Title	スマートホームにおける人間中心のサイバーフィジカルシステムのためのパーソナル熱的快適性モデルの研究
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Doctoral Dissertation

Personal Thermal Comfort Model for Cyber-Physical Human Centric Framework in Smart Homes

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Abstract

The current human society faces many problems, such as greenhouse gas (GHG) emissions, depletion of resources, and aging of the population. Future human centric society is that balances economic advancement with the resolution of social problems, and that is a system that highly integrates cyberspace and physical space using new technologies, such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Artificial Intelligence (AI). In another view, the human centric society (HCS) understood as a smart and skilled operator who performs not only cooperative work with robots but also work aided by machines as and if needed by means of human CPS, advanced human-machine interaction technologies and adaptive automation towards achieving human-automation symbiosis work systems. To realize our future society, it is also essential to look at the mimic of a future society in the field of smart homes, which is the best practice for the viewpoint of system implementation of the CPS approach with human centric module.

The most central place of life and work scenes of HCS is the home environment that provides a safe living environment and comfort for the residents to meet people's physical and psychological needs. Smart Homes use the computation technology, the sensing technology, and the control technology to provide comfort and energy saving. The Cyber-Physical Home System (CPHS) comprises a smart system for a variety of services and applications in the home environment to provide home automation control, especially for the aims of comfortability and energy savings. Thermal comfort is an assessment of one's satisfaction with the environment surroundings. Personal satisfaction of thermal comfort is affected by many factors belongs the human centric domain.

CPS is the core technology to implement the HCS system. There is deep interaction between the cyber world and the physical world. CPHS is one of the most valuable domains for CPS applications. For future HCS system, the human has deep interaction of the cyber world and the physical world. However, several significant problems need to be solved in the CPS-based human centric system, the first is the computation problem, which is current CPS system does not consider the human centric, which leads to the event-

driven task, the usage of time-delay model in the CPS system cannot meet the human demands and needs. The second problem is human centric model is generalized by a group of people, in which the control methods that use this model still cannot achieve the best target set for an individual. The third problem is that the CPHS is successfully verified and implemented, but this system cannot meet the thermal comfort of user preference. Personal thermal comfort should be pointed out to address this problem.

The purpose of this dissertation is to propose a Cyber-Physical Human Centric framework and to implement its Cyber-Physical Human Centric system with the personal thermal comfort model in smart homes domain. To accomplish this purpose, three research objectives in this dissertation are proposed.

First, this dissertation is to propose a Cyber-Physical Human Centric (CPHC) framework by focusing on the deep interaction between the human centric and CPS application, the human centric control, and the implementation of human centric CPS system application. The current CPS model is designed fundamentally for the system of systems, and it does not consider the human factor. Aiming the CPS computation problem, which leads to the consideration of the event-driven task, the usage of the time-delay model in the CPS system cannot meet the mixed requirement of time-driven and event-driven tasks scheduling. To mitigate this problem, I propose a new time task model with two algorithms, i.e., a mixed time cost and deadline first (MTCDF) algorithm, and a human-centric MTCDF algorithm into the Cyber-Physical Human Centric (CPHC) Framework.

Second, the control module is one of the essential modules in the CPS system to ensure the entire system operates according to the achievable target set. Most of the CPS system is designed to meet a single target value or multiple target values of the system. Although many control methods, e.g., conventional PID and MPC, are proposed not only to minimize the processing time of the controller to achieve the target set but also to ensure the high accuracy of the controller. However, those control methods do not consider the human centric module due to the difficulties of modeling human factors. As mentioned in the previous research works, the human factor model is generalized by a group of people, in which the control methods that use this model still cannot achieve the best target set. In this dissertation, a generalized thermal comfort model is focused first. Based on the collected data, a personal thermal comfort (PTC) model

is derived. Since the PTC is a comprehensive evaluation influenced by complex factors and random variables, it is difficult to apply the results in the real environment of the smart homes. With the development of IoT technology, a wearable device becomes our daily objects and also have the advantage of connected to the service platforms. This means that the measured data can be personalized. In this dissertation, a well-known wearable device is used to measure human heart rate, then the heart rate, heat sensation, environmental parameters, and so on as inputs into the artificial neural network (ANN) model for predicting the PTC model. In this dissertation, the PTC model is proposed and extend the existing energy efficient thermal comfort control (EETCC) system to achieve a better thermal comfort sensation while saving more energy. Through these, the differences between system computation and human needs are determined, then provide necessary for improving the personal thermal comfort control system. Besides that, the physiology parameter from the heart rate is well-studied, and its correlation with the environmental factors, i.e., PMV, airspeed, temperature, and humidity, are deeply investigated to reveal the human thermal comfort level of the existing system in the smart home environment.

Third, although the EETCC system is successfully verified and implemented in the iHouse environment, the thermal comfort of a resident does not be considered by the EETCC system. Notably, the personalization character of the PTC model with an artificial neural network (ANN), long short-term memory (LSTM) deep learning technique, which is not considered either. In this dissertation, the challenges of the EETCC/PTC are focused on achieving both high accuracy and high energy efficiency. In this way, the CPHC framework can be verified for its implementation with a human centric module. And this dissertation the improving the personal thermal sensation and reducing energy consumption through the experiments with CPHC system Implementation of smart home in the winter season.

Keywords: human centric society, cyber-physical system, smart homes, time task model, cyber-physical human centric framework, personal thermal comfort, energy efficient and thermal comfort control, heart rate predication, artificial neural networks

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List of Abbreviations

ANN	Artificial Neural Networks
CPHCS	Cyber-Physical Human Centric Systems
CPHS	Cyber-Physical Home System
CPS	Cyber-Physical Systems
CPSS	Cyber-Physical Social System
DE	Discrete-Event
ECG	Electrocardiogram
EDF	Earliest Deadline First
EETCC	Energy Efficient and Thermal Comfort Control
HCS	human centric society
HF	High Frequency
HRV	Heart Rate Variability
HVAC	Heating, Ventilation, and Air Conditioning
ICT	Information and Communications Technology
IoT	Internet of Things
LF	Low Frequency
MDTH	Mixed deadline first, time cost and human centric
MPC	Model Predictive Control
MTCDF	Mixed time cost and deadline first
PID	Proportional Integral Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PTC	Personal Thermal Comfort
PTIDES	Programming Temporally Integrated Distributed Embedded Systems
RM	Rate Monotonic

RTS	Real-time System
SCL	Subjective Comfort Level
SoS	System of Systems
TDM	Time Delay Model
TTM	Time Task Model

List of Symbols

Chapter 3

$T_{physical}$	a set of physical time
T_a	arrival time
T_d	deadline time
$T_{logical}$	a set of logical time
T_e	execute time
T_{model}	a set of model time
T_{delay}	time delay
T_s	start time
T_f	finished time
T_w	waiting time
$Prio$	event priority
$Human$	human centric value created by framework calculate
p_i	a dependency relation (edge)
$T_{i,j}$	the j time task of i platform
$S_{i,j}$	the state of the elements
$V_{i,j}$	value of the time task $T_{i,j}$ with state $S_{i,j}$
Γ	the optimal scheduling index

Chapter 4

PMV	Predicted Mean Vote index
PPD	Predicted Percentage Dissatisfaction
M	metabolic rate
W	effective mechanical power
P_a	water vapor partial pressure
T_r	room air temperature

f_{cl}	clothing surface area factor
t_{cl}	clothing surface temperature
$\bar{T}_r$	mean radiant temperature
h_c	convective heat transfer coefficient
R_{clo}	clothing surface radiative energy
C_{clo}	clothing surface convection energy
I_{clo}	clothing insulation
v_r	relative air velocity
T_i	surface temperature of wall i
Chapter 5	
HR_m	denote the measured heart rate
HR_{rest}	the heart rate at rest
AGE	the user's age
$E_{aircond}$	energy consumption of HVAC
COP	the coefficient of performance
t_{start}	the start time of the implementation
t_{end}	the end time of the implementation
$Q_{aricond}$	heat gain due to air conditioner

Chapter 1

Introduction

In society up to now, we have to face many challenges that endanger the survival of humankind such as global environmental problems, growing economic disparity, and the depletion of resources. Many countries facing critical social problems, such as the declining birthrate and aging population, labor shortage, rural depopulation, and increased fiscal spending. The human centric society with Cyber-Physical Systems, Internet of Things, and Artificial Intelligence as the core technology community is considered to be the most effective way to solve these problems.

Future society is a human centric society. In [1] , Thoma, et al. have proposed that the new Human Centric Intelligent Society, which results from these social problems will connect information from many different sources across the physical and virtual worlds, using a human centric information and communication technology (ICT) system to connect both physical and virtual worlds. Besides that, Srivastava, et al. [2] have surveyed the important opportunities in human centric sensing that identifies those said social problems and describes the emerging solutions to these social problems. Meanwhile, Bryson and Theodorou in [3] have reviewed the necessity and tractability of maintaining human control and its related mechanisms by which such human control can be achievable. They also claimed that what makes the human control problem both most interesting and most threatening are that achieving consensus around any human-centered approach requires at least some measure of agreement on broad existential concerns.

