DEVELOPING DATA-DRIVEN APPROACH FOR OCCUPANTS-BASED ON ENVIRONMENTAL CONTROL

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ABSTRACT: The design and operation of building systems frequently face a conflict goals between providing acceptable thermal comfort conditions and reducing building system's relevant energy consumption. Integrating individually different occupants' thermal comfort preferences into the building thermal environment control strategy has high potential to contribute to overcoming this conflict issue. Therefore, the goal of this study was to develop an intelligent control algorithm to maximize energy conservation efficiency while enhancing the occupants' thermal comfort and satisfactions. Considering individual occupants' different thermal preferences, two occupancy conditions were selected in this study: single-occupancy condition (SOC) and multi-occupancy condition (MOC). The control logic is different between SOC and MOC, but the control for SOC can be adopted as the fundamental principle of the multi-occupancy condition. The SOC experiments were conducted to survey subjects' thermal preference pattern while the thermal environmental conditions changed from 18 °C to 30 °C in the climate chamber. Meanwhile, subjects' physical parameters were collected by heart rate sensors and survey forms to confirm the correlation between the indoor thermal condition and subjects' individual features. With the consideration of real-time environment conditions and human individual features (such as gender, BMI, and heart rate), subject's individual thermal preference pattern were captured and learned by machine learning algorithm. The occupants' thermal comfort preference under different environmental condition can be predicted by the developed machine learning algorithm. Based on individuals' thermal preference pattern, Overall Thermal Dissatisfied (OTD) index was developed to determine the optimal set point temperature for minimizing the overall thermal dissatisfactions. The study result revealed the energy conservation potential up to 42% savings while significantly increased occupants' thermal comfort in a workplace environment.

KEYWORDS: Data-driven; Thermal comfort; Machine learning; Building system; Energy conservation

INTRODUCTION

Heating, ventilation and air conditioning (HVAC) systems has been playing an important role in providing occupants comfortable thermal environment, and are the largest energy consumption part in buildings (Vahid Vakiloroaya et al. 2014). The energy cost of the building operation accounts for approximately 40% of the world energy consumption. One of the most cost-effective method to save energy is increasing the energy efficiency of the building operations (Atilla Y. 1995). Improperly configured building systems waste approximately 20% of building energy usage, which is about 8% of the total energy usage in the United States (Brambley et al. 2005). Therefore, topic of saving on energy consumption of the building operation attract great attention by companies and scientist (Kolokotsa, D., et al. 2001). However, energy saving should not sacrifice user's welfare (F. Nicol, M. Humphreys, 2002.) occupants thermal comfort is the fundamental task of the HVAC system. It is necessary to adopt advanced control strategies on HVAC systems. The main objective is providing comfortable thermal environments for the occupants, and minimizing energy consumption at the same time (A. Hernández, 1994).

The multi-occupancy condition (MOC) is the occupancy condition that several occupants share one thermal zone. Occupants have different thermal preference and thermal stress tolerance, which make the control of the typical central HVAC system difficult to balance different occupants' thermal requirement. However, multi-occupancy condition is dominant, especially in office building. Simply finding a consensus cannot solve the problem since different individuals' thermal comfort range might not overlap.

With the rapid development of the artificial intelligence technologies researchers made effort to develop intelligent system for HVAC system considering both energy conservation and users' thermal comfort conditions (Huang S, Nelson RM. 1994.). Started in 1990s, artificial intelligence (AI) method has been applied to the control of the building systems. Both conventional and bioclimatic buildings adopted artificial intelligence (AI) techniques to improve the system control. The development of evolutionary algorithms optimizes the intelligent controllers, which can contribute to the control of the intelligent buildings' subsystems (Lopez L, et al., 2004). The synergy of the neural networks technology and evolutionary algorithms optimize the control of system to overcome the non-linear features of PMV calculations, time delay, and system uncertainty. (Dounis AI, Manolakis DE. 2001; Singh J, Singh N, Sharma JK. 2006 ; Kolokotsa, 2001; Kolokotsa, 2001)Taking occupants' participation into the control system is becoming more and more popular control strategy, since occupants directly involvement can significantly improve occupants' thermal comfort condition. There are many artificial product coming into the market and became very popular, even though there are some limitation of these products. Nest Learning thermostat is one of the most popular artificial thermostat product in the market. Even though it got a great success in consumer market and had a good performance in energy saving as well as thermal comfort improvement, there are still some limitations that cannot be ignored. Nest only focus on residential buildings and cannot solve multi-occupants thermal requirement conflict. Moreover, Nest did not consider occupants physical condition. The only learning feature is users' living pattern, which is not reliable enough. However, users-based control strategy is a significant merit of Nest learning thermostat.

