.3 shows. But the normal image could only provide the clothing information in the outermost layer. To be more accurate, ASHRAE Handbook (2017) also listed the relationship between insulation value, body surface temperature and clothing surface temperature. Therefore, we could calculate the insulation value accurately by analyzing clothing surface temperature from infrared images.

As for the metabolic rate, although ASHRAE Handbook (2017) listed typical metabolic heat generation for various activities, the actual metabolism was personalized. The table only provided information for average adult. Another method but much less accurate of estimating metabolic rate physiologically was to measure the heart rate, as ISO8996 (ISO, 2004) indicated and we also used this factor in Chapter 6. The rate of metabolic heat produced by the body was most accurately measured by the rate of respiratory O_2 consumption and CO_2 production. An empirical equation for metabolic rate was given by Nishi (1981). To calculate the carbon dioxide production, researchers always used gas flow rate meter to measure inhaled O_2 and exhaled CO_2 previously, which was hard to operate for many building occupants. We plan to use a CO_2 gas detection camera as Figure 7.3 shows. It used a special lens to capture a certain gas. By analyzing the images captured by this kind of camera, we could use image classification algorithm to estimate the exhaled CO_2 flow rate and then metabolic rate in real time. This method will be more accurate than using table values, and more convenient to operate in most buildings.

7.2.4 Inverse design of personal zonal HVAC system for multi-occupant office

In order to reduce the behavior impact on building energy efficiency, it is crucial to further improve the indoor thermal comfort. Therefore, we also developed the personalized thermal comfort models by using the occupants' physiological signals from wristband in Chapter 6. However, the thermal sensation conflict issue of multi-occupant was not well-solved in the offices. If the thermal preferences of some occupants were contradictory, current system could only compromise. What is more, although thermal comfort was improved by the developed wristband control system, energy use was not saved very much. There are still some potentials to improve the HVAC system for thermal comfort and energy saving. Hence, we will design personalized zonal control of the HVAC system in multi-occupant offices. Such system could not only condition the room for different zones with different air temperatures, but also use the energy where it is needed and save more energy than conditioning the whole space.

We will use inverse design method. In forward simulation, we could calculate the fluid domain and obtain the velocity and temperature distribution in a room with given boundary conditions, such as the supply velocity and temperature. The governing equation is NS equation. As for inverse problem, the objective temperature in some certain locations is given as input for the fluid domain. However, there are some variable boundaries that we want to identify the velocity and temperature as output. We will enhance the efficiency of the inverse design algorithm and develop a new algorithm. After developing the inverse simulation method with high efficiency, we will use it for designing the zonal control HVAC system in multi-occupant office. However, as for designing the personalized ventilation system in office, the objective is that the air temperatures in various zones are different. There are a lot of temperature combinations for various occupants. Therefore, we will use the developed high efficiency inverse design algorithm.

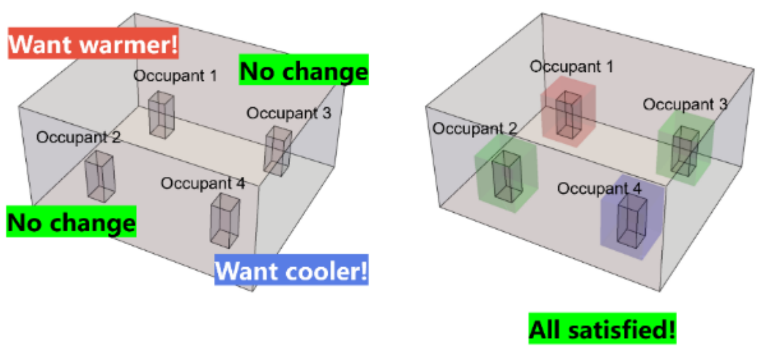


Figure 7.4. A four-occupant office that occupants have difference thermal preferences (left) and the design condition that all occupants feel satisfied (right).

Figure 7.4 shows the final deliverable. We will be able to do the personalized zonal control for each occupant for this complex situation in the multi-occupant room. We will be able to solve the thermal comfort conflict issue, so that every occupant will feel satisfied.

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