On the other hand, Chujo, et al. [4] have proposed a Human Centric Engine system that is dedicated for mobile phone by aiming for the development of ubiquitous computation. In the future society, Romero, et al. [5] conclude the need of the human centric society by presenting early concepts and future projections of the so-called Operator 4.0, understood as a smart and skilled operator who performs not only cooperative work with robots but also work aided by machines as and if needed by means of human Cyber-Physical Systems (CPS), advanced human-machine interaction technologies and adaptive automation towards achieving human-automation symbiosis work systems. Through these discussions, I could conclude that the elements of CPS and human centric society are essential to build our future society.

To realize our future society, it is also important to look at the mimic of a future society in the field of smart homes, which is the best practice for the viewpoint of system implementation of the CPS approach with human centric module. In smart homes, a home is the most crucial place that provides a safe living environment and comfort for the residents to meet people's physical and psychological needs. It is also a place not only where people gather with families and friends, but also people can relax, do any activities, obtain entertainment and enjoyment, and go to sleep. Besides that, smart homes that represent a branch of ubiquitous computing involves incorporating smartness into houses for comfort, healthcare, safety, security, and energy conservation. Edward Lee [6] has introduced the concept of CPS, Yuto, et al. [7] have extended this concept to the Cyber-Physical Home System (CPHS), which comprises a smart system for a variety of services and applications in the smart home environment to provide home automation control, especially not only for the aim of comfortability, but also energy savings. Today, many active researches on CPHS have led to a plethora of smart home system solutions for various application domains that influence our daily life and the way we live. One example of CPHS applications is the thermal comfort with energy saving service, in particular the Energy Efficient Thermal Comfort Control (EETCC) system [7], which operates and controls the home appliances, devices, sensors, and actuators in a timely manner assists residents to live on their own comfortable, convenient, relax, restful, and pleasant. Since smart homes provide ambient environmental conditions for the residents to live, this also means that the residents are the most important factor for the implementation of human-like system implementation. In other words, the residents have a strong interaction with all the smart home systems and their surrounding environments.

Unlike the previous works on smart homes and human interaction, Ooi, et al. [8] have presented an adaptive Model Predictive Control (MPC) based controller that is integrated into the existing EETCC system for the CPHS environment. One of the significant this work is that the adaptive MPC based controller can monitor the temperature in a real-time manner by using the sensed raw environmental data from the experimental house, iHouse. Meanwhile, Chen, et al. [9] have proposed a human-centric smart home energy management system that integrates ubiquitous sensing data from the physical and cyber spaces to discover the patterns of power usage and cognitively understand the behaviors of human beings. The relationship between physical and cyber spaces is established to infer residents demands for electricity dynamically, and then the optimal scheduling of the home energy system is triggered to respond to both the residents requirements and electricity rates.

In summary, the intensive study and implementation of human centric system for smart home environment are still limited nowadays.

1.1 Research Background

1.1.1 Smart Homes and its Implementations

In 1984, smart home is firstly used by the American Association of House Builders (now National Association of House Builders). Smart homes [10] is a home-like environment that possesses ambient intelligence and automatic control, in which it responds to the behavior of residents with various facilities. Alam, et al. [11] have proposed the smart homes provide comfort, health care, and security services to their inhabitants. Comfort and health care services can be provided locally as well as remotely. Smart Homes are home environments that incorporate ambient intelligence and automatic control that reacts to the behavior of its residents with various home appliances and devices. Smart Homes are one of the CPS application domains. The smart home is one of the key technologies to solve the problem of an aging society. In the future, a smart home will integrate into daily life with dedicated artificial intelligence, computational power, communication skills, monitoring, and controlling abilities needed to improve everyday activities. The interaction between people and home appliances will be devoted to improving comfort, healthcare, safety, security, and energy savings [12, 13]. There are numerous researchers focus on a smart home in different domains. Chan, et al. [14] have reviewed a selection of projects in developed countries on smart homes examining the various technologies available. Future perspectives on smart homes as part of a home-based health care network are presented facing an aging world, maintaining good health and independence for as long as possible is essential. In [15], old aging people application is proposed in smart home. In [16], smart home is an application of ubiquitous computing in which the home environment is monitored by ambient intelligence to provide context-aware services and facilitate remote home control. In [17], the concept of the smart home investigates technologies for smart homes, in which advanced technological systems that allow the automation of domestic tasks are developing rapidly. In [18], the authors have proposed a holistic framework that incorporates different components from Internet of Things (IoT) architectures introduced, to integrate smart home objects efficiently in a cloud-centric IoT based solution to contribute towards narrowing the gap between the existing state-of-the-art smart home applications and the prospect of their integration into IoT enabled the environment. In [19], data transmissions within the smart home system are secured by asymmetric encryption schemes with secret keys being generated by chaotic systems. In the smart home thermal comfort area, Zhu, et al. [20] have proposed a novel hybrid intelligent control system to manage space heating devices in a smart home with advanced technologies to save energy while to increase the thermal comfort level. Lim and Tan [21] have compared to the conventional temperature control system, a thermal comfort control (TCC) system can provide better human comfort. Due to system complexity, the TCC system is usually designed as a hybrid system. To ensure the design of a highly energy efficient thermal comfort control, the authors address the time delay modeling issues.

There is the current implementation of the smart home environments, one is Aware Home project [22], built-in 1999 from Georgia Tech. It is a living laboratory for research in ubiquitous computing for everyday activities. Another one is the experiment environment, iHouse that is used in this dissertation is located at Nomi City, Ishikawa Prefecture, Japan. iHouse stands for Ishikawa, internetted, inspiring, and intelligent house, which is an advanced experimental environment for future smart homes in Japan, and it has been implemented according to Standard House Design by Architectural Institute of Japan. It is a conventional two-floor Japanese style house featuring more than 300 sensors, home appliances, and electronic house devices that are connected using ECHONET Lite version 1.1 and ECHONET version 3.6.2. An ECHONET Lite system incorporates groups of devices with the same management of properties, security, and so on. Therefore, the largest area that ECHONET Lite can manage is referred to as a domain. A domain will be specified as the range of controlled resources (home equipment, appliances and consumer electronics, sensors, controllers, remote controls, etc.) present within the network range determined by ECHONET Lite. A system is defined as that which performs communication and linked operations between devices and the controllers that monitor/-control/operate them and between devices themselves. A system lies within one domain and does not extend over a number of domains. A domain includes one or more systems. Thus, the same device or controller can exist in more than one system. When connecting a system to another system lying outside the domain, an ECHONET Lite gateway is used as an interface. Through this ECHONET, iHouse can be developed for the research of smart home environment monitoring, energy savings, human thermal comfort, and so on.

1.1.2 Cyber-Physical Systems and its Applications

Cyber-Physical Systems (CPS) are defined as tight integration of computation, com- munication, and control with deep interaction between physical and cyber elements in which embedded devices, such as different sensors and actuators, are wireless or wired networked to sense, monitor and control the physical world [23, 24]. Jifeng [25] has interpreted the CPS as controllable, credible, and scalable networked physical equipment systems, which is in-depth integration of computation, communications, and control ability based on environmental perception. CPS enables the cyber world to interact with the physical world to monitor and control the intended parameter on a real-time basis. The systems of CPS represent the intersection of several system trends, such as real-time embedded systems, distributed systems, control systems, and networked wireless systems. Liu, et al. [26] have reviewed the most critical part is the physical system and the core part is the cyber system. In recent years, CPS has enlivened many fields of manufacturing, automotive systems, military systems, smart homes, smart transportation systems, power generation and distribution, energy conservation, heat ventilation air-conditioning (HVAC) system, aircraft, and smart city. In a typical CPS application, sensor nodes collect information from the physical world as a source of CPS input. Upon receiving the input information, a controller makes a corresponding decision by computing, and actuators perform a relevant action in the physical world through the closed-loop feedback. The significance of CPS is to connect physical devices to the Internet, so that physical devices have five major functions such as computing, communication, precise control, remote coordination, and autonomy. CPS is essentially a network with control properties, but it is different from existing control systems. CPS puts communication on the same footing as computing and control, because the coordination between physical devices in distributed application systems emphasized by CPS is inseparable from communication. CPS's remote coordination ability, autonomy ability, and the type and number of control objects for the internal equipment of the network, especially the network scale far exceeds the existing industrial control network. The National Science Foundation (NSF) believes that CPS will connect the entire world. Just as the Internet has changed human interaction, CPS will change our interaction with the physical world. CPS is the system of systems where its physical and computational resources are strictly interlinked together. In some home domains, Cyber-Physical Home System (CPHS) offers residents to live more comfortably, conveniently, cost effectively, and more securely using the CPS approach. A typical CPHS, where it is comprised of the cyber world, physical world, and the communication network in between them. The control domain, which includes data logging and supervisor controller is part of the cyber world while the sensor domain and actuator domain are part of the physical world. Both cyber and physical worlds can be linked together by networks and communication protocols that are not limited to wired networks but also wireless networks. One example of CPHS systems is the implementation of Energy Effcient and Thermal Comfort Control (EETCC) system [7], in which the home appliances, devices, sensors, and actuators are synergized in a timely manner to assist people to live on their own comfortable, convenient, relax, restful, and pleasant. In the viewpoint of Japan, JEITA (Japan Electronics and Information Technology Industries Association) defines CPS is a wide range of data is collected from the physical world via sensor networks, analyzed and transformed into knowledge in cyberspace using big data processing technologies and other tools to create information and value that will energize the industry and solve social problems. As shown in Figure 1-1. In housework support smart houses area. Multiple menu suggestions provided based on refrigerator contents, coordination with microwave for automatic adjustment of cooking time, etc. In addition to cleaning robots, laundry robots divide clothing up, automating laundry detergent input and menu selection. Household robots help with child-raising, look after pets and water the plants. Combining solar power, batteries and electric cars, etc., not only save energy in daily life but also secure power in times of emergency.

