Transforming thermal comfort model and control in the tropics : a machine-learning approach

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Transforming Thermal Comfort Model and Control in the Tropics: A Machine-Learning Approach

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School of Computer Science and Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

2020

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I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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This thesis contains material from [2 number] paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Part of Chapter 1, Part of Chapter 2, Part of Chapter 3, Part of Chapter 4, and part of Chapter 6 are published as [Weizheng Hu, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng, “iTCM: Toward Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings,” in *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831](#)

The contributions of the co-authors are as follows:

- I completed all the experiments and drafted the manuscript.
- Prof. Wen provided the initial idea and research direction.
- Dr. Guan guided me to revise the manuscript and improve my paper writing.
- Dr. Jin shared his experiences on sensing techniques and data collection.
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The contributions of the co-authors are as follows:

- I completed all the experiments and drafted the manuscript.
- Dr. Luo provided technical guidance on transfer learning and also help to improve my paper writing.
- Prof. Lu guided me to revise and improve my manuscript.
- Prof. Wen provided the initial idea and research direction.

5 January 2020

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Abstract

The building sector is one of the primary energy consumers in Singapore. According to the report of Building and Construction Authority (BCA), Singapore's building sector consumes up to 38% of the nation's electricity, and the Heating, Ventilation and Air Conditioning (HVAC) systems account for 40~50% of the total energy consumed by buildings. As a result, the reduction of HVAC systems energy expenditure would save a lot of energy and lower the electricity bill. However, the HVAC systems directly impact the occupants' indoor thermal comfort, which influences people's productivity and health. Existing studies suggested that office tenants in comfortable thermal environments are more productive. In contrast, Sick Building Syndrome (SBS) symptoms have been attributed to thermal discomfort, potentially leading to long-term health hazards. It follows that it is a challenge to reduce the energy consumption of the HVAC systems while ensuring occupants' thermal comfort.

In this thesis, we investigate the challenge mentioned above to strike the trade-off between occupants' thermal comfort and energy saving of HVAC systems. First, we validate the canonical Fanger's Predicted Mean Vote (PMV) model, survey the related literature and find that it suffers from three major issues: 1) Inadequate modeling parameters; 2) Insufficient modeling dataset; and 3) Inaccurate comfort prediction. For the first issue, the PMV model only considers six thermal comfort parameters: air temperature, mean radiant temperature, relative humidity, air velocity, metabolic rate, and clothing insulation. However, we survey the existing literature and find that other than the six PMV parameters, some other environmental and personal factors, especially the human vital signs (e.g., skin temperature, heart rate, etc.), also link to human thermal comfort. To address this issue, we adopt the off-the-shelf wearable device (e.g., Microsoft Band 2) for human vital sign tracking and the mature wireless sensor network (WSN) product is used for environmental data monitoring. For the second issue, the PMV model was developed in 1970 by using the paper-based questionnaires to collect data from

test subjects manually. However, from the view of current big-data standard, the obtained modeling dataset is relatively small, which potentially affect the model accuracy. To address this issue, we develop an Internet of Things (IoT) based data acquisition system, including a back-end server, iOS & Android mobile Apps and a management website, and then use it to support our in-situ measurements and conduct one-year data collection experiments to obtain our own dataset. For the last issue, existing research works indicate that the PMV is inaccurate to predict human thermal comfort. Moreover, the PMV model is a static model which makes it difficult to adapt to the different thermal environment with various occupants dynamically. To address this issue, we propose to use the emerging deep learning techniques to develop next-generation thermal comfort models for improving the prediction accuracy. Our developed Heterogeneous Transfer Learning (HTL) based Intelligent Thermal Comfort Neural Network (HTL-ITCNN) outperforms the PMV model by on average 73.9%. In addition, for learning-based approaches, it is flexible to introduce new parameters to an existing model or update the developed models by training with newly obtained training data, to further improve the performance.

Then, we aim to reduce the HVAC energy consumption based on our developed learning-based thermal comfort models. Since PMV model has been adopted by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard 55, it significantly affects the building design and operation, especially the thermal control (e.g., HVAC control). Currently, based on the PMV model, a fixed set-point temperature (e.g., 23°C or 24°C) is set for the whole building. However, a building has multiple zones, and occupants in different zones may have heterogeneous thermal comfort demands. Considering the inaccurate comfort prediction issue of the PMV model, we argue that the PMV model may not provide the proper guidance on the thermal control of a multi-zone building. To address this issue, we use the deep reinforcement learning technique to develop the smart thermal comfort mechanism for multi-zone buildings. Our Multi-Agent Deep Reinforcement Learning (MADRL) based approach can achieve from 2.8% up to 15.4% energy saving under different thermal comfort demands. Eventually, we integrate all our solutions introduced above for striking the trade-off between occupants' thermal comfort and energy saving of HVAC systems to build an intelligent thermal comfort management (iTCM) system.

With iTCM system, we design and implement a novel human behavioral study with a gamification approach to encourage human behavioral changes towards greener, smarter and healthier buildings. It is well-known that there is no perfect HVAC control mechanism which can fulfill every occupant's thermal comfort demand. To mitigate those occupants who may be in discomfort, we aim to derive the economic model and use it to judiciously balance between the HVAC electricity cost saving and the incentive expenditure, maximizing the total cost saving while maintaining occupants' satisfaction levels over 84%. Moreover, we develop an interesting demo website by using Digital-Twin technology. Digital-Twin technology is used to create the digital replica of various entities (e.g., processes, systems, people) in the real world, and then use them to build the related virtual world to simulate the dynamics of the real world.

The aforementioned system, solutions and novel studies can efficiently reduce the HVAC energy consumption while maintaining occupants' indoor satisfaction levels. Also, the collected dataset will benefit the human thermal comfort research community. Furthermore, the proposed approaches and obtained results may provide the guidelines to future research on indoor thermal comfort model and control.

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Chapter 1

Introduction

In this chapter, we present the background and motivation of our research. Then, we describe the objective and scope of our study. After that, we summarize the major contributions and insights of the thesis. Finally, we introduce the chapter organization of the thesis.

1.1 Background and Motivation

In this section, we present the background and motivations of our machine learning based research on human thermal comfort and indoor thermal control.

1.1.1 Human Thermal Comfort

Thermal comfort¹ [1], as one of the most crucial factors, has been playing an important role in designing and operating buildings. A previous study [2] shows the positive correlation between office environmental thermal comfort and the productivity of occupants. In contrast, Sick Building Syndrome (SBS) symptoms [3] have been linked to thermal discomfort, potentially leading to the long-term health hazards and the loss of productivity. As a result, thermal comfort related research has

¹**Weizheng Hu**, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng, “iTCM: Toward Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings,” in *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831

received much attention from both industry and academia over the past decades. In industry, these research efforts lead to various standards [4–6] that specifies the minimum requirements for the indoor thermal environments. Meanwhile, in academia, canonical thermal comfort models, such as Predicted Mean Vote (PMV) model [7] and Adaptive model [8], are developed and adopted by industry standards to provide an acceptable indoor environment for building occupants. The output of the PMV model is the predicted human thermal sensation, as shown in Table 1.1. It is designed to guide the adjustment of the indoor thermal environment based on occupants’ thermal comfort feelings. While the output of the Adaptive model is the indoor air temperature. It is designed to directly adjust the indoor thermal environment based on various empirical assumptions of occupants’ thermal comfort feelings.

TABLE 1.1: 7-Level Thermal Comfort Sensations

Index	Thermal Sensation
3	Hot
2	Warm
1	Slightly Warm
0	Neutral (Comfortable)
-1	Slightly Cool
-2	Cool
-3	Cold

However, some existing research works [9–11] argue that these canonical models are inadequate to evaluate human thermal sensations. Their experimental results show that in different climates, these models often underestimates or overestimates the human thermal comfort levels with significant biases. We believe that these prediction biases are due to insufficient modeling parameters. For example, the PMV model is determined by six parameters, as shown in Fig. 1.1, and the Adaptive model generally only considers the outdoor temperature. As a matter of fact, our literature survey shows that more parameters/signals linking to the human thermal comfort have been explored in the past two decades, for example, environmental parameters: CO2 concentration [12, 13], visual (e.g., color) and acoustic (e.g., noise) [14]; personal vital signs: gender [15, 16], age [17], heart rate [18, 19], skin temperature [20], etc. Therefore, it is necessary to rethink the human thermal comfort and develop the next-generation thermal comfort models.

FIGURE 1.1: Six parameter inputs of the PMV model.

1.1.2 Indoor Thermal Control

Heating, Ventilation, and Air Conditioning (HVAC) systems play an essential role in providing a comfortable indoor environment in buildings. The high-quality indoor thermal conditions would benefit for occupants' long-term health while improving their working productivity. However, based on the latest report of the International Energy Agency (IEA) [21], HVAC systems consume 30~50% of the total energy of a building. For example, setting a higher set-point temperature and relative humidity in the tropics would significantly reduce the energy expenditure of the HVAC systems and lower the total electricity bill, but it also directly affects occupants' thermal comfort feelings. Therefore, it is challenging to explore the balance between the occupants' thermal sensations and the energy expenditure of the HVAC systems.

Nowadays, the most widely adopted HVAC control mechanism in modern Building Management System (BMS) is the rule-based heuristic control method, as shown in Fig. 1.2. Its goal is to keep a pre-set room temperature (e.g., 23.0°C or 24.0°C) for the whole building based on the improved Proportional-Integral-Derivative (PID) algorithm [22]. This control method generally belongs to the single-objective optimization research, which aims to solely optimize the energy expenditure of the HVAC systems. In the past decades, a large number of research works [23–38] make great contributions to the energy optimization of the HVAC systems. However, these approaches highly rely on the empirical “comfortable” set-point temperature

FIGURE 1.2: The workflow of automatic HVAC control. First, the IoT-based system tracks the indoor thermal conditions via wired/wireless IoT sensors. Then, the PMV model predicts occupants' average thermal comfort index based on the sensed data. Finally, the HVAC controller adjusts the indoor environment based on the recommended air temperature determined by the PMV model.

and face difficulty to fulfill occupants' dynamic thermal comfort demands for the indoor environment.

To overcome the limitations of the single-objective optimization research, many research works propose to apply the multi-objective optimization concept to HVAC control. Among them, the majority of research works [39–45] aim to explore the trade-off between two optimization objectives: thermal comfort and energy consumption. They apply the canonical thermal comfort models (e.g., Predicted Mean Vote (PMV) [7] or adaptive model [8]) to predict occupants' thermal sensations to control the HVAC systems dynamically for energy optimization. However, existing papers [46, 47] indicate that these canonical thermal comfort models are inaccurate to predict occupants' thermal comfort. Moreover, these solutions are generally verified in the single-zone case (e.g., a room or an office), without considering the diverse comfort demands of multiple zones. To further optimize the HVAC control, some other research works [48–53] propose to raise the challenge to investigate the trade-off among three optimization objectives: thermal comfort, energy consumption, and multi-zone control. They suggest developing the multi-agent system to allocate one agent to each zone for optimizing the energy consumption of this zone while maintaining zone occupants' thermal comfort. However, these multi-agent solutions still adopt the canonical thermal comfort models, which suffer from

inaccurate parameter estimates. Moreover, they mainly adopt the conventional optimization algorithms, which suffer from improper control operations. Therefore, it is necessary to innovate the multi-objective control algorithm to develop the next-generation HVAC management mechanism.

1.1.3 Deep Learning Techniques

Recent years, with the rapid development of computing hardware (e.g., GPU) and machine learning techniques, especially the deep learning approaches, show their significant potentials on problem-solving.

FIGURE 1.3: The schematic diagram of Neural Network Learning and Reinforcement Learning.

1.1.3.1 Deep Neural Network Learning

One of the most widely used deep learning techniques is the Deep Neural Network, which is inspired by the biological neural networks of animal brains.

The schematic diagram of Neural Network is shown in Fig. 1.3a. The general design of Neural Network has full-connected structure with one input layer, multiple hidden layers and one output layer. Each node is called neurons. Weight is assigned for adjustment during the learning process. In addition, with multiple hidden layer design, deep learning can extract high-level modeling features from the original inputs, which enables it to efficiently learn knowledge from the raw data. They have been successfully applied to the Speech Recognition [54–56], Nature Language Processing (NLP) [57–59] and Computer Vision (CV) [60–62].

1.1.3.2 Deep Reinforcement Learning

Another hot deep learning technique is Deep Reinforcement Learning (DRL), which is inspired by the psychology of behavioral studies.

The schematic diagram of reinforcement learning is shown in Fig. 1.3b. First, agent takes actions based on the environmental status. Then, environment is affected by the taken actions and then returns the related reward to agent. Finally, environment moves to the next status. The objective of agent is to learn the policy which can maximize the received rewards. Overall, DRL aims to interact with an environment for knowledge learning via trial and error. For most problems approaching real-world complexity, the state space is high-dimensional (and possibly continuous). To learn an approximator of the environment model, the value function or the policy, there are two main advantages to adopt deep neural network learning: 1) Neural networks can handle high-dimensional inputs (e.g., high-dimensional state) and outputs (e.g., complicated actions) well; and 2) these neural network based approximators can be trained incrementally and make use of additional samples obtained as learning happens. This technique began to attract attention in academia due to its successful application on the gameplay in 2015 [63]. Next, in 2016, Google's DeepMind team developed the DRL-based AlphaGo program [64] that could beat the human Go champions.

Owing to the powerful learning abilities of these Deep Learning techniques, it enables researchers in the smart building research field to apply them to some application scenarios of built environment, such as thermal comfort modeling, intelligent thermal control.

1.2 Objective and Scope

The objective of this thesis is to strike the trade-off between the energy consumption of the HVAC systems and occupants' thermal comfort for the evolution of thermal comfort and control in tropics. Specifically, we aim to adopt the emerging deep learning techniques to develop the intelligent Thermal Comfort Management (iTCM) system to minimize the energy consumption of the HVAC system while maintaining occupants' thermal comfort. The overall workflow of the iTCM system is presented in Fig. 1.4.

FIGURE 1.4: The overall workflow of the intelligent Thermal Comfort Management (iTCM) system. First, wearable devices are used for in-situ measurement and Wireless Sensor Network (WSN) is adopted for environment monitoring. Then, database is built to store all sensed data. After that, based on the collected data, AI module predicts occupants' thermal comfort and performs the thermal control operations via the Building Management System (BMS).

In this thesis, we have four research & development stages to build the proposed iTCM system.

- **Stage 1. Thermal Comfort Information Collection:** In this stage, we first develop the Internet-of-Things (IoT) based data collection system, which consists of both hardware (i.e., smart wristband and Wireless Sensor Network (WSN)) and software (i.e., Back-end Web service, Android & iOS mobile Apps, and demo websites). Then, we use the developed system to conduct one-year data collection experiment and obtain the iTCM datasets for thermal comfort modeling.
- **Stage 2. Learning-Based Thermal Comfort Modeling:** In this stage, we first verify the canonical thermal comfort model (e.g., Predicted Mean

Vote (PMV) Model). Then, with our collected iTCM datasets, we adopt the Deep Neural Network and Deep Transfer Learning techniques to develop the learning-based thermal comfort models, and compare them with various traditional machine learning methods (e.g., k -Nearest Neighbours (k -NN), Support Vector Machine (SVM), and Random Forest) on thermal comfort prediction performance.

- **Stage 3. Intelligent Thermal Control of the HVAC Systems:** In this stage, we adopt the Multi-Agent Deep Reinforcement Learning (MADRL) technique to develop the thermal control strategies for multi-zone buildings. First, we adopt the learning-based thermal comfort models developed in stage 2 to predict occupants' thermal sensations and use the prediction results for intelligent thermal control. Our goal is to minimize the energy consumption of the HVAC system while maintaining occupants' thermal comfort in multiple zones simultaneously.
- **Stage 4. Human Behavioral Study & Digital-Twin Demo:** In this stage, we demonstrate a novel application built upon the iTCM system by encouraging human behavioral changes to form energy-saving habits for greener, smarter, and healthier building. We adopt the Deep Reinforcement Learning (DRL) technique to develop an incentive-based economic model to characterize the economic value of thermal comfort to the building occupants. Also, we use Digital-Twin technology to create the 3D visualized demo website.

1.3 Thesis Contributions and Insights

Key contributions of this thesis are outlined as follows:

- We propose and develop the intelligent Thermal Comfort Management (iTCM) system for smart thermal control in multi-zone buildings. This system consists of back-end web server, Android & iOS mobile Apps, wireless sensor network and demo websites. With this system, we conduct one-year data collection experiments to build our iTCM datasets, which contain rich features for thermal comfort modeling.

- We adopt the Deep Neural Network (DNN) and Deep Transfer Learning (DTL) technique to develop the thermal comfort models, and use both the ASHRAE RP-884 Dataset and our iTCM datasets² for model training. First, for performance comparison purpose, we implement the PMV model as the baseline and also develop the related thermal comfort models by using various traditional machine learning methods. Then, we develop the DNN-based thermal comfort model, named as Intelligent Thermal Comfort Neural Network (ITCNN). After that, to further improve the prediction accuracy, we adopt the DTL concept to develop the DTL-based thermal comfort model, named as Heterogeneous Transfer Learning (HTL) based Intelligent Thermal Comfort Neural Network (HTL-ITCNN). Results show that both ITCNN and HTL-ITCNN outperforms the PMV model, and HTL-ITCNN achieves the best prediction accuracy.
- We use the Multi-Agent Deep Reinforcement Learning (MADRL) technique to develop the thermal control strategies for multi-zone buildings. Specifically, we adopt the Multi-Agent Deep Deterministic Policy Gradients (MADDPG) algorithm to develop the multi-agent thermal control system. To verify the effectiveness of our proposed approach, we use the professional TRN-SYS software to build a multi-zone simulation environment for control policy model training and testing. Simulation results demonstrate that compared to the rule-based heuristic control method that is widely used in modern Building Management System (BMS), our approach can achieve from 2.8% up to 15.4% energy saving under different thermal comfort demands.
- We propose a novel application built upon the iTCM system for human behavioral study. It is a Deep Reinforcement Learning (DRL) based gamification approach for motivating occupants' behavioral changes to form energy-saving habits. Our goal is to fulfill the minority of occupants' discomfort by offering incentive gifts (e.g., movie ticket or voucher). Particularly, we adopt the classic Actor-Critic method to develop an economic model and use it to balance energy cost saving and incentive expenditure. Digital-Twin based simulation results show that our proposed approach has great potential to achieve the building energy-saving while maintaining occupants' satisfaction levels.

²<https://github.com/cap-ntu/iTCM-Datasets>

FIGURE 1.5: Main content and organization of the thesis.

This thesis provides fundamental insights and guidance for applying various deep learning techniques (e.g., deep neural network, deep transfer learning, and deep reinforcement learning) to the smart building related research, such as thermal comfort modeling, indoor thermal control and human behavioral study. Our results demonstrate that compared to the conventional methods, deep learning based approaches have enormous problem-solving ability and significant performance advantages. Our findings and insights will make contributions to the future research in the smart building research field.

1.4 Outline of the Thesis

Fig. 1.5 shows the main content and organization of the thesis. Specifically, we can divide the main content into three parts, including platform, theory, and application. The first part of the thesis (Chapter 3) is from the perspective of the platform. Specifically, in Chapter 3, we introduce the developed intelligent Thermal Comfort Management (iTCM) system and the obtained dataset. The second part of the thesis (Chapter 4 and 5) is from the perspective of the theory. Specifically, in Chapter 4, we focus on developing the learning-based thermal comfort models. Then, in Chapter 5, we investigate the optimization problem of the multi-zone thermal control. The third part of the thesis (Chapter 6) is from the perspective of the application. Specifically, we design a novel human behavioral study to encourage occupants to form energy-saving habits.

The rest of this thesis is organized as follows:

- **Chapter 2** surveys the existing works on thermal comfort modeling and indoor thermal control.
- **Chapter 3** introduces the details of the iTCM system and the collected iTCM datasets.
- **Chapter 4** illustrate the detailed procedures of using deep neural network learning and deep transfer learning for thermal comfort modeling, respectively.
- **Chapter 5** optimizes the thermal control for the multi-zone buildings by using the multi-agent deep reinforcement learning.
- **Chapter 6** designs a novel application based on the iTCM system to motivate occupants' behavioral changes for building energy saving.
- **Chapter 7** summarizes the thesis, discusses the limitations and shares our further plans.

The next chapter provides literature review of the research in this thesis.

Chapter 2

Literature Review

In this chapter, we provide an overview of smart building and the detailed literature survey of thermal comfort models, thermal comfort modeling methodologies, and indoor thermal control approaches. First, we introduce the canonical thermal comfort models adopted by the industry standards. Next, we survey the existing methodologies of thermal comfort modeling. Finally, we review the development of thermal control with the HVAC systems.

2.1 Smart Building

Smart building refers to a building that is controlled by a Building Management System (BMS) or a Building Automation System (BAS). BMS or BAS is a centralized computer-based control system developed based on the Internet of Things (IoT) technologies and installed in a building that monitors and controls the mechanical, electrical, and thermal conditions of this building, such as HVAC, power, lighting, fire, sensing, and security systems. In 2013, *Dragoicea, Monica et al.* [65] proposed a service oriented modeling and simulation architecture to build an ecosystem for the IoT-based smart building management. At that time, the core objective of smart building for non-residential buildings and smart home for residential buildings is to make the commercial and industrial data communication protocols (e.g., BACnet [66]), and use these protocols to link different systems of a building together to allow BMS or BAS for centralized management. Indeed,

FIGURE 2.1: The relationship among Internet of Things (IoT), smart grid, and smart building.

with these protocols, building administrators can manage different building systems easily and achieve significant energy saving. However, the control logic of existing BMS or BAS is still based on various predefined rules or policies (e.g., fixed set-point temperature for HVAC systems, difficult individual room control, static lighting scheduling control, etc.), which make the building looks still not “smart” enough.

Based on our research in the past several years as well as the latest survey [67], we consider that existing BMS or BAS enables the building automation, but it is still far from the building intelligence, as shown in Fig. 2.1. After 2000, with the development of IoT technologies, especially data communication protocols, conventional buildings have evolved into automated buildings. The IoT technologies enable the BMS or BAS to interact with various subsystems of a building and realize the centralized control and building automation. In recent years, with the rapid development of Artificial Intelligence (AI) technologies, especially machine learning techniques, there are a lot of smart applications that have come into our daily life,

such as smart TV, smart music player, smart voice assistant, smart robot and so on. Therefore, we believe that combining the IoT and AI technologies enables us to develop more intelligent management systems and moves conventional buildings to further evolve into real smart buildings.

Advances in smart building technologies have driven to the extensive development of five key components in existing automated buildings, including Sensors & Actuators, Data Communication, Security & Access Control, System Control, and Management Software. In this thesis, our research mainly focuses on thermal comfort improvement and HVAC control optimization, which are closely related to all five key components.

- **Sensors & Actuators:** Wired and wireless sensors and actuators [68] are used for data measurement and monitoring. The decision-making of the centralized management software highly relies on the measured data from these sensors and actuators. For example, if the environmental sensors provide the wrong data, then the centralized management software will make the actuators of the HVAC systems to take the wrong cooling or heating operations.
- **Data Communication:** Data communication [69] is used for data transmission among various subsystems of a building. It enables centralized management software to track the statuses and control the behaviors of various subsystems. Data transmission failure will cause serious issues in the decision-making of the centralized management software. For example, if the measured data of environmental sensors cannot reach the management software, then HVAC systems cannot make subsequent decisions to adjust the indoor thermal conditions.
- **Security & Access Control:** Security and access control [70] are used for ensuring occupants' safety and preventing unauthorized access to restricted building facilities. For example, if an unauthorized person accesses the centralized management software and manipulates the thermal comfort settings, then the HVAC system will follow the wrong settings for thermal comfort management.
- **System Control:** System Control [71] allows centralized management software to have permission to send out operation commands or control strategies to different subsystems, including HVAC, power, lighting, fire, sensing, and

security systems. For example, if the predefined HVAC control strategy is configured in the centralized management software, then the HVAC systems will ignore the dynamics of the indoor environment and follow the command to take operations.

