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Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband

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Abstract

Since people spend most of their time indoors, it is important to create comfortable indoor environments for building occupants. However, unsuitable thermostat settings lead to energy waste and an undesirable indoor environment, especially in multi-occupant rooms. This study aimed to develop and validate a control strategy for the HVAC systems in multi-occupant offices using physiological parameters measured by wristbands. We used an ANN model to predict thermal sensation from indoor environmental and physiological parameters such as air temperature, relative humidity, clothing level, wrist skin temperature, skin relative humidity and heart rate. The model was trained by data collected in seven multi-occupant offices in the course of a year, and it was able to predict the thermal sensation with high accuracy. Next, we developed a control strategy for the HVAC system 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 validated the system by means of both experiments and numerical simulations. In most cases, we improved the occupants' thermal comfort level. After using the wristband control, over half of the occupants experienced a neutral sensation, and fewer than 5% still felt uncomfortable. The energy consumption by the HVAC system with the wristband control was almost the same as when the constant set point was used. 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, in interior offices. Therefore, the smart HVAC control system can effectively control the indoor environment for thermal comfort and energy saving.

Keywords

Thermal comfort, artificial neural network, air temperature, skin temperature, skin relative humidity, heart rate, thermostat set point, wearable devices

1. Introduction

Currently, people in North America spend roughly 90% of their time indoors [1]. Therefore, it is important to create comfortable, healthy, and productive indoor environments for occupants. Such environments are typically achieved by the use of heating, ventilating, and air-conditioning (HVAC) systems. Unfortunately, our resulting indoor environments are still very poor, as demonstrated by a survey in which the predominant complaint by office occupants was that “it is too hot and too cold simultaneously” [2].

In many buildings, although occupants can actively adjust indoor environment settings, studies [3-4] 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 [5]. In addition, a previous study [6] 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. To solve these issues, we need to automate HVAC control systems and create “smart” systems that can ascertain occupants’ thermal sensation [7].

Thermal sensation encompasses the physiological and subjective response of occupants to the thermal environment in buildings, in vehicles and outdoors [8-9]. To evaluate thermal sensation, Fanger developed predictive mean vote (PMV) and predicted percentage dissatisfied (PPD) models in the 1970s [10]. 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 [11] that achieve better accuracy with more individualized parameters, and may also be used to control the indoor environment [12-14]. These personalized models [15-18] 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 [19-21], facial temperature [22-23], heart rate (HR) [24-25], blood pressure [26-27], pulse waves [28], brain waves [16, 29], and sweat rate [30-31]. These personalized thermal comfort models were able to predict occupants’ thermal sensation with high accuracy. Several studies [30, 32, 33] 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 to use this correlation to control HVAC systems for thermal comfort.

To measure and monitor human physiological parameters, some studies [18, 30, 34, 35] 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 [34, 36, 37]. However, only a few studies have used human physiological data for HVAC system control. For example, Li et al. [37] 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 [22] and Cosma [23, 38] 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. [36, 39] 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.

Hence, the purpose of this study was to develop and validate a control strategy for HVAC systems in multi-occupant offices using wristbands to provide thermal comfort. For this purpose, we collected the indoor environmental parameters and occupants' thermal sensation and human physiological data in several multi-occupant offices. Next, we trained an artificial neural network (ANN) model to predict the thermal sensation. Based on this model, we developed an HVAC control algorithm that could better ascertain the thermal sensation of multiple occupants. Occupants can then effectively operate and control the indoor environment for thermal comfort.