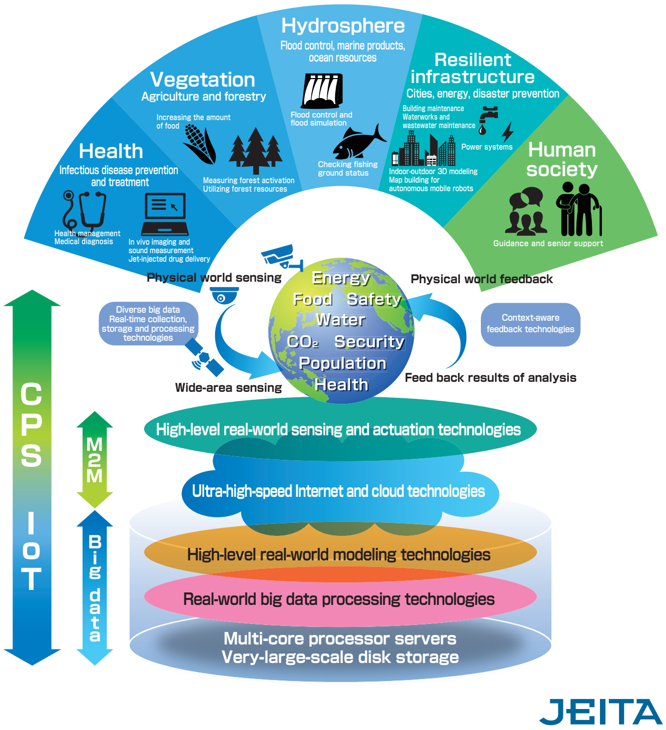


Figure 1-1: What is Cyber-Physical Systems by JEITA.[1]

1.1.3 Human Centric Systems

Human centric system is the design, development, and deployment of the system with human centric needs. It emerges from the convergence of multiple disciplines that are concerned both with understanding human beings which must consider human's physiological, needs, health, preference, security, social, wisdom, and so on, which can exactly match the needs of Maslow's pyramid model. [27]. In this dissertation, the human needs extend in the data-information-knowledge-wisdom-service-social (DIKWSS) hierarchy in

[1]Figure source: https://www.jeita.or.jp/cps/about/

IoT society from the physical world to the cyber world. The CPHC models must be modified and integrated on the basis of the existing human, physical world, and cyber world.

The Architecture of Human Centric System

A kind of the CPHC system structure model is proposed which can be based on the three-dimensional knowledge and technology architecture. The three vertical levels are I. Physical layer, II. Cyber layer, and III. Human layer. The horizontal expansion of the three aspects, **(a)**.Cyber-Physical to Human (CP2H) technical implementation, **(b)**. DIKWSS concept and **(c)**.Information Flow (computation and control). Based on this architecture of human centric system for CPHS framework, the human factors are defined in three layer.

Personal Thermal Comfort

Thermal comfort is an assessment of one's satisfaction with the environment surroundings in which an individual is depending on factors such as indoor temperature, activity level, clothing, and relative humidity. Thermal comfort is an important goal of HVAC system design engineers. Today, the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) model [28] is well-established evaluating the environmental thermal comfort model and it is also assessed by the subjective evaluation of the ANSI/ASHRAE Standard 55 [29]. The said environmental thermal comfort model is widely used in the calculation and evaluation of environments such as offices and classrooms for the groups of people. This leads to many people feeling either cold or hot in the built environment as it is supposed to be thermally comfortable for most people.

However, in smart homes, the human thermal comfort takes an attribute for an individual resident as the unit of analysis rather than the groups of people. Compared to the environmental thermal comfort model, the human thermal comfort is a highly subjective feeling and hard to be measured objectively in a single person. Although PMV and ASHRAE Standard 55 are widely used as an indoor thermal comfort scale, they have not yet been able to fully elucidate the relationship between individual's feelings and environment parameters, especially in smart home domains. Rupp, et al. [30] have reviewed and proposed the human thermal comfort in the resident building by considering light, noise, vibration, temperature, relative humidity, etc. But, it is not considered the human thermal comfort relationship in between the environmental parameters and the human physiological parameters.

The relationship between the human thermal comfort and the physiological parameters should be investigated to get a better understanding of the mechanisms underlying the thermal comfort for automation control in smart homes. For many decades, the human thermal comfort has been studied in terms of environmental factors and physiology parameters.

Several sophisticated theories and objective indicators have been developed, such as the operative temperature, sufficient temperature, and effective standardized temperature. Luo, et al. [31] have explored the notion of comfort expectations and ask the question of whether the change as a result of long term exposure to mild indoor climates. Okamoto, et al. [32] have revealed new physiological markers of the response to indoor airflow sensation that airflow alter the feelings of the participants. Heart rate variability (HRV) as a predictive bio-marker of thermal comfort. The result of this study suggests that it could be possible to design automatic real-time thermal comfort controllers based on people's HRV. Both research teams from Nkurikiyeyezu, et al. [33] and Zhu, et al. [34] have been studied on the Electrocardiogram (ECG) data. The frequency domain method is adopted to obtain the HRV results and to explore the human thermal comfort under different environments. The results are shown that the observation of different low frequency/high frequency (LF/HF) values under different situations, the air temperature has the most significant effects on the LF/HF values. These changes in the air temperature could easily lead to the excitation of the sympathetic nerve that could also promote the activities of the thermoregulatory effectors, i.e., thermal dis-comfort. Additionally, the relationships between the LF/HF, the thermal sensation and the thermal comfort are also revealed. Hasan, et al. [35] have proposed the sensitivity of the PMV thermal comfort model with relative to its environmental factors and personal parameters using the wearable devices. It is found that the expected error range of PMV is high when the other parameters are ignored, such as clothing and metabolic rate. Besides that, Zhu, et al. [36] have focused on the dynamic thermal environment that gives an effect to the human thermal comfort.

In [37], Salamone, et al. have described a workflow for the assessment of the thermal conditions of users through the analysis of their specific psychophysical conditions overcoming the limitation of the physic-based model in order to investigate and consider other possible relations between the subjective and objective variables. Anvari-Moghaddam, et al [38] have proposed a multi-objective mixed integer nonlinear algorithm to ensure an optimal task scheduling and a thermal comfort zone for the inhabitants in smart home. Verhoeven and Hester [39] have proposed a thermal modeling which can be implemented in a thermal control system and can be used by that thermostat to enhance control of a heating, ventilation, and air conditioning system. Vanus, et al [40] have described the basic principles and methods of evaluation of thermal comfort by using objective and subjective factors. The experimental measurements of objective parameters of the internal environment and thermal comfort evaluation were conducted in a smart home. Zhu, et al [20] have presented a novel hybrid intelligent control system to manage space heating devices in a smart home to save energy while to increase thermal comfort level. The approach combines a meta-heuristic algorithm used to compute a set point from the PMV model with a Proportional-Integral-Derivative (PID) controller for indoor temperature regulation.

Over the previous researches, the personal thermal comfort in the field of smart homes has reported the relationship between air temperature, air speed, and relative humidity with dynamic control of PMV and PPD value. However, the personal physiological is not obtained in a real-time manner and its correlation with environmental factors is not well-investigated, especially in smart home environment. Although many theoretical models that based on the PMV as an index of thermal comfort are the most commonly used and well-accepted in worldwide researchers, several studies pose that these models are not accurate for predicting the thermal sensation of residents in the buildings with natural ventilation, and these models tend to be underestimated or overestimated the actual conditions of thermal comfort. With the continuous development of the IoT paradigm, we can easily obtain human physiological data from the IoT devices, such as smart wearable devices, thermal cameras, medication equipment, and so on. Heart rate is one of the human physiological data that can be measured by using the smart wearable device daily and timely. The sensing technologies of the smart wearable device with the measured data are providing a novel opportunity to understand human behavior and intention. Besides that, the measured data is identical and unique to an individual person. However, the measured data forms a challenge to the relationship with the aforementioned environmental thermal comfort model, which cannot well-match to the personalized data. Many recent pieces of research are focusing on investigating the beneficiary of wearable technologies. For example, Kobiela, et al. [41] have aimed the person's individual momentary thermal sensation and comfort that involve physiological data, especially skin temperatures and Heart rate (HR)/HRV features based on the heart activity, then investigate those features to improve the prediction accuracy, which includes physiological data based on two data sources a smartwatch and a portable chest belt device. Georgiou, et al. [42] have investigated the smart wearable devices that provide the reliable and high-precision measurement compared to the classic heart rate measurement. Seshadri, et al. [43] have provided a comprehensive review of the applications of wearable technology for assessing the biomechanical and physiological parameters of the athletes. Wang, et al. [44] have brought forward the human centric interactive clothing concept applied in daily wearable under the CPS framework.