2.0 OBJECTIVE

Importance of the smart HVAC control system and problems the current HVAC system faced especially the thermal requirement of the multiple occupants' condition. The current industry standard and PMV model cannot meet the occupants' thermal requirement. The goal is to develop the control algorithm that can improve the thermal comfort condition while reduce the energy consumption. The proposed algorithm can generate the set-point considering the multiple occupants' thermal preference in one HVAC zone. Thus, the objectives of this research is to develop occupants-based data-driven thermal environment control approach that maximize energy conservation efficiency while enhancing the occupants' thermal comfort and satisfactions.

3.0 METHODOLOGY

3.1. Overview of methodology

In this research, both individual and multi-occupants experiments were conducted in the climate chamber B11, located in the basement of Watt Hall at the University of Southern California. The individual experiment is single occupancy experiment. Each participants took individual experiment to track their thermal preference pattern. Data of each participant's experiment was collected in individual database. Based on the individual experiment data, individual artificial neural network (ANN) model was developed. The ANN model can predict participant's thermal comfort for the similar environmental condition. Overall thermal dissatisfied index was developed to solve the multi-occupants thermal conflicts based on their individual thermal comfort curve. The optimal set-point temperature was generated by calculating the overall thermal dissatisfied index, and was compared with the performance of common industry HVAC set point.