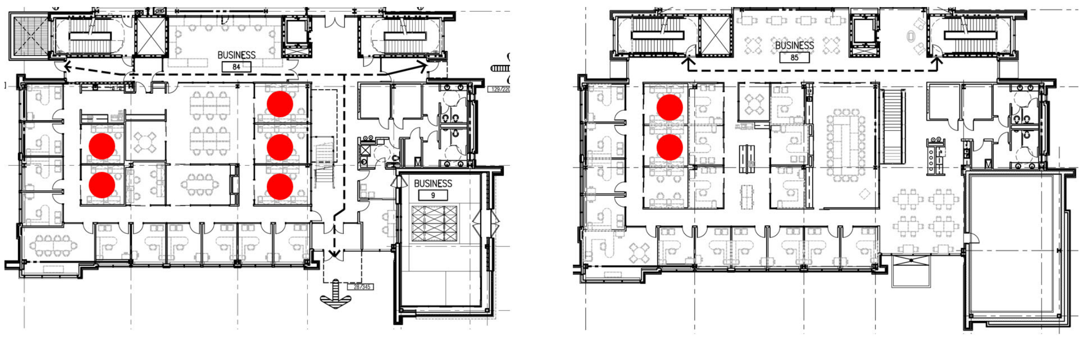
The layout of this paper is organized as follows: Section 2 describes the methods for collecting data, predicting thermal sensation, and developing and validating HVAC control strategies. Section 3 provides the results of data collection and comfort control system analysis. Sections 4 and 5 discuss the results and summarize conclusions of this study, respectively.

2. 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.

2.1 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 Fig. 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)

Fig. 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.

Each of the offices had a thermostat (Siemens 544–760A) as shown in Fig. 2(a) which enabled the building automation system (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 800,049) as shown in Fig. 2(b) in each office to record the room air temperature and RH every ten minutes. In the early mornings before the occupants' arrival, we adjusted the thermostat set point in each office to a different temperature to expand the data range. We used wristbands (Hesvit S3) as shown in Fig. 2(c) to record the occupants' physiological data in the Ray W. Herrick Laboratories (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.

We also used a questionnaire to collect the thermal sensation vote (TSV) [40] according to a seven-point scale (−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 every ten minutes when they were inside the offices.

(a) (b) (c)

Fig. 2. Data collection devices used in this study. (a) thermostat on the wall, (b) data logger, (c) wristband.

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.

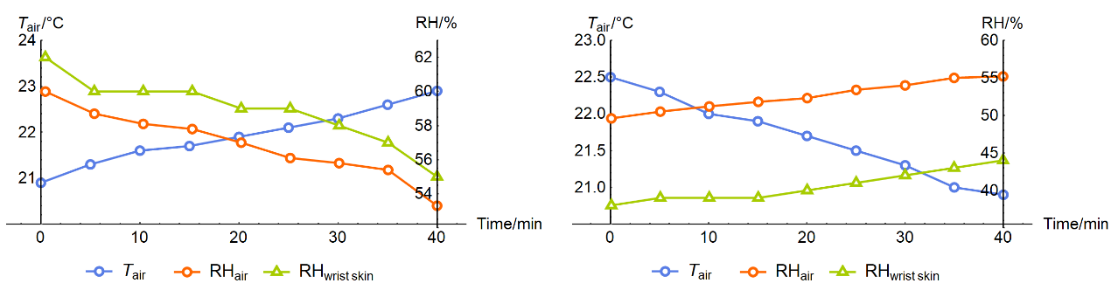
2.2 Artificial neural network model for thermal comfort

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 Fig. 1.
- Based on the collected data and published literature [22, 41], the wrist skin temperature difference in each time step was almost 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:

$$T_{skin,f} - T_{skin,i} = C(T_{air,f} - T_{air,i}) \tag{1}$$

  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.



(a) (b)

Fig. 3. Typical cases of collected air RH variation and wrist skin RH variation with air temperature in 40 minutes: (a) heating case, (b) cooling case.

- Room air RH changed when the thermostat set point was adjusted. Fig. 3 shows the typical cases of collected air RH variation and wrist skin RH variation with air temperature in 40 minutes in heating and cooling, respectively. The data were collected every 5 minutes. When the thermostat set point and air temperature were raised, the air relative humidity decreased, and vice versa. We calculated the humidity ratio and found it kept almost constant during this adjustment period. Although the room humidity ratio may be also impacted by the supply air humidity ratio, outdoor weather and the number of occupants in the room. As for the skin