- **Management Software:** Management software [72, 73] is a centralized computer-based software, which is the brain of the building management. The objective of the management software is to minimize the total building energy consumption while maintaining occupants' indoor thermal comfort. Therefore, management software plays an important role in optimizing building management. For example, if the adopted management software is not intelligent enough, then the building owners will suffer from economic loss and occupants' complaints.

In conclusion, from the above descriptions, we believe that the thermal comfort and HVAC control play important roles in building intelligence. In the subsequent sections, we present the literature review on thermal comfort models, thermal comfort modeling, and HVAC control optimization.

2.1.1 Thermal Comfort Datasets

Datasets play a critical role in developing thermal comfort models. Datasets with high-quality features and a sufficient number of data samples can significantly affect the prediction accuracy of the built models.

The most widely used dataset is the ASHRAE Research Project 884 (RP-884) Dataset [8]. The objective of building this dataset is to develop the adaptive model. It comprises 25,617 raw thermal comfort data collected from 52 studies across ten different climate zones around the world by 1998. It mainly collects six modeling features: air temperature, mean radiant temperature, relative humidity, air velocity, metabolic rate, and clothing insulation. We can find that the RP-884 dataset follows the insights of Fanger's Predicted Mean Vote (PMV) model [7] proposed in 1970 to develop the adaptive thermal comfort model. These six modeling features are the same as the six input parameters of the PMV model. In recent years, to catch up with the modern big data standard and further improve the prediction accuracy of the thermal comfort models, researchers from the

University of California, Berkeley (UCB) to build the ASHRAE Global Thermal Comfort Database II [74]. It contains 107,463 raw data in total, 81,846 rows of them are collected from 62 field studies between 1995 and 2015 around the world. The rest of the 25,617 samples are from the RP-884 dataset. So far, the ASHRAE Global Thermal Comfort Database II is the largest dataset in the thermal comfort research field.

Other than the ASHRAE Global Thermal Comfort Database II, there are some other datasets are available online for open access. These research works attempt to collect additional modeling features rather than only considering the six PMV features. *Hirashima et al.* [75] built a dataset with 1,693 raw data. They collected other features, such as height, weight, age, and gender. In addition, they also prepared the questionnaires to conduct the survey-based study. Their results show that other than the six PMV features, there are a lot of other features also linking to human thermal comfort. *Barrios et al.* [76] proposed to adopt the wearable device to collect users' heart rate, and use it as one of the key features for thermal comfort modeling. Their results show that human thermal comfort is significantly determined by the heart rate. Moreover, they had shared their dataset in GitHub¹. *Kim et al.* [77] built a dataset with 4,866 data samples. Different from the previous studies, they collected data from the primary and secondary school students. Their findings show that people at different age groups have diverse thermal comfort demands. Recently, in the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys 2019) conference, some research works [78, 79] also shared their datasets and research findings. These studies aim to involve new features (e.g., thermal comfort preferences [78]²) and new modeling algorithms (e.g., deep transfer learning [79]³) to innovate the thermal comfort modeling methodologies while improving the prediction accuracy of models. Their results show the effectiveness of their solutions in improving thermal comfort prediction accuracy.

In the current big-data era, data determines the quality of the model. More and more datasets will be released to make contributions to this research field.

¹<https://github.com/LilianaB/ComfstatDataSet>

²<https://zenodo.org/record/3363987>

³<https://github.com/cap-ntu/iTCM-Datasets>

2.1.2 Thermal Comfort Models

There are two canonical thermal comfort models: Predicted Mean Vote (PMV) model [7] and Adaptive comfort model [8], which have been adopted by the ASHRAE Standard 55 [4], European EN15251 Standard [80], and ISO/DIS 7730 Standard [81].

For the PMV model, it is the most well known thermal comfort model, which was developed by *Fanger et al.* [7] in 1970. The thermal comfort score of the PMV model is measured by the ASHRAE sensation ranging from -3 to 3, where the seven ascending integers in the range represent cold, cool, slightly cool, neutral, slightly warm, warm, and hot, respectively. PMV takes into account four environmental factors (air temperature, mean radiant temperature, relative humidity and air velocity) and two vital factors (metabolic rate and clothing insulation). The corresponding comfort level takes the form of the nonlinear regression function. For the Adaptive comfort model, it was developed by *Dear et al.* [8] in 1998. Different from the PMV model, the adaptive model is built upon the concept that indoor thermal comfort is mainly affected by the outdoor thermal conditions. The output of the adaptive comfort model is the optimum indoor air temperature, which varies linearly with the changes of mean outdoor effective temperature. Hence, it is a linear regression function. From the PMV model (1970) to the Adaptive comfort model (1998), we can find that the design purpose of thermal comfort models is to simplify the model complexity and make thermal comfort models easier to implement in the HVAC systems. Therefore, industrial communities prefer simple, practical and straightforward solutions for ensuring system stability and reducing the implementation difficulty. This is the main reason why industrial standards only adopt these two thermal comfort models. Another minor reason is that although the smart building is becoming an emerging research topic, most researchers mainly target to intelligent management and control, rarely focus on improving human thermal comfort models.

Since the PMV model is widely used by the existing BMS for thermal control for decades, we consider the PMV model as the performance comparison baseline in this thesis. However, recent researches [46, 47] indicate that the PMV model is inaccurate to evaluate human thermal comfort. With our literature survey, we summarize two major drawbacks of the PMV model: 1) thermal comfort parameter inadequacy; and 2) modeling data inadequacy. For the former, other than the

six PMV factors, there are a variety of parameters linking to the human thermal comfort, such as environmental factors: acoustic (e.g., noise) [14] and CO2 level [12]; personal information: age [17], gender [15], heart rate [18], skin temperature [20]. For the latter, compared to other data-driven research fields (e.g., Computer Vision, Nature Language Processing), collecting data from human subjects is a quite challenging and time-consuming task. The largest available open-source dataset of the community is the ASHRAE Global Thermal Comfort Database II [74], which only contains 81,846 samples collected from 49 field studies conducted between 1995 and 2016 from around the world. Even for the canonical Fanger’s PMV model [7], it is developed based on a relatively small dataset which only collects the data from a thousand American and European subjects. Therefore, it is necessary to innovate the modeling methodology to develop next-generation thermal comfort models.

2.1.3 Thermal Comfort Modeling

The development and advance of modeling methodologies for thermal comfort have thus far spanned the following two generations.

The first generation is the chamber study. It is a *survey-based approach* [7], for which data are collected manually via paper-based questionnaires provided by test subjects in a climate chamber, as shown in Fig. 2.2a. Test subjects, with many sensors attached, are required to stay in a closed space for a significant amount of time. Due to these stringent requirements for time and other resources, chamber studies have the drawback that they often ignore individual differences and suffer from data inadequacy. Moreover, within the controlled settings, it is challenging to exclude the psychological bias of the test subjects.

The second generation is the *IoT-based approach* [82], for which measured data are automatically collected via the IoT-based wireless sensing technologies, such as wireless sensor network (WSN) [83, 84]. This in-situ study is shown in Fig. 2.2b. Furthermore, the ever-popular smartphone offers a promising way to gather test subject’s feedback via the mobile App, which drastically facilitates the data acquisition process. Among the recent developments with the IoT-based approach, there is a personalized HVAC control system built by [85]. They developed an IoT-based portable node, which can be worn on a user’s wrist to measure the environmental

FIGURE 2.2: Thermal comfort modeling studies. With the fast development of IoT-based sensing techniques, the thermal comfort study moves from the first generation (i.e., survey-based chamber study) to the second generation (i.e., IoT-based in-situ study).

parameters around the user. Then, they fed the sensing data to the PMV model to predict user's personal thermal comfort. Another latest IoT platform proposed by [86] used various self-powered IoT-based wireless sensors to measure the environmental parameters (e.g., light, air temperature, relative humidity, door/window state, and room activity), and then inputted them to the PMV model for thermal comfort prediction. It is worth mentioning that all these systems only use IoT-based wireless sensing technologies to measure the environmental parameters. None of them attempt to consider occupants' preferences, vital signs and psychological biases. In addition, these systems still evaluate occupants' thermal comfort based on the estimation results of the PMV model, which is questioned by its prediction accuracy. Furthermore, none of them attempt to develop new machine learning based thermal comfort models.

Recent years, with the rapid development of Artificial Intelligence (AI) technologies, the thermal comfort modeling methodology moves to the new generation, the *learning-based approach*. Various efforts have been made to apply the machine learning techniques to the human thermal comfort modeling. Many of them focus on using traditional machine learning algorithms. Research work [87] proposed to use the off-the-shelf sensors to track occupants' heart rate as a proxy of the metabolic rate and adopt the linear and logistic regression approaches to develop the thermal comfort models. Paper [89] designed a dynamic Bayesian network for personal thermal comfort modeling. Recent work [88] built an IoT platform

TABLE 2.1: Comparison of thermal comfort modeling generations

Generation		<i>Survey-Based</i>	<i>IoT-Based</i>	<i>Learning-Based</i>
Data Collection	Mode	Manual	Automatic	Automatic
	Cost	High	Low	Low
	Sample Size	Small	Big Data	Big Data
	Feature Space	Small	Large	Large
	Error Rate	Median	Low	Low
Modeling Methods	Algorithms	Traditional Nonlinear Regression [7]	Traditional Nonlinear Regression [7], Traditional Linear Regression [8]	Learning-based Linear and Logistic Regression [87], SVM, Kernel Ridge Regression, k -NN, Gaussian Process Regression, Quadratic Discriminant Analysis [88], Bayesian network [89], Neural Network [90], deep learning [91], [92]
	Mode	Offline	Offline	Offline & Online
	Flexibility	Static	Static	Dynamic
	Scalability	Low	Low	High
References		[7], [8]	[82], [85], [86]	[87], [89], [88], [90], [91], [92]

for data sensing and compared the modeling performance among various classic machine learning algorithms (e.g., SVM, Kernel Ridge Regression, k -NN, Gaussian Process Regression, Quadratic Discriminant Analysis). Other studies take the Neural Network (NN) into consideration. Existing paper [90] presented an evaluation model for personal thermal comfort based on Back Propagation (BP) NN. In 2018, the published papers [91, 92] of our research team evaluated a Deep Neural Network Learning approach to model thermal comfort. The comparison of three modeling generations are summarized in Table 2.1. However, owing to the powerful learning ability of the deep learning techniques, the further revolution of thermal comfort modeling methodology is possible.

2.1.4 HVAC Control Optimization

Based on our literature survey, many research works have proposed various approaches to optimize the thermal control in the past 50 years, which can be divided into two major categories: 1) Single-objective optimization; and 2) Multi-objective optimization.

Research works of the first category only target to optimize the energy expenditure of the HVAC systems. During the 1970s, conventional mechanisms (e.g., basic ON-OFF method [93], Proportional-Integral-Derivative (PID) [22]) were developed, but these conventional solutions suffer from the unavoidable overshoots in the set-point temperature. Improper settings of various gains would result in inappropriate control operations and potentially increase energy consumption. To address their drawbacks, various optimized methods upon conventional mechanisms [23–27] were developed during the 1980s and 1990s. Meanwhile, a few of research works had attempted to adopt some learning-based methodologies (e.g., genetic algorithm [31], neural network [32], reinforcement learning [33]) for intelligent HVAC control. Nevertheless, these approaches were not deployed in practice due to the implementation issue at that time. After the millennium, model-based predictive control (MPC) approaches [28–30] were proposed to optimize the HVAC control. However, these techniques highly rely on pre-set models. Inappropriate models of the system could result in poor performance. Recent several years, the fast development of machine learning techniques enables researchers to apply the emerging deep learning methodologies (e.g., deep neural network [34, 35] and deep reinforcement learning [36–38]) to the smart thermal control. Although these approaches demonstrate significant energy saving, they generally maintain room temperature within a pre-defined comfort temperature range without considering occupants' dynamic thermal sensations. The comparison of various single-objective approaches is summarized in Table 2.2. In summary, the limitations of the single-objective control optimization are obvious. Towards the multi-objective control optimization is the trend.

Research works of the second category aim to investigate the trade-off among multiple optimization objectives. One of the major multi-objective optimization problems in thermal control research is to seek the balance between the energy expenditure of the HVAC systems and occupants' thermal comfort. Researchers propose to use the canonical Predicted Mean Vote (PMV) [7] or adaptive thermal comfort

TABLE 2.2: Comparison of HVAC control approaches

Category	Type	Algorithms	Issues
Single-Objective Optimization	Conventional	ON-OFF method [93] Proportional-Integral-Derivative (PID) [22]	Rule-based static control. Unavoidable overshoots in set-points. Improper gain settings result in wrong control operations. Offline modeling.
	Optimized	Optimal Control [23], [24], [25] Model-based Predictive Control (MPC) [26], [28], [29], [30] Linear Quadratic PID [27]	Rule-based static control. Unavoidable overshoots in set-points. Inappropriate models result in poor performance. Offline modeling. Complicated to deploy in practice.
	Intelligent	Genetic Algorithm [31] Neural Network [32] Reinforcement Learning [33] Deep Neural Network [34], [35] Deep Reinforcement Learning [36], [37], [38]	Dynamic control with poor performance. Difficult to deploy in practice.

model [8] for predictive thermal control. Based on the predicted results, some research works [39–41] continue to adopt the conventional mathematical algorithms for control strategy optimization, while some others propose to apply the emerging deep learning methodologies [42–45] to develop the intelligent HVAC control policies. Nevertheless, these techniques emphasize on the thermal control optimization for a single space (e.g., one room, a zone, or an office) without considering the parallel thermal control optimization of multiple zones. However, there are three challenges to move from the single-zone case to the multi-zone case:

- First, the single-zone case only focuses on one zone whose thermal conditions are relatively simple. However, the multi-zone case requires the control

policy to react to the inputs of different zones, face heterogeneous thermal conditions, and then select the related suitable actions. It is challenging to design and formulate optimization problems.

- Second, the single-zone case only needs to handle the events in a single zone and generally assume that it only interacts with the outdoor environment. However, in the multi-zone case, each zone may interact with other zones or outdoor environment (e.g., heat exchange between a zone with 23°C and a zone with 25°C). Thus, it is challenging to build a suitable simulation environment to verify the developed control policies.
- Third, the control policy obtained in the single-zone case is applicable to the thermal conditions of the verified zone. However, it may not be applicable to other zones. It is challenging to develop the multi-zone control policy to handle the thermal conditions of different zones simultaneously.

This raises another multi-objective optimization problem, which is to optimize the total energy consumption while maintaining occupants' thermal comfort in multiple zones. To address this issue, plenty of multi-agent systems [48–53] are developed to allocate one agent to each zone for achieving the optimal thermal control. However, these approaches mainly adopt the conventional optimization algorithms (e.g., Particle Swarm Optimization [48], MPC [49], Nash-bargaining [50], and Alternating Direction Multiplier Method [51]), which suffer from inaccurate parameter estimates. Significant differences in inputs would result in improper outputs and control operations. The comparison of various multi-objective approaches is summarized in Table 2.3. Therefore, it is necessary to apply advanced algorithms to further optimize multi-zone thermal control.

2.1.5 Human Behavioral Studies

Human behavior recognition is one of the key factors to improve the human-machine system (e.g., smart building system). Earlier in 1999, *Pentland et al.* [94] from the Massachusetts Institute of Technology, Cambridge proposed that if the machine could recognize the human's behaviors or even better, then the machine can adjust itself to serve human's needs better. Therefore, it is necessary to

TABLE 2.3: Comparison of HVAC control approaches

Category	Type	Algorithms	Issues
Multi-Objective Optimization	Conventional	Model-based Predictive Control (MPC) [39], [40], [41]	Static thermal comfort model. Inaccurate parameter estimates. Multi-zone control case is ignored. Offline modeling. Complicated to deploy in practice.
	Optimized	Multi-zone based Particle Swarm Optimization (PSO) [48] Multi-agent based distributed optimization algorithm [49], [50], [53] Alternating Direction Multiplier Method (ADMM) based algorithm [51], [52]	Static thermal comfort model. Significant differences in inputs result in improper control operations. Offline modeling. Difficult to deploy in practice.
	Intelligent	Neural Network based MPC [42], [44] Random Neural Network [43] Recurrent Neural Network [45]	Static thermal comfort model. Multi-zone control case is ignored. Difficult to deploy in practice.

conduct human behavioral studies to make smart building management system to serve occupants better.

Based on our survey, machine learning based human behavioral studies in the smart building research field are still in the undeveloped stage. Only a few related research works have been published in the recent two years. In 2018, *Shelke et al.* [95] proposed to adopt various machine learning techniques to analyze human activities in common areas. Different from the Computer Vision research field, they did not use any camera or microphone devices. Instead, they use the sensor-based embedded system. Their results show that their solution can provide up to 99.95% of classification accuracy. Meanwhile, *Yang et al.* [96] proposed a novel WiFi-enabled approach to detect the occupancy for human behavior analysis in smart homes. They collected channel state information (CSI) measurements via

a lightweight communication protocol. Their results show that the accuracy of the occupancy detection and recognition is up to 96.8% and 90.6%, respectively. However, these two research works did not verify their solution in the real-world environment. Hence, their findings cannot indicate how human behaviors affect building energy consumption or improve the existing building management system. Later, our paper [91] proposed to develop an intelligent thermal comfort management (iTCM) system. One of the key applications of this iTCM system is a novel deep reinforcement learning-based human behavioral studies. Our findings show that human behaviors, especially energy-saving habits, can affect the energy consumption of a building for achieving further energy saving. However, in the earlier stage of research, although we show the linkage between human behaviors and building energy-saving, we still verify our solution in the simulation environment. Recently, one of the latest related work [97] proposed a gamification approach to motivate occupants to consider their personal energy usage for achieving the energy-saving of smart building infrastructure. They adopt the Recurrent Neural Networks to develop the related benchmark utility learning framework to evaluate occupants' behaviors toward energy efficiency. Their results show that they can build an accurate model to estimate occupants' resource usage status. However, they also do not verify the actual building energy-saving by using their approach.

In summary, the number of highly correlated research works are still limited. However, from another view of point, this research direction still has great potential.

2.2 Summary

In this chapter, we presented the literature survey on canonical thermal comfort models with their drawbacks, various thermal comfort modeling methodologies with their limitations, and existing indoor thermal control approaches with their disadvantages, respectively. Next, motivated by those discussed problems and challenges mentioned above, we will present our research details on how to address them in the following chapters.

Chapter 3

iTCM System & Dataset

In this chapter¹, we first introduce the developed intelligent thermal comfort management (iTCM) system and then describe the self-collected iTCM datasets. In addition, we conduct the pressure test to verify the web service throughput of the iTCM system. Moreover, we estimate the costs of capacity planning for system deployment in the public cloud. Part of this chapter has been published in [1].

3.1 Introduction

The emergence of wearables, the adoption of cloud computing, and the rapid advancement in machine learning techniques herald in a new phase of thermal comfort management system development, which offers tremendous opportunities and advantages. The pervasive and persistent sensing capability, enabled by the wearable devices [98, 99], offers a convenient way to track occupants' vital signs, which can be used for thermal comfort modeling and intelligent thermal control in an online way. Moreover, cloud-based back-end architecture, deep learning techniques, and big-data analytics [100, 101] provide an opportunity to derive unprecedented insights on human thermal comfort and control policy optimization by processing

¹**Weizheng Hu**, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng, "iTCM: Toward Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings," in *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831

and analyzing the massive amount of collected data. With the objectives of advancing the thermal comfort modeling and thermal control to the next generation and showing a viable path forward, a smarter management system is required.

In this chapter, we design and develop the intelligent Thermal Comfort Management (iTCM) system. The iTCM system consists of infrastructure, modeling framework, and application, all leveraging the state-of-the-art technology in real-time sensing as well as recent advances in the deep learning techniques. Moreover, iTCM provides the flexibility and the scale for developing and testing new thermal comfort models and thermal control, which can maintain occupants' thermal comfort while potentially leading to building energy saving. Specifically, we have made the following contributions.

- We build the iTCM system, which consists of three main components: a wireless sensor network, mobile Apps with wearable devices, and a back-end web server. Moreover, we integrate the AI module into the back-end server to perform the intelligent HVAC control based on the predicted occupants' thermal comfort. The whole system has been deployed in a lab of NTU and used for real-world experiments.
- We design the system capacity planning based on the cloud instance information from the Amazon Web Services. We first conduct the pressure test to benchmark the performance of our iTCM system and then carry out the cost analysis for system deployment in the public cloud.
- We adopt the iTCM system to conduct one-year data collection experiments to create our iTCM datasets. Compared to the famous ASHRAE RP-884 Dataset, our datasets contain more thermal comfort modeling features. Besides, we have released the datasets ² to contribute to the community.

This chapter provides fundamental insights and guidance for developing the Internet-of-Things (IoT) based intelligent thermal management system. We provide a general system design of including both front-end applications and back-end services, which can be deployed in the public clouds. The pressure test shows that our designed system has the enterprise-level request processing ability. Our insights will

²<https://github.com/cap-ntu/iTCM-Datasets>

make contributions to future research about the smart thermal comfort management system development in the smart building field.

The rest of this chapter is organized as follows. Section 3.2 introduces the proposed iTCM system in detail. Section 3.3 presents the system capacity planning, which contains the system benchmark and deployment cost analysis. Section 3.4 introduces the collected iTCM datasets. Section 3.5 concludes this chapter.

3.2 iTCM: Intelligent Thermal Comfort Management System

In this section, we describe the proposed iTCM system. The architecture is illustrated in the first diagram of Fig. 3.1. We leverage the off-the-shelf hardware and devices to develop the iTCM system, which includes three major modules: a wireless sensor network (WSN), mobile Apps and a back-end system.

3.2.1 Wireless Sensor Network

The wireless sensor network (WSN) is adopted by the iTCM system to measure and acquire the environmental data (e.g., air temperature, relative humidity, etc.).

In the WSN, various environmental sensors are embedded in the wireless sensor nodes. All wireless nodes are connected to a common wireless gateway which transmits the sensing data to our back-end servers via the Internet. In addition, with the bi-directional communication design of modern WSN, we can control various sensor activities (e.g., sampling rate, working mode, logging patterns, etc.) via the iTCM system to fulfill the experiment and application requirements. In our research, we adopt the Building-in-Briefcase (BiB) device [102] developed by Berkeley engineers funded by Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) program. BiB is a kind of portable energy-efficient wireless monitoring system. Its communication protocol is TCP/IP protocol. It contains one wireless router and eight battery-based sensor nodes. Each node covers between 25 and 100 m^2 based on building makeup and can continuously sense data for up to three months depending on the sampling rate.

FIGURE 3.1: iTCM System overview. The proposed architecture consists of three major modules: wireless sensor network (WSN), mobile Apps and back-end system. First, WSN monitors the environmental parameters of a building space and update to the back-end server. Then, mobile Apps track occupants' vital signs and upload the sensing data to the back-end server. Finally, back-end server is responsible to store the received data, analyze the data and perform the thermal comfort prediction as well as HVAC control.

3.2.2 Mobile App

The mobile App is developed to track the occupants' vital signs through the wearable devices in real time. Measured data will be automatically transmitted to the

FIGURE 3.2: iOS Mobile App and Microsoft Band 2. In iTCM system, we develop both Android and iOS mobile applications and the Android App has the same user interfaces as the iOS App. Also, we adopt the powerful Microsoft Band 2 for human vital signs tracking.

occupants' smartphones in a private manner via Bluetooth. At any time, occupants can send their feedbacks as well as the aggregated data to our back-end server via cellular network or WiFi. Several typical user interfaces (UIs) of the mobile App are presented in the second diagram of Fig. 3.1. For the overall UI design and workflow, please refer to Fig. A.1 in Appendix A.

3.2.2.1 Dashboard Tab

It displays two types of information. One is the environmental data which is collected via the WSN, and the other is the user's vital signs (e.g., heart rate, skin temperature, etc.) measured by wearable devices. Such a dashboard function offers a convenient way for occupants to track their surrounding environment and personal healthy status. Fig. 3.2 presents the working iOS mobile App with the dashboard UI along with the paired Microsoft Band 2. For the detailed State Diagram is shown in Fig. A.5 in Appendix A.