1.2 Problem Statement and Motivation

Cyber-Physical Human Centric System needs to solve many problems,

1. Computation problem. Most scheduling strategies used in existing CPS systems are event-based task strategies using a timestamp. [45] [46] [47] The system executes the command from the system computation strategy and people's command. But there is a different time delay and time requirement between humans and the system.

2. Control problem. Current control methods, e.g. PID and MPC are proposed not only to minimize the processing time of the controller to achieve the target set, but also to ensure the height accuracy of the controller. [48] [49] However, those control methods do not consider the human centric module due to the difficulties of modeling the human factors.

3. Communication problem. Different networks use different communication protocols, and it is necessary to establish reasonable middleware [50] [51] to convert different

network protocols.

4. Implementation problem. The implementation problems faced by various application systems based on the CPS system are about the management of scheduling tasks and how to achieve the energy saving , safety and reliability of the application requirements. [46] [52] [53] [54]

5. Security and privacy protection problem. The combination of the cyber system, physical system, and human is promoting the performance of the CPHCS. At the same time, it also introduces a new integrated security threat into CPHCS, which combines engineering safety [55] threat of physical system, information security threat of cyber system and human error operation.

6. Collaboration of distributed systems problem. Different systems have different computing capabilities, transmission capabilities and control capabilities. To achieve the purpose of collaborative work, the problem of distributed systems need to be solved.

7. Multi-systems heterogeneous data fusion problem. Although the data obtained from IoT devices or physical sensors come from different data source systems, they may represent the same information (such as the same event or individual). In particular, the information obtained from these data source system is complementary, which can help the system of systems enhance the understanding of the perceived information.

According to the aforementioned related works, there is no clear research work on the smart home system using CPS approach with human centric module and its implementation study. This leads to my motivation is to use the concept of CPS to build a smart home system with human centric module in order to realize our future society. There are three main problems in this research. First, the device, system or platform can provide efficient and effective performance based on the desired value, but, human's need and social do not consider at all. Second, many existing research works consider human factors into the system design, but no tight synchronization in between the human preference and the system. Third, many implementation issues are not considered when the smart home system using the CPS approach with human centric module. These three main problems are further discussed in the following sections.

1.2.1 Computation Problem

The CPS system is designed fundamentally for system of systems. The CPS system strictly needs to meet the requirement of real-time when multi-platform and multi-system are considered. Besides that, the CPS system uses a time delay model for its applications. Since the current CPS system does not consider the human factor, which leads to the factor of event-driven task, the usage of time delay model in the CPS system cannot meet the mixed requirement of time-driven and event-driven tasks schedulling. To mitigate this problem, I propose a novel time task model with two algorithms, i.e., a mixed time cost and deadline first (MTCDF) algorithm and a human-centric MTCDF algorithm into the Cyber-Physical Human Centric (CPHC) Framework.

1.2.2 Control Problem

In the CPS system, the control module is one of the importance modules to ensure the entire system operate according to the achievable target set. Most of the CPS systems are designed to meet single target value or multiple target values of the system. Although many control methods, e.g., conventional PID and MPC are proposed not only to minimize the processing time of the controller to achieve the target set, but also to ensure the high accuracy of the controller. However, those control methods do not consider the human centric module due to the difficulties of modeling the human factors. As mentioned in the previous research works, human factor model is generalized by a group of people, in which the control methods that use this model still cannot achieve the best target set. Moreover, the human factor model becomes more difficult when individual or single person is considered. In this dissertation, a generalized thermal comfort model is focused first. Based on the collected data, a personal thermal comfort (PTC) model is derived. Since the PTC is a comprehensive evaluation influenced by complex factors and random variables, it is difficult to apply the smart home application that results to the real environment. With the development of IoT technology, a wearable device becomes our daily objects and also have the advantage of connected to the service platforms. This means that the measured data can be personalized. In this dissertation, a well-known wearable device is used to measure human heart rate, then the heart rate, heat sensation, environmental parameters, and so on as inputs into the artificial neural network (ANN) model for predicting the PTC model. In this dissertation, I propose the PTC model and extend the existing EETCC system to achieve a better thermal comfort sensation while saving more energy.

1.2.3 Implementation Problem

The implementation of CPS system for smart home domain can be found in [7], i.e., EETCC system. Although the EETCC system is successfully verified and implemented in the iHouse environment, this system not only cannot meet the thermal comfort of an resident, but also the EETCC system does not consider the PTC model with artificial neural network (ANN), long short-term memory (LSTM) technique. In this dissertation, the challenges of the EETCC/PTC is focused to achieve both high accuracy and high energy efficiency. By this way, the CPHC framework can be verified for its implementation with human centric module.

1.3 Purpose and Objectives

The purpose of this dissertation is to propose a Cyber-Physical Human Centric framework and to implement its Cyber-Physical Human Centric system with the personal thermal comfort model in smart homes domain. To accomplish this purpose, three research objectives are summarized as follows:

1. To present a computation module of Cyber-Physical Human Centric (CPHC) framework for computation time delay model problem. The CPHC framework is introduced into the CPS system, which expands the theoretical framework of the CPS. A time task model for different time requirements and cross-platform is proposed to solve the problem of the success rate of task scheduling between complex systems and people. (Material related to this objective appears in published papers [3], [4], [5], [9], [10] and in an as yet unpublished paper [2])

2. To propose personal thermal comfort model for control problem between CPS and human requirements. For the study of the relationship between people, environment and system, especially the relationship between human physical and psychological factors and environment and system. A significant part of this research is to use the commercial smart wearable devices as the measurement device incorporated with

the other sensors and actuators to build and propose the generic CPHC framework (Material related to this objective appears in published papers [1], [8], [7] and in an as yet unpublished paper [2])

3. To propose implementation PTC model of CPHC System in Smart Homes. Besides the environmental factors, the physiology parameter from the heart rate is well-studied and its correlation with the environmental factors, i.e., PMV, airspeed, temperature, and humidity are deeply investigated to reveal the thermal comfort level of the plain air-conditioner (Air-con) and EETCC systems in the smart home environment. Through the questionnaire method, the subjective comfort level (SCL) of the human thermal comfort is directly obtained and verified with the thermal comfort level of the EETCC systems. In this way, a generic human thermal comfort model that can be applied to the CPHCS framework is attained in which the coefficients of this model can be fine-tuned to well-fix to the individual thermal comfort. Based on artificial intelligence algorithms, simulation and experiment of different levels of prediction models are realized. These include human heart rate prediction and human thermal comfort prediction. (Material related to this objective appears in published papers [1], [8] and in an as yet unpublished paper [2])

1.4 Structure of Dissertation

The remainder of this dissertation is organized as follows:

- Chapter 2. Cyber-Physical Human Centric Framework

  In Chapter 2, some of the key related theories and technologies for the human centric society, especially for smart homes will be introduced. To propose the Cyber-Physical Human Centric framework, the Human Centric CPS architecture is also be analyzed. Follow the architecture, three components, which are computation, communication, and control, are introduced for the proposed framework. At the end of chapter 2, the overview and main motivation of proposed Cyber-Physical Human Centric framework is explained.

- Chapter 3. Time Task Model for Computation Module

  In this chapter, we propose two mixed weight scheduling algorithms of the CPHC framework scheme. One is the mixed time cost and deadline-first (MTCDF) algorithm, other is human-centric MTCDF base the time task model of CPHC framework. MTCDF is used to priorities the scheduling of tasks with a time deadline and records the computation time. human-centric MTCDF is used to priorities the scheduling of tasks with a time deadline and human centric requirement. Based on the MTCDF and human-centric MTCDF, the successful ratio is also be analyzed through simulation.

- Chapter 4. Personal Thermal Comfort Model for Control Module
  In Chapter 4, a personal thermal comfort prediction model scheme is proposed, which incorporates the proposed CPHC framework and Energy Efficient and Thermal Comfort Control (EETCC) algorithm. Through an experiment to collect six participators' heart rate, subjective comfort level, environment sensing data, and EETCC computation and control data in the morning session and the afternoon session. The thermal comfort gap in the system comfort evaluation and personal is found. Analysis of the experiment data, the correlation between the personal thermal comfort factors and environment factors in the CPHC framework would be optimized. The CPHC framework scheme would achieve better person thermal comfort performance. Besides, this experiment uses a commonly used IoT wearable device for heart rate measuring, which also provides a prerequisite for future work expansion.

  For discussing the personal thermal comfort prediction, there are two simulation studies in this chapter. The prediction direction is divided into the human physiological prediction (heart rate) and the personal thermal sensation prediction. The general simulation scheme design is based on neural networks. The Long Short-Term Memory (LSTM) algorithm and Back Propagation (BP) network algorithm are used. There are two case studies in this chapter. The simulation results are discussed at the end of each case.

- Chapter 5. Implementation of Cyber-Physical Human Centric System for Smart Homes
  Based on chapter 4 simulation, the implementation of personal thermal comfort prediction is discussed in chapter 5 in the morning session and afternoon session.

There are ten participators in the experiment. The EETCC and EETCC/PTC are compared by experiments in the system thermal comfort, human thermal comfort sensation, and energy efficiency.

- Chapter 6. Conclusion and Future Work

  Chapter 6 summarizes the dissertation and draws some future trends.