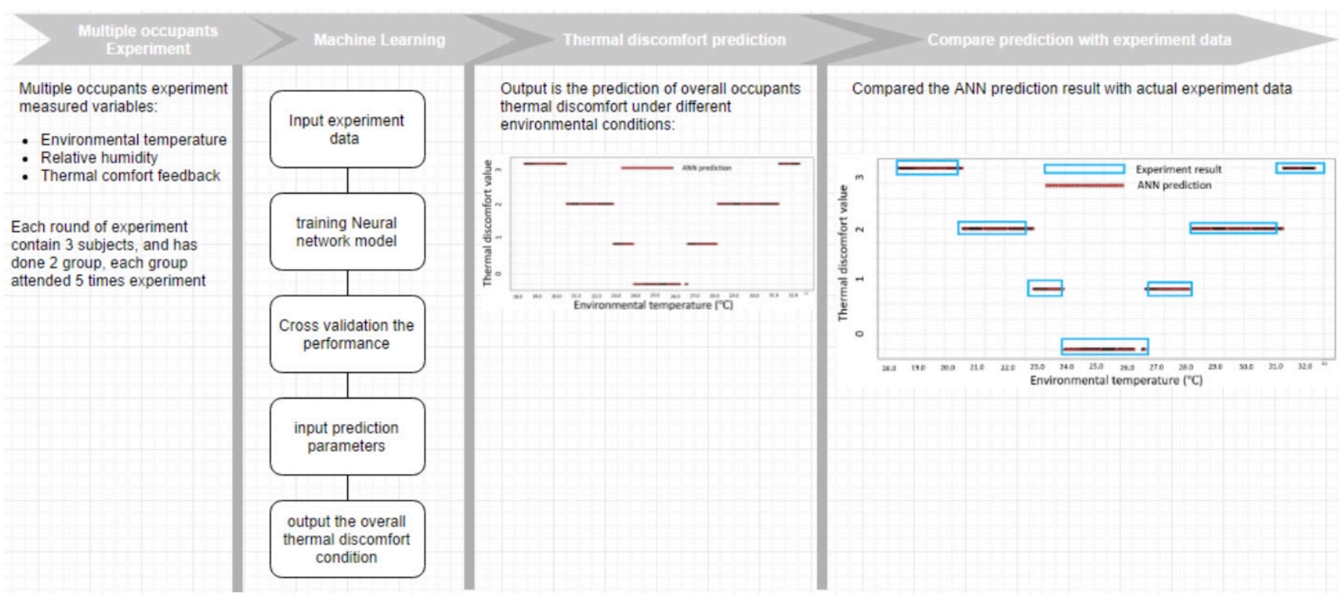


Figure 1: Research methodology workflow

3.2 Overall Thermal Dissatisfied (OTD) index

In order to solve the thermal comfort problem for multi-occupancy condition, the Overall Thermal Dissatisfied (OTD) index was developed. F(t) is the function to calculate the OTD index, which can indicate overall thermal uncomfortable condition of the multi-occupant condition. The lowest value of the F(t) is the optimal condition, and the corresponding value t should be adopted as setpoint of HVAC system.

$$F(t) = \sum_{i=1}^{n} D_i(t)$$

$D_i(t)$ ----- The i^{th} person's thermal discomfort value when the environmental temperature is t °C

t ----- The environmental temperature

The benefit of this OTD index evaluation method can minimum the total number of occupants who feel uncomfortable. By finding the lowest value of OTD index, the optimal environment condition can be found.

3.3 Experiment design

3.3.1 Climate chamber setting

The human thermal comfort experiment was conducted in the B11 climate chamber (Fig.2), which located in the USC Watt Hall at the University of Southern California. B11 climate chamber provide a heat-balance environment and carefully controlled with lab AC system connected with LabVIEW. The air-speed in the chamber was controlled within 0.2 m/s according to the ASHRAE-55 standard. The CO2 density was controlled around 700 ~ 900 ppm during the experiment. The amount of radiant heat transferred from a surface can be ignored since there is no window in the chamber and it's located in the basement. In the center of the chamber, a chair and a desk were placed in order to provide a working condition for subjects. The metabolic rate of the subjects was 1.0 as seated in the office condition. The environmental temperature and relative humidity was measured by tripod sensor package at 1.1m level. All the data were recorded per 10 seconds, and automatically transported into LabVIEW database. For this study, the environmental condition is the climate chamber setting, which is more stable and less variable than actual working space. Only the air temperature is considered as environmental factor that will influence the thermal comfort. Others factors such as relative humidity, mean radiant temperature (MRT), clothing index, air speed and etc. can be ignored because of the strictly controlled environmental condition in climate chamber.

Figure 2: Fisheye photo of chamber setting

3.3.2 Physiological measurement

There are 13 subjects attended the experiments. Subjects' individual information including body mass index (BMI) and gender were recorded by the survey form. The real-time heart rate, surrounding environment temperature, and surrounding environment relative humidity were collected by wireless Heart Rate sensor, temperature, and relative humidity sensors. The data were automatically transmitted to the DAQ system with the LabVIEW software.

3.3.3 Procedure

The experiment lasted around 65 minutes, and environmental temperature was gradually increasing from 18 °C to 30 °C (Fig.3). Before the experiment start, there is 15 minutes adjusting time for subjects prepare and get used to the chamber environment. The chamber environmental temperature maintained 20 °C during the adjusting period. Subjects filled the consent form and individual information form for recording BMI and gender. After 15 minutes adjusting and preparation, the experiment started. The environmental temperature gradually increase from 18 °C to 30 °C in 65 minutes.