3.2.2.2 Preference Tab

This feature allows occupants to choose their personal preferences and acceptable thermal comfort range. With such personalized profiles, the iTCM system can

aggregate the information and improve the configurations to achieve better thermal comfort with an economical expense. Moreover, these preference data can be used to conduct some interesting analysis (e.g., age-based or gender-based thermal comfort preference analytics) to obtain some novel insights. For the detailed State Diagram is shown in Fig. A.6 in Appendix A.

3.2.2.3 Reward Tab

iTCM strives for improving the thermal comfort for all occupants. But in certain circumstances, it is possible to achieve the significant saving on energy and monetary expense with some proper incentive schemes. When an occupant's comfort preference is too "expensive" to meet, this feature offers the occupant with some rewards (e.g., T-shirts, thumb drives, movie tickets or other vouchers), such that the overall saving can be realized. Furthermore, such a feature can be used for characterizing the economic model of thermal comfort, which will be described in detail in Chapter 6. For the detailed State Diagram is shown in Fig. A.7 in Appendix A.

3.2.3 Back-end System

The back-end system is designed for data management and analytics. To provide stable and reliable services, we adopt the enterprise-level back-end framework, named *Spring* [103], which is a Java-based open-source software. The third diagram of Fig. 3.1 illustrates the back-end system architecture with the following three major service layers.

3.2.3.1 Scalable Services Layer

In this layer, we adopt the message broker framework *RabbitMQ* [104], to decouple the non-core services (e.g., email service, push notification service, etc.) from the core service layer. The benefit to doing this is that any operations (e.g., add, delete or modify functions) in this layer do not affect the core service layer, so as to significantly improve the system scalability and maintainability.

3.2.3.2 Core Service Layer

This layer only provides the system core services, the Artificial Intelligence (AI) module, which contains the thermal comfort modeling and reinforcement learning based intelligent thermal control. First, We implement the traditional statistics disciplines, the classical machine learning methods and the emerging deep learning approaches in this layer for prediction performance of various thermal comfort models. Then, we integrate the multi-zone thermal control mechanism into this layer to collaborate with the previously developed learning-based thermal comfort models for multi-zone intelligent HVAC control. Moreover, to fulfill the big-data driven based data processing and analytics, the architecture of this layer is designed to support the distributed parallel computing.

3.2.3.3 Database Layer

This layer supports data storage and management. Our current prototype has one master database and one slave database to enhance the data reliability and integrity. In addition, we also adopt the cache framework (e.g., Redis) to boost the I/O process for web services and machine learning tasks. In addition, similar to the core service layer, this layer is also scalable for distributed architecture to meet the likely increased demands in the future. For the detailed database design, please refer to Fig. A.2 in Appendix A.

3.3 iTCM System Capacity Planning

With the emerging cloud computing technologies, we would like to deploy our iTCM system in the public cloud, to facilitate the system management and maintenance. In this chapter, we specifically consider the Amazon Web Services (AWS) [105], and implement the capacity planning task based on the instance information (e.g., server specifications and instance pricing) from the AWS. In the following subsections, we first conduct the performance benchmark for the iTCM system and then perform the cost analysis to derive the optimal costs for cloud deployment.

TABLE 3.1: The Capacity of Different Instance Types with Detailed Specifications & Pricing from AWS

Category	Low-end	Middle-end	High-end
Model	t2.small	t2.medium	t2.xlarge
Number of CPU	1	2	4
MEM(GiB)	2	4	16
CPU Usage(%)	99.9	99.8	99.9
MEM Usage(%)	78.9	67.6	52.6
Disk IO(%)	3.2	5.3	10.4
Throughput(rps)	321	624	1,030
Price(SGD)	0.03 per Hour	0.06 per Hour	0.24 per Hour

3.3.1 Performance Benchmark

The cloud-based solution is to build a server cluster, which is constructed by a lot of server instances. To design the appropriate capacity plan for fulfilling the performance demands with the optimal costs, it is necessary to evaluate the request processing performance of a single server instance with different specifications. In this section, three typical AWS instance types are chosen for the iTCM capacity planning. The detailed instance specifications and pricing are listed in Table 3.1. We adopt the *Apache JMeter* [106] to simulate the sending actions of HTTP request performed by users. Each HTTP request will trigger the actual logic processing operations in the back-end server, such as data processing and database operations.

For each instance type, we consider its capacity regarding the throughput as the number of handled requests per second (rps). We also record the resource utilization of CPU, memory, and disk. The detailed results are shown in Table 3.1. As we can see, iTCM is a computation intensive application, as the CPU resource is saturated while the memory and disk resources have much surplus. Indeed, higher-end instance with more CPUs achieves higher throughput compared to lower ones. Hence, we also plot the number of CPU cores in relation to both service price and system throughput in Fig. 3.3.

It is worth to mention that, during the capacity tests, iTCM remains stable without any crashes and provides sufficient throughput to handle the incoming requests.

FIGURE 3.3: The number of CPU cores in relation to the service price and system throughput. Both service price and instance throughput increase with the increment of the number of CPUs. However, the price is a convex function of the number of CPU while the throughput is the concave function, resulting in the best option of selecting the low-end instance for cloud deployment.

3.3.2 Cost Analysis

In this subsection, we adopt a back-of-the-envelope calculation to estimate iTCM's cloud deployment cost, regarding instance rental, data transfer, and data storage. Below are the details.

3.3.2.1 Instance Rental Cost

As seen in Fig 3.3, the instance throughput is a concave function of the number of CPU cores, while the price is a convex function. As a result, the optimal choice with the best deployment cost for the iTCM system is to use the low-end instance. Moreover, to ensure the system stability, the server must have the ability to handle a large number of requests during the peak time, which can be considered as the worst case. As such, let us assume that there are roughly 4 million working people in Singapore [107]. In the peak time, we suppose each person will send one HTTP request to the iTCM system every 10 minutes, leading to a maximum throughput requirement of 6,667 rps. To fulfill such demand, we first group 21 low-end instances as a cluster, and then, use one middle-end instance for load balancing. We also assume the instances are running through the whole year. In total, the instance cost of the iTCM system will be S\$6,044 per year.

3.3.2.2 Data Transfer Cost

Data transfer cost between the AWS and the Internet is charged monthly [105] with tiered pricing, i.e. S\$0.12 per GB for the first 10TB and S\$0.085 for the next 40TB. The data transfer costs heavily depend on the number of requests between users and server. In practice, the peak time may not last for a whole year. As such, we consider the average case, which combines the data transfer in both peak time and off-peak time. Therefore, let us assume that the average daily active users are 30% of the total 4 million workforces, each person sends ten requests to iTCM per day and the average data size of HTTP request is 121KB. We also consider that five working days a week. Therefore, we have 27,695GB monthly transferred data, which will cost S\$2,712 per month. In total, the annual data transfer cost of the iTCM system will be S\$32,544.

3.3.2.3 Data Storage Cost

Most data in the iTCM system is in the text format and not storage heavy. The primary storage cost of the iTCM system comes from the operating system files, software packages and various frameworks. Totally, they typically consume less than 100GB hard disk space in our prototype. With S\$0.03 monthly storage pricing per GB, the annual cost of the iTCM system will be only S\$36.

In conclusion, summing up the costs for instance rental, data transfer and data storage, the annual cloud service deployment cost of the iTCM system in Singapore will be S\$38,624.

3.4 iTCM Datasets

In this section, we introduce our self-collected iTCM datasets. We first describe the experimental environment and then illustrate the collected modeling features.

TABLE 3.2: List of variable sampling intervals

#	Variable	Interval
1	Actual thermal comfort votes (ASHRAE 7-point scale) with timestamp (date & time)	5-25 min
2	Burned calories (kcal)	5-25 min
3	Air temperature ($^{\circ}\text{C}$)	2 min
4	Relative humidity (%)	2 min
5	Heart rate (bpm)	1 sec
6	Skin temperature ($^{\circ}\text{C}$)	1 sec

3.4.1 Controlled Experiments

We conducted the data collection experiments in a controllable chamber equipped with an independent HVAC systems. Moreover, we also deploy the Wireless Sensor Network (WSN) to this chamber for measuring the environmental parameters. For the deployed WSN, we adopt the Building-in-Briefcase (BiB) device [102] developed by Berkeley engineers funded by Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) program.

Before the start of each experiment, we set up both hardware (HVAC systems, BiB device, smartphones, and Microsoft Bands) and software (mobile App and back-end server). Table 3.2 lists the collected various variables and the corresponding sampling intervals.

Each experiment consists of a 30-minute preparation session and a 3-hour data collection session. To obtain participants' actual comfort votes from different room temperatures, we implement each experiment session under one of the following six thermal environments: 1) 18°C - 20°C ; 2) 20°C - 22°C ; 3) 22°C - 24°C ; 4) 24°C - 26°C ; 5) 26°C - 28°C ; 6) 28°C - 30°C . Moreover, one research student is allocated to be in charge of conducting each experiment.

- During the preparation session, first, we pass the consent forms to all participants for reading and signing. Then, we briefly introduce our experiment processes and guide them to use our developed mobile App (e.g., save personal information, set clothing settings, submit thermal comfort votes).

- During the data collection session, we only allow participants to do some light-weight tasks (e.g., read books, do homework) to simulate the general indoor environment (e.g., classroom, office). Every 10 minutes, research student will remind participants to send their thermal comfort votes. To obtain accurate feedback, we require participants to submit their votes within several seconds. Since it is difficult to ensure everyone to send the vote simultaneously, the submission interval is from 5 to 25 minutes, as listed in Table 3.2. Meanwhile, we also record each participant’s total amount of calories burned during the submission interval to calculate the personal metabolic rate.
- After the completion of each experiment, to avoid affecting the next session and ensure the accuracy of the measured data, the research student will reset all Microsoft Bands to remove previous participants’ bio-information.

Following the above experimental procedures, we divide our data collection experiments into the following three stages.

- *Three-Week Preliminary Experiment:* In this stage, we recruited 30 participants. Our goal is to test and debug our iTCM system, especially the mobile App. Meanwhile, we want to collect some data for preliminary analytics.
- *Three-Month General Experiment:* In this stage, we recruited 241 participants. Our objective is to collect sufficient data to support our machine learning research for the generic thermal comfort modeling.
- *One-Month Particular Experiment:* In this stage, since there are no female applicants, we only recruited three fixed male participants. We aim to collect some data for personal thermal comfort modeling.

In total, we collect 6,257 raw votes from 274 participants, of which there are 141 males and 133 females. The male-female ratio is roughly 1:1. The age group of the participants is from 17 to 32 years old. Also, data privacy is under the supervision and protection of the Institutional Review Board (IRB) of our university.

Before applying the collected datasets to model training, we conducted pre-processing operations. First, we find that the interval between two adjacent votes from certain participants is too short (e.g., less than 5 minutes or even less than 1 minute),

TABLE 3.3: Information of modeling datasets

Dataset Name	Size	*AT Range	^RH Range
ASHRAE dataset	11,005	15.9-31.9°C	10.0-97.8%
iTCM generic dataset	4,293	19.6-30.6°C	37.3-83.6%
	345		
iTCM personal datasets P ₁ , P ₂ , and P ₃	380	19.6-29.9°C	42.4-75.5%
	341		

*AT refers to air temperature.

^RH refers to relative humidity.

which can be considered as duplicate votes. Hence, we remove these duplicate votes from the datasets. Then, we notice that the total number of +3 (hot) votes is deficient. There are only 31 “hot” votes received from 14 participants in our datasets. ASHRAE dataset also suffers from the same issue. The reason is that the upper bound temperature (i.e., 30.6°C & 29.9°C in iTCM datasets or 31.9°C in ASHRAE dataset) is still not higher enough to make participants feel hot. Thus, we consider that these “hot” votes cannot correctly reflect most of the participants’ hot sensations, and decide to remove them from both iTCM datasets and ASHRAE dataset. As a result, we will focus on the 6-point thermal comfort scale ranging from -3 to +2. Eventually, we obtain four datasets: the ASHRAE dataset, one iTCM generic dataset and three iTCM personal datasets for thermal comfort modeling, as listed in Table 3.3.

3.4.2 Feature Introduction

Table 3.4 lists the collected features for thermal comfort modeling. Based on the data source, we divide them into four categories.

3.4.2.1 Mobile App

Since the human body status (e.g., vital signs) is varying over the whole day, we use the mobile App to record the hour of a day when participants send thermal comfort votes.

TABLE 3.4: Modeling feature list of the iTCM datasets

#	Feature	Data Source	Description
F_1	hour	Mobile App	The hour of a day (24-hour format) when participant sends the thermal comfort vote
F_2	age	Participants	Participant's age in years
F_3	gender	Participants	Participant's gender (1: male, 2: female)
F_4	weight	Participants	Participant's weight in kilograms (kg)
F_5	height	Participants	Participant's height in meters (m)
F_6	clothing insulation (CI)	Participants	Participant's clothing insulation plus the general office chair insulation
F_7	air temperature (AT)	BiB Device	Average room air temperature in degrees Celsius ($^{\circ}\text{C}$)
F_8	relative humidity (RH)	BiB Device	Average room relative humidity in percentage (%)
F_9	metabolic rate (MR)	Microsoft Band 2	Participant's metabolic rate in metabolic equivalent (met)
F_{10}	heart rate (HR)	Microsoft Band 2	Participant's heart rate in beats per minute (bpm)
F_{11}	skin temperature (ST)	Microsoft Band 2	Participant's skin temperature in degrees Celsius ($^{\circ}\text{C}$)

3.4.2.2 Participants

We collect personal information from participants directly. For the basic personal data, like age, gender, weight, and height, participants can input and save them in their account profiles of our mobile App. For the clothing insulation (CI), we let participants set their clothing ensemble from a list of typical dress combinations in the tropical area (e.g., Singapore) via the mobile App, as shown in Table 3.5. Since we do not have infrared sensors to measure the CI directly, we adopt the CBE thermal comfort tool [108] developed by the University of California Berkeley to estimate the CI based on participants' dress combinations. During the experiment,

TABLE 3.5: Estimated clothing ensemble & insulation for male and female participants

Clothing Ensemble (Male)	Insulation
[^] MSAS + (Short-sleeve shirt & Walking shorts) or similar	0.47
[^] MSAS + (Short-sleeve shirt & Thin Trousers) or similar	0.54
[^] MSAS + (Long-sleeve shirt & Walking shorts) or similar	0.51
[^] MSAS + (Long-sleeve shirt & Thin Trousers) or similar	0.58
Extra Clothing	Insulation
	0.81
+ Long-sleeve swear shirt or similar	0.88
	0.85
	0.92
[^] MSAS (Men’s underwear + Shoes or Sandals + Ankle socks + Standard office chair): 0.18	
Clothing Ensemble (Female)	Insulation
*WSAS + (Short-sleeve shirt & Walking shorts) or similar	0.46
*WSAS + (Short-sleeve shirt & Thin Trousers) or similar	0.53
*WSAS + (Long-sleeve shirt & Walking shorts) or similar	0.50
*WSAS + (Long-sleeve shirt & Thin Trousers) or similar	0.57
Extra Clothing	Insulation
	0.80
+ Long-sleeve swear shirt or similar	0.87
	0.84
	0.91
*WSAS (Women’s underwear + Shoes or Sandals + Ankle socks + Standard office chair): 0.17	

we allow participants to take on/off the extra clothing (e.g., long-sleeve swear shirt or similar), but they need to change their clothing settings subsequently.

3.4.2.3 BiB Devices

BiB sensors monitor the air temperature (AT) and relative humidity (RH) of the chamber. Since our chamber is relatively small and can only accommodate up to

six participants, two BiB sensors are deployed to cover the whole chamber. We record the average values of the AT and RH from two BiB sensors and then store them in the database.

3.4.2.4 Microsoft Band 2

It is equipped with various sensors and the detailed sensor information of Microsoft Band 2 is listed in Table A.2 in Appendix A. The reason why we select the Microsoft Band 2 is that after comparing with other famous brands (e.g., Fitbit, Samsung, Apple), Microsoft is the only brand which provides the Bluetooth API, which means we can directly collect the data from the wearable device without downloading the data from the web server. Microsoft Band 2 enables us to collect occupants' vital sign data in real time. It can measure participants' vital signs, such as burned calories, heart rate (HR), and skin temperature (ST). Among them, we adopt the burned calories to calculate the metabolic rate (MR) according to the work [109] with the following equation :

$$M = \frac{C * 3600}{W * T}, \quad (3.1)$$

where M is the metabolic rate in met, W is the participant's weight in kg, T is the activity time interval between a participant's two adjacent votes in seconds, and C is the total number of calories burned during the duration T in kcal.

3.4.3 Dataset Observations

With the collected iTCM datasets, we describe the following two key observations:

- Participants' heart rate in the warm environment is higher than that in the cool/cold environment. Figure 3.4a shows the heart rate variation concerning different thermal sensation indexes. This finding is confirmed by *Achten et al.* [110], which indicates that the heart rate is one of the critical factors linking to human thermal comfort.
- Female participants' heart rate is slightly higher than male participants on average, as shown in Figure 3.4b. This observation is proved by *Umetani et*

FIGURE 3.4: The heart rate varies with different thermal sensation scales. Overall, when the thermal sensation scale increases from -3 to 2, the heart rate also increases no matter male or female. Moreover, the female's heart rate is slightly higher than the male's.

al. [111] in the age group of 10-29 years old, but it does not apply to other age groups. As a result, it is necessary to develop multiple thermal comfort models based on the age group and gender.

3.5 Conclusion

In this chapter, with the goal of advancing the thermal comfort management to the next generation, we develop the intelligent thermal comfort management (iTCM) system, which leverage state-of-the-art machine learning techniques and IoT-based pervasive sensing technologies. First, we introduce the iTCM system, including wireless sensor network (WSN), mobile App and back-end system. Second, we evaluate system performance by using the pressure test and discuss the correlated deployment costs. Third, we describe the self-collected iTCM datasets with two key observations. Furthermore, the experimental procedures and collected parameters are illustrated in details.

In the next chapter, we will consider using the iTCM datasets for thermal comfort modeling by using the emerging deep learning techniques.

Chapter 4

Learning-Based Thermal Comfort Modeling

In this chapter, we adopt the emerging deep learning techniques to develop the thermal comfort models. First, we present a Deep Neural Network (DNN) based thermal comfort model and evaluate its performance. Then, we adopt the advanced Deep Transfer Learning technique to build the thermal comfort model for improving the prediction accuracy further.

4.1 Introduction

Thermal comfort is used to express the occupants' satisfaction with their surrounding thermal environment. Existing studies [3, 112] show that thermal discomfort not only affects occupants' productivity but also influences their long-term health. The current building comfort management strategy of the heating, ventilation, and air conditioning (HVAC) system [113] is to maintain a “comfort” set-point temperature over the whole day. This fixed value is generally obtained from the empirical results of canonical predicted mean vote (PMV) model [7], developed by *Fanger et al.* in 1970, which has been adopted by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard 55 [4].

In this chapter, we use various deep learning techniques for thermal comfort modeling, which consists of two research stages. In the first stage, we adopt the Deep

Neural Network (DNN) to build the thermal comfort model with the six PMV parameters and achieves the improvement of prediction accuracy. However, we still need to solve the two major issues: inadequate modeling parameter and insufficient modeling dataset. In the second stage, to improve the prediction accuracy further, we apply the Deep Transfer Learning (DTL) to the thermal comfort modeling built upon the DNN-based approach. First, we take more thermal comfort parameters into consideration, such as time (i.e., the hour of a day), personal information (i.e., age, gender, weight, height, and clothing insulation) and vital signs (i.e., metabolic rate, heart rate and skin temperature). Moreover, for learning-based approaches, it is flexible to append new parameters as the modeling parameters in the future. In this way, we can overcome the thermal comfort parameter inadequacy issue. Second, we adopt the transfer learning techniques to transfer the knowledge learned from multiple source domains (i.e., different but related datasets) to the target domain (i.e., our self-collected iTCM datasets) for model training. However, after investigating a lot of available datasets from the community, we find that their feature spaces are different from our datasets, resulting in the difficulty of transferring the learned knowledge. To overcome this difficulty, we propose a Heterogeneous Transfer Learning (HTL) approach to conduct effective knowledge transfer based on deep neural network, by noticing that most of the existing datasets share several overlapped features (e.g., air temperature, relative humidity) with our dataset. In this way, although we could not solve the modeling data inadequacy issue entirely, we can mitigate its impacts at a certain level by utilizing the transferred knowledge obtained from the existing and related datasets. Our contribution can be broken down into the following three aspects:

- We implement a Deep Neural Network (DNN) based approach, referred to as the intelligent thermal comfort neural network (ITCNN), for thermal modeling. We compare the performance of ITCNN with the PMV model and various machine learning approaches. Experimental results show that ITCNN achieves the best performance and outperforms the PMV model by on average 13.1% and up to 17.8%.
- We design a Deep Transfer Learning (DTL) based approach for the thermal comfort modeling, named as Heterogeneous Transfer Learning (HTL) based Intelligent Thermal Comfort Neural Network (HTL-ITCNN), which adopts a two-stage learning paradigm. The performance comparison results show that

the HTL-ITCNN model built upon the iTCM datasets significantly outperforms the PMV model by on average 73.9%.

- We analyze the factors that produce performance improvement of the HTL-ITCNN, including the newly added modeling features and knowledge transferred from existing datasets. Moreover, we use the personal iTCM datasets for HTL-ITCNN based individual thermal comfort modeling and present the enormous potential of personal thermal comfort models.

This chapter provides fundamental insights and guidance for applying various deep learning techniques (i.e., Deep Neural Network (DNN) and Deep Transfer Learning (DTL)) to develop the next-generation human thermal comfort models. First, the derived DNN-based method outperforms the PMV model. Then, the DTL-based approach achieves much better prediction accuracy than both the DNN-based and the PMV model. Our findings will make contributions to the future research of the human thermal comfort modeling research field.

The rest of this chapter is organized as follows. Section 4.2 presents the details of ITCNN and the related experimental results. Section 4.3 describes the learning paradigm of HTL-ITCNN in details and evaluates its performance. Section 4.4 concludes this chapter.

4.2 ITCNN: Intelligent Thermal Comfort Neural Network

In this section¹, we leverage Deep Neural Network (DNN) to develop the thermal comfort models. Both white-box and black-box machine learning approaches are investigated. To evaluate the modeling performance, the PMV model is considered as the baseline model. The main reason why we choose the PMV model as the baseline is that although it suffers from the issue of low prediction accuracy, its design purpose is to estimate people’s thermal comfort sensation, which is the same as ours. The details will be presented in the following subsections.

¹**Weizheng Hu**, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng, “iTCM: Toward Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings,” in *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831

4.2.1 White-Box Machine Learning Approaches

The white-box approaches derive the thermal comfort model as a function of a set of input parameters, called *feature set* [114], and their prediction results can be explained with clear mathematic theories. In this chapter, we derive the thermal comfort models by using three traditional white-box machine learning approaches:

- **Naive Bayes:** It is a classical classifier based on the Bayes probabilistic theorem, assuming independent parameters. It can be trained very efficiently in a supervised learning setting. In addition, it is also possible to construct a semi-supervised training algorithm which can learn from the combination of labeled and unlabeled data. Such an approach can generate good performance in many practical applications with complex reality situations, even with a small training set.
- **k -Nearest Neighbor:** k -NN is a non-parametric method in pattern recognition, which is an important branch of machine learning field. It is a supervised learning algorithm, which can be used for both classification and regression. Although k -NN is considered as the simplest machine learning algorithm, it can provide competitive results with a large training dataset.
- **Decision Tree:** DT is another popular white-box tool in machine learning. Each node of the tree structure will make a decision and propagate the result to the next node via each branch until the final prediction decision is made. It is also a supervised learning algorithm, including the classification trees and regression trees. Moreover, DT has the advantage of easy implementation in practical deployment.