RH variation, we found that the skin RH variation was similar with the air RH variation during the adjustment period. Although the skin RH may be also impacted by metabolism, emotion and individual difference. Therefore, during the short time when control system works, 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. Thus, we have

$$AH(T_{air,i}, RH_{air,i}) = AH(T_{air,f}, RH_{air,f}) \tag{2}$$

$$RH_{skin,f} - RH_{skin,i} = RH_{air,f} - RH_{air,i} \tag{3}$$

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

- Metabolic rate was related to HR, according to the literature [42] and ISO8996 [43]. Occupants' clothing level and HR remained the same in the offices before and after the control system adjusted the thermostat set point. Thus,

$$HR_i = HR_f \tag{4}$$

$$Clo_i = Clo_f \tag{5}$$

With the above hypothesis, this study could predict the occupants' TSV. In many previous studies, [6, 44-46] 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 Fig. 4, 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.

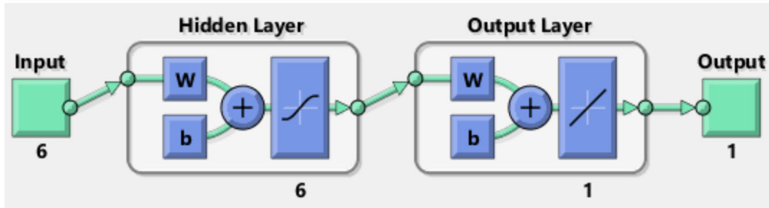


Fig. 4. Structure of the ANN model in this study. There are six input parameters, six neutrons in the hidden layer and one output parameter.

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

$$TSV = \mathbf{w}_{output}\{1+\exp[-(\mathbf{w}_{hidden}\mathbf{X}+\mathbf{b}_{hidden})]\}^{-1}+b_{output} \qquad (6)$$

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. According to the PMV thermal comfort model [10], six parameters have an impact on thermal comfort: air temperature, air RH, 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 the room air temperature. Therefore, we assumed that the radiant temperature was the same as the room air temperature. Our measurements also indicated that the air velocity in the offices was lower than 0.2 m/s. According to ASHRAE Standard 55 [47], acceptable comfort zones have air velocity below 0.2 m/s, and thus the impact of air velocity on thermal comfort could be neglected in this study. As for the metabolic rate, a review paper [42] and ISO 8996 [43] have identified a correlation between HR and metabolic rate. High HR typically indicates high metabolic rate. Choi [24] and Kizito [25] 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 [48] and is therefore a crucial factor in individual thermal comfort [49]. In addition, previous studies have found a correlation between thermal sensation and sweat rate or skin wetness [30-31].

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), and the input vector $\mathbf{X}$ of the six input parameters is

$$\mathbf{X} = [T_{air}, RH_{air}, T_{skin}, RH_{skin}, HR, Clo]^T \quad (7)$$

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 Deep Learning Toolbox [50] in Matlab R2019a 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 [51] used the following approximation to approach the unknown weight coefficients:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}\mathbf{J}^T + \mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e} \quad (8)$$

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.

2.3 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. Fig. 5 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.