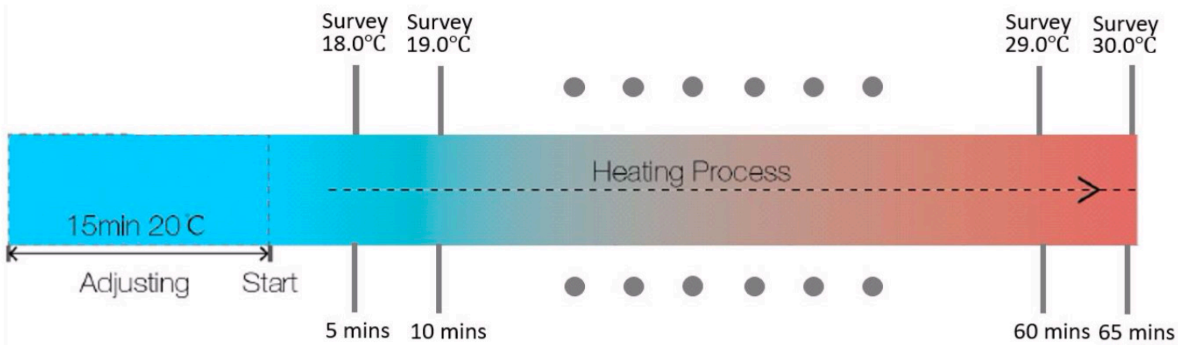


Figure 3: Experiment process

Every 5 minutes, subjects were asked the feedback of Thermal Sensation (Table 1) and Thermal comfortable condition (Table 2). The feedback from subjects were recorded by the survey form with corresponding experiment time. All their data were collected in the individual database.

Table 2: Thermal Discomfort Condition

Value	Thermal Uncomfortable
0	Comfortable
1	Slightly Uncomfortable
2	Uncomfortable
3	Very Uncomfortable

3.4 Scope of the work

The scope of this research is only focus on lab setting with the strict environmental control. The purpose of this work is to explore the potential use of artificial intelligence in thermal comfort control. Therefore, the ideal environment is necessary in order to prove the theory. Based on the result of lab setting research, the application in the real world could be discussed.

There are two precondition for the application of ANN based thermal control, one is how to collect occupant's thermal comfort preference data without disturbing occupants work. It would be annoying if we do survey every 5 minutes to collect their feedback. Another precondition is how to identify occupant who stay in the room. Because MOC ANN-based control is based on the individual thermal preference data, it is important to identify who stay in the room and their individual thermal preference

The above two precondition can be potentially solved by application of smart device such as smart watch and smart thermostat. Smart watch such as APPLE WATCH can collect user's feedback without filling some paper survey. Smart watch can send the data and corresponding time to the control center. Similarly, smart thermostat can collect the real-time environment condition and send the data to the control center. The control center use the ANN-based control algorithm to analysis the data and adjust the environment condition based on occupants individual thermal preference. The workflow is displayed in Fig.4.