The proposed conceptual framework for Cyber-Physical Human Centric system as shown in Figure 1-2 and structure of dissertation.

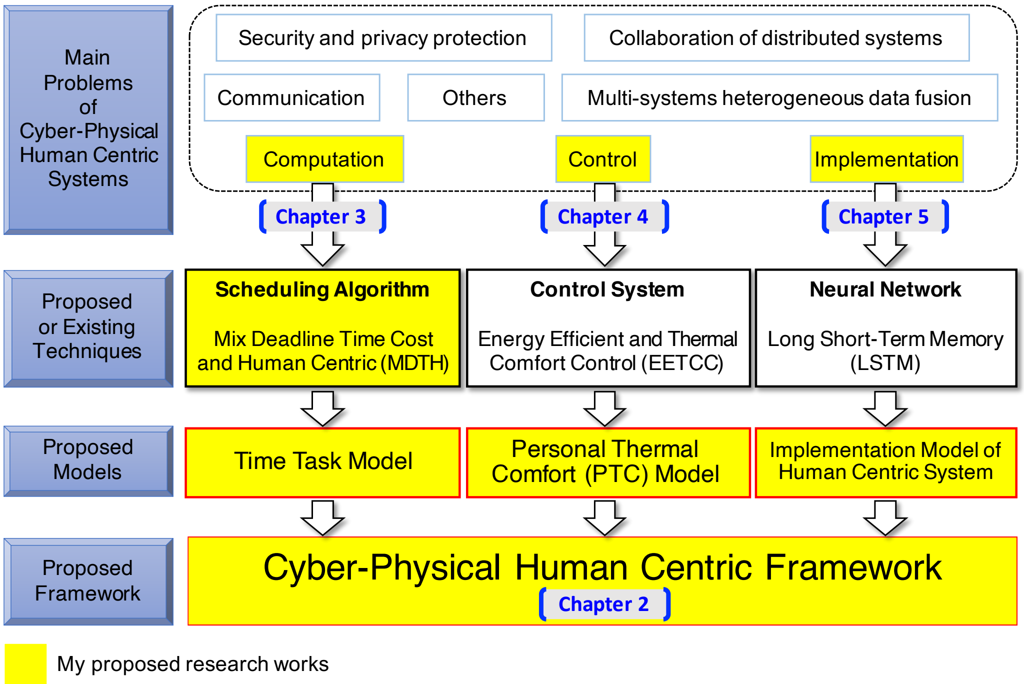


Figure 1-2: Proposed conceptual framework for Cyber-Physical Human Centric System.

Chapter 2

Cyber-Physical Human Centric Framework

2.1 Introduction

In this chapter, the theoretical basis and related works of the proposed Cyber-Physical Human Centric (CPHC) framework are discussed. The structure of CPHC is explained in detail. Finally, how to use the proposed CPHC framework, corresponding solutions are provided for the two key technical points of time delay model to time task model and thermal comfort to personal thermal comfort.

2.2 Related Works

2.2.1 The Hierarchical Human Need

Maslow's hierarchy of needs is a theory in psychology proposed by Abraham Maslow in his 1943 paper "A Theory of Human Motivation" in Psychological Review.[27] Maslow subsequently extended the idea to include his observations of humans' innate curiosity. His theories parallel many other theories of human developmental psychology, some of which focus on describing the stages of growth in humans. He then decided to create a classification system which reflected the universal needs of society as its base and then proceeding to more acquired emotions.[56] Maslow's hierarchy of needs is used to study how humans intrinsically partake in behavioral motivation. Maslow's need [57] used the terms "physiological", "safety", "belonging and love", "social needs" or "esteem", and "self-actualization" to describe the pattern through which human motivations generally move. This means that in order for motivation to arise at the next stage, each stage must be satisfied within the individual themselves. The Maslow's hierarchy of needs to Cyber-Physical Human Centric System shown in Figure 2-1.

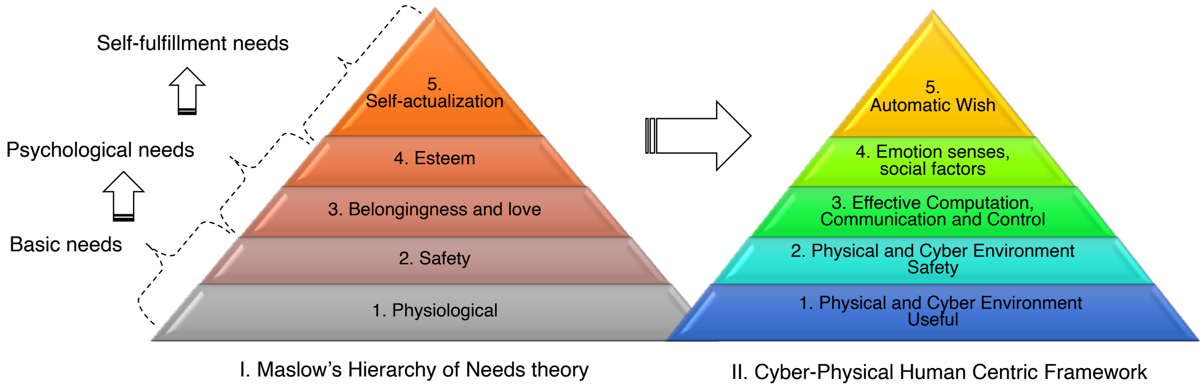


Figure 2-1: Maslow's hierarchy of needs to Cyber-Physical Human Centric System.

2.2.2 Cyber-Physical Social System

Human and system cannot be separated. A system is designed for human requirements; at the same time, a human using a system to make his life better. With the high development of CPS and IoT technology, the performance inner requirements of human centric keep on increasing. Up to now, previous studies have shown that interaction is essential between the CPS and humans. A cyber-physical social system (CPSS) in Liu et al. [58] regards human factors as a part of a system instead of placing them outside the system boundary. Higashino and Uchiyama [59] proposed the human centric cyber-physical system application where the effects of human activities are taken into consideration for designing and developing CPS based societal systems. So, CPSS is the human need and social based on the desired value, but do not consider device, system, or platform can provide efficient and effective performance at all.

2.2.3 Human-in-the-loop CPS

Schirner et al. [60] proposed a prototyping platform and a design framework for rapid exploration of a novel human-in-loop application serves as an accelerator for new research into a broad class of systems that augment human interaction with the physical world. Sowe et al. [61] presents people in a loop of cyber-physical-human systems. Ma et al. [62]propose a human-in-the-loop reference model for CPS, which extends the traditional cyber-physical interaction into a closed-loop process based on cyber, physical, and human factors. Nunes et al. [63] survey research on human-in-the-loop applications towards the Internet of all. However, those research are use the human as the control factor in CPS systems. So, the lack of human-in-the-loop is to consider human factors into the system design, but no tight synchronization between human preference and the system.

2.2.4 Human Thermal Comfort

Thermal comfort is described as the state of the mind that expresses satisfaction with its thermal surrounding. Assessing thermal comfort is primarily regulated using models based on static heat model transfer equations. P.O. Fanger has been proposed the predicted mean vote/predicted percentage of dissatisfied (PMV/PPD) model in 1970 [28]. This model has been presented by ISO-7730 (2005) [64]. The static thermal models, however, have some limitations. For example, the PMV/PPD model is based on laboratory experiments on adults in highly controlled thermal chambers for a relatively extended period. It is not suitable for different age range of people at home. Halawa et al. [65] review the studies on adaptive thermal comfort and look critically at the foundation and underlying assumptions of the adaptive model approach and its findings. Craenendonck [66] review the experiments of human thermal comfort in controlled and semi-controlled environments.

Although the PMV/PPD model gives us a way in judging the thermal comfort level, the human's subjective evaluation is essential. In this paper, we use the ASHRAE 55 [29] to make the subjective evaluation level into seven-level evaluation, as shown in Table 4.1. It contains seven thermal sensation levels, that are "cold (-3)", "cool (-2)", "slightly cool (-1)", "neutral (0)", "warm (1)", "slightly warm (2)" and "hot(3)", respectively. In [40, 67, 68], the subjective comfort evaluation methods are given in smart homes. This subjective evaluation level is modified as a subjective comfort level (SCL) to be used for the participant to answer their direct thermal sensation via the online questionnaire with the intention to study the difference in between human's subjective thermal comfort and system's thermal comfort level.

Table 2.1: The average human's comfort degree on the 7-point ASHRAE scale

Cold	**Cool**	**Slightly cool**	**Neutral**	**Slightly warm**	**Warm**	**Hot**
-3	-2	-1	0	$+1$	$+2$	$+3$

According to the standard ISO 7730 of the indoor environment comfort index, in summer season the environment temperature is in range of 23 and 28 °C, relative humidity is in range of 30% and 70%, body vertical temperature difference is less than or equal to 3 °C, average wind speed is less than 0.25 m/s. In winter season, the environment temperature is in range of 20 and 24 °C, relative humidity is in range if 30% and 70%. During these specification ranges, a human will feel comfort in indoor environments.

On the other hand, the predicted mean vote (PMV) is a particular combination of air temperature, mean radiant temperature, relative humidity, air speed, metabolic rate, and clothing insulation.