4.2.2 Black-Box Machine Learning Approaches

A White-box method generates an explicit expression that relates the environmental parameters to comfort levels. However, the comfort level is a subjective indicator, which might depend on many physiological and psychological factors, as well as environmental settings. Therefore, the performance of any white-box model, by design, could be degraded due to the following issues:

- *Occupant Dynamics:* Occupants' comfort may depend on human dynamics in the office. For example, the comfort level of the supervisor may affect subordinates' comfort level. Different occupants may weight various contributing factors differently in determining the overall comfort level.
- *Complex Relationships:* The relationships between different individual environment parameters and comfort level are very complex. The comfort level can be a linear or nonlinear function of each individual parameters. Moreover, some parameters may have the first-order impact on the overall comfort level, while others only have the second-order impact.
- *Interaction Among Parameters:* The various parameters cannot be simply considered as independent from each other. Some parameters are inter-related. For example, a higher temperature may lead to lower humidity.
- *Confounding Factors:* In addition to the physical parameters, several external factors also directly or indirectly affect an occupant's comfort level. For instance, the comfort level measured with the same environment setting during a work-day right before a public holiday may be higher.

To address these challenges, we aim to adopt the black-box machine learning approaches [115]. Different from the white-box methods, which rely crucially on the feature selection process, the black-box approaches can automatically learn the inherent coupling among different features from the dataset. With their state-of-the-art performances, the black-box approaches are widely used in many domains. In this chapter, we implement the following two classic black-box machine learning approaches for performance comparison.

- **Support Vector Machine:** SVM is a hyperplane fitting based classifier. SVM constructs hyperplanes in a high-dimensional space to classify the input data points. It is a supervised learning approach used for classification and regression analysis. Although SVM is built upon a conceptually easy-to-understand and mathematically sound foundation, the high dimensional space makes explaining the rationale behind a particular prediction result a very difficult task. Therefore, SVM is generally considered as a black-box method. In this chapter, we implement two types of SVMs: LINEAR SVM and RADIAL BASIS FUNCTION (RBF) SVM.

FIGURE 4.1: The prediction error of the PMV model, three white-box methods, three traditional black-box approaches and one black-box based neural network approach are used for thermal comfort modeling. The six existing popular machine learning algorithms, including NAIVE BAYES, k -NN, DECISION TREE, LINEAR SVM, RBF SVM, and RANDOM FOREST. Lower prediction error means better performance on thermal comfort modeling. Our proposed ITCNN achieves the best performance.

- **Random Forest:** RF constructs for the same input with multiple DTs and fuses decisions from each DT into a final one. It is a supervised ensemble learning approach and encourages the diversity from different randomized trees to improve the prediction accuracy. Like SVM, RF depends on the DT, where DT is a white-box method. However, the randomization involved in creating many DTs also makes the results very difficult to interpret. Therefore, RF is also considered as a black-box approach in general.

In addition to the above introduced black-box methods, we also adopt the neural network (NN) [116] approach, named as the intelligent thermal comfort neural network (ITCNN), to model the high-level abstraction between occupant comfort score and in-situ measurement data. In iTCM system, the back-end server updates the average environmental status (e.g., air temperature, relative humidity, etc.) every ten minutes, by extracting the collected raw data from the sensor logs. Meanwhile, the mobile phone updates user’s instant vital signs (e.g., heart rate, skin temperature, etc.) every minute, via Microsoft Band 2 over the Bluetooth connection. Then, when a user sends his/her thermal comfort feedback (e.g., ASHRAE

7-point sensations), user’s instant vital signs will be linked to this feedback and transferred to the back-end server. Next, when the server receives this feedback, the latest environmental status will be appended to it and saved in the database as one sample. After that, the Python executor of ITCNN will load these collected samples from the database as the dataset for training and testing. For ITCNN, the number of hidden layers is a design choice that depends on many factors, such as the size of the dataset. Since our dataset is not relatively big (around 1,200 samples), we currently use only two hidden layers to avoid overfitting. Moreover, we also utilize various optimizers (e.g., SGD [117], Adam [118], AdaGrad [119] and etc.) and regularization techniques (e.g., L1/L2 regularization [120], dropout [121] and etc.) to improve the performance of ITCNN.

4.2.3 Performance Verification

To evaluate the performance of different thermal comfort modeling approaches, we deploy our iTCM system on the Nanyang Technological University (NTU) campus and collect data from 20 students and 10 staff volunteers for three weeks period. Personal information and data privacy are under the supervision and protection of NTU Institutional Review Board (IRB). The dataset is shuffled and split into training and testing sets by using the 10-fold cross validation. In addition, we adopt the standard 7-point ASHRAE sensation (from -3 to 3) to indicate the thermal comfort level. Each instance of the collected data consists of a feature set and an occupant’s comfort feedback as ground truth. To fairly compare the performance between the PMV model and various machine learning approaches, we only select the six PMV factors as the feature set, which is used for computing the comfort level. Moreover, to quantify the modeling performance, we use the mean absolute error (MAE) of algorithm $\mathcal{A}$ defined as follows.

$$\text{MAE}(\mathcal{A}) = \frac{1}{n} \sum_{m=1}^n |\hat{y}_m - y_m(\mathcal{A})|, \quad (4.1)$$

where for each data instance m , $\hat{y}_m$ is the ground truth of occupant’s thermal comfort and $y_m(\mathcal{A})$ is the predicted comfort index of algorithm $\mathcal{A}$. $\text{MAE}(\mathcal{A})$ is the average of the absolute errors $|\hat{y}_m - y_m(\mathcal{A})|$ for all of the n collected data instances, with a lower MAE indicating a better performance.

Fig. 4.1 presents the modeling performance in MAE metric. The figure shows that the MAE of PMV is 0.97, a significant gap towards the ground truth. Six machine learning approaches achieve diverse modeling performances. Due to the stochastic nature of the tested algorithms, the performance of each algorithm also varies for different runs. With regard to the average MAE, among three white-box approaches (the orange bars), two out of the three, NAIVE BAYES and k -NN, are not as competitive as PMV, with 6.1% and 4.8% higher MAE, respectively. However, the DECISION TREE outperforms PMV by 4.6%. Black-box approaches (the blue bars) achieve better performance compared to the white-box counterparts – all of them, LINEAR SVM, RBF SVM and RANDOM FOREST, outperform PMV, by 5.2%, 6.9% and 10.3%, respectively. Moreover, we can see that ITCNN (the green bar) achieves the best modeling performance and outperforms PMV by on average 13.1% and up to 17.8%.

Our conclusion is that the canonical Fanger’s PMV model, which is based on human expertise, outperforms simple white-box machine learning methods, such as NAIVE BAYES and k -NN, except DECISION TREE. Moreover, four selected black-box machine learning approaches perform better than all three white-box methods and also the PMV model. Furthermore, the NN-based black box approach, such as ITCNN, achieves the best modeling performance. We attribute the NN’s superior performance in the thermal comfort prediction to its flexibility and capability as a good function approximator. Therefore, we believe that the advanced machine learning techniques, such as artificial neural network, are going to play an important role in the next generation of thermal comfort modeling.

4.3 HTL-ITCNN: Heterogeneous Transfer Learning based ITCNN

In this section ², we introduce the proposed HTL-based learning paradigm for thermal comfort modeling. First, we introduce the adopted ASHRAE RP-884 Dataset. Then, we analyze the feature correlation of our iTCM datasets. Next, we

²**Weizheng Hu**, Yong Luo, Zongqing Lu, and Yonggang Wen. “Heterogeneous Transfer Learning for Thermal Comfort Modeling.” *In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys ’19)*, pp. 61–70. ACM, 2019. DOI: 10.1145/3360322.3360843

illustrate the details of the two-stage HTL learning paradigm. Finally, we evaluate the performance of HTL-ITCNN.

4.3.1 ASHRAE RP-884 Dataset

In this section, other than our collected iTCM Datasets, we introduce the adopted source-domain dataset: ASHRAE RP-884 Dataset [8]. It is one of the most widely used public datasets in the human thermal comfort research field. The objective of building this dataset is to develop the adaptive model. It comprises more than 20,000 user comfort votes collected from 52 studies across ten different climate zones around the world.

For this dataset, we extract the data based on three basic properties:

- *1) Selecting the votes collected from the HVAC environment:* Since there are a lot of data in the RP-884 dataset is collected under the nature ventilation environment. In this thesis, we mainly focus on the HVAC environment. Therefore, we prefer to extract the data collected from the HVAC environment.
- *2) Selecting the votes that contain all six PMV parameters:* When checking the RP-884 dataset, we found that some data votes miss some parameters. For example, some data do not have the metabolic rate, some do not have air velocity, etc. Without six PMV parameters, we cannot obtain the prediction result by using the PMV model. Therefore, we clean out those samples with missing parameters.
- *3) Selecting the votes that contain occupants' actual thermal comfort feedback:* When checking the RP-884 dataset, we also found that a lot of data votes do not contain occupants' actual thermal comfort sensation. Our goal is to compare the predicted results obtained from various algorithms with the ground truth (i.e., occupants' actual thermal comfort feelings). Therefore, we clean out those samples without the actual thermal comfort sensations.

In total, we selected 11,164 votes from the original database.

TABLE 4.1: Pearson correlation coefficient r analysis

#	Feature	*Coefficient r	p-value
F_{11}	skin temperature (ST)	0.532	< 0.05
F_7	air temperature (AT)	0.485	
F_{10}	heart rate (HR)	0.248	
F_6	clothing insulation (CI)	-0.236	
F_8	relative humidity (RH)	0.113	
F_2	age	-0.059	
F_1	hour	0.058	
F_5	height	-0.055	
F_9	metabolic rate (MR)	0.017	0.271
F_4	weight	0.016	0.281
F_3	gender	0.014	0.353

*Coefficient r has the strong association if $0.5 \leq |r| \leq 1$, the medium association if $0.3 \leq |r| < 0.5$, and the weak association if $0 \leq |r| < 0.3$.

4.3.2 Feature Correlation Analysis

We adopt the widely used Pearson correlation statistics to measure the degree of the relationship between each feature of the iTCM datasets and the actual thermal comfort index, as shown in Table 4.1.

In the table, we list the absolute value of the calculated correlation coefficient in descending order. Meanwhile, we also calculate the related p-value for each feature. First, we can find that ST is the only feature that has a strong association, and AT is the only feature that has a medium association. Moreover, the rest of the features have weak associations. Among them, the p-values of MR, weight, and gender are greater than the general cutoff value 0.05, which indicates weak evidence against the null hypothesis. Here, the p-value is the probability of obtaining the observed results of a test, if the null hypothesis is correct. A threshold value for p , called the significance level of the test, traditionally 0.05 or 0.01. For example, in our test, the p-value of a feature is less than 0.05, then this feature is highly relevant to human thermal comfort. From the table, we have to admit that most of the features we collected only have weak associations to the actual thermal comfort index in the Exploratory Data Analysis (EDA) process. However, we still decide to adopt all features for modeling. The main reason is that our feature space is tiny (only 11 features), these features of weak association may not be able to play important roles in model training, but the developed models will still benefit

FIGURE 4.2: The class distribution of adopted datasets varies with the thermal sensation scale. We can find that all datasets have the class imbalance issue. The majority of thermal comfort votes are -1 (slightly cool), 0 (comfortable), and +1 (slightly warm).

from them. In subsection 4.3.4 of the performance evaluation, we analyze the performance improvement with the different set of features.

4.3.3 HTL Based Thermal Comfort Modeling

We propose to leverage the HTL approach to develop thermal comfort models. First, we use a basic class weight mechanism to mitigate the class imbalance issue. Then, we illustrate the two-stage learning paradigm in details.

4.3.3.1 Class Weight Mechanism

We aim to develop the learning-based models to classify participants' thermal comfort votes based on the ASHRAE 6-point thermal sensation scale (hot = +3, warm = +2, slightly warm = +1, comfortable = 0, slightly cool = -1, cool = -2). In general, the existing thermal comfort models (e.g., PMV model, adaptive model) are regression models. However, the truth is that people generally cannot distinguish between two thermal comfort index values (e.g., 0 v.s. 0.5, 1.0 v.s. 1.3). Compared to these numbers, people prefer to understand the thermal sensation categories (e.g., comfortable, cool, slightly warm) based on their real feelings. Therefore, in this chapter, we consider the thermal comfort modeling as a classification problem, but still, our datasets and proposed modeling methodology can be used to develop regression thermal comfort models.

To develop a fair classifier which can effectively classify each label, we need to address the class imbalance issue, as discussed in existing research [122, 123]. For example, in a binary classification problem, 90% of labels are 1, and only 10% of labels are 0. Without considering the class imbalance issue, the derived classifier will prefer to predict label 1 to get high prediction accuracy. However, such a classifier is not meaningful. As such, we plot the label distribution of the ASHRAE dataset and our iTCM datasets for analysis, as shown in Figure 4.2. We can see that the label distribution of all datasets is not balanced. More than half of the received votes are -1 (slightly cool), 0 (comfortable) or +1 (slightly warm), where the major reason is that the experimental thermal environments of all datasets are still within participants' acceptable comfort zone. Therefore, we aim to reduce the impact of class imbalance issue by assigning the weight to each label with the following equation,

$$w_i = \lambda_i \frac{p_{max}}{p_i}, \quad (4.2)$$

where w_i is the weight assigned to label i , p_{max} is the distribution of a label which has the maximum amount of samples, and p_i is the distribution of label i . Here, $i = 0, 1, 2, \dots, n - 1$ denotes that there are n labels. λ_i is the factor used for fine-tuning the weight of each label. Using the same binary classification problem as the example, if $\lambda_0 = 0.8$ and $\lambda_1 = 1.2$, then, the weight for label 0 is $(90 \div 10) \times 0.8 = 7.2$ and the weight for label 1 is $(90 \div 90) \times 1.2 = 1.2$. In this way, we can assign the higher weights to those labels with the lower distribution. Moreover, during the model training, the cost function will consider learning more knowledge from those labels with the smaller sample size, rather than mainly focusing on the labels with the bigger sample size.

4.3.3.2 Learning Paradigm

In this chapter, we propose the Heterogeneous Transfer Learning (HTL) based Intelligent Thermal Comfort Neural Network (HTL-ITCNN) for thermal comfort modeling via a two-stage learning paradigm, as shown in Figure 4.3. Our objective is to use the dataset of each source domain to develop the related pre-trained classification model via the Deep Neural Network (DNN) technique, and then use it to map the features of the original target domain which are overlapped with that of itself to the high-dimension space. Here, “source domain” can be considered as a problem which has been solved. For example, we build a model which can accurately recognize American English. “target domain” can be considered as a new problem which we aim to solve. For example, we aim to build a model which can accurately recognize British English. In this way, the mapped features not only hold its original natures but also contain the transferred knowledge from the related source domain. To simplify the problem, we assume that the feature space of each source domain is a subset of that of the original target domain.

- *Stage 1. Base Classifier Modeling:* In this stage, we develop the pre-trained classification models for all source domains and the original target domain, as the base classifiers.

First, as plotted in Figure 4.3, we use D_S to denote the multiple source domains, D_T to denote the original target domain, and D_T^* to denote the optimized target domain. Also, we suppose that there are m source domains

FIGURE 4.3: The schematic diagram of the two-stage HTL-based learning paradigm. In the first stage, we use each source-domain dataset to develop the related pre-trained base classifier via the Deep Neural Network (DNN) technique, respectively. In the second stage, we obtain the knowledge transferred features of target-domain dataset via the previously developed base classifiers and then input them into a new DNN for training the HTL-based classifier.

and $D_S = (D_S^0, D_S^1, \dots, D_S^{m-1})$. Next, we develop the base classifier f_S^j by using the dataset of the related source domain D_S^j , where $j = 0, 1, 2, \dots, m-1$. Meanwhile, we also use the dataset of original target domain D_T to train the corresponding base classifier f_T . Finally, we can obtain $m+1$ pre-trained base classifiers in total, which will be adopted for feature mapping in the second stage.

- *Stage 2. Feature Mapping & HTL-Based Modeling:* In this stage, we first use the developed $m+1$ base classifiers in the first stage to obtain the mapped features, and then feed them into a DNN to develop the HTL-Based thermal comfort model.

First, we use (x_T, y_T) to denote the data-label pair of the original target domain D_T , where x_T denotes the data space with full features, and y_T denotes the label space. Then, based on the feature space of each source domain D_S^j , we split x_T into m subsets and $x_T = (x_T^0, x_T^1, \dots, x_T^{m-1})$. Each subset can be presented as the data-label pair (x_T^j, y_T) , where $j = 0, 1, 2, \dots, m-1$. After that, we can obtain the mapped features $\hat{z}_T^j$ of each subset (x_T^j, y_T) with the following function,

$$\hat{z}_T^j = f_S^j(x_T^j), \quad \forall j, \quad (4.3)$$

where $z_T^j \in z_T$ and $\hat{z}_T = (\hat{z}_T^0, \hat{z}_T^1, \dots, \hat{z}_T^{m-1})$ is the set of mapped features. Moreover, f_S^j is the base classifier of the source domain D_S^j . $D_S^j \in f_S$ and $f_S = (f_S^0, f_S^1, \dots, f_S^{m-1})$ is the set of base classifiers of all source domains. Next, we obtain the mapped features z_T of set (x_T, y_T) via the base classifier f_T of the original target domain D_T as follows,

$$z_T = f_T(x_T). \quad (4.4)$$

Eventually, we concatenate $\hat{z}_T$ and z_T as the input x_T^* and then feed x_T^* into a new DNN to obtain the final classifier f_T^* of the optimized target domain D_T^* as follows,

$$y_T^* = f_T^*(x_T^*), \quad (4.5)$$

where f_T^* is the HTL-based classifier and y_T^* is the optimal prediction results.

Furthermore, to achieve the optimal multi-classification performance for all classifiers in both stages, we tune the weights $w = (w_0, w_1, \dots, w_{n-1})$ for n labels by adjusting the related weight factors $\lambda = (\lambda_0, \lambda_1, \dots, \lambda_{n-1})$ during the training process via Eq. (4.2).

4.3.4 Performance Evaluation

In this section, we evaluate the performance of HTL-ITCNN. First, we briefly describe the experiment settings. Then, we analyze the performance of the generic HTL-ITCNN thermal comfort model. Finally, we verify the performance of the personal HTL-ITCNN thermal comfort model.

4.3.4.1 Experiment Settings

In this chapter, we assume that there is only one source domain (ASHRAE dataset) which means $m = 1$ and one target domain (iTCM dataset). After analyzing the modeling features of both datasets, we find that there are four overlapped features: AT, RH, MR, and CI. In this case, HTL-ITCNN consists of three DNN-based classifiers: 1) One source-domain base classifier; 2) One original target-domain base classifier; and 3) One optimized target-domain classifier. For the detailed

DNN settings of all three classifiers, we use the fully-connected structure with two hidden layers, select the tanh function as the activation function, and adopt the categorical cross-entropy as the cost function. In the training process, we use the batch normalization technique for normalizing the input layer as well as the hidden layer, encode the labels with one-hot encoder, and train the models via the Adam optimizer with the learning rate 0.001. Besides, to mitigate the over-fitting issue, we also adopt the L2 regularization technique and set the L2 factor as 0.0001. Moreover, we use the fixed random seed for dataset shuffling and model training. The rest of the settings are listed below,

- For the source-domain base classifier f_S^0 , each hidden layer has 32 neurons, respectively. The batch size is 128.
- For the original target-domain base classifier f_T , each hidden layer has 256 neurons, respectively. The batch size is 64.
- For the optimized target-domain classifier f_T^* , each hidden layer has 512 neurons, respectively. The batch size is 64.

Also, we select the accuracy, macro-F1 score, and Matthews correlation coefficient (MCC) as the evaluation metrics. Among them, macro-F1 score and MCC are sensitive to rare labels. Higher scores indicate that the classifier has better classification performance on those labels with the lower distribution.

Furthermore, as mentioned in section 3.4, we only consider the 6-point thermal sensation (from -3 to +2). Each instance of the collected data consists of various features and the occupant’s actual vote as the ground truth. To train the HTL-based thermal comfort models, we split all datasets into training and testing sets by using the 10-fold cross-validation (CV) approach. For the ASHRAE dataset, since it is independent of our iTCM datasets, we only select the best model derived via the 10-fold CV as the source-domain base classifier f_S^0 . For the iTCM dataset, we use it for training both original target-domain base classifier f_T and optimized target-domain classifier f_T^* . Different from the training process of the ASHRAE dataset, we save the ten models derived via the 10-fold CV and then use each of them to train the optimized target-domain classifier f_T^* in each fold, respectively.

TABLE 4.2: Multi-classification performance analysis

Source domain			
Algorithm	Accuracy (%)	Macro-F1 (%)	MCC (%)
PMV	32.68	17.08	6.07
Base Classifier f_S^0	32.36	28.63	15.02

Target domain			
Algorithm	Accuracy (%)	Macro-F1 (%)	MCC (%)
PMV	36.27	22.65	9.71
Base Classifier f_T	62.15	51.97	44.15
MLP	62.19	49.56	42.32
HTL-ITCNN	63.08	53.6	45.50

FIGURE 4.4: Confusion matrix diagrams of the source domain. We can see that compared to the PMV model, the DNN-based classifier can better distinguish among all labels.

For the comparison baseline, we select the predicted mean vote (PMV) model. It predicts the average comfort vote from a group of occupants based on four environmental factors (air temperature, relative humidity, mean radiant temperature, and air velocity) and two personal factors (clothing insulation and metabolic rate). Since the prediction results of the PMV model are non-integer, we round its outputs

to integers for classification performance comparison,

$$y_{pmv}^* = \begin{cases} +3, & \text{if } y_{pmv} \geq +3, \\ -3, & \text{if } y_{pmv} \leq -3, \\ \text{Round}(y_{pmv}), & \text{otherwise,} \end{cases} \quad (4.6)$$

where y_{pmv} is original PMV score and y_{pmv}^* is the 7-point thermal comfort scale ranging from -3 to +3, where the ascending integers denote cold, cool, slightly cool, neutral, slightly warm, warm and hot, respectively. Moreover, since we do not have related sensors to measure the mean radiant temperature (MRT) and air velocity (AV), we assume that the MRT is equal to the AT and the AV is equal to 0.1 m/s to calculate the PMV score.

4.3.4.2 Generic Thermal Comfort Model

We evaluate the performance of the generic thermal comfort model trained by the iTCM Generic Dataset.

- **Multi-classification Performance Analysis:** With the class weight (CW) mechanism proposed in Section 4.3.3.1, we analyze the multi-classification performance of all classifiers for the source domain and the target domain, respectively.
 - *Source Domain:* As shown in Table 4.2, the accuracy of the PMV model is slightly higher than the source-domain base classifier f_S^0 . However, for another two metrics, f_S^0 is around twice as good as those of the PMV model. Also, from Figure 4.4, we can see that the PMV model prefers to predict the label 0 rather than other labels. In contrast, the f_S^0 can achieve average 31.0% accuracy on every class.
 - *Target Domain:* Table 4.2 shows that the performance of all DNN-based approaches outperforms the PMV model significantly. The accuracy of MLP is almost equal to the original target-domain base classifier f_T , but for another two metrics, f_T performs better than the MLP. HTL-ITCNN achieves the best performance on all three metrics. Besides,

FIGURE 4.5: Confusion matrix diagrams of the target domain. We can find that compared to the PMV model, HTL-ITCNN has the remarkable advantages of prediction performance.

Figure 4.5 shows that the PMV model still cannot classify each label of the target-domain dataset effectively. The MLP already achieves excellent multi-classification performance, but it has a high probability of misjudging label +2. In contrast, HTL-ITCNN has average 53.8% accuracy on every class. The prediction accuracy of the label +2 is the lowest, and even though it also achieves 43% accuracy.

In conclusion, we prove that the PMV model is inaccurate to predict participants' thermal comfort sensations. In contrast, all DNN-based approaches have better multi-classification performance than the PMV model. Especially

TABLE 4.3: Prediction result comparison with different features

#	Classifiers	Accuracy(%)	Macro-F1(%)	MCC(%)
s_1	Base Classifier f_S^0	32.36	28.63	15.02
s_1		44.89	36.14	25.07
s_2	Base Classifier	50.17	41.28	29.87
s_3	f_T	54.60	44.63	34.42
s_4		62.15	51.97	44.15
s_1		53.39	42.91	31.97
s_2	HTL-	54.30	43.63	32.96
s_3	ITCNN	58.09	47.47	38.15
s_4		63.08	53.06	45.50

with our proposed class weight mechanism, HTL-ITCNN achieves the best performance and can classify labels effectively.