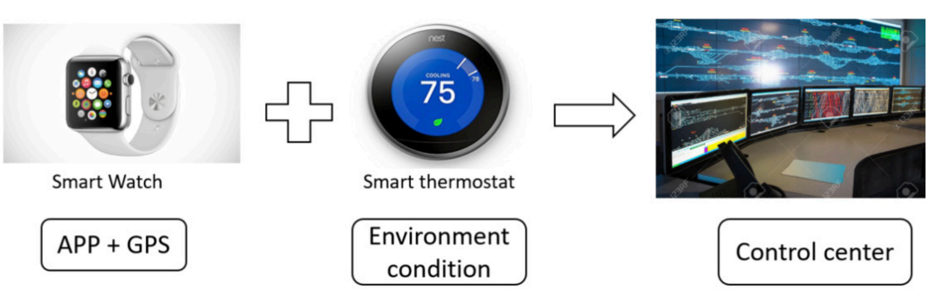
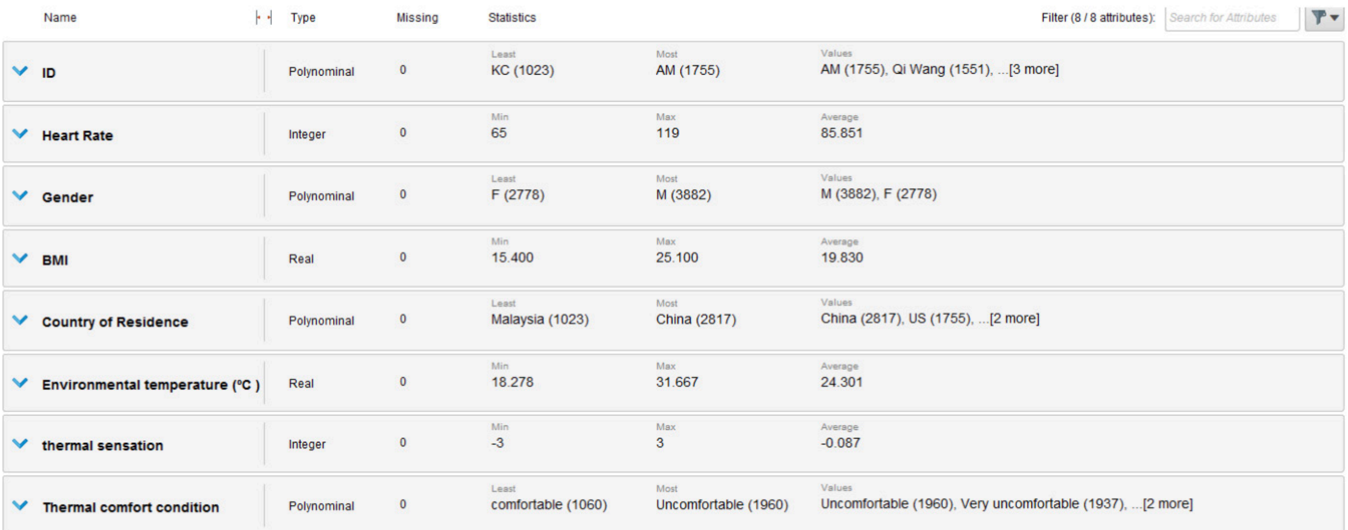


Figure 4: Potential workflow of MOC ANN application

4.0 DATA ANALYSIS

4.1 Database summary

There are 5 participants in the experiment. The collected data was imported from LabVIEW database and integrated with the subjective recorded data. Database was built based base on the experiment data (Fig.4). There are 8 attributes in the database including Identification information. The total record is 6660 including male record 3882 and female record 2778. The Heart Rate, Gender, BMI, Relative Humidity, Environmental temperature are 5 attributes (Input attribute) were used to training the ANN model. The label attribute (Output attribute) is Thermal comfort condition.



Name	Type	Missing	Statistics		
ID	Polynominal	0	Least KC (1023)	Most AM (1755)	Values AM (1755), Qi Wang (1551), ...[3 more]
Heart Rate	Integer	0	Min 65	Max 119	Average 85.851
Gender	Polynominal	0	Least F (2778)	Most M (3882)	Values M (3882), F (2778)
BMI	Real	0	Min 15.400	Max 25.100	Average 19.830
Country of Residence	Polynominal	0	Least Malaysia (1023)	Most China (2817)	Values China (2817), US (1755), ...[2 more]
Environmental temperature (°C)	Real	0	Min 18.278	Max 31.667	Average 24.301
thermal sensation	Integer	0	Min -3	Max 3	Average -0.087
Thermal comfort condition	Polynominal	0	Least comfortable (1060)	Most Uncomfortable (1960)	Values Uncomfortable (1960), Very uncomfortable (1937), ...[2 more]