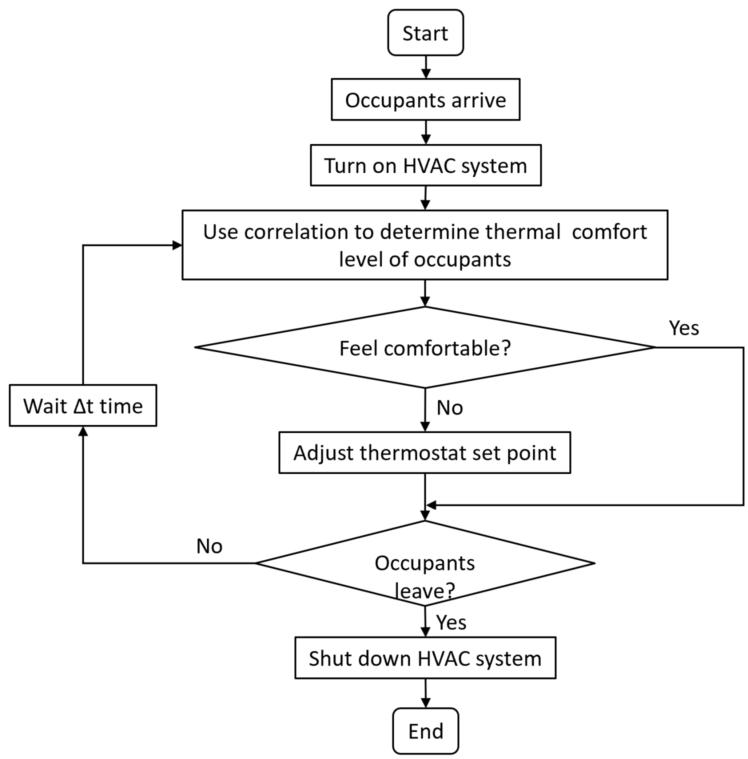


Fig. 5. Working principle of the control algorithm for using physiological parameters from wristbands

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):

$$\mathbf{w}_{hidden}\mathbf{X} = -\mathbf{b}_{hidden} - \ln\left(-1 - \frac{\mathbf{w}_{output}}{b_{output}}\right) \tag{9}$$

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 [52], 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. (1) through (5), the room air temperature is the variable. Thus, at the minimum we have

$$\frac{\partial(\sum TSV^2)}{\partial T_{air}} = \sum 2TSV \frac{\partial TSV}{\partial T_{air}} = 0 \tag{10}$$

With Eq. (10), 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 applying the chain rule and using Eq. (6) in Eq. (10), we obtain

$$\frac{\partial(\sum TSV^2)}{\partial T_{air}} = \sum 2TSV \cdot \left(-\frac{w_{output}}{[1+\exp(-\mathbf{w}_{hidden}\mathbf{X}-\mathbf{b}_{hidden})]^2} \right) \cdot \exp(-\mathbf{w}_{hidden}\mathbf{X}-\mathbf{b}_{hidden}) \cdot \left(-\mathbf{w}_{hidden}[1, \frac{\partial RH_{air}}{\partial T_{air}}, \frac{\partial T_{skin}}{\partial T_{air}}, \frac{\partial RH_{skin}}{\partial T_{air}}, 0, 0]^T \right) \tag{11}$$

where $\frac{\partial RH_{air}}{\partial T_{air}}$ can be calculated directly by psychrometric relationship, while $\frac{\partial T_{skin}}{\partial T_{air}}$ and $\frac{\partial RH_{skin}}{\partial T_{air}}$ can be calculated by Eqs. (2) and (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.

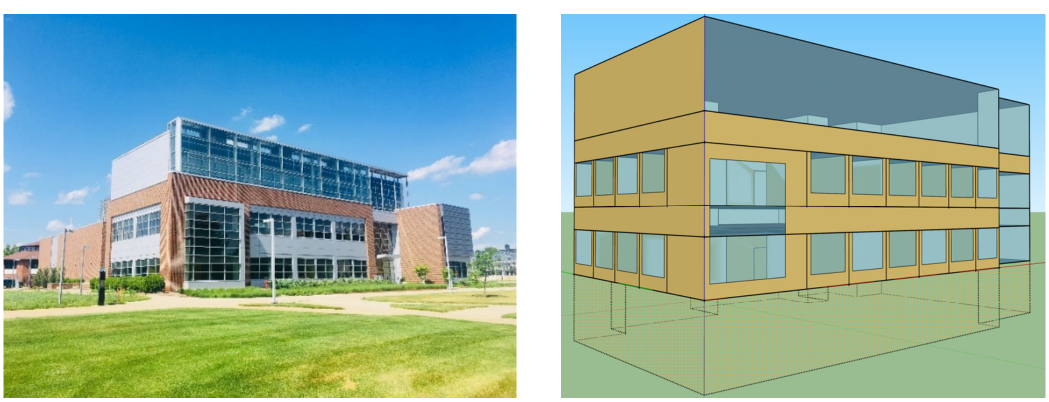
As a previous study [6] observed the occupants of multi-occupant offices may compromise according to others' thermal preferences. When occupants do not know the thermal needs of others, they often choose not to adjust the HVAC system. As a result, thermal comfort for all occupants is hard to achieve, 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.