- **Performance Improvement Analysis:** The performance improvement of HTL-ITCNN is boosted by two key factors: 1) the growing number of features; and 2) the transferred knowledge from the source domain. Since both factors are tightly linking to the modeling features, we define the following four feature sets to analyze the performance improvement.

- s_1 : It contains four PMV factors: CI (F_6), AT (F_7), RH (F_8), and MR (F_9).
- s_2 : It contains s_1 plus two vital signs factors: HR (F_{10}) and ST (F_{11}).
- s_3 : It contains s_2 plus one time factor: hour (F_1).
- s_4 : It contains s_3 plus four personal factors: age (F_2), gender (F_3), height (F_4), and weight (F_5).

After that, for comparison of the performance improvement, we use the same hyper-parameter settings to train the models based on each feature set. The results are listed in Table 4.3.

FIGURE 4.6: The performance improvement achieved by transferred knowledge with different feature sets. We can see that with the incremental number of non-overlapped features, the performance improvement achieved by knowledge transfer of overlapped features would decrease.

With the growing number of features from s_1 to s_4 , the performance of the original target-domain base classifier f_T and HTL-ITCNN is increasing. Although we do not verify all features one by one, we still show that the newly added features have positive impacts on the thermal comfort modeling. Especially the personal factors, they can significantly improve the performance of HTL-ITCNN on all metrics. In contrast, the improvement boosted by transferred knowledge from the source domain is decreasing with the growing number of features, as shown in Figure 4.6. It is interesting that when adopting the same features for modeling, the transferred knowledge from the source domain has the highest compatibility on the target domain. With the growing number of features in the target domain, the positive impacts of the transferred knowledge from the source domain are diluted by newly added modeling features. The insight we can obtain is that Homogeneous Transfer Learning can achieve significant performance improvements via the better effectiveness of knowledge transfer than Heterogeneous Transfer Learning.

TABLE 4.4: Prediction result comparison among algorithms

Algorithm	Accuracy(%)	Macro-F1(%)	MCC(%)
Random Guess	33.57	16.96	0.03
PMV	36.27	22.65	9.71
Naive Bayes	46.61	30.18	17.12
Linear SVM	53.58	18.62	15.48
RBF SVM	59.10	35.18	30.75
Decision Tree	60.01	49.07	40.76
MLP	62.19	49.56	42.32
k -NN	62.31	49.17	42.30
HTL-ITCNN	63.08	53.06	45.50
Random Forest	66.32	53.90	47.79

In summary, for modeling features, seeking highly-related new thermal comfort factors can observably improve the model prediction accuracy. For knowledge transfer, although the performance improvements are not impressive, we show the potential to apply the transfer learning principles to the thermal comfort research.

- **Performance Comparison:** We compare the performance of HTL-ITCNN with some classic machine learning algorithms. The results are presented in Table 4.4.

First, we can find that the PMV model is just slightly better than the Random Guess. Then, with the increment of modeling features, all learning-based approaches outperform the PMV model. Among the machine learning algorithms, the Native Bayes has the lowest performance. But it still outperforms the PMV model by 28.5%, 33.2%, and 76.3% on the accuracy, macro-F1, and MCC, respectively. Compared to the Native Bayes, Linear SVM has higher accuracy but has lower macro-F1 and MCC. RBF SVM has much better performance than the Linear SVM by 10.3%, 88.8%, and 98.6% on the accuracy, macro-F1, and MCC, respectively. The overall performance of the Decision Tree is better than RBF SVM, especially the macro-F1 and MCC. The k -NN has quite good performance, whose accuracy is slightly higher than the MLP, but its macro-F1 and MCC scores are slightly lower than the MLP. It

TABLE 4.5: Prediction results on three iTCM personal datasets

#	Algorithm	Accuracy(%)	Macro-F1(%)	MCC(%)
P ₁	PMV	41.16	31.69	22.58
	HTL-ITCNN	39.13	19.13	12.07
	HTL-ITCNN-P ₁	62.85	49.07	45.06
P ₂	PMV	19.47	19.29	1.26
	HTL-ITCNN	28.16	16.12	2.47
	HTL-ITCNN-P ₂	65.26	54.99	53.43
P ₃	PMV	30.50	20.93	10.10
	HTL-ITCNN	45.16	23.59	18.44
	HTL-ITCNN-P ₃	64.20	46.84	47.26

is surprising that k -NN achieves such outstanding performance. After analysis, the reason is that k -NN cannot handle the class imbalanced dataset which results in high prediction accuracy. For our proposed HTL-ITCNN, it outperforms the PMV model by 73.9%, 134.3% and 368.6% on the accuracy, macro-F1, and MCC, respectively. Moreover, we notice that compared to MLP and k -NN, HTL-ITCNN does not achieve remarkable improvements on the accuracy, but it significantly outperforms them on macro-F1 and MCC scores which presents its advantages of the high prediction accuracy on those labels with the lower distribution. However, HTL-ITCNN still fails to beat the Random Forest, which is recognized by academia as the best algorithm on small datasets (e.g., iTCM datasets).

Overall, machine learning techniques present significant advantages in thermal comfort modeling. Although our proposed HTL-ITCNN does not beat the Random Forest on small datasets, we will verify the performance of HTL-ITCNN on the large datasets to compare it with Random Forest in our future work.

4.3.4.3 Personal Thermal Comfort Model

To better fulfill the individual's thermal comfort demand, some research [88, 89] propose to build personal thermal comfort models for individuals rather than a

group of people. As such, we also develop personal HTL-ITCNN for performance evaluation.

As shown in Table 4.5, it is not surprising that all participants' personal thermal comfort models have the best accuracy. However, the prediction results of the PMV model and the generic HTL-ITCNN on different personal datasets are quite interesting.

- For the first participant P_1 , the PMV model performs better than the generic HTL-ITCNN on all metrics. This case shows that the PMV model has better compatibility on this person than our approach, which confirms the value of PMV model.
- For the second participant P_2 , the overall performance of the PMV model is quite bad. Although our generic HTL-ITCNN also performs much better than the PMV model, the overall performance on all metrics is still relatively low. This case indicates that the generic thermal comfort cannot fulfill the demands of all participants.
- For the third participant P_3 , the PMV model achieves the acceptable performance, but our generic HTL-ITCNN outperforms the PMV model significantly on all metrics. This case shows that our approach has better compatibility on this person than the PMV model.

Overall, the performance of the generic HTL-ITCNN (average 37.48% accuracy) is better than the PMV model (average 30.38% accuracy). However, it still cannot predict every participant's thermal comfort accurately. In contrast, personal HTL-ITCNN demonstrates its outstanding prediction performance (average 64.10% accuracy). Therefore, we indicate that personal thermal comfort modeling, as one of the critical future research directions, has great potential.

4.4 Conclusion

In this chapter, intending to enhance the prediction accuracy of the thermal comfort, we first implement the Deep Neural Network (DNN) based ITCNN. Second, we proposed an Heterogeneous Transfer Learning (HTL) based approach built upon

ITCNN for thermal comfort modeling. By using the ASHRAE RP-884 Dataset and our self-collected iTCM datasets, the experimental results show that both approaches outperform the PMV model and most of the machine learning algorithms. Especially for HTL-ITCNN, the growing number of features and the transferred knowledge from the source domain have significant positive impacts on its performance improvement. Moreover, we also verify the performance of personal HTL-ITCNN and demonstrate the tremendous potential of the research direction on personal thermal comfort modeling.

In the next chapter, we will consider using the developed learning-based thermal comfort models to predict occupants' thermal sensations for intelligent HVAC control in the multi-zone buildings.

Chapter 5

Intelligent Thermal Control for Multi-Zone Buildings

In this paper, we propose to adopt the Multi-Agent Deep Reinforcement Learning (MADRL) techniques, for optimizing the multi-zone thermal control. Our approach not only considers the energy consumption and occupants' thermal comfort of each zone but also allows the control agents to learn from each other to speed up the learning process of the optimal control strategy for all zones.

5.1 Introduction

With the rapid development of the Deep Reinforcement Learning (DRL) techniques [63, 64], various MADRL systems are developed to address the complex control problems. For example, AlphaStar [124] is trained by MADRL to play the game StarCraft II and beats human professional players. MADRL shows its outstanding learning ability to learn the optimal control policy for handling a large volume of state information and complicated control actions. Up to our knowledge, the most related multi-objective optimization research work is *Tianshu et al.* [125]. This paper adopts the Deep Q-Learning (DQN) approach [63], one of DRL techniques, to create multiple DQN agents to optimize the energy consumption of multiple zones. However, the goal of this work is to maintain the room temperature of each zone within a specific temperature range without taking occupants' dynamic thermal comfort into consideration. Also, this work trains the individual agent for

each zone, respectively, which is not realistic if there are a large number of zones in a building.

In this chapter, we propose to adopt the advanced deep learning technique for intelligent multi-objective thermal control in multi-zone buildings. First, rather than using the canonical thermal comfort model (i.e., PMV model), we adopt our in-house Intelligent Thermal Comfort Neural Network (ITCNN) [91] model to predict occupants' thermal sensations. Then, we design the workflow of the multi-zone HVAC control system and formulate the multi-objective optimization problem. Next, we adopt the cutting-edge Multi-Agent Deep Reinforcement Learning (MADRL) technique to solve the formulated optimization problem and design the Multi-Zone Thermal Control (MZTC) algorithm. Finally, we build a simulation environment for evaluating the performance of our multi-zone thermal control approach by using professional TRNSYS software [126]. Our contribution can be summarized into the following three aspects:

- We design the system workflow and formulate the optimization problem of the multi-zone HVAC control operations as a Markov Decision Process (MDP). Besides, we apply our in-house ITCNN to achieve higher thermal comfort prediction accuracy.
- We develop an intelligent multi-zone thermal control system by using the MADRL technique. In addition, we design the MZTC algorithm to solve the formulated optimization problem.
- We verify our proposed approach in the simulation environment. Results show that our approach can achieve considerable energy saving while maintaining occupants' thermal comfort in multiple zones.

This chapter provides fundamental insights and guideline for applying the MADRL techniques to the intelligent multi-zone HVAC control optimization. We aim to develop an intelligent HVAC control mechanism to seek the trade-off among human thermal comfort, energy consumption of the HVAC systems, and the multi-zone thermal control. Our simulation results show that compared to the existing algorithm adopted by BMS, our MADRL-based solution can save considerable energy of the HVAC systems while maintaining occupants' thermal comfort in multiple

FIGURE 5.1: The overall workflow of intelligent multi-zone HVAC control. According to the updated zone information (e.g., indoor sensing data and energy expenditure of the HVAC systems) and outdoor sensing data (e.g., outdoor air temperature and relative humidity), the learning-based algorithm keeps optimizing the thermal control policy to send out the control actions (e.g., change the set-point temperature and/or the set-point relative humidity) to the HVAC controller for zone-based thermal condition adjustment.

zones of a building. We believe that our findings will make contributions to future researches in the smart building research field.

The rest of this article is organized as follows. Section 5.2 introduces our system design and formulate the optimization problem. Section 5.3 presents the intelligent multi-zone thermal control algorithm. Section 5.4 evaluates the performance of our proposed approach. The last section concludes this article.

5.2 System Design & Problem Formulation

In this section, we first describe the overall workflow of the system design and then formulate the optimization problem of the multi-zone HVAC control operations.

5.2.1 System Design & Workflow

We illustrate the system design and the corresponding multi-zone control workflow in Fig. 5.1, which consists of the following four major modules.

- *Building Zones:* Based on different functionalities, buildings can be divided into various zones (e.g., working area, meeting rooms). The HVAC systems are responsible for maintaining the thermal conditions for these zones.
- *Indoor & Outdoor Sensors:* They are used to monitor the weather changes and zone thermal conditions, respectively. The measured environmental variables (e.g., air temperature and relative humidity) will be inputted to the learning-based algorithm for control decision making.
- *Learning-Based Algorithm:* With the updated indoor and outdoor sensing data, the learning-based algorithm keeps learning the control strategies and sending out the optimal control actions (e.g., change the set-point temperature or relative humidity) to the HVAC controller.
- *HVAC Controller:* After receiving the optimal control actions, the HVAC controller starts to execute these operations to adjust the thermal conditions of each zone.

In this application scenario, the overall workflow forms a self-learning loop for optimizing the control policies. First, the algorithm learns to take control actions based on the received indoor and outdoor sensing information. Then, the thermal environment of each zone is affected by the executed control actions and then sensed by indoor sensors. Meanwhile, the weather changes are monitored by the outdoor sensors. Next, the learning-based algorithm continues this self-learning loop with the newly obtained sensing data.

5.2.2 Problem Formulation

In this paper, we model the multi-zone HVAC control operations as a Markov Decision Process (MDP) to formulate the optimization problem. First, we utilize a time-slotted model with the discrete time slot $t = 0, 1, \dots, X$. Then, we consider that there are n zones in the environment E , as shown in Fig. 5.2. Each zone i is managed by agent i , where $i = 0, 1, \dots, n-1$. The details are presented as follows.

5.2.2.1 State

The state of an environment E denotes a group of factors that can reflect its current conditions. For example, indoor environmental factors: air temperature, relative humidity, CO² level, noise, and air velocity; outdoor environmental factors: air temperature, relative humidity; some other factors: energy consumption of each zone and occupants' thermal comfort.

We use s_t^i to denote the state of zone i at time slot t . Combining the states of n zones, we can obtain,

$$s_t = (s_t^0, s_t^1, \dots, s_t^{n-1}), \quad (5.1)$$

where s_t is the set of all states observed from n zones of the environment E at time slot t . Subsequently, according to the actions taken by n agents at time slot t , the environment E moves to the next state s_{t+1} at time slot $t + 1$.

5.2.2.2 Action

The action refers to various control operations taken by the intelligent agents. Each agent controls the HVAC systems to adjust the thermal conditions of environment E . Different brands of air-conditioning devices support diverse operations, but all of them support to adjust air temperature T_t^i and relative humidity H_t^i .

At time slot t , agent i attempts to “think” and takes the proper action a_t^i to adjust the thermal conditions of zone i based on the observed state s_t^i , as shown in Fig. 5.2. The behavior of each agent is determined by the corresponding deterministic control policy $\mu_t^i : s_t^i \rightarrow a_t^i$, which can be presented as follows,

$$a_t^i = \mu_t^i(s_t^i), \quad (5.2)$$

where $a_t^i \in \mathcal{A}$ and $\mathcal{A}$ is the set of possible actions taken by all agents. Combining the actions of n agents, we can get,

$$a_t = (a_t^0, a_t^1, \dots, a_t^{n-1}), \quad (5.3)$$

where a_t is the set of possible actions taken by all agents at time slot t . Besides, let μ_t be the set of all agents' control policies and $\mu_t = (\mu_t^0, \mu_t^1, \dots, \mu_t^{n-1})$ at time

FIGURE 5.2: The schematic diagram of the Multi-Agent Markov Decision Process (MDP). For zone i , the related agent i observes the state s_t^i , takes the action a_t^i , and receives the reward r_t^i at time slot t , where $i = 0, 1, \dots, n - 1$.

slot t .

5.2.2.3 Rewards

Reward function plays a vital role in the policy learning process of Refinement Learning (RL), which significantly impacts the convergence of the model training. In this paper, we consider to design the reward function based on the following two aspects.

- *Energy Consumption:* The energy expenditure of the HVAC systems mainly consists of the energy consumed by cooling, heating, ventilation, humidification, and dehumidification. However, we would not take the energy expenditure of the heating, humidification, and ventilation into consideration. There are two major reasons. First, since our testbed locates in the tropics, the year-round hot and wet climate makes the local HVAC systems rarely equip the heating and humidification modules. Second, ventilation function

is essential to ensure the indoor air quality, which significantly affects occupants' health. It is risky to optimize the energy consumption of this function. In addition, compared to the energy consumed by other modules, its energy expenditure is insignificant which can be omitted. Therefore, in this paper, we only consider the energy expenditure of cooling and dehumidification, and calculate the total energy expenditure of the HVAC systems in zone i at time slot t via the following equation,

$$\varepsilon_t^i = c_t^i + d_t^i, \quad (5.4)$$

where ε_t^i is the summation of cooling energy consumption c_t^i and dehumidification energy consumption d_t^i .

- *Thermal Comfort:* Thermal comfort is a critical factor to evaluate occupants' satisfaction levels of their surrounding environment. In this paper, we adopt our previously developed ITCNN model [91] for thermal comfort prediction. The related experimental results show that the prediction accuracy of ITCNN outperforms the PMV model by on average 13.1% and up to 17.8%. Therefore, we predict the occupants' average thermal comfort index p_t^i of zone i at time slot t by using the pre-trained ITCNN model $\mathcal{I}$, as follows,

$$p_t^i = \mathcal{I}(T_t^i, H_t^i, V_t^i, M_t^i, I_t^i, B_t^i), \quad (5.5)$$

where the function inputs are six PMV parameters: 1) air temperature T_t^i ; 2) relative humidity H_t^i ; 3) air velocity V_t^i ; 4) mean radiant temperature M_t^i ; 5) clothing insulation I_t^i ; and 6) metabolic rate B_t^i . Moreover, the value of the output p_t^i is from -3 to $+3$, which is defined by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [4].

Based on Eq. (5.4) and Eq. (5.5), we define the reward function $\mathcal{R}$ to jointly consider the total energy expenditure of the HVAC systems ε_t^i and the occupants'

average thermal comfort index p_t^i for zone i , as follows,

$$r_t^i = \mathcal{R}(\varepsilon_t^i, p_t^i) = -\delta_i \varepsilon_t^i + \begin{cases} 0, & \text{if } L_p \leq p_t^i < 0, \\ p_t^i, & \text{elif } 0 \leq p_t^i \leq U_p, \\ -|p_t^i|, & \text{else,} \end{cases} \quad (5.6)$$

where δ_i is the control parameter to balance the impact of energy consumption and thermal comfort in the reward function. δ is the set of energy-comfort weights of all zones, $\delta = (\delta_0, \delta_1, \dots, \delta_{n-1})$, and we can set different weights for each zone to fulfill specialized energy-comfort optimization goals. Moreover, we set the thermal comfort upper bound U_p and lower bound L_p , where $0 \leq U_p \leq 3$ and $-3 \leq L_p < 0$, for guiding the algorithm to maintain the average occupants' thermal comfort within the desired range. For example, ASHRAE standard suggests maintaining occupants' thermal comfort within $[-0.5, 0.5]$. Here, $L_p = -0.5$ and $U_p = 0.5$. Furthermore, this reward function is designed for the HVAC systems under the cooling-dehumidification mode. With proper modifications, our approach can be used for heating-humidification mode.

Combining the rewards received from n zones, we can get,

$$r_t = (r_t^0, r_t^1, \dots, r_t^{n-1}), \quad (5.7)$$

where r_t is the set of all possible rewards received from n zones of the environment E at time slot t .

5.2.2.4 Problem Formulation

We formulate the multi-zone thermal control optimization problem to minimize the total energy expenditure of the HVAC systems while maintaining occupants' average thermal comfort.

Following the Reinforcement Learning framework, we aim to optimize the summation of discounted future reward R_t of each agent i , as shown below,

$$R_t^i = \sum_{j=1}^{\tau} \lambda_i^{j-1} r_{t+j}^i, \quad (5.8)$$

where r_{t+j}^i is the reward at time slot $t+j$ and $j = 1, 2, \dots, \mathcal{T}$. Moreover, λ_i denotes the discounted factor attached to agent i and $\lambda_i \in [0, 1]$. With n agents, λ is the set of discounted factors of all agents, $\lambda = (\lambda_0, \lambda_1, \dots, \lambda_{n-1})$ and we could set a different value of discounted factor to each agent.

In this paper, we aim to learn the optimal control policy for all agents by maximizing their expected summation of discounted rewards $\sum_{i=0}^{n-1} \mathbb{E}[R_t^i]$ over the long-term future, subject to the constrained control range of both set-point temperature and set-point relative humidity. Mathematically, we formulate the optimization problem based on Eqs. (5.4)-(5.8), as follows,

$$\max_{T_t^i, H_t^i} \sum_{i=0}^{n-1} \sum_{j=1}^{\mathcal{T}} \lambda_i^{j-1} \mathcal{R}(\varepsilon_{t+j}^i, p_{t+j}^i), \quad (5.9)$$

$$\text{s.t.} \quad L_{T_t^i} \leq T_t^i \leq U_{T_t^i}, \quad (5.10)$$

$$L_{H_t^i} \leq H_t^i \leq U_{H_t^i}, \quad (5.11)$$

where $\mathcal{R}$ is the reward function Eq. (5.6), ε_{t+j}^i is the total energy expenditure of the HVAC systems of zone i at time slot $t+j$, which can be calculated by Eq. (5.4), and p_{t+j}^i denotes the predicted occupants' average thermal comfort of zone i at time slot $t+j$, which can be predicted by Eq. (5.5). Moreover, T_t^i is the zone air temperature controlled by agent i , which is constrained by Eq. (5.10). H_t^i is the zone relative humidity controlled by agent i , which is constrained by Eq. (5.11). The corresponding lower bounds ($L_{T_t^i}$ and $L_{H_t^i}$) and upper bounds ($U_{T_t^i}$ and $U_{H_t^i}$) are determined by the hardware specifications of air-conditioning devices.

5.3 Problem Solving & Algorithm Design

In this section, we solve the formulated optimization problem Eq. (5.9) by adopting the Multi-Agent Deep Deterministic Policy Gradients (MADDPG) algorithm [127], one of MADRL techniques, to learn the control policies for multiple zones.

MADDPG is a general-purpose deep learning algorithm that extends the Deep Deterministic Policy Gradient (DDPG) [128] to the multi-agent applications. It is build upon the classic Actor-Critic structure that each agent is designed with the architecture of centralized critic and decentralized actor, where both actor and

FIGURE 5.3: The architecture of MADDPG algorithm. Each agent contains a centralized critic which can observe the global information (i.e., other zones' states and agents' actions) and a decentralized actor which takes action based on the local state.

critic are approximated via the deep neural networks, as shown in Fig. 5.3. Different from the single-agent DRL, MADRL is designed to allow multiple agents to collaborate and solve a complex problem together by interacting with the environment(s). In MADDPG, agents could learn from each other via the shared global information (e.g., other agents' states and actions) to optimize their local action-taking policies. In this way, MADDPG not only improves the policy learning efficiency but also avoids the overfitting issue to a specific environment.

5.3.1 Multi-Zone Thermal Control (MZTC) Algorithm

Following the MADDPG framework, we design the Multi-Zone Thermal Control (MZTC) Algorithm.

5.3.1.1 Critic Network

Critic network is the approximator of action-value function, which measures how good the action taken by the actor network is, generally named as Q -function.