2.2.5 Problem and Motivation

Through in-depth research on the above issues, the existing problems are summarized as follows:

(1) Many research works consider human factors into the system design, but no tight synchronization between human preference and system;

(2) Human thermal comfort model ignores the variation of subjects' state of mind over time. Subjects' long-term adaptation and changes are not taken into consideration in existing model;

(3) Human needs based on the desired value, but do not consider devices, systems, or platforms can provide efficient and effective system implementation at all.

The main content of this section is a novel framework that fully integrates human centric system requirements utilizes the CPS approach.

2.3 Cyber-Physical Human Centric Framework

2.3.1 Concept of Human Centric CPS

The current CPS is developed from embedded systems, which is the automatic sensing and interaction of the cyber world and the physical world through network communication. As Fig. 2-2 show, human centric CPS is mainly interactions between human and CPS. Human has lots of factors, such as preference, physical health, need and want, social norm, role and knowledge, personality trait, background and so on.

The human centric CPS application has the following three aspects. The first aspect is that the system is centered on the subjective needs of human. The typical application is human-in-Loop CPS. The second aspect is that the system is centered on the behavior of human. The exemplification is to predict human behavior to service. The third aspect is that the system is centered on human factors. In this dissertation, we focus on the third aspect of human factors centric.

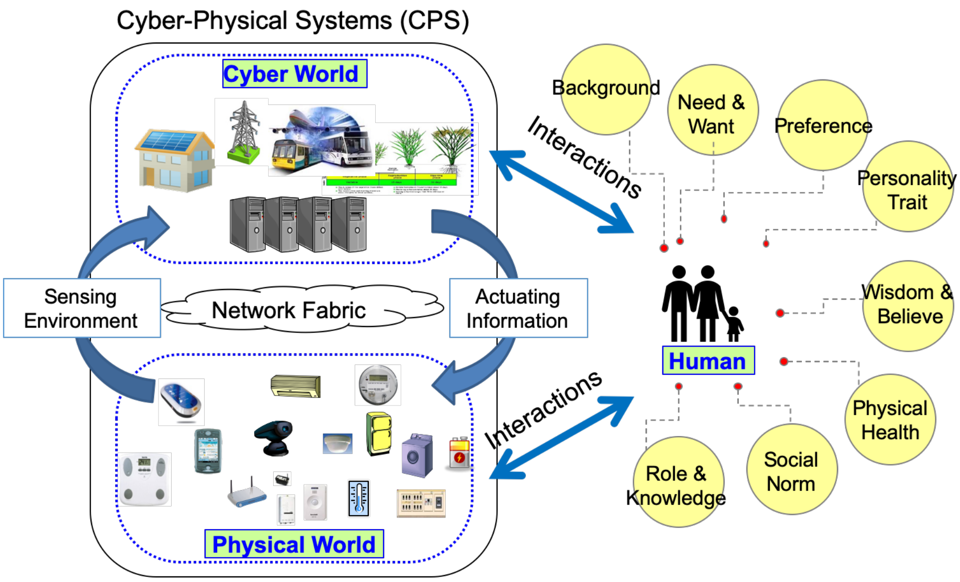


Figure 2-2: Concept of human centric CPS.

2.3.2 Architecture of Cyber-Physical Human Centric Framework

Modeling can be considered as the technology to describe the target system before completion. In human centric CPS, named Cyber-Physical Human Centric System (CPHCS), we must consider human's physiological, needs, health, preference, security, social, wisdom, and so on, which can exactly match the needs of Maslow's pyramid model. [27] According to the Wang [44] and Huang [69] research, there is data-information-knowledge-wisdom-service (DIKWS) hierarchy in IoT society from physical world to cyber world. The CPHCS architecture is the base of research and development, and CPHCS models must be modified and integrated on the basis of the existing human, physical world and cyber world. Abstraction and modeling of communication, computation and physical dynamics in different scales and sizes of time are also needed to accommodate the development of CPHCS.

We propose a kind of the CPHCS system structure model shown in Figure 2-3 which can be based on the three-dimensional knowledge and technology architecture. The three vertical levels are I. Physical layer, II. Cyber layer, and III. Human layer. From the three layers of the horizontal expansion of the three aspects, **(a)**.Cyber-Physical to Human (CP2H) technical implementation, **(b)**. DIKWSS concept and **(c)**.Information Flow (computation and control). The vertical direction in this model represents the functional relationship of progressive interaction from the Physical level to the Cyber and human level, and the horizontal direction corresponding is the technical principle relationship in three levels between CP2H technical implementation (inside the blue dotted box), DIKWS, and CPS loops (inside the red dotted box). The dotted double arrows represent interactions and effects, and solid line wide arrows represent development directions.

(a) DIKWSS Concept. From the top to the bottom, the meaning of the concept in the following,

- Service: combining the physical world, the cyber world with human needs and requirements.
- Wisdom: appreciation and evaluation of "why".
- Knowledge: application of data and information; answers "how" questions.
- Information: data that are processed to be useful; provides answers to "who", "what", "where", and "when" questions.
- Data: facts, individuals, signals, events.

(b) CP2H Technical Implementation. There are included sensors, networks, devices, etc, taking charge of the collection and transmission of information and the execution of control signals, as it is the foundation of the CPHCS in physical layer. In cyber layer, there are three elements, computation, communication, and control. Through the deep interaction of the three elements, the physical world, the cyber world, and human can be connected. At the highest human layer, there are human needs including emotion, action comfortable, health care, and so on with two application area individual and groups.

(c) Information Flow (Computation and Control). There is 8 sub-process, ① Data; ② Connection; ③ Conversion; ④ Machine Learing; ⑤ Knowlege Minning and Data Computation; ⑥ Humaninsitic Evaluation; ⑦ Cognition; ⑧ Interaction. The information flow is from ① to ⑦, after that using ⑧ to finish the interaction with ④ and ①. This is a loop among the physical layer, the cyber layer, and the human layer.

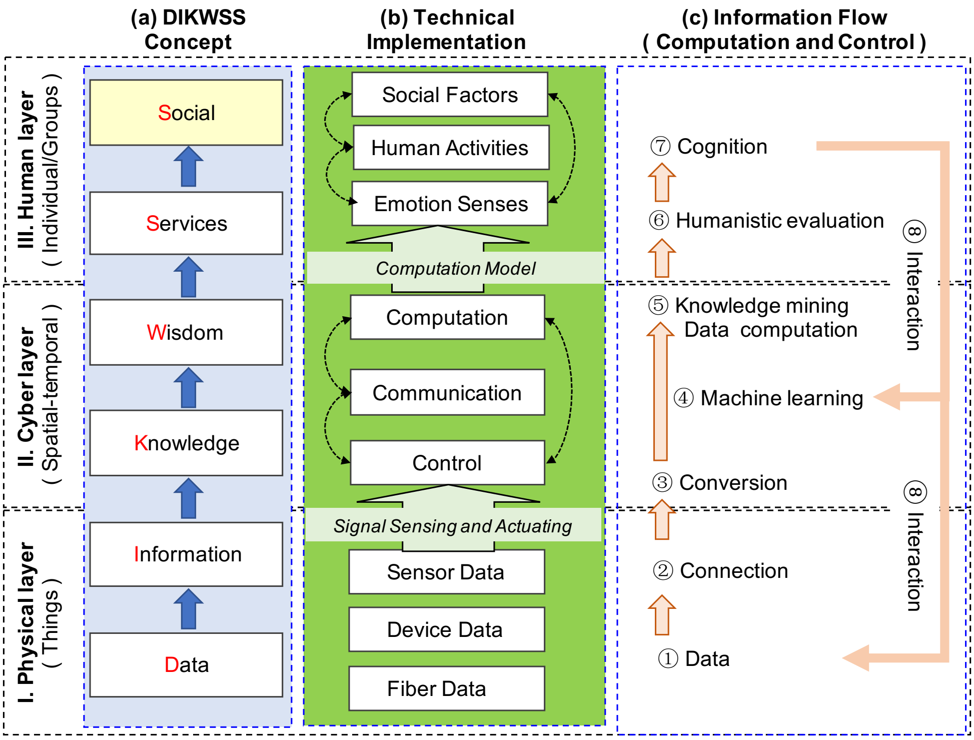


Figure 2-3: The architecture of CPHCS based on the DIKWS.

2.3.3 Contents of Cyber-Physical Human Centric Framework

In designing this framework, we consider the focus of computation, communications, and control module. Especially in the calculation module, we fully combine the human factors with scheduling.

The CPHC framework is shown in Figure 2-4, which consists of four modules, Computation Module, Communication Module, Control Module, and Human Factor Module.

Underneath the CPHCS framework is the network fabric, which used to connect to physical World (e.g. sensors, actuators, robots, cameras). Above the CPHCS framework is Cyber World, which included many applications (Smart factory, Smart City, Smart Homes, Smart Traffic) from human needs and requirements. Other service platforms are connected to the right of the CPHCS framework. Human as the core element in the whole scheme, interact with the surrounding physical environment and the user applications in the cyber world.