2.4 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 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. 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. It was hard that the actual control parameters such as air temperature, skin temperature, skin RH and HR went 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.

2.5 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 Fig. 6, 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 [53]. 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.



(a) (b)

Fig. 6. (a) Photograph of the HLAB building and (b) geometric model of the HLAB building for EnergyPlus simulation

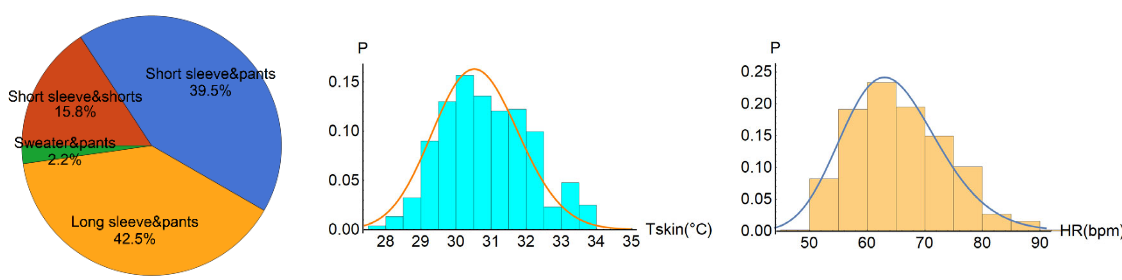
3. Results

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.

3.1 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.

Fig. 7 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 [54-55], collected from over 2000 people. Therefore, the bias of the data collection was small.



(a) (b) (c)

Fig. 7. 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 distributions.

3.2 ANN model training

We used the above collected data from the three seasons to train the ANN model by means of the LM algorithm. Fig. 8 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 $R^2 = 0.89$. Compared with the $R^2 = 0.75$ [6] when physiological parameters were not used, the ANN model in this study was more accurate.

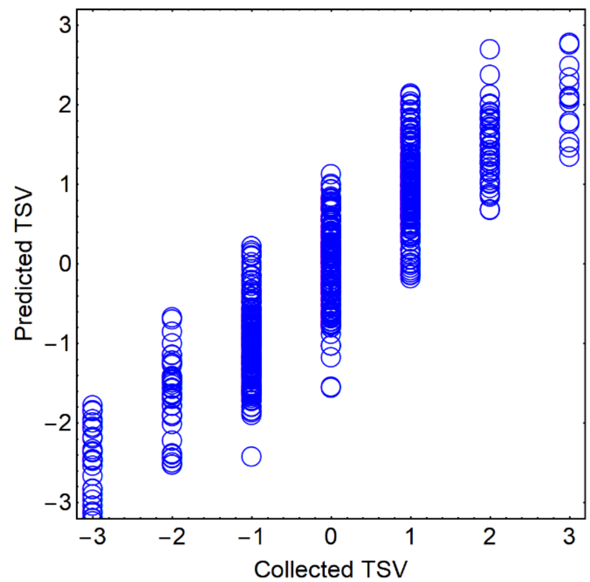


Fig. 8. The training results for the ANN model.

3.3 Control system for multi-occupant office

3.3.1 GUI of the control system

After training the ANN model, we developed an HVAC control system for the offices. Fig. 9 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 2.3 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 Fig. 9. The light red arrow and the red arrow in the thermostat diagram point to the current and optimal set points, respectively. For example, Fig. 9 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.