Algorithm 1: Multi-Zone Thermal Control (MZTC) Algorithm

```

1: Initialize the replay memory  $\mathcal{D}$ 
2: for agent  $i = 0, 1, \dots, n - 1$  do
3:   Initialize the critic network  $Q_i^\mu(s, a|\omega^i)$  with random weights  $\omega^i$ , where
      $s = (s^0, s^1, \dots, s^{n-1})$  and  $a = (a^0, a^1, \dots, a^{n-1})$ 
4:   Initialize the actor network  $a^i = \mu^i(s^i|\theta^i)$  with random weights  $\theta^i$ 
5: end for
6: for episode = 0,1, ..., Z do
7:   Initialize a random process  $\eta$  for action exploration
8:   All agents observe the initial state of the multi-zone environment  $E$ 
9:   for  $t = 0, 1, \dots, X$  do
10:    for agent  $i = 0, 1, \dots, n - 1$  do
11:      Observe the current state  $s_t$  of the environment  $E$ 
12:      Select and execute action  $a_t^i$  via Eq. (5.17) based on the current local
        zone state  $s_t^i$ , predict occupants' average thermal comfort  $p_t^i$  via Eq.
        (5.5) and calculate the reward  $r_t^i$  via Eq. (5.6)
13:      Observe the next state  $s_{t+1}$  of the environment  $E$  and obtain the local
        transition  $(s_t, a_t^i, r_t^i, s_{t+1})$ 
14:    end for
15:    Combine the local transitions of  $n$  agents and buffer the global transition
       $(s_t, a_t, r_t, s_{t+1})$  in the replay memory  $\mathcal{D}$ 
16:    if Exploration is completed then
17:      for agent  $i = 0, 1, \dots, n - 1$  do
18:        Sample a random mini-batch of  $K$  transitions from the replay
          memory  $\mathcal{D}$ 
19:        Update the critic network via minimizing the loss function Eq.
          (5.14) and the network weight  $\omega^i$  via Eq. (5.16)
20:        Update the actor network via the sampled policy gradients Eq.
          (5.20) and the network weight  $\theta^i$  via Eq. (5.21)
21:      end for
22:    else
23:      Continue the exploration to sample sufficient transitions and store
        them in the replay memory  $\mathcal{D}$ 
24:    end if
25:  end for
26: end for

```

Let $o_t = (o_t^0, o_t^1, \dots)$ denote the set of observations which consists of partial state information of an environment. For agent i , the critic network parameterized by ω_t^i aims to learn a centralized action-value function with respect to all agents' policies $\mu_t = (\mu_t^0, \mu_t^1, \dots, \mu_t^{n-1})$, denoted as the following general equation,

$$Q_i^{\mu_t}(o_t, a_t^0, a_t^1, \dots, a_t^{n-1}|\omega_t^i), \quad (5.12)$$

where $o_t = s_t$, which contains all agents' states of the multi-zone environment E . Also, a_t^i is the action taken by agent i , and a_t^i belongs to the action set a_t based on Eq. (5.3). Then, we get the below simplified equation,

$$Q_i^{\mu_t}(s_t, a_t | \omega_t^i), \quad (5.13)$$

where ω_t^i belongs to $\omega_t = (\omega_t^0, \omega_t^1, \dots, \omega_t^{n-1})$ and ω_t is the set of weights of all agents' critic networks at time slot t .

Then, the weight of each agent's critic network is updated by minimizing the following loss function,

$$\ell(\omega_t^i) = [Q_i^{\mu_t}(s_t, a_t | \omega_t^i) - y_i]^2, \quad (5.14)$$

where $\ell(\omega_t^i)$ is the squared Temporal-Difference (TD) error [129] and y_i is the target action-value function of agent i , which can be presented as follows,

$$y_i = r_t^i + \lambda_i Q_i^{\mu_{t+1}}(s_{t+1}, a_{t+1} | \omega_{t+1}^i), \quad (5.15)$$

where μ_{t+1} is the set of target policies at time slot $t + 1$.

Finally, the critic network of agent i is updated with the following updating rule,

$$\omega_{t+1}^i \leftarrow \tau_c \omega_t^i + (1 - \tau_c) \omega_{t+1}^i, \quad (5.16)$$

where τ_c is used for target update of the critic networks.

5.3.1.2 Actor Network

Actor network is the approximator of policy function, which controls agent's action guided by the critic network.

For agent i , the actor network parameterized by θ_t^i aims to learn a decentralized policy function based on the local zone state s_t^i . Meanwhile, random noise is added to do better exploration. Then, based on the Eq. (5.2), we get the following exploration policy function at time slot t ,

$$a_t^i = \mu_t^i(s_t^i | \theta_t^i) + \eta_t, \quad (5.17)$$

where η_t is the exploration noise generated by the Gaussian random process. In addition, θ_t^i belongs to $\theta_t = (\theta_t^0, \theta_t^1, \dots, \theta_t^{n-1})$ and θ_t is the set of weights of all agents' actor networks.

During the exploration, first, based on the current zone observation o_t^i , agent i executes the action a_t^i , receives the reward r_t^i , and observes the next zone observation o_{t+1}^i . Applying to all agents, the general transition is expressed as follows,

$$(o_t, a_t^0, a_t^1, \dots, a_t^{n-1}, r_t^0, r_t^1, \dots, r_t^{n-1}, o_{t+1}), \quad (5.18)$$

where $o_t = s_t$ as discussed in the previous Section 5.3.1.1. Then, combining with Eq. (5.3) and Eq. (5.7), we can obtain the following transition for our application scenario,

$$(s_t, a_t, r_t, s_{t+1}), \quad (5.19)$$

where given the current state s_t of multi-zone environment E , n agents take n actions $a_t = (a_t^0, a_t^1, \dots, a_t^{n-1})$ and receive n rewards $r_t = (r_t^0, r_t^1, \dots, r_t^{n-1})$, leading to the new state s_{t+1} of multi-zone environment E . After that, these transitions will be buffered in the replay memory $\mathcal{D}$ for the mini-batch sampling to train the actor-critic networks of all agents.

Then, based on the Q -function Eq. (5.13) and the policy function Eq. (5.17), with one sampled transition $(\hat{s}_t, \hat{a}_t, \hat{r}_t, \hat{s}_{t+1})$ from $\mathcal{D}$, the actor network of agent i is updated with the following sampled policy gradient $\nabla_{\theta_t^i} J(\theta_t^i)$,

$$\nabla_{\theta_t^i} J(\theta_t^i) \approx \nabla_{\theta_t^i} \mu_t^i(\hat{s}_t | \theta_t^i) \nabla_{\hat{a}_t^i} Q_i^{\mu_t}(\hat{s}_t, \hat{a}_t | \omega_t^i) |_{\hat{a}_t^i = \mu_t^i(\hat{s}_t | \theta_t^i)}. \quad (5.20)$$

At last, the actor network of agent i follows the below updating rule,

$$\theta_{t+1}^i \leftarrow \tau_a \theta_t^i + (1 - \tau_a) \theta_{t+1}^i, \quad (5.21)$$

where τ_a is used for target update of the actor networks.

Moreover, we present the detailed training procedures of MZTC algorithm in Algorithm 1.

FIGURE 5.4: The design diagram of the multi-zone thermal control simulation environment in TRNSYS software. It consists of various modules, such as lighting configuration, weather data loader, radiation settings, multi-zone building model, and MATLAB communication channel.

5.4 Performance Evaluation

In this section, we first introduce the implemented simulation environment. Then, we illustrate the experimental settings. Finally, we analyze the experimental results and evaluate the performance of our proposed MZTC approach.

5.4.1 MZTC Simulation Environment

To verify the effectiveness of our approach, we create a multi-zone simulation environment with the HVAC systems by using the professional TRNSYS software

[126]. As shown in Fig. 5.4, it consists of the following two major components.

5.4.1.1 Building Model

We follow the multi-zone building modeling tutorials [130] of TRNSYS software to create a basic building model with four zones. Each zone is equipped with an individual air-node for thermal control, and we only enable the cooling, ventilation and humidification functions of each air-node. Other settings (e.g., construction of walls, floors, ceilings, roofs and windows, lighting scheduling control, basic radiation settings) are initialized by TRNSYS with the default values. Moreover, we configure the built-in monitor components to track the energy consumption and thermal conditions of each zone in real time.

5.4.1.2 Control Interface

In this paper, we implement our MZTC algorithm via the PyTorch framework [131]. TRNSYS does not provide the Application Programming Interfaces (APIs) to enable the Python program to communicate with it directly. As such, we use the MATLAB software to create a proxy communication channel for parameter exchange between our Python-based algorithm and TRNSYS-based simulation environment. Moreover, each operation (e.g., the variation in thermal conditions of each zone and the control operations conducted by our algorithms) of the interaction is recorded in the MySQL database.

5.4.2 Experimental Settings

In this subsection, we describe the experiment settings of simulation environment and control algorithm, respectively.

TABLE 5.1: Human and device heat gain settings of each zone

Zone	Functionality	# of People	# of Computers
Zone 0	Project Demo Area	3 People	12 Computers
Zone 1	Student Self-study Area	10 People	12 Computers
Zone 2	Meeting Room Area	4 People	6 Computers
Zone 3	Research Staff Working Area	16 People	20 Computers

5.4.2.1 Simulation Environment

We create such multi-zone simulation environment based on our research laboratory, which is a $300.8m^2$ square area. It is divided into four equal-size zones, as shown in Fig. 5.1. Also, we configure the heat gains for each zone. In this paper, we mainly consider two heat sources: people and computers. Due to the different functionalities of each zone, we list the detailed heat gain settings in Table 5.1. In addition, we set the air change rate as 67% per hour for all zones. Moreover, we assume that the daily working period is from 9:00 to 18:00 (i.e., nine hours a day). Furthermore, we load the built-in weather dataset *SG-Singapore-Airp-486980* of TRNSYS to simulate the variation in the outdoor thermal environment.

5.4.2.2 Control Algorithm

In our implemented MZTC algorithm, there are a lot of parameter settings. We define two hidden layers for both actor network and critic network of each agent, where the number of neurons for each hidden layer is 128. Also, the Adam optimizer is adopted for the actor network with the learning rate of 0.0001 and the critic network with the learning rate of 0.001. Here, the critic network is used to evaluate the actions taken by the actor network. With the given training samples, the critic network must learn faster than the actor network to provide better guidance. Therefore, the learning rate of the critic network must be larger than that of the actor network. In addition, we set the discounted factor $\lambda = 0.95$ and the training

(A) Total rewards

(B) Rewards of each zone

FIGURE 5.5: The rewards in training vary with the increment of episodes. Both figures show that after episode 54, the policy learning of each zone has converged.

batch size as 128 for all agents. Besides, we set the size of the replay memory as 10^6 and configure $\tau_c = \tau_a = 0.01$ for the target updates.

For modeling training, we sample one transition every hour (i.e., the duration of each time slot is one hour). After sampling every 100 transitions (i.e., 100 hours per

episode) and storing them in the replay memory, we update the actor-critic network weights. Moreover, we use 5,000 hours (i.e., 50 episodes) of the simulation data for action exploration and transition buffering, 10,000 hours (i.e., 100 episodes) of simulation data for control policy learning. In total, the number of episodes for model training is 150, as presented in Section 5.4.3. After that, we use extra 5,000 hours (i.e., 50 episodes) of simulation data for modeling testing. The testing results are analyzed and discussed in Section 5.4.4 and 5.4.5. Besides, due to the limitation of TRNSYS, the developed simulation environment only supports to adjust the indoor set-point temperature and set-point relative humidity. Hence, in this paper, we only consider changing the indoor set-point temperature ranging from 20.0°C to 30.0°C and set-point relative humidity ranging from 50% to 70%. Furthermore, we set the same energy-comfort weight δ for all zones. However, our solution allows to set different zone-specified weights as well.

still supports to set the weight for a specific zone.

5.4.3 Training Convergence Performance

In this subsection, we analyze the convergence performance of our proposed MZTC algorithm.

We set the thermal comfort lower bound $L_p = -0.5$ and upper bound $U_p = 0.5$, respectively, and then optimize the energy-comfort trade-off by fine-tuning the hyper-parameters. The variation in returned rewards during training with the increment of episodes is shown in Fig. 5.5. From Fig. 5.5a, we can see that after episode 49, this algorithm starts to sample the stored transitions for training. In episode 54, the learning process has already converged. Meanwhile, Fig. 5.5b shows that in fact, each agent has learned the optimal control policy for the related zone after episode 54. Also, as shown in Table 5.1, different settings of heat gains for each zone results in distinct cooling-dehumidification demand, which is also the input of the reward function Eq. (5.6). As such, the variation in zone rewards of each zone is distinguishing from each other, but the variation in trend is similar to each other. At last, both total rewards and zone rewards fluctuate around the converged reward threshold in the rest of the training episodes.

FIGURE 5.6: The average outdoor air temperature and relative humidity vary with the hour of a day. Overall, the outdoor air temperature and relative humidity link to each other tightly. The outdoor relative humidity decreases with the increment of the outdoor air temperature.

In Summary, MZTC algorithm demonstrates its outstanding learning ability and convergence performance in our application scenario.

5.4.4 Thermal Control Performance

In this subsection, we present the thermal control performance of MZTC algorithm. First, we present the variation in indoor and outdoor thermal conditions as well as energy consumption with the hour of a day. Second, we show the variation in indoor thermal conditions and the related energy consumption under different thermal comfort demands. The details are described as follows.

5.4.4.1 Thermal Control at Each Hour of a Day

We analyze the daily thermal control performance by using the 5,000-hour testing data. Then, we present the average statistical data per hour from 10:00 to

FIGURE 5.7: The average air temperature, relative humidity, thermal comfort index, and cooling-dehumidification energy consumption of each zone during 5,000 hours vary with the hour of a day. First, compared to the relative humidity, air temperature is the major factor that affects occupants' thermal comfort. Second, the energy consumption slightly increases over the whole day, but the maximum difference is only 1.08kWh.

18:00, as shown in Fig. 5.6. For example, the average outdoor air temperature and relative humidity are 26.6°C and 85.5% at 10:00, respectively. Besides, although the algorithm starts to manage the zone thermal conditions at 9:00, the control settings require some time (i.e., roughly 30 minutes to one hour) to take effect on the indoor environment, which can be observed at 10:00. As such, the start point of Fig. 5.6 and Fig. 5.7 is 10:00. Moreover, the thermal comfort bound of this analyzed case is the $[-0.5, 0.5]$ (i.e., $L_p = -0.5$ and $U_p = 0.5$) suggested by the ASHRAE standard.

- *Outdoor Thermal Condition:* We plot Fig. 5.6 to show the average variation

FIGURE 5.8: The variation in the average air temperature, relative humidity, thermal comfort index, and cooling-dehumidification energy consumption of each zone under different thermal comfort demands during the 5,000 hours. First, the thermal comfort index of each zone has the same variation trend as that of the air temperature. Second, the variation in relative humidity of each zone is very tiny. Third, the energy consumption of each zone decreases with the increment of the thermal comfort bound.

in outdoor air temperature and relative humidity over time. We can see that the average outdoor air temperature increases from 26.6°C at 10:00 to the maximum 29.8°C at 15:00, and then decreases to 28.7°C at 18:00. Meanwhile, the related average outdoor relative humidity decreases from the maximum 85.5% at 10:00 to the minimum 72.0% at 15:00, and then increases to 77.1% at 18:00. It is the typical outdoor thermal condition in the tropics. Overall, the outdoor relative humidity decreases with the increment of the outdoor air temperature.

- *Indoor Thermal Condition of Each Zone:* With the same outdoor thermal

condition, we plot Fig. 5.7 to demonstrate the average variation in air temperature, relative humidity, thermal comfort index, and cooling-dehumidification energy consumption for each zone over time. First, Fig. 5.7a shows that the average air temperature of each zone fluctuates up and down around 26.6°C. Among all zones, the largest difference of air temperature is observed in Zone 3, which is only 0.5°C. Then, Fig. 5.7b shows that the variation in the average relative humidity of each zone is very tiny. Among all zones, the largest difference of relative humidity is observed in Zone 1, which is only 0.5%. Next, due to the stable variation in both air temperature and relative humidity, the average thermal comfort index of each zone is also well-controlled, as shown in Fig. 5.7c. Although our algorithm cannot exactly limit the thermal comfort of each zone within the range $[-0.5, 0.5]$, it still can maintain occupants' thermal comfort within the acceptable levels. The maximum average thermal comfort index is observed in Zone 3, which is 0.65. Compared to the upper bound 0.5, the difference is 0.15, which is hardly distinguishable for occupants. Finally, Fig. 5.7d shows that the cooling-dehumidification energy consumption of each zone increases slowly over time, which is mainly affected by the variation in outdoor thermal condition. Among all zones, the largest difference in energy consumption is observed in Zone 2, which is only 1.08kWh. Moreover, due to different heat gain settings (i.e., human and device heat gain) and according to Table 5.1, we can find that the zone with more occupants and computers would consume more energy. Generally, these parameters do not vary too much through a day and our experimental observations follow such common realistic settings.

In summary, our approach can successfully maintain a relatively comfortable indoor environment under different outdoor thermal conditions. Besides, we find that the air temperature is the key factor that affects occupants' thermal comfort. Moreover, although our approach has the biases on controlling the set-point temperature, occupants generally cannot feel such tiny differences.

5.4.4.2 Thermal Control Under Different Comfort Bounds

In this subsection, we analyze the thermal control performance of our proposed MZTC algorithm with different thermal comfort demands. We adjust the energy-comfort weight to guide the algorithm to fulfill different thermal comfort bounds (i.e., $[-0.1, 0.1]$, $[-0.3, 0.3]$, $[-0.5, 0.5]$, $[-0.8, 0.8]$, and $[-1.0, 1.0]$). For each bound, we calculate the average statistical data (i.e., air temperature, relative humidity, thermal comfort index, and cooling-dehumidification energy consumption) of 5,000 hours, as shown in Fig. 5.8.

Overall, with the increment of the thermal comfort bound, the air temperature and thermal comfort index increase while the energy consumption decreases, and the relative humidity remains mostly the same. First, Fig. 5.8a and Fig. 5.8c shows that the average air temperature and thermal comfort index of each zone have a linear relationship with the thermal comfort bound. The average air temperature and thermal comfort index of four zones increase linearly from 25.3°C and 0.11 at $[-0.1, 0.1]$ to 27.9°C and 0.99 at $[-1.0, 1.0]$, respectively. Then, the average variation in relative humidity of each zone is very stable and almost the same to each other, as shown in Fig. 5.8b. The only abnormal point is observed in Zone 0, which is 64.4% at $[-0.1, 0.1]$. However, compared to other data points of relative humidity in Zone 0, the difference is still within 2.0%. Finally, Fig. 5.8d presents that cooling-dehumidification energy consumption of each zone has a linear relationship with the thermal comfort bound. Beside, the total energy consumption of four zones decreases from 39.57kWh at $[-0.1, 0.1]$ to 34.57kWh at $[-1.0, 1.0]$. Moreover, we can observe the same finding in Section 5.4.4.1, which is that even under different thermal comfort bounds, the zone with more occupants and computer would consume more energy.

In summary, our simulation results demonstrate the effectiveness of our approach on multi-zone energy management. Under different thermal comfort demands, our approach can learn the corresponding control policy to fulfill the energy-comfort balance of each zone, respectively.

5.4.5 Energy Saving Performance

In this section, we analyze the energy saving performance of our MZTC algorithm. First, we compare our approach with the baseline method to discuss the energy saving of each zone under different thermal comfort bounds. Then, we further compare our approach with other learning-based methods to demonstrate the advantages of our approach.

5.4.5.1 Algorithm Introduction

In this subsection, we provide a brief introduction to selected algorithms.

- *Rule-Based Heuristic Control Method*: It aims to maintain the room temperature based on a pre-configured set-point temperature (e.g., 23.0°C or 24.0°C) via Direct Digital Control (DDC) systems [132]. Its control algorithm is an improved PID [22]. Due to its easy implementation and acceptable performance, it is the most widely used air-conditioning control method in the modern BMS. Therefore, we select it as the comparison baseline.
- *DDPG*: It is a model-free off-policy actor-critic algorithm [128], which is developed based on Deterministic Policy Gradient (DPG) [133] and DQN [63]. Initially, DQN only works in discrete space. DDPG extends it to the continuous space. We design two algorithms based on DDPG: 1) **Single-DDPG**: It creates a super agent to control four zones simultaneously; 2) **Multi-DDPG**: It creates a single agent for each zone for independent control. There is no information sharing among agents.

In the subsequent subsections, we conduct a series of energy-saving related analysis based on four algorithms: **Rule-Based Heuristic Control Method (baseline)**, **Single-DDPG**, **Multi-DDPG**, and **MZTC**.

TABLE 5.2: Comparison Among Different Approaches

Air Temperature ($^{\circ}\text{C}$)					
Approach	Zone 0	Zone 1	Zone 2	Zone 3	Average
Baseline	24.0	24.0	24.0	24.0	24.0
Single-DDPG	26.6	26.5	27.9	28.0	27.2
Multi-DDPG	26.6	26.5	26.4	26.4	26.5
MZTC	26.5	26.4	26.5	26.6	26.5

Relative Humidity (%)					
Approach	Zone 0	Zone 1	Zone 2	Zone 3	Average
Baseline	60.0	60.0	60.0	60.0	60.0
Single-DDPG	66.0	65.1	66.1	66.1	65.8
Multi-DDPG	66.0	66.1	66.1	66.1	66.1
MZTC	66.0	66.1	66.1	66.1	66.1

Thermal Comfort Index					
Approach	Zone 0	Zone 1	Zone 2	Zone 3	Average
Baseline	-0.39	-0.39	-0.39	-0.39	-0.39
Single-DDPG	0.52	0.50	0.98	1.01	0.75
Multi-DDPG	0.53	0.51	0.47	0.48	0.50
MZTC	0.49	0.46	0.51	0.55	0.50

Energy Consumption (kWh)					
Approach	Zone 0	Zone 1	Zone 2	Zone 3	Total
Baseline	9.43	10.30	8.40	12.58	40.71
Single-DDPG	8.55	9.46	6.89	11.00	35.90
Multi-DDPG	8.55	9.43	7.60	11.75	37.33
MZTC	8.60	9.51	7.55	11.65	37.31

5.4.5.2 Energy Saving Comparison

We select and implement four algorithms, introduced in Section 5.4.5.1, for performance comparison. In addition, to better compare the performance among different approaches, we fix the thermal comfort bound as $[-0.5, 0.5]$.

FIGURE 5.9: The variation in the energy saving of each zone varies under different thermal comfort bounds. Larger thermal comfort bound can achieve more energy saving for all zones. Also, the zone with less number of occupants and computers has a higher potential to save more energy.

The thermal control simulation results of the four approaches are listed in Table 5.2. First, the baseline method aims to maintain all zones with the fixed set-point temperature 24.0°C and relative humidity 60%, which results in the fixed average thermal comfort index. However, due to the different heat gain settings of each zone, the energy expenditure of each zone is distinct. Compared to other learning-based approaches, the total energy consumption of the baseline method is the highest. Then, for the Single-DDPG approach, it achieves the lowest total energy consumption. However, this approach fails to maintain the air temperature and the related thermal comfort for Zone 2 and Zone 3. Finally, the energy-saving performance of both Multi-DDPG and MZTC is very close. MZTC saves slightly more energy than Multi-DDPG.

In summary, compared to the baseline method, Single-DDPG cannot fulfill occupants' thermal comfort demands of multiple zones, while both Multi-DDPG and MZTC can balance the energy-comfort trade-off successfully. However, among all selected approaches, MZTC achieves the best energy-saving performance.

5.4.5.3 Energy Saving of Each Zone

In this subsection, compared to the energy consumption of baseline method listed in Table 5.2, we calculate the energy saving of each zone with different thermal comfort bounds, as shown in Fig. 5.9.

Overall, the energy saving of each zone increases with the increment of the thermal comfort bound. First, when the bound is $[-0.1, 0.1]$, the energy saving of each zone is very limited, and the average energy saving of all zones is only 2.8%. Then, with the bound $[-0.3, 0.3]$, the average energy saving of four zones is 5.6%, which is roughly twice than that of the bound $[-0.1, 0.1]$. Here, we can find that the largest energy saving is observed in Zone 2, followed by Zone 0, Zone1 and Zone 3, respectively. Moreover, the same observation can be found in the rest of three bounds. Finally, the average energy saving of four zones with bounds $[-0.5, 0.5]$, $[-0.8, 0.8]$, and $[-1.0, 1.0]$ is 8.5%, 12.8%, and 15.4%, respectively.

Moreover, we adopt back-of-envelop calculation to estimate the annual electricity cost saving under different thermal comfort bounds. As shown in Table 5.2, the total energy consumption of baseline method is 40.71kWh. Based on the energy saving percentage: 2.8% $[-0.1, 0.1]$, 5.6% $[-0.3, 0.3]$, 8.5% $[-0.5, 0.5]$, 12.8% $[-0.8, 0.8]$, and 15.4% $[-1.0, 1.0]$, we can obtain the related estimated energy saving: 1.14kWh, 2.28kWh, 3.46kWh, 5.21kWh, and 6.27kWh. Let us assume that nine working hours a day, 22 working days a month, and 12 months a year, then we can obtain the annual energy saving 2708.64kWh, 5417.28kWh, 8220.96kWh, 12378.96kWh, 14897.52kWh, respectively. Finally, according to the latest Singapore electricity tariffs S\$0.26 per kWh, the related annual electricity cost saving of a 300.8m² laboratory is S\$704.25 $[-0.1, 0.1]$, S\$1408.49 $[-0.3, 0.3]$, S\$2137.45 $[-0.5, 0.5]$, S\$3218.53 $[-0.8, 0.8]$, S\$3873.36 $[-1.0, 1.0]$, respectively.