Figure 4: Database summary in Rapidminer

4.2 Artificial Neural Network (ANN) model development

In order to ensure that all attributes are in numerical form and on same scale, all the data from database was transfer from nominal type into numerical type by Nominal to Numerical operator in Rapidminer. Dummy coding type was used to deal with un-ordered values such as Gender and thermal comfort condition. Min-max normalization method (S.B. Kotsiantis 2006) was used to transform feature values into the same scale. Input preprocessed data into training set in the Rapidminer software and developed the ANN model (Fig. 5). 10-fold cross-validation was used to detect the performance of ANN model. The one of the participants ANN model performance was taken as an example (Table.3). The overall accuracy of the ANN model is 79.06% +/- 3.57%. The ANN model has better performance of comfortable prediction (88.72%) and very uncomfortable prediction (86.29%). The performance of accuracy of slightly uncomfortable prediction is 76.26% and the uncomfortable prediction is 69.59%. The reason of the ANN model's better performance in extreme condition is the thermal comfort feeling is easier of the participants to sense extreme conditions. The sensation of slightly uncomfortable and uncomfortable is more difficult for people to determine, which results in larger difference sensation feedback record among different experiment.

Table 3: Performance of the one of participants' ANN model under 10-fold cross validation

	Ture very uncomfortable	Ture uncomfortable	Ture slightly uncomfortable	Ture comfortable	Class precision
Pred. very uncomfortable	151	24	0	0	86.29%
Pred. uncomfortable	65	206	25	0	69.59%
Pred. slightly uncomfortable	5	48	257	27	76.26%
Pred. comfortable	0	0	29	228	88.72%
Class recall	68.33%	74.10%	82.64%	89.41%	

Accuracy: 79.06% +/- 3.57% (mikro: 79.06%)

The accuracy of all participants ANN models (Table 4) indicate the artificial neural network had a good performance in prediction of human thermal comfort condition.

Table 4: Accuracy of all participants ANN models

ANN model	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5
Overall Accuracy	79.06% +/- 3.57%	79.37% +/- 2.72%	72.82% +/- 6.95%	75.82% +/- 5.36%	82.98% +/- 1.98%