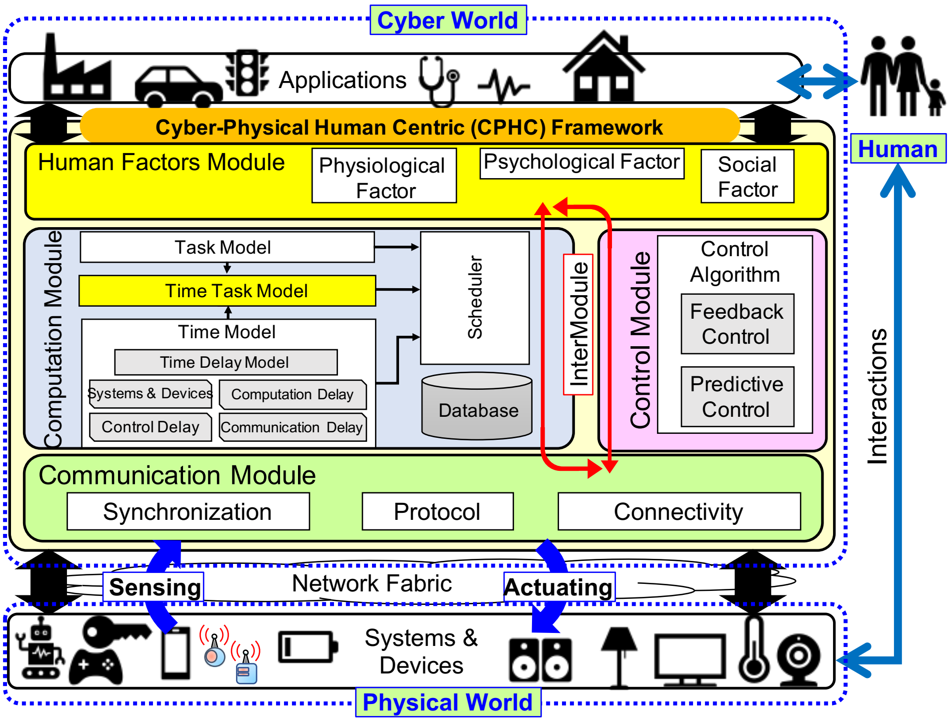


Figure 2-4: The CPHC framework.

Computation Module

Computation module is the core module in CPHCS framework. Time model, task model, time task model, human factor model, scheduler and database are included in this module. The time model consists of time delay model, system and devices process, computational delay process, control delay process, and communication delay process, which is primarily responsible for compatibility with current time model computation. The task model is used to process real-time tasks. The time task model is a novel model including the human factor model which computerate the human factor parameter. After the task model, time model, and time task model computation, the task will to the scheduler that scheduling to other modules.

Control Module

The second sub-model is Control Model. All the components of the approximate control operation are integrated into this model. The control model is mainly proposed in the control model, especially the feedback control algorithm, which includes feedback control and predictive control.

Communication Module

Communication Module follows the existing communication protocols. It mainly includes the network synchronization unit and connectivity of the CPHCS framework. In this dissertation Chapter 5, the UDP communication middleware developed by Python is used.

Human Factor Module

Ergonomics (or human factors) is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance. In [70] book, practitioners of ergonomics and ergonomists contribute to the design and evaluation of tasks, jobs, products, environments, and systems in order to make them compatible with the needs, abilities, and limitations of people. As [71] paper, the heart rate can be as a human factor for thermal sensation model.

ISO 9241-210:2010 provides requirements and recommendations for human-centered design principles and activities throughout the life cycle of computer-based interactive systems. It is intended to be used by those managing design processes and is concerned with ways in which both hardware and software components of interactive systems can enhance human-system interaction. According to the ergonomics theory and ISO 924-210:2010, we give human factors in CPHCS, shown in the following Table 2.2.

Table 2.2: Human factor level of CPHCS

Domain	**Elements**	**Parameter**
Social	Social network, Salary, Fixed assets, Profession	H_{so}
Service	Low energy cost service, Best comfort service	H_{se}
Wisdom	Correlation of human biological information, physical information and cyber information	H_{wi}
Knowledge	System monitors the human activity, capabilities and limitations	H_{kn}
Information	Who, Where, What, When	H_{in}
Data	Status of sensors, actors, device	H_{da}

2.3.4 Time Delay Model to Time Task Model of Computation Module

The model based on CPS follows the scheduling of the time delay model. The problem of the Time Delay Model is to meet the real-time scheduling priority. The system's delay is given in the model design stage to a nearly consistent delay to increase the scheduling success rate of the system, such as the PTIDES system. However, it ignores differentiation issues such as execution time and calculation time. In addition, human time needs are not taken into account. In the CPHC framework, a new time task model (TTM) is proposed to solve the shortcomings of model calculation problems. The specific content is introduced in detail in Chapter 3.

2.3.5 Personal Thermal Comfort of Control Module

Personal thermal comfort is a comprehensive evaluation influenced by complex factors. Personal thermal comfort used to start with relatively invariant studies because it is more difficult to study random variables. The personal thermal comfort proposed by the CPHC framework is based on the prediction of the individual's physiological and psychological data, combined with the system computation and scheduling of the computation module, and the communication of the IoT-based common wearable device with the communication module.

2.4 Summary

This chapter presents some key technologies for the personal thermal comfort model for the cyber-physical human cenrtic framework, especially in smart homes. To propose the high-performance human centric CPS, we analyzed the CPHC framework architecture. Follow the framework, we introduced three components of the framework, which are computation, communication, and control module. At last, the time task model and personal thermal comfort are proposed as this dissertation motivation.

Chapter 3

Time Task Model for Computation Module

3.1 Introduction

Cyber-Physical Home System (CPHS) is widely used a typical CPS application. People play the most important role in CPHS. In the current CPHS modeling, most of the system model is single based on time-driven or event-driven. Research on human centric is the relationship with the prediction model of human thermal comfort and extends to system interaction. Based on this context, we propose a solution for human centric time task scheduling using a time task model. Specifically, we focus on time task scheduling with hybrid time requirements. This scheduling algorithm enables different time task weights to meet the human centric target scheduling success ratio requirement.

3.1.1 Modeling of CPS

CPS modeling requires a portrayal of how interactions between the process and physical processes are calculated and how they behave when they are merged [72]. The model-based analysis provides a better understanding of CPS behavior, and model-driven design can improve design automation and reduce errors in refinement. Edward Lee proposed CPS is integrated computing power and physical process of the system[6], which uses embedded computers and networks to monitor the physical processing process, with the feedback loop, the physical process, and the computation process affect each other. For a system modeling, simulation and verification, computational science and control science have different ways. However, in the control science, the research on the physical world is often based on time, abstracting the system as a continuous-time model, and time is the most critical factor in the model this will result in collisions and random failures in the interaction between the computational unit and the physical entity model. There are various interactive entities involved in the CPS system. It can be a natural environment, building, machine, a physical device, human beings, etc. The situation can be a real-time sensing part (such as the physical entity) that can also be controlled.

CPS in [73] and [74] is usually defined as tight integration of computation, communication, and control with deep interaction between physical and cyber elements in which embedded devices, such as different sensors and actuators, are wireless or wired networked to sense, monitor and control the physical world. With CPS is becoming more popular, many types of research have devoted to their development. The modeling and analysis play an essential part in the safety and mission-critical system of systems (SoS) development in CPS. Researches in [75] have contributed to the modeling of CPS. Some of the modelings of the discrete and continuous behavior of heterogeneous systems have been developed recently, such as Ptolemy II [76] and PTIDES [72], those models for a deterministic modeling paradigm suitable for CPS application at any scale. All most of the current modeling structure is platform to platform, and it follows discrete-event (DE) semantics. Furthermore, time is the first parameter because it is the interaction that requires the physical world and the cyber world in CPS.

The model-driven development method first needs to solve the structure of the model, then to solve the task scheduling. The existing CPS modeling method is the procedure, and the initial process of the modeling is still highly complicated. Furthermore, time is very consuming because it requires a full and in-depth understanding of the details of the physical environments. Its the weakness which it is difficult, even impossible, to adapt some existing scheduling algorithms different systems or to different scheduling targets. When we design a scheduling algorithm for a newly developed system, it is difficult to benefit from the existing scheduling algorithms, which usually results in a high cost.

For many existing CPS scheduling algorithms, to enhance them to support some practical requirements is difficult, even impossible. Due to system complexity, time task modeling purpose method for CPS application.

The objectives of this section are to propose a time task model for human centric scheduling in the CPHC framework to meet the requirements of modeling and analysis with a combination of the time and event requirements. This model based on a proximity method, which is used to model each component of sensing, fabric network, and actuating in the reality multiple platforms model as a computation model, control model, and communication model, respectively. Second, Mixed Time Cost and Deadline-First (MTCDF) algorithm were proposed to address the problem of multi-programming scheduling in the CPHC framework computation model. At last, the successful ratio and optimal scheduling index were shown in the simulation results.