In summary, compared to the baseline method, our approach can learn the corresponding control policy based on the heterogeneous thermal conditions of each zone to maximize the energy-saving, respectively. Moreover, we also can find that the zone with less number of occupants and computers can achieve more energy saving.

5.5 Conclusion

In this chapter, we present a MADRL-based solution to investigate the energy-comfort trade-off for multi-zone buildings. First, we predict occupants' thermal comfort by adopting our in-house ITCNN model. Second, we design the MZTC algorithm to solve the optimization problem of the multi-zone thermal control operations. Third, we use professional TRNSYS software to build the multi-zone thermal control simulation environment to evaluate the performance of our solution. Finally, simulation results demonstrate that our solution can achieve considerable electricity saving of the HVAC systems while maintaining occupants' thermal comfort in multiple zones of a building.

In the next chapter, we will present a novel application based on the iTCM system.

Chapter 6

Human Behavioral Study & Digital-Twin Demo

In this chapter¹, we propose a novel application based on the iTCM system with a gamification approach to encourage human behavioral changes towards greener, smarter and healthier buildings. First, we introduce the developed Deep Reinforcement Learning (DRL) based economic model. Then, we present the Digital-Twin based demo website for this behavioral study. Moreover, part of this chapter has been published in [1].

6.1 Introduction

Occupants' behaviors are highly related to the energy consumption of the HVAC systems and their thermal comfort, as indicated in research work [134]. In Chapter 5, we proposed the intelligent thermal control approach to address the energy-comfort trade-off in multiple zones. However, since the thermal comfort is quite subjective, there is no perfect solution that can fulfill every occupant's comfort demand. To mitigate the minority of occupants' discomfort, we design the novel incentive-based human behavioral study as an application of the iTCM system

¹**Weizheng Hu**, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng, "iTCM: Toward Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings," in *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831

to explore the possibility of improving these occupants' satisfaction level while achieving building energy saving.

In this application scenario, the iTCM system interacts with occupants in a typical office building. First, the iTCM system will track occupants' vital signs while monitoring the indoor environmental parameters. Then, based on the acquired data, the iTCM system will attempt to select the suitable incentive actions to maintain occupants' satisfaction levels under different settings of the HVAC systems. Finally, the iTCM system will receive occupants' real-time feedback for the received incentive offers. During the interaction process, we intend to investigate the trade-off between the cost of incentive gifts and the electricity cost saving of the HVAC system under different set-point temperatures. The reason to consider the incentive mechanism is that existing research [135] suggests that incentives could effectively enhance people's satisfaction and make a certain level of discomfort more tolerable. Therefore, understanding to what degree people would trade their thermal discomfort with the incentive gain is of great importance.

In this chapter, we aim to develop an economic model to characterize the economic value of thermal comfort to the building occupants, under different set-point temperature settings. It follows that our main research objective is to use the developed economic model to judiciously balance between the HVAC electricity cost saving and the incentive cost, maximizing the total cost saving while maintaining occupants' satisfaction levels. Specifically, we have made the following contributions.

- We involve occupants' behaviors into intelligent thermal comfort modeling and HVAC control research by considering the incentive scheme. Moreover, we use our iTCM system as the development platform to implement this novel application.
- We adopt the Deep Reinforcement Learning (DRL) technique to develop the proposed incentive-based economic model for the human behavioral study. Specifically, we formulate the optimization problem as a Markov Decision Process (MDP) and apply the classic Actor-Critic algorithm to solve it.
- We conduct the crowds simulation to simulate the interaction between the iTCM system and occupants. Our simulation results show that our proposed

economic model has great potential to save the building electricity bill. Moreover, we develop a 3D visualized website to demonstrate the simulation results by using the Digital-Twin technology.

This chapter provides fundamental insights and guidance for applying the Deep Reinforcement Learning (DRL) techniques to the crowds simulation for human behavioral study. Our objective is to use the incentive scheme to develop an economic model to quantify occupants' thermal comfort. Simulation results and case study show that our proposed approach has great potentials to maintain occupants' satisfaction levels while achieving the building energy-saving. Our findings will make contributions to future research on the human energy-saving behavioral study for the smart building field.

The rest of this chapter is organized as follows. Section 6.2 formulates the optimization problem. Section 6.3 adopts the classic Actor-Critic approach to solve the problem and design the related algorithm. Section 6.4 discusses the experimental results. Section 6.5 describes the Digital-Twin based 3D visualized website demo. Section 6.6 concludes this chapter.

6.2 System Modeling & Problem Formulation

In this section, to develop the proposed economic model, we adopt the Reinforcement Learning (RL) [136] framework, which is an important branch of machine learning inspired by behavior psychology. It can be used to predict human actions and motivate people to form better behaviors and habits. Next, we will illustrate the learning-based economic model and formulate the optimization problem.

6.2.1 Learning-Based Economic Model

We follow the standard reinforcement learning framework to derive the economic model and consider that the RL agent is iTCM system and the environment E is a common indoor space with N occupants in the typical office building.

We model the reinforcement as Markov Decision Processes (MDPs), as shown in Fig. 6.1. At each timestep t , first, iTCM system observes the current state s_t ,

FIGURE 6.1: Workflows of the Reinforcement Learning Based Economic Model. First, the current original states of the environment are observed by the RL agent. Then, the RL agent converts the current original stats to the current proxy states via the ITCNN. Next, Actor-Critic algorithm takes the actions based on the current proxy states. Finally, the RL agent receives the occupants' feedback and observes the next original states.

which denotes the occupants' vital signs as well as the measured environmental data. $s_t = (s_t^0, s_t^1, \dots, s_t^{N-1})$, where s_t^i represents the personal state of occupant i , for $i = 0, 1, 2, \dots, N-1$. Here, due to the complicated combination of features on human vital signs and environmental parameters, the original state s_t can be considered to have infinite state dimensions. As such, we innovatively adopt the thermal comfort model derived by ITCNN in Chapter 4.2 as a function approximator to reduce the original state space to the proxy state $\hat{s}_t$, as follows:

$$\hat{s}_t = ITCNN(s_t), \quad (6.1)$$

where $\hat{s}_t = (\hat{s}_t^0, \hat{s}_t^1, \dots, \hat{s}_t^{N-1})$ and $\hat{s}_t^i \in \mathbb{S}$. Here, $\mathbb{S}$ is the set of discrete states, which refers to the 7-point ASHRAE thermal sensation levels. Using proxy states not only simplifies the problem, but also accelerates the learning convergence. We also

note that in this setup, ITCNN is a pre-trained NN, which will not be affected by the back propagation (BP) of actor-critic networks.

Next, based on the proxy states $\hat{s}_t$, the iTCM system will attempt to “think” and select the suitable incentive actions for all occupants. Such behavior is determined by a policy μ , which is our desired economic model. It maps proxy states $\hat{s}_t$ to a probability distribution over the incentive actions a_t and $a_t = (a_t^0, a_t^1, \dots, a_t^{N-1})$, where a_t^i represents the incentive reward offered to each occupant and $a_t^i \in \mathbb{A}$. Here, $\mathbb{A}$ is the set of discrete actions, which refers to the 5-point normalized actions ranging from 0, 1, 2, 3 to 4, which represents the incentive monetary reward S\$0, S\$2, S\$5, S\$8 to S\$10, respectively. In addition, we design such an incentive scheme based on our collected data and questionnaire surveys.

Next, after taking the action a_t , iTCM system will receive the occupants’ satisfaction feedback f_t for the received incentive offers, where $f_t = (f_t^0, f_t^1, \dots, f_t^{N-1})$. Here, f_t^i represents the individual feedback received from each occupant and $f_t^i \in \mathbb{F}$, where $\mathbb{F}$ is the set of discrete feedback, which refers to the 3-point satisfaction levels: dissatisfied, neutral and satisfied, represented as -1, 0, and 1, respectively. In the context of our problem setup, we cannot directly use occupants’ feedback as the reward. The reason is that with rationality assumption, even if one person feels satisfied with S\$5 reward, generally, the same person will not refuse better offers, such as S\$8 or S\$10 reward. As a result, the asymptotic optimal policy to guarantee occupants’ satisfaction feedback in the long-term run would always be selecting the action with a highest monetary offer (e.g., action 4 with S\$10), which would contradict our goal of minimizing the total incentive costs while maintaining occupant’s satisfaction levels. Therefore, we define the normalized reward r_t , which is a function (denoted as k) of feedback f_t and action a_t .

$$r_t = k(a_t, f_t), \quad (6.2)$$

where $r_t = (r_t^0, r_t^1, \dots, r_t^{N-1})$, with r_t^i denoting the individual normalized reward calculated for each occupant. Here, r_t^i can be obtained by the following equation:

$$r_t^i = k(a_t^i, f_t^i) = \begin{cases} -a_t^i + 5, & \text{if } f_t^i \geq 0, \\ 1, & \text{otherwise} \end{cases} \quad f_t^i \in \mathbb{F}, \forall i, \quad (6.3)$$

where $r_t^i \in \mathbb{R}$ and $\mathbb{R}$ is the 5-point discrete normalized rewards ($\mathbb{R} = \{1, 2, 3, 4, 5\}$). The reward function punishes the actions (incentive offers) with higher monetary values. For example, action 0 ($a_t^i = 0$) offers zero incentives to the occupant i and receives the highest normalized reward value five. In contrast, action 4 ($a_t^i = 4$) offers the highest incentive reward S\$10 to the occupant i and thus receives the lowest normalized reward value one. Moreover, to maintain occupants' satisfaction levels, if an occupant feels dissatisfied, no matter what actions are taken by the iTCM system, the normalized reward will be the minimum value one.

Finally, the environment E will make transition to the next state s_{t+1} according to the current state s_t and action a_t , by following a transition probability denoted as $P(s_{t+1}|s_t, a_t)$, which is unknown to the iTCM system.

6.2.2 Problem Formulation

In this section, we present a mathematical formulation to develop the proposed learning-based economic model.

Following the convention of RL framework, we use the future reward as the optimization objective. Specifically, we define the following summation of discounted future reward $\mathcal{R}_t$ after timestep t :

$$\begin{aligned}\mathcal{R}_t &= R_{t+1} + \lambda R_{t+2} + \lambda^2 R_{t+3} + \dots + \lambda^{\mathcal{T}-1} R_{t+\mathcal{T}}, \\ &= \sum_{j=1}^{\mathcal{T}} \lambda^{j-1} R_{t+j},\end{aligned}\tag{6.4}$$

where λ is the discounted factor and $\lambda \in [0, 1]$. $R_{t+j} = \sum_{i=0}^{N-1} r_{t+j}^i$ and denotes the summation of normalized reward for N occupants at timestep $t + j$, for $j = 1, 2, \dots, \mathcal{T}$.

Our goal is to maximize the expected summation of discounted normalized rewards for all occupants over the long-term future by learning a policy μ , subject to the bounded set-point temperatures. Mathematically, we formulate the following constrained optimization problem,

$$\max_{T_{temp}} \quad \mathbb{E}_{\mu}\{\mathcal{R}_t\},\tag{6.5}$$

$$\text{s.t.} \quad L_{T_{temp}} \leq T_{temp} \leq U_{T_{temp}},\tag{6.6}$$

where T_{temp} is the decision variable, which is limited by the constraint Eq. (6.6) with the lower bound set-point temperature $L_{T_{temp}}$ and the higher bound set-point temperature $U_{T_{temp}}$. In this chapter, we adjust the room temperature by controlling T_{temp} . It directly impacts the observed state s_t of environment E , which denotes the environmental parameters and occupants' vital signs. Then, s_t will affect the correlated proxy state $\hat{s}_t$, which is derived by ITCNN.

6.3 Problem Solving & Algorithm Design

In this chapter, we combine Temporal Difference (TD) learning approach [137] and Actor-Critic (AC) method [138] to solve the problem (6.5)-(6.6).

6.3.1 Temporal-Difference Learning

TD learning is an unsupervised technique, which is used by an RL agent to learn the state-value function from a sequence of states via various optimizers, such as SGD, Adam, etc.

In our optimization problem, $\mathcal{R}_t$ is the target state-value function we want to derive, which is the Eq. (6.4) defined in section 6.2.2. However, $\mathcal{R}_t$ is generally an unknown quantity, an estimation is needed. Here, let v_t be a prediction to approximate the true value function $\mathcal{R}_t$. The unbiased TD error δ_t at timestep t will be

$$\delta_t = \mathcal{R}_t - v_t. \quad (6.7)$$

Next, based on the Bellman equation [139], we transform the $\mathcal{R}_t$ (Eq. (6.4)) into the following recursive relationship,

$$\begin{aligned} \mathcal{R}_t &= \sum_{j=1}^{\infty} \lambda^{j-1} R_{t+j}, \\ &= R_{t+1} + \lambda \sum_{j=1}^{\infty} \lambda^{j-1} R_{t+j+1}, \\ &= R_{t+1} + \lambda \mathcal{R}_{t+1}, \end{aligned} \quad (6.8)$$

where R_{t+1} is the immediate returned reward at timestep $t + 1$ and $\mathcal{R}_{t+1}$ is the summation of discounted future reward after timestep $t + 1$. By replacing $\mathcal{R}_t$ in Eq. (6.7) with the final format of Eq. (6.8), we have

$$\delta_t = [R_{t+1} + \lambda \mathcal{R}_{t+1}] - v_t. \quad (6.9)$$

Similar to the relationship between $\mathcal{R}_t$ and v_t , $\mathcal{R}_{t+1}$ can be replaced by an imperfect proxy v_{t+1} as

$$[R_{t+1} + \lambda \mathcal{R}_{t+1}] - v_t \approx [R_{t+1} + \lambda v_{t+1}] - v_t, \quad (6.10)$$

where the right hand side of Eq. (6.10) is considered as the generalized error equation in TD learning theory. Let us use $\hat{\delta}_t$ to denote it,

$$\hat{\delta}_t = [R_{t+1} + \lambda v_{t+1}] - v_t, \quad (6.11)$$

where $\hat{\delta}_t \approx \delta_t$. The core concept of TD learning is to minimize this generalized TD error $\hat{\delta}_t$ to make the prediction function v_t close to the true value function $\mathcal{R}_t$. Generally, $\hat{\delta}_t$ is multiplied by a learning rate φ and used to update the weights. It follows the general updating rule at timestep t as

$$v_t \leftarrow v_t + \varphi \hat{\delta}_t. \quad (6.12)$$

In the next subsequent section, we will present the AC method to solve the problem by adopting the TD error.

6.3.2 Actor-Critic Method

AC method is a classical on-policy algorithm, which is proposed by *Williams et al.* [140] in 1990. It aims at combining the advantages of actor-only and critic-only methods to achieve faster convergence speed and desirable convergence properties.

In this chapter, we follow the conventional AC architecture to derive the incentive policy μ and adopt the artificial neural networks (ANNs) as the function approximators to build the actor network and the critic network, respectively. Since the critic network is in charge of learning, the value function is then used to guide the actor network to improve the policy, we will first introduce the critic network followed by the actor network.

- *Critic Network:* The critic network is also named as the value network. It is used to estimate the action-value function and evaluate the value of current policy to improve the actor network.

Let $V^\mu(\hat{s}|\omega)$ be the value function learned by the critic network parameterized by ω with respect to the policy μ . Following the same transformation from Eq. (6.7) to Eq. (6.10) described in section 6.3.1, we obtain the following approximate TD error at timestep t ,

$$\delta_t^\mu = [R_{t+1} + \lambda V^\mu(\hat{s}_{t+1}|\omega)] - V^\mu(\hat{s}_t|\omega). \quad (6.13)$$

where δ^μ is also considered as the estimated *advantage function* to reduce the variance of policy gradient.

Next, we update $V^\mu(\hat{s}_t|\omega)$ by minimizing the following loss function of squared TD error to find the weights ω of neural network,

$$L(\omega) = [\delta_t^\mu]^2, \quad (6.14)$$

with the following general updating rule,

$$\omega \leftarrow \omega + \alpha \nabla_\omega V^\mu(\hat{s}_t|\omega) \delta_t^\mu, \quad (6.15)$$

where α is the learning rate of critic network. In addition, the TD error δ^μ will also be used to drive the learning in actor network, which will be illustrated in the subsequent section.

- *Actor Network:* The actor network is also called the policy network. We aim to represent the incentive policy μ by a neural network to map the proxy state $\hat{s}$ to the incentive actions a . Such an actor neural network for the incentive policy is named as μ -network parameterized by θ , which can be represented as follows,

$$a = \mu(a|\hat{s}, \theta) \quad (6.16)$$

where θ is the weight vector for actor network.

In AC method, θ will be updated under the evaluation of critic network. Here, we directly utilize the TD error δ^μ derived by critic network to compute

the policy gradient for actor network, which follows below updating rule,

$$\theta \leftarrow \theta + \beta \nabla_{\theta} \log \mu(a_t | \hat{s}_t, \theta) \delta_t^{\mu}, \quad (6.17)$$

where β is the learning rate of actor network and $\beta < \alpha$.

Besides, we also present the actor-critic algorithm, which is shown in Algorithm 2.

Algorithm 2: Actor-Critic Algorithm

Input :

- Discounted factor λ .
- Learning rate α for critic network.
- Learning rate β for actor network.

Output :

- Policy $\mu(a | \hat{s}, \theta)$.

- 1: Initialize critic network $V^{\mu}(\hat{s} | \omega)$ with weights ω ;
 - 2: Initialize actor network $\mu(a | \hat{s}, \theta)$ with weights θ .
 - 3: **for** episode = 1, 2, ..., M **do**
 - 4: Initialize s and observe the initial state s_1 .
 - 5: **for** t = 1, 2, ..., T **do**
 - 6: Observe the state s_t and derive the proxy state $\hat{s}_t = ITCNN(s_t)$;
 - 7: Select action a_t based on policy $\mu(a_t | \hat{s}_t, \theta)$;
 - 8: Take action a_t and obtain reward $R_t = \sum_{i=0}^{N-1} r_t^i$, where $r_t^i = k(a_t^i, f_t^i)$ for N occupants;
 - 9: Observe the next state s_{t+1} and derive correlated proxy state $\hat{s}_{t+1} = ITCNN(s_{t+1})$;
 - 10: Update the TD error:
 $\delta_t^{\mu} \leftarrow [R_{t+1} + \lambda V^{\mu}(\hat{s}_{t+1} | \omega)] - V^{\mu}(\hat{s}_t | \omega)$;
 - 11: Update critic by minimizing the loss $L(\omega) = [\delta_t^{\mu}]^2$.
 - 12: Update the weights ω, θ for actor and critic network:
 $\omega \leftarrow \omega + \alpha \nabla_{\omega} V^{\mu}(\hat{s}_t | \omega) \delta_t^{\mu}$
 $\theta \leftarrow \theta + \beta \nabla_{\theta} \log \mu(a_t | \hat{s}_t, \theta) \delta_t^{\mu}$
 - 13: $s_t \leftarrow s_{t+1}$.
 - 14: **end for**
 - 15: **end for**
-

6.4 Performance Evaluation

In this section, we first introduce the experiment settings. Next, we present the preliminary simulation results and a case study. Finally, we discuss the implications of these results.

6.4.1 Experiment Settings

In the preparation phase of the experiment, we first construct a simulation environment based on the principle of statistics with the collected data and questionnaire surveys from 20 students and 10 staff volunteers during a three-week period. Such simulated environment will mimic occupants' feedback for the received rewards by following the statistical probability distribution. For example, when the set-point temperature is 23°C and the reward is S\$5, person *A* feels satisfied, neutral and dissatisfied with the probability of 40%, 50%, and 10%, respectively. Second, we implement two neural networks for actor and critic modules. Each neural network is fully-connected structure and has one hidden layer with 20 hidden units. The learning rate α for critic network is 0.01, and the learning rate β for actor network is 0.001. We set discounted factor λ to 0.99.

For the simulation, we assume that occupants spend 10 hours per day, 22 days per month in the office, with one month as an episode. We also assume that iTCM system interacts with the occupants every 2 hours to collect data and acquire feedback related to the received incentive actions. In our simulation, one timestep accounts for one hour. As such, there are a total of 110 timesteps per episode. We run a total of 500 episodes. In addition, we change the set-point temperature T_{temp} in the range of $L_{T_{temp}} = 21^\circ\text{C}$ and $U_{T_{temp}} = 27^\circ\text{C}$, which covers the acceptable set-points between 22.5° to 25.5° suggested by BCA indoor thermal comfort standard [141].

6.4.2 Simulation Results

First, we present the relationship between episodes and normalized rewards, as shown in Fig. 6.2. The plot shows that the normalized rewards increase rapidly

FIGURE 6.2: The episode in relation to the normalized rewards. We can clearly find that the normalized rewards start to converge to the optimal after episode 75, and the value is slightly varying between 488.1 and 503.7.

at the beginning. After episode 75, the normalized rewards start to converge to the optimal value. In the subsequent 425 episodes, the optimal normalized rewards vary slightly between 488.1 and 503.7.

Next, we demonstrate the set-point temperatures in relation to the monthly incentive cost and monthly satisfaction level, as shown in Fig 6.3. It is seen that, with the derived optimal policy, starting at 21°C, the monthly incentive cost first decreases fast until reaching the minimum value of S\$11.74 per occupant at 24°C. Then, from 24°C to 27°C, the cost rises with increasing set-point temperature. Meanwhile, the monthly satisfaction level increases quickly in the beginning and reaches the maximum value with 96.9% per occupant. After that, the satisfaction level begins to decrease with the increment of set-point temperature.

Finally, we show the total monthly cost saving in relation to the set-point temperature in a 400m² office with a different number of occupants. The total monthly

FIGURE 6.3: The set-point temperature in relation to the monthly incentive cost and correlated satisfaction level. At 24°C, the monthly incentive cost reaches the minimum value with S\$11.74 per occupant, and the satisfaction level reaches the maximum value with 96.9% for each occupant.

cost saving C_{Total} is calculated by the following equation:

$$C_{Total} = C_E - C_I, \quad (6.18)$$

where C_E denotes the monthly electricity cost saving of the HVAC systems. To obtain it, we adopt the empiric experiment results obtained from a recent research work [142], which presents the relationship between HVAC system energy saving percentage and set-point temperatures in the hot and humid climate based on the baseline energy consumption at 22°C. We plot the results in Fig. 6.4 and use them to calculate the HVAC system electricity cost saving at different set-point temperatures. To derive C_I , which represents the total monthly incentive cost. To derive it, we use the results in Fig. 6.3 to calculate the total monthly incentive expenditure for all occupants with different set-point temperatures. Next, we will adopt the following fundamental calculation to get the monthly total cost saving by increasing the set-point temperature from 22°C to 24°C for a 400m² office.

- *Monthly Electricity Cost Saving of HVAC Systems:* Based on the BCA's annual report [143], the estimated average energy consumption of HVAC system for a typical office building is $0.12\text{kWh}/\text{m}^2$. We assume that occupants spend 10 hours per day, 22 days per month in this office, then, the monthly HVAC system energy consumption is $10,560\text{kWh}$. Following the electricity tariffs [144] in Singapore, which is S\$0.2 per kWh, we can get the monthly electricity cost is S\$2,112. From Fig. 6.4, compared to the baseline 22°C , the HVAC system energy saving by increasing to 24°C is 23.6%. Thus, the monthly electricity cost saving of the HVAC system is S\$498.4.
- *Total Monthly Incentive Cost for All Occupants:* According to ASHRAE Standard 62.1 [145], the desired occupancy density is 20m^2 per person in an office building, which results in 20 occupants in this 400m^2 office. Based on the derived results in Fig. 6.3, the average monthly incentive cost for each person is S\$11.74. As a result, we calculate the total monthly incentive cost for 20 occupants to be S\$234.8.