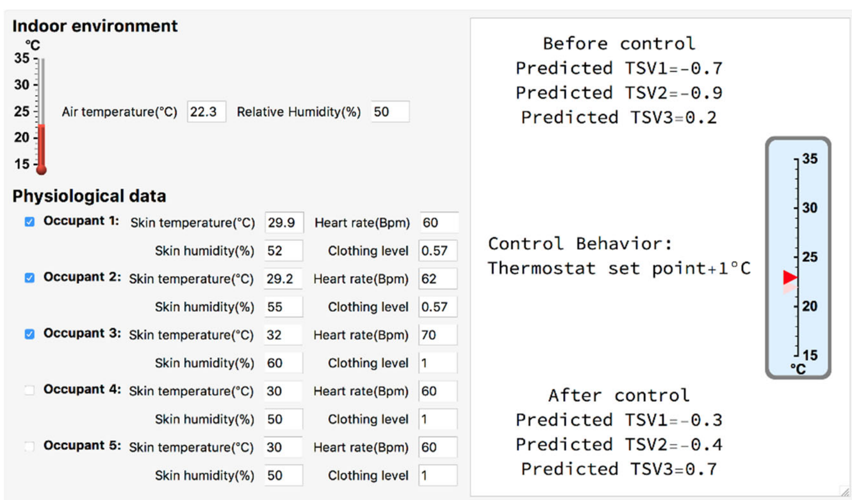


Fig. 9. The GUI of the developed control system using wristbands with three occupants.

3.3.2 Experimental validation of the control system

After designing this control system, we validated it by experiments in summer, shoulder and winter seasons as described in Section 2.4. 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.

Fig. 10(a) displays the collected TSV of the occupants, as recorded on a questionnaire before and after the control behavior. Fig. 10(b) shows the TSV predicted by the ANN model that was used in the control system. Fig. 10(c) to shows the comparison of each ANN result 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 Fig. 9. Thus, we experimentally validated the developed control system that uses wristbands and the ANN model.

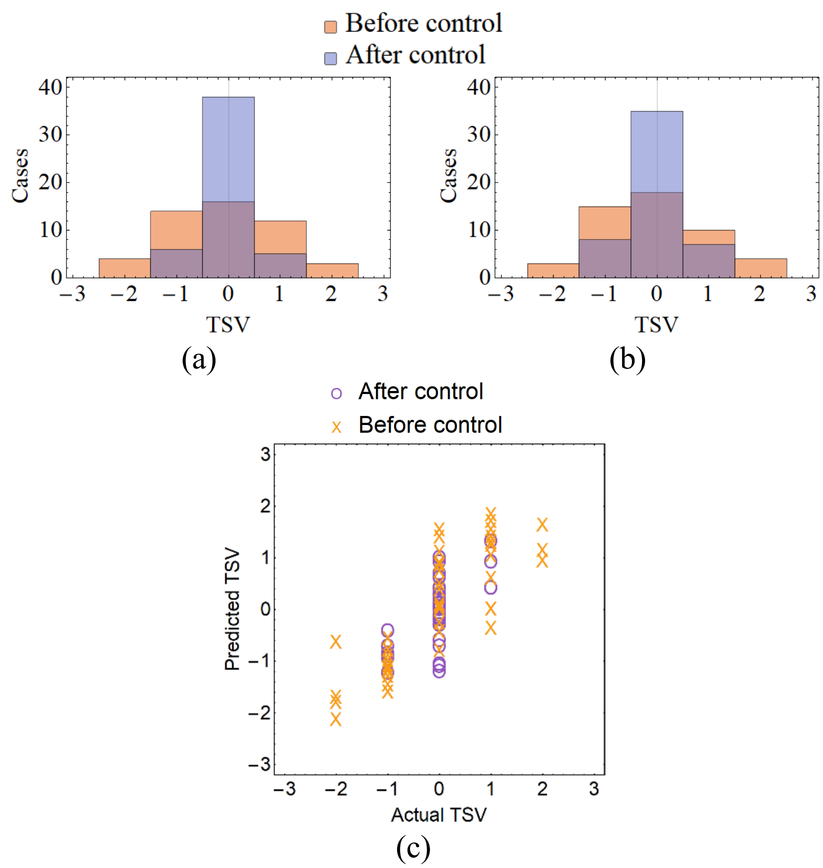


Fig. 10. Results for the experimental validation cases before and after using the developed control system: (a) collected TSV; (b) TSV predicted by ANN model; (c) comparison of the ANN results with collected TSV data.