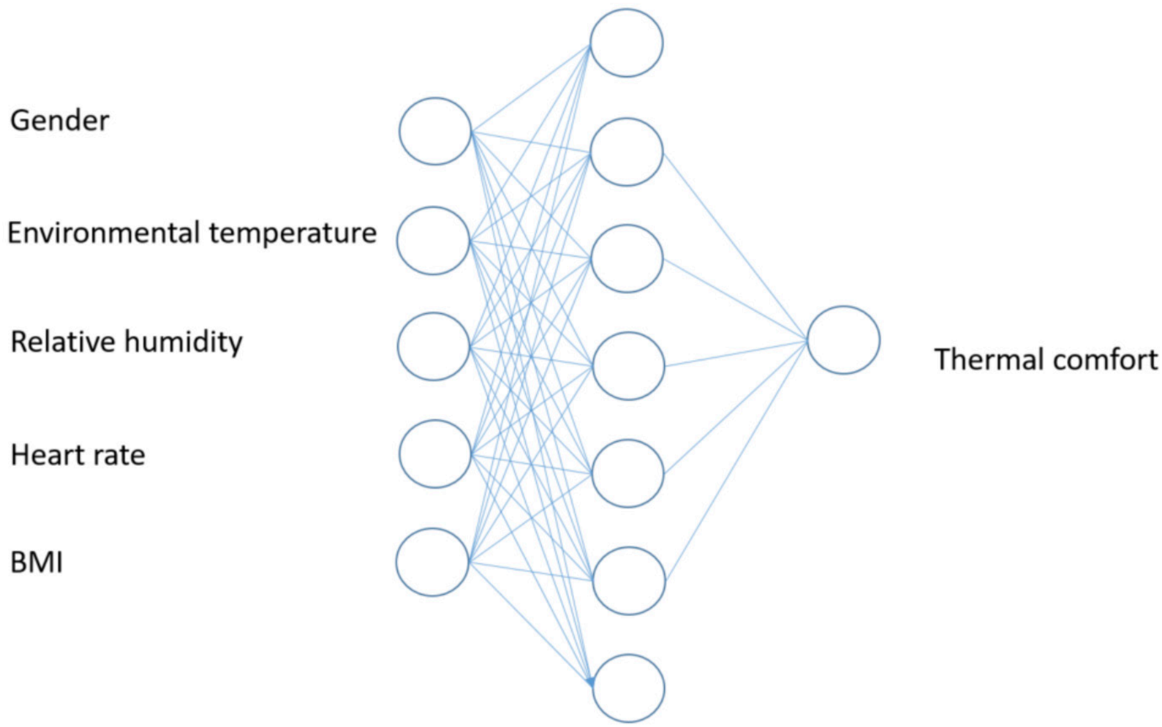


Figure 5: Artificial Neural Network model

4.3 Individual thermal comfort curve

Participants' thermal comfort curve were generated by ANN model. One of the participants ANN prediction thermal comfort curve was taken as an example. According to the comparison between prediction curve and actual experiment data (Fig. 6), the ANN model has a good performance of the prediction, and can generally capture participant's thermal comfort pattern.

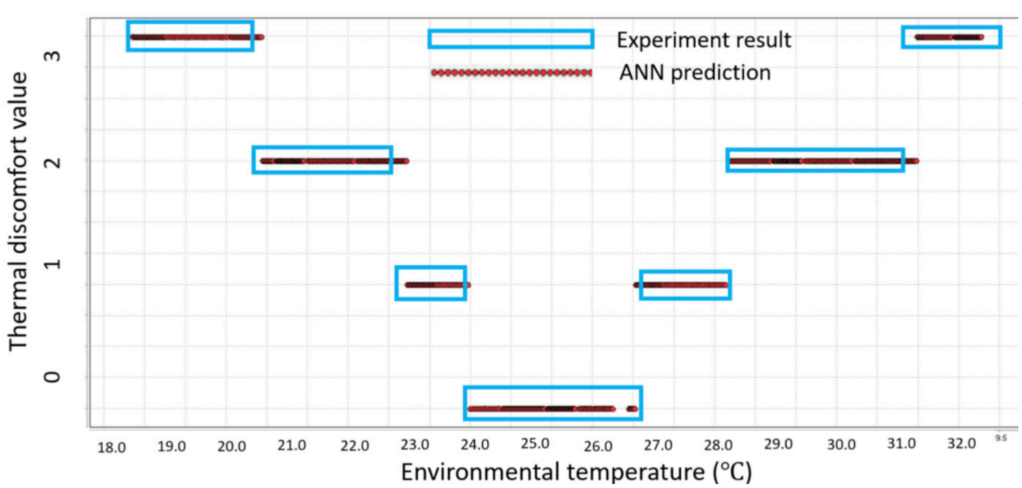


Figure 6: Comparison between ANN prediction model and experiment value

Correspondingly, paired t-test (Table 5) were conducted to test whether there is a significant difference in the boundary temperature between prediction value and actual value. Boundary temperature is the minimum and maximum environmental temperature in a certain thermal comfort condition. For example, the comfort boundary temperature of above prediction sample is tmin= 22.6 °C and tmax=25.3 °C. The T-Test compare the boundary temperature of comfortable, slightly uncomfortable, uncomfortable, very uncomfortable conditions to examine the performance of ANN model prediction.

Table 5: Paired T-Test of boundary temperature in the ANN prediction vs Experiment data

	N	Mean	StDev	Difference	p-value
ANN prediction	18	23.383	3.995	0.2	0.005
Experiment data	18	23.472	3.954	0.2	0.005

The resulted p-value of paired T-Test of boundary temperature in the ANN prediction and experiment data indicates that there was no significant difference between the ANN model prediction and experiment data. The difference value of 0.2 °C indicated that the ANN prediction has a good performance to prediction the boundary temperature of participant's thermal comfort condition.