With Eq. (6.18), we obtain the total monthly cost saving of S\$263.6 for this 400m^2 office with 20 occupants, by increasing the set-point temperature from 22°C to 24°C . However, in the real world, the occupancy density is generally lower than the ASHRAE Standard 62.1 [145]. Therefore, we conduct the experiments with a different number of occupants from 20, 25, 30, 35 to 40, and then plot the results in Fig. 6.5. From the figure, we can clearly observe that the total cost saving decreases with increasing number of occupants. In addition, we notice that when the number of occupants is 20, 25 and 30, the cost saving increases with the incremental of set-point temperature, while when the number of occupants is 35 and 40, the cost saving starts to decrease above 24°C . Moreover, below 23°C , our solution almost cannot achieve any cost saving except the situation with 20 occupants. This can be explained as that when increasing the set-point by 1°C , the electricity energy saving is a single event, but the total incentive cost is proportional to the number of occupants and can offset or override the energy saving. Furthermore, based on Fig. 6.3, the estimated occupants' satisfaction can maintain at the higher level, such as 96.6%, 96.9% and 95% at 23°C , 24°C and 25°C , respectively.

In summary, our proposed incentive approach has great potential in helping building owners to reduce the HVAC energy consumption and to save the electricity bill,

FIGURE 6.4: The set-point temperature in relation to the HVAC system energy saving measured in the hot and humid climate with the baseline set-point temperature at 22°C.

while maintaining occupants' satisfaction levels. In addition, we find that the preferred set-point temperature for people living in the hot and humid climate (e.g., Singapore) is 23° or 24°.

6.4.3 Case Study

To further evaluate the system performance and calculate the potential energy cost saving benefit of the iTCM system, we conduct an ongoing case study that involves a specific office building [146] in Singapore as the testbed environment to verify our proposed learning-based economical model in a more realistic setting. The detailed building information is listed in Table 6.1.

In the initial phase, for simulating the users' feedback and actions under different set-point temperatures, we adopt our derived incentive policy in Fig. 6.3, which is based on the collected data from 20 students and 10 staff volunteers for three weeks

FIGURE 6.5: The set-point temperature in relation to the total cost saving, with different number of occupants. We can observe that when there are 40 occupants in the 400m² office, the total cost saving is quite limited. However, if there are 20 occupants in the same office. Our solution can saving significant cost by increasing the set-point temperature to 25°C and 26°C.

period. For evaluating the cost saving, we adopt the same two parameters described in the previous section: average energy consumption of HVAC and electricity tariffs in Singapore, which are 0.12kWh/m² and S\$0.2 per kWh, respectively. Also, we use the same variation of the HVAC systems energy saving in relation to the set-point temperatures, which is presented in Fig. 6.4.

We calculate the annual cost saving of this building using the aforementioned parameters. The total monthly energy consumption of HVAC systems is 23,943.5kWh with current set-point temperature 23°C. We consider two interesting scenarios: 1) increasing the set-point temperature by 1°C; and 2) increasing the set-point temperature by 2°C.

- When increasing the set-point by 1°C from 23°C to 24°C, the energy saving of HVAC systems is 11.4%, which is estimated from the Fig. 6.4. Since the total monthly energy consumption of the HVAC system at 23°C is 23,943.5kWh,

TABLE 6.1: Detailed Building Information

Building Type	Office Building
Building Name	Advanced Digital Sciences Center
Building Location	Singapore University of Technology and Design (SUTD), Singapore
Building Area	824.5m ²
Building Staff Number	40
Current Set-Point Temperature	23°C
Staff Working Hours	9:00 AM - 8:00 PM

we can get the monthly energy saving is 2,729.6kWh. Following the electricity tariffs in Singapore, which is S\$0.2 per kWh, we can get the monthly electricity cost saving is S\$545.9. Based on our incentive policy in Fig. 6.3 at set-point 24°C, we know that the average monthly incentive cost for each staff at 24°C is S\$11.74. There are 40 staffs in this office building. Then, we can get the total average monthly incentive cost is S\$469.6. Finally, we can obtain the monthly total cost saving is $545.9 - 469.6 = \text{S\$}76.3$, and the corresponding annual total cost saving will be S\$915.6.

- When increasing the set-point by 2°C from 23°C to 25°C, the energy saving of HVAC systems is 21.3%, which is estimated from the Fig. 6.4. This time, we can get the monthly energy saving is 5,099.9kWh. With the S\$0.2 per kWh electricity tariffs in Singapore, the monthly electricity cost saving is S\$1,020.0. Similarly, based on the Fig. 6.3, we can get the average monthly incentive cost for each person is S\$16.52 at set-point 25°C. Then, we can get the total average monthly incentive cost is S\$660.8 for all 40 staffs. Lastly, the monthly total cost saving is $1,020.0 - 660.8 = \text{S\$}359.2$, and corresponding annual total cost saving will be S\$4310.4.

6.5 Digital-Twin Demo

In this section, we introduce the 3D visualized demo website, which is developed to better demonstrate our simulation results. The demo website is a sub component of the iTCM management website. In the current stage, there are two kinds of users: 1) Normal User (Use Case Diagram is shown in Fig. A.3 in Appendix A) and 2) Admin User (Use Case Diagram is shown in Fig. A.4 in Appendix A). Both normal user and admin user can access the demo website. However, only admin user can access the iTCM management website. The detailed State Diagrams are shown in Fig. A.8, Fig. A.9, Fig. A.10, Fig. A.11, Fig. A.12, and Fig. A.13 in Appendix A.

6.5.1 Digital-Twin Technology

The concept of Digital Twins is proposed by *El et al.* [147] in 2018, which aim to create the digital replica of various entities (e.g., processes, systems, people) in the real world, and then use them to build the related virtual world to simulate the dynamics of the real world.

In this thesis, we adopt the Digital-Twin technology to create an abstraction of the thermal control management with the incentive scheme of the physical world to better demonstrate our proposed novel application. Specifically, first, we create the digital replicas of our laboratory and occupants. Then, we define the related properties of each digital replica, such as occupant's thermal comfort sensations, HVAC control, occupant's personal incentive preference, and occupant's behavior. Finally, we integrate the developed virtual world with our designed Actor-Critic interaction algorithm for incentive-based simulation.

6.5.2 Demo Website

In this subsection, we demonstrate the Digital-Twin demo website based on the screenshots, as shown in Fig. 6.6, Fig. 6.7 and Fig. 6.8.

FIGURE 6.6: Screenshot of the demo website: the 3D visualized simulation environment. We create a digital replica of our real-world laboratory. The incentive interactions are simulated in this virtual environment.

First, Fig. 6.6 shows the 3D visualized simulation environment, which is designed based on the floor-plan of our real-world laboratory. All occupants' digital replicas behave based on our pre-defined behavioral properties (e.g., thermal comfort preferences). Next, Fig. 6.7 shows the variation in incentive cost changes with the simulation timesteps. In the beginning, the RL agent prefers to offer expensive gifts to occupants for ensuring their satisfaction levels. During the learning process, the RL agent attempts to gradually decrease the cost of incentives to seek the trade-off between the building energy-saving costs and the incentive costs. When the training converges, the RL agent learns the optimal incentive policy to minimize the incentive costs while maintaining occupants' satisfaction levels. At last, Fig. 6.8 shows the variation in satisfaction level changes with the simulation

FIGURE 6.7: Screenshot of the demo website: the incentive costs vary with the simulation timesteps. Our approach can efficiently learn the economic model to maintain occupants' satisfaction levels with the lowest incentive costs.

timesteps. Simulation results show that our approach can maintain occupants' average satisfaction levels around 84%.

In summary, our simulation results demonstrate the possibility of applying the Deep Reinforcement Learning (DRL) technique for human behavioral study. Moreover, our approach has the great potentials to motivate occupants' behavioral changes to form the sustainable energy-saving habits.

FIGURE 6.8: Screenshot of the demo website: the satisfaction level varies with the simulation timesteps. Our approach can maintain occupants' average satisfaction levels around 84%.

6.6 Conclusion

In this chapter, we demonstrate an innovative deep reinforcement learning based application to encourage and motivate energy-saving habits of occupants for greener, smarter, and healthier building. First, formulate the optimization problem by following the Markov Decision Process (MDP). Then, we adopt the Actor-Critic framework to design the algorithm to solve the formulated problem. After that, we analyze the simulation results and show the effectiveness of the proposed incentive-based approach. Finally, we demonstrate our developed 3D visualized demo website by using the Digital-Twin technology.

In the next chapter, we will summarize this thesis.

Chapter 7

Summary and Future Work

In this chapter, we summarize this thesis, discuss the limitations and share our future work.

7.1 Summary

This thesis has presented the developed intelligent Thermal Comfort Management (iTCM) System to transform the thermal comfort model and control in the tropics by using the emerging machine learning techniques. Specifically, we first introduce the overall design of the iTCM system and the self-collected iTCM datasets. We then use the deep learning techniques to develop the learning-based thermal comfort models and intelligent thermal control. We finally design and implement a novel iTCM system application on human behavioral study. The details are summarized as follows.

7.1.1 iTCM System & Dataset

In this thesis, we propose to build a system to assist the existing Building Management System (BMS) to better manage occupants' indoor thermal comfort.

In Chapter 3, we first build the intelligent Thermal Comfort Management (iTCM) system. It adopts the wireless sensor network (WSN) to collect environmental data

and utilizes the wearable device for vital sign monitoring. In addition, a cloud-based back-end system, with cost-efficient deployment fees, is developed for data management and analysis. To verify the performance, we benchmark the iTCM system by using the pressure test. Then, with the iTCM system, we conduct the data collection experiments for one year and create the iTCM datasets for the research on thermal comfort modeling and thermal control. Moreover, we describe the detailed experiment procedures and collected parameters of the iTCM datasets.

7.1.2 Thermal Comfort Modeling and Thermal Control

In this thesis, we propose to adopt the deep learning techniques to develop the next-generation thermal comfort models for the iTCM system to better manage the indoor thermal environment.

In Chapter 4, we consider to adopt the Deep Neural Network (DNN) and Deep Transfer Learning (DTL) for thermal comfort modeling, respectively. First, we develop the DNN-based approach, named as Intelligent Thermal Comfort Neural Network (ITCNN). To evaluate the performance of ITCNN, we compare it with the PMV model, three traditional white-box machine learning approaches and three classical black-box machine learning methods. Our results show that four black-box methods achieve better performance than the PMV model and the three white-box approaches. The ITCNN achieves the best performance and outperforms the PMV model by on average 13.1% and up to 17.8%. Second, we develop the DTL-based approach, named as Heterogeneous Transfer Learning (HTL) based Intelligent Thermal Comfort Neural Network (HTL-ITCNN) to address the two drawbacks of the PMV model and ITCNN: modeling parameter inadequacy and modeling data inadequacy. For the first issue, we add more relevant factors as the modeling features except for the six PMV parameters. Due to the flexibility of learning-based approaches, newly found thermal comfort parameters can be appended to extend the number of modeling features. For the second issue, to mitigate the impact of the data inadequacy issue, we adopt the deep transfer learning techniques to train the thermal comfort model, where the model training would benefit from the transferred knowledge from the existing datasets. Due to the heterogeneity of the features among different datasets, we follow the HTL concept to conducting effective knowledge transfer among heterogeneous domains,

which are the different but related datasets with varied features. To validate HTL-ITCNN, we conduct five-month data collection experiments and build our datasets. With the HTL-based two-stage learning paradigm, the experimental results show that the accuracy of HTL-ITCNN outperforms the PMV model by on average 73.9%. Besides, we verify the impacts of newly added features and knowledge transfer on model performance. Moreover, we demonstrate the enormous potential of personal thermal comfort modeling research.

In Chapter 5, we consider to apply the cutting-edge Multi-Agent Deep Reinforcement Learning (MADRL) technique to develop the more intelligent multi-zone adaptive HVAC control approach. First, compared to the classic Predicted Mean Vote (PMV), we utilize our previously developed Deep Neural Network (DNN) based model for achieving better thermal sensation prediction accuracy. Next, we formulate the optimization problem of the multi-zone HVAC control operations as a Markov Decision Process (MDP). Then, we adopt the Multi-Agent Deep Deterministic Policy Gradients (MADDPG) approach to solve the formulated problem and design the optimization algorithm. Finally, we build the multi-zone thermal control simulation environment for performance evaluation by using professional TRNSYS software. Simulation results show that our approach can efficiently learn the optimal control policy for each zone with different thermal conditions. Besides, compared to the widely used rule-based heuristic control method, our approach can achieve from 2.8% up to 15.4% energy saving under different thermal comfort demands. Moreover, in comparison with other learning-based methods, our approach performs the best energy-saving performance.

7.1.3 iTCM System Application

In this thesis, we design a novel human behavioral study based on the iTCM system.

In Chapter 6, we consider to adopt the deep reinforcement learning technique to develop an economic model for the incentive-based human behavioral study. It is a gamification approach to encourage human behavioral changes to form energy-saving habits for greener, smarter, and healthier building. First, we formulate the optimization problem to maximize the total cost saving by seeking the balance between the incentive costs and HVAC energy cost saving, while maintaining occupants' satisfaction levels. Then, we adopt the classic Actor-Critic algorithm to

solve the formulated problem. Next, our simulation results show the potential of our proposed approach. Finally, to better demonstrate this novel application, we use the Digital-Twin technology to develop the 3D visualized demo website.

7.2 Discussions and Future Work

In this section, we discuss the limitations of our work at the current stage and share our future actions.

7.2.1 Wearable Devices of iTCM System

In iTCM system, we innovatively adopt the wearable devices (e.g., wristband) to measure building occupants' vital signs (e.g., heart rate). The limitation of these devices is their measurement accuracy, which has been questioned. Recent experiments and testing [148, 149] show that, in comparison with the clinic electrocardiography (ECG) sensors, the photoplethysmography (PPG) sensors used by wearable devices (e.g., wristband, smartwatch) have 1% to 9% error rate. The Microsoft Band, which is used in our system, has the mean absolute percentage error of 4.8% for the heart rate sensor [148].

In the future, we will pay close attention to the commercial wearable products to find a more advanced replacement for Microsoft Band 2. Also, we believe that wearable devices will be ever widely used for personal health monitor and will follow closely the technological innovations in this area.

7.2.2 iTCM Datasets & Thermal Comfort Modeling

In this thesis, we adopt the Deep Neural Network (DNN) to model the thermal comfort for iTCM system. First, our ITCNN approach achieves the best prediction performance over various classic white-box and black-box machine learning methods. Then, we apply the concept of transfer learning to develop HTL-ITCNN upon ITCNN. HTL-ITCNN can achieve better prediction performance than ITCNN. However, we aware that the size of our dataset is still relatively small. Consequently, the prediction accuracy of ITCNN and HTL-ITCNN could be affected.

Moreover, our results show that the random forest algorithm benefits from the collected more modeling features and achieves better prediction performance than our HTL-ITCNN.

In the future, we will first work with our university administration to conduct large-scale data collection experiments to acquire more data to extend the iTCM datasets, and then optimize the design of HTL-ITCNN or develop new learning paradigm to improve the thermal comfort prediction accuracy further and aim to beat the random forest algorithm. Moreover, we will keep working on the research direction of the personal thermal comfort modeling.

7.2.3 Thermal Control for Multi-Zone Buildings

In this thesis, we adopt the Multi-Agent Deep Reinforcement Learning (MADRL) techniques to develop the intelligent HVAC control for the iTCM system. Results show that compared to the single-agent thermal control, multi-agent thermal control is a more reasonable way to solve the real-world control optimization problem. However, first, since TRNSYS software cannot simulate the variation in human vital signs, it is a pity that we cannot apply the advanced HTL-ITCNN for thermal comfort prediction. Second, although TRNSYS is a professional building simulation software, the performance verified in this simulation-based environment may still have significant biases in comparison with that of the real world.

In the future, first, we plan to survey existing research works to explore the possible software or frameworks which could be used to simulate the human vital signs for applying our developed advanced HTL-ITCNN to the thermal control. Second, we will collaborate with our university and related government institutions to build real-world testbed to evaluate our solution.

7.2.4 iTCM System Application

For this novel application, we innovatively use the Deep Reinforcement Learning (DRL) technique to derive the economic model to quantify the economic value to the building occupants, and use it to explore the trade-off between cost saving of

HVAC systems and incentive expenditure while maintaining occupants' satisfaction level. However, we note that this application has the following two limitations:

- The simulation environment for RL training process only follows a statistical distribution based on a small number of surveys. As a result, the prediction accuracy of the economic model could be affected. In addition, the transition dynamics of the environment may not precisely reflect the invoked reactions of occupants for various incentive offers and thus may produce biased incentive policy.
- The cost saving calculation is based on some estimated parameters (e.g., the average energy consumption of the HVAC systems per square meters for a typical office building). Also, at this stage of the study, since we have yet to conducted in-field experiments in the introduced office building of case study, participants' real satisfaction levels cannot be presented and discussed for the time being.

In the future, we plan to work with the human behavioral study experts in our university to improve the existing questionnaire surveys. We aim to use machine learning techniques to build a more precise simulation environment for our RL-based economic modeling and human behavioral studies.

7.2.5 iTCM System Implementation

To better integrate with the existing BMS, we propose to the following three stages to implement our iTCM system in practice.

- Stage 1: Collect data from a practical environment, and then use the collected data to develop a basic thermal comfort model. Alternatively, we can use the model developed based on our iTCM dataset.
- Stage 2: System continues to collect data. Scheduler can be developed to update the thermal comfort model periodically, such as every three months.
- Stage 3: When the model updating is processing, system does not need to train a model from scratch. Instead, system can use the weights of the

previous model for initialization and model update. Then, system only uses the newly collected data for model training.

In this way, models can be updated and adjusted in an online to adapt to any changes (e.g., some occupants leave, and new occupants move in) of the environment, which is possible to be implemented in the real-world buildings. By our approach, we can develop a practical and human evaluated system.

7.2.6 Conclusion of Future Work

In the future, we will collaborate with the Building & Construction Authority (BCA) Singapore to build the real testbed for solution verification. The ultimate goal is to integrate our iTCM system with the Building Management System (BMS) of the testbed and conduct long-term experiments to verify our proposed DNN-based thermal comfort models, MADRL-based HVAC control approach, and DRL-based economic model for realistic thermal comfort improvement, HVAC energy management, and building energy saving. Beyond this, we will explore the integration of thermal comfort model and control with other parts of the smart grid such as demand-side management, EV charging, energy storage system.

Appendix A

iTCM System & Dataset

A.1 Mobile App UI Design and Workflow

The overall and workflow of mobile App UI design is shown in Fig. [A.1](#).

A.2 Microsoft Band 2 Sensor Information

The detailed sensor information of Microsoft Band 2 is listed in Table [A.1](#).

A.3 Database Design

The database table design and relationship are shown in Fig. [A.2](#).

A.4 Use Case Diagrams

The Use Case Diagram of normal user is shown in Fig. [A.3](#).

The Use Case Diagram of admin user is shown in Fig. [A.4](#).

A.5 State Diagrams

The State Diagram of iTCM management front-end (mobile app and website) is shown in Fig. [A.5](#).

The State Diagram of user profile function (mobile app and website) is shown in Fig. [A.6](#).

The State Diagram of user reward function (mobile app and website) is shown in Fig. [A.7](#).

The State Diagram of iTCM District Management (website only) is shown in Fig. [A.8](#).

The State Diagram of iTCM District-Company Management (website only) is shown in Fig. [A.9](#).

The State Diagram of iTCM District-Company-Building Management (website only) is shown in Fig. [A.10](#).

The State Diagram of iTCM District-Company-Building-Occupant Management (website only) is shown in Fig. [A.11](#).

The State Diagram of iTCM District-Company-Building-ControlSystem Management (website only) is shown in Fig. [A.12](#).

The State Diagram of iTCM District-Company-Building-Sensor Management (website only) is shown in Fig. [A.13](#).

FIGURE A.1: The User Interface (UI) and workflow of both Android and iOS mobile applications.

TABLE A.1: Sensor list of Microsoft Band 2

Sensor Type	Sensor Description	Measured Parameters
Ultraviolet (UV) sensor	Get a snapshot of the ultraviolet light level on the environment.	UV Index Level
Skin temperature sensor	Used to measure user's skin temperature when wearing the band.	Skin Temperature
Microphone	Record voices/sounds and also used to speak to Cortana.	Sound/Voice
Optical heart rate sensor	Band continuously monitors and reports user's current heart rate.	Heart Rate and RR Interval
3-axis accelerometer & Gyrometer	The accelerometer/gyrometer in the Band detects motions. This info is used to calculate statistics like number of steps taken and estimate how many burned calories.	Acceleration X, Acceleration Y, Acceleration Z, Angular Velocity X, Angular Velocity Y, Angular Velocity Z, Total Steps, Activity Motion Type, Distance, Band Contact State, Calories, Flights Ascended, Flights Descended, Rate, Stepping Gain, Stepping Loss, Steps Ascended, Steps Descended, Total Gain, and Total Loss
Galvanic skin response sensor	Used to measure the conductivity of user's skin between the GSR sensor.	Skin Resistance
Barometer	Used to detect changes in atmospheric pressure to determine the vertical distance you travel.	Air Pressure and Air Temperature
Ambient light sensor	The ambient light sensor is used to adjust the touchscreen brightness automatically.	Ambient Brightness

FIGURE A.2: The database table design and relationship.

FIGURE A.3: Use Case Diagram of normal user (mobile app and website).

FIGURE A.4: Use Case Diagram of admin user (website only).

FIGURE A.5: State Diagram of iTCM management front-end (mobile app and website).

FIGURE A.6: State Diagram of user profile function (mobile app and website).

FIGURE A.7: State Diagram of user reward function (mobile app and website).

FIGURE A.8: State Diagram of iTCM District Management (website only).

FIGURE A.9: State Diagram of iTCM District-Company Management (website only).

FIGURE A.10: State Diagram of iTCM District-Company-Building Management (website only).

FIGURE A.11: State Diagram of iTCM District-Company-Building-Occupant Management (website only).

FIGURE A.12: State Diagram of iTCM District-Company-Building-ControlSystem Management (website only).

FIGURE A.13: State Diagram of iTCM District-Company-Building-Sensor Management (website only).

Awards and Publications

Awards

- [Best Paper Awards] **Weizheng, Hu**, Weiwen Zhang, Han Hu, and Yonggang Wen. “Wearable computing going green: Energy-optimal data transmission for multi-sensor wearable devices.” *In Communications and Networking in China (ChinaCom), 2015 10th International Conference on*, pp. 532-537. IEEE, 2015. DOI: 10.1109/CHINACOM.2015.7497996

Journal Articles

- Wei Zhang, **Weizheng, Hu**, and Yonggang Wen. “Thermal Comfort Modeling for Smart Buildings: A Fine-Grained Deep Learning Approach” *IEEE Internet of Things Journal*, 2018, vol. 6, no. 2, pp. 2540-2549, April 2019. DOI: 10.1109/JIOT.2018.2871461
- **Weizheng, Hu**, Yonggang Wen, Kyle Guan, Guangyu Jin, and King Jet Tseng. “iTCM: Towards Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings” *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4164-4177, Oct. 2018. DOI: 10.1109/JIOT.2018.2861831
- **Weizheng, Hu**, Wei Zhang, Han Hu, Yonggang Wen, and King-Jet Tseng. “Toward Joint Compression-Transmission Optimization for Green Wearable Devices: An Energy-Delay Tradeoff.” *IEEE Internet of Things Journal*, vol. 4, no. 4, pp. 1006-1018, Aug. 2017. DOI: 10.1109/JIOT.2017.2704605

Conference Proceedings

- **Weizheng, Hu**, Weiwen Zhang, Han Hu, and Yonggang Wen. “Wearable computing going green: Energy-optimal data transmission for multi-sensor wearable devices.” *In Communications and Networking in China (ChinaCom), 2015 10th International Conference on*, pp. 532-537. IEEE, 2015. DOI: 10.1109/CHINACOM.2015.7497996
- **Weizheng Hu**, Yong Luo, Zongqing Lu, and Yonggang Wen. “Heterogeneous Transfer Learning for Thermal Comfort Modeling.” *In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '19)*, pp. 61–70. ACM, 2019. DOI: 10.1145/3360322.3360843

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