3.3.3 Numerical validation of the control system

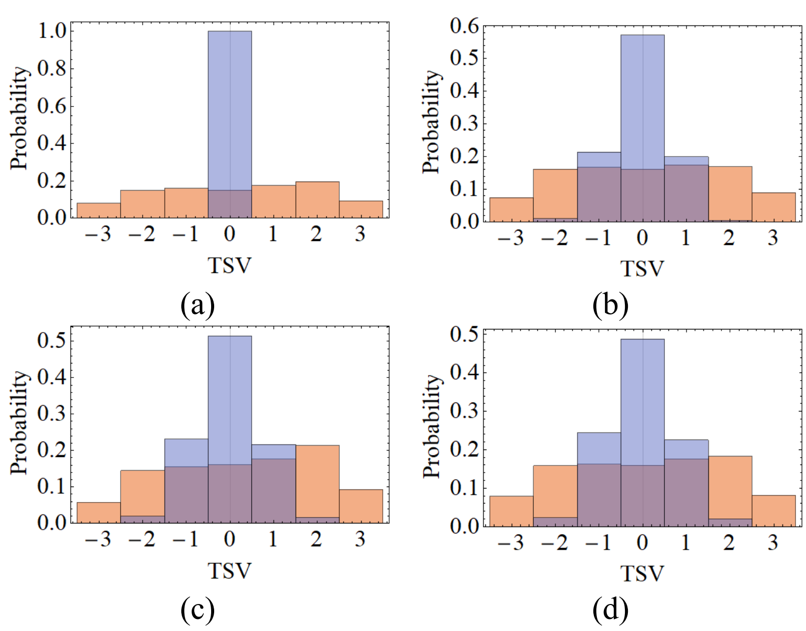
Since the experimental validation tests were very time-consuming, we also performed numerical simulations. The purpose of these simulations was to increase the test size and explore more cases, especially extreme cases. For numbers of office occupants ranging from 1 to 5, we ran 1000 numerical cases 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 [56-57] 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

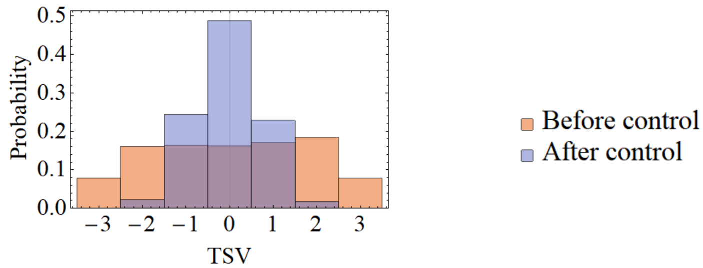
$$P = \frac{1}{x\sigma\sqrt{2\pi}} e^{-(\ln x - \mu)^2/2\sigma^2} \tag{12}$$

where μ and σ are the 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 Fig. 7. These curves fitted the collected data well.

Fig. 11 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 Fig. 11(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 Fig 9(b). A similar phenomenon occurred more often in the offices with greater numbers of occupants, as shown in Fig. 11(b) through (e).





(e)

Fig. 11. Distribution of TSV in the numerical validations before and after the developed wristband control system was used. The number of occupants ranges from one to five in (a) through (e).

Table 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 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%

3.3.4 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 3.3.3. 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 Fig. 5. 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 Fig. 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 [40], the set points for the winter, shoulder and summer seasons were 21°C, 25°C and 27°C, respectively.

Table 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 [36].

Table 2 Comparison of average heating and cooling loads per area between the control system using wristbands and the constant set point in a one-year period

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

4. 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 real conditions [58]. However, the heart rate may be influenced by other individualized factors, such as physical fitness, health, mood and age [59-60]. 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 really 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 [61]. 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 [7, 62].

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.

5. 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.

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Conflict of Interest

None.

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Highlights

Accurately predict TSV in offices in real time with physiological signals from wristband

Develop and validate a smart HVAC control system in multi-occupant offices by using physiological and indoor environmental parameters

Improve the overall thermal comfort in multi-occupant offices by using the wristband control system

Energy use of the developed wristband control system was almost the same as using constant set point