4.4 Optimal setpoint temperature

All participants ANN prediction thermal comfort curved was generated (Fig. 7). Input participants' thermal comfort prediction into the Overall Thermal Dissatisfied (OTD) index to determine the optimal setpoint temperature. The value of F(t) is 0 when the temperature is between 24.6 °C and 25.7 °C. The blue highlighted area (Fig. 7) is the optimal setpoint temperature. The calculation indicated that all occupants would be satisfied in the climate chamber setting environment (Relative humidity is between 30%-40%) with temperature is between 24.6 °C and 25.7 °C.

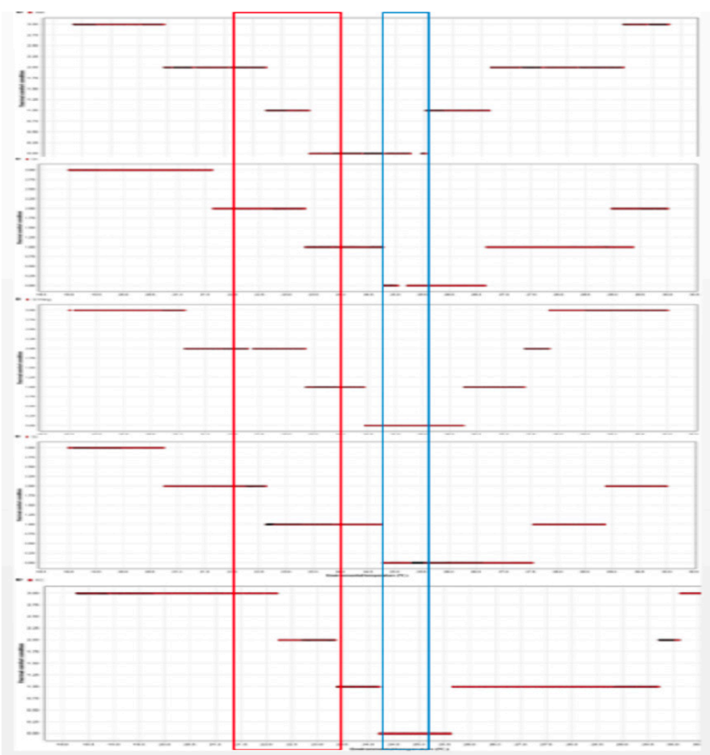


Figure 7: All participants' ANN thermal comfort prediction

The industry common designed temperature in U.S.is between 22 °C and 24 °C (Hoyt, Tyler et al. 2005) during the cooling season (see red highlighted area in Fig.7). The Overall Thermal Dissatisfied (OTD) index is from 16 ~ 121. The best result would be 4 occupants slightly uncomfortable and 1 occupant uncomfortable. The worst condition is 4 occupants uncomfortable and 1 occupant very uncomfortable. The difference of multi-occupants thermal comfort condition is significant between U.S. industry common designed temperature and proposed data-driven optimal setpoint. Moreover, increasing the one degree setpoint temperature during the cooling season can potentially save 7~15% energy. (Hoyt, Tyler et al. 2005) The optimal setpoint temperature has a significant energy saving potential while maintain the certain level of occupants' thermal comfort condition. The difference setpoint temperature between data-driven optimal setpoint and industry common designed temperature is 0.5 °C ~ 2.8 °C, which indicated a potential 4%~42% energy saving.

CONCLUSION

In this study proposed a data-driven approach for user-based thermal environmental control. The approach consist of the artificial neural network (ANN) model and the overall thermal dissatisfied (OTD) index. ANN model was used to predict occupants' thermal comfort condition and OTD index was used to determine the optimal set point temperature that can minimize the overall thermal dissatisfaction. Experiment data indicated that ANN model has a good performance in capturing occupants' thermal preference pattern and making the thermal comfort prediction (over accuracy is between 72.82% +/- 6.95% to 82.98% +/- 1.98%) based on individual features and environmental conditions. For this research settings including environmental setting and occupants features, data-driven approach for user-based environmental control conducted a good performance in both energy-saving side (up to 42% energy-saving) and thermal comfort significant improvement. Above all, the data-driven approach revealed a great potential significance in smart thermal environmental control for both energy-saving and thermal comfort aspect.

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