3.1.2 Time Delay Model

The current reality model of CPS in Figure 3-1, most of them are multiple platforms structure. Time delay model of CPS is that the generation, transmission, and processing of the sequence of events in this model are based on a certain time delay. The ***time model*** has encompassed the overall approach to handling time sequencing. The PTIDES is typical time model is defined by a time delay model. There are sensors, actuators, computation units in the platform. If there is a *Service* need all the platforms 1, 2 and 3. The *Service* will be in computation time $\sum_{i=1}^{4} com_i$, and the all the delay is $\sum_{i=1}^{5} d_i$. There is an example shown in the Figure 3-2. The basic time delay model's time equation is shown in Equation 3.1.

$$TimeDelay_{id} = \{T_{physical}, T_{logical}, T_{model}\} \tag{3.1}$$

where $T_{physical}$ is a set of physical time $T_{physical} = \{T_a, T_d\}$, T_a is arrival time, T_d is deadline time, $T_{logical}$ is a set of logical time $T_{logical} = \{T_e\}$, T_e is execute time, $T_{model} = \{T_{delay}, TimeStamp\}$ is a set of model time, T_{delay} is time delay, $TimeStamp$ is the system timestamp.

PTIDES deals with homogenous devices or systems. We need a simple framework to deal with homogenous devices/systems. PTIDES deals with delay without considering the task's condition or requirements. Time delay + Task event should be considered at

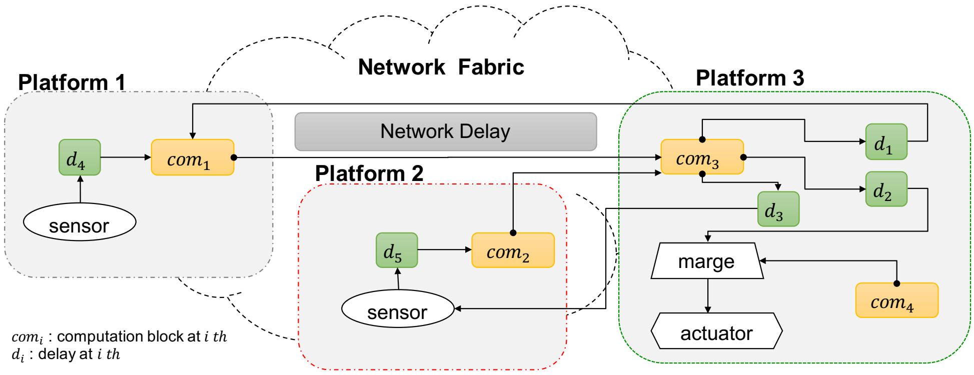


Figure 3-1: General time model for CPS.

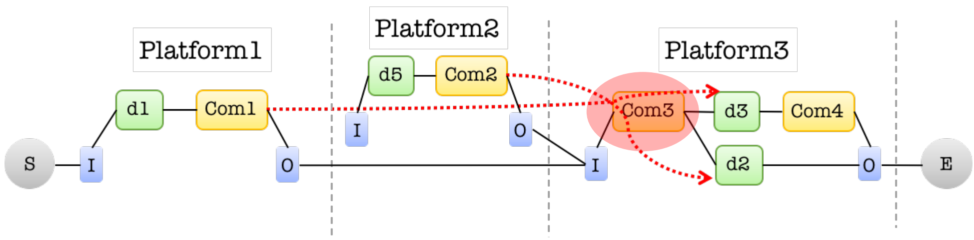


Figure 3-2: Example of time delay model.

the same time when scheduling algorithm is performed. PTIDES does not consider the task load in each computation unit of a platform. There is two main problem with this model: *i)* the platform usually uses a single algorithm to schedule. For services with different time requirements, time efficiency is not optimal.*ii)* some computation time is repeated. From the perspective of the entire system, different computing capabilities have different effects on the time of service. Accumulating these effects together will cause the time and task of the next service to miss deadlines and cannot be implemented, which reduces the efficiency of the system.

3.1.3 Time Task Model

Discrete-Event (DE) is used to model time, discrete interactions between concurrent actors. [6] There *event* is in each communication, conceptually understood to be an instant message sent from one actor to another. The time elements in the time task model contain the physical time of the generation, transmission, and processing of the event sequence, as well as the related factors such as the logical time generated by the calculation process and the corresponding event priority. As shown in Figure 3-3.

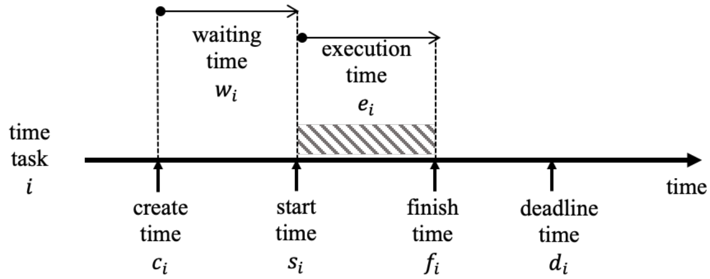


Figure 3-3: Example of time task model.

The basic time task model (TTM) time equation is shown in Equation 3.2.

$$TimeTask_{id} = \{T_{physical}, T_{logical}, TimeState\} \tag{3.2}$$

where $T_{physical}$ is a set of physical time $T_{physical} = \{T_a, T_d, T_s, T_f\}$, T_a is arrival time, T_d is deadline time, T_s is start time,T_f is finished time,$T_{logical}$ is a set of logical time $T_{logical} = \{T_e, T_w\}$, T_e is execute time, T_w is waiting time, $TimeState = \{Prio, Human\}$, $Prio = \{i | i \in \mathbb{Z}\}$ is event priority, $Human$ is human centric value created by framework calculate.

3.2 Time Task Model of CPHC Framework

Cyber-Physical Human Centric (CPHC) framework is illustrated in Figure 3-4. There are four module included in the frame. The first module is ***Computation Module***. All the components with computational requirements from the different platform are approximated by this model. A service request requires connecting different platforms in a specific order. Each platform has different devices that complete the tasks. The operation generated by each device is called a *Time Task*. In a CPS service, time tasks are required to be completed before their deadlines. To satisfy this requirement, their required computation resources should be allocated to tasks at the right time. The allocated result is called *schedule*, while the allocating process is called *scheduling* which is conducted by a scheduler equipped in the system. The second module is ***Control Module***. All the components of the approximate control operation are integrated into this model. The control model is mainly proposed in the control model, especially the feedback control

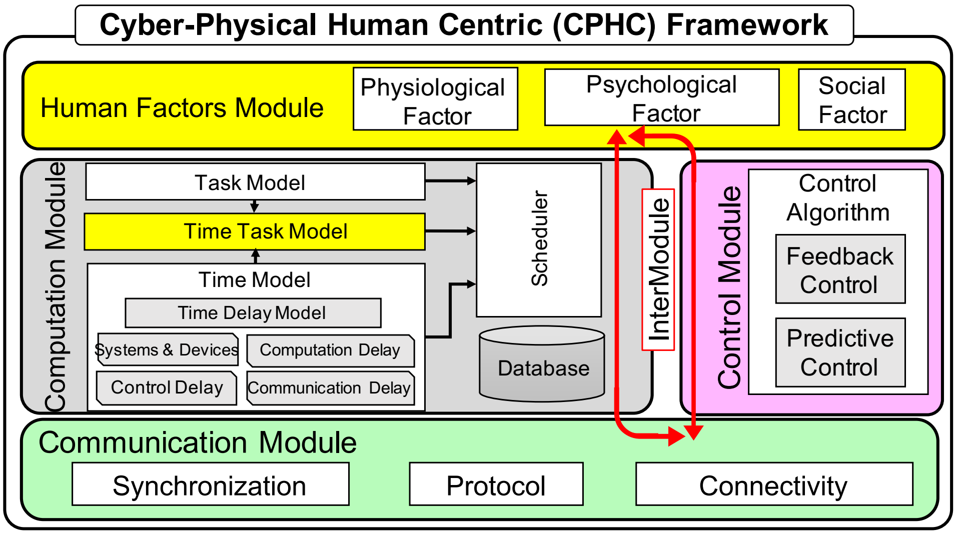


Figure 3-4: CPHC framework.

algorithm, which includes online and offline forms. ***Communication Module*** follows the existing communication protocols. It mainly includes the network synchronization unit and the time offset of the CPHC framework. The fourth module is ***Human Factors Module*** including physiological factor, psychological factor, and social factor. The main function of the human factors module is to stratify and classify the factors from the human centric, and perform different processing according to different stratification.

Definition 1. ***Time Task Dependency Graph.*** *A time task dependency graph is a directed non-cyclic graph. $G = (P, E)$, where P is a platform set, $E \subseteq P \times P$ is a dependency relation (edge) set, with $(p_i, p_j) \subset E$,$i \neq j$,where $p_i, p_j \subset P$. An edge (p_i, p_j) in the task dependency graph means platform p_j can start to execute only after platform p_i has been completed. $p_i \prec p_j$ is used to illustrate this dependency relation, and the this relation is transitive.*

Definition 2. ***Time Task.*** *A time task is a multidimensional set $TT = (T, S, V)$. It includes a subset of time T, a subset of states S, and a subset of values V. The j time task of i platform is $T_{i,j} = \{A_{i,j}, E_{i,j}, D_{i,j}\}$, $A_{i,j}$ is the arrival time in a task scheduling, $E_{i,j}$ is the execute time, and $D_{i,j}$ is the deadline. Each task $S_{i,j} = \{s_{i,j}\}$, $s_{i,j}$ is the state of the elements. $V_{i,j}$ is value of the time task $T_{i,j}$ with state $S_{i,j}$. i is means the i time task, and j is means the j platform, $(i, j) \subseteq N$.*

Definition 3. ***Service.*** *A service is defined by the operation of the platforms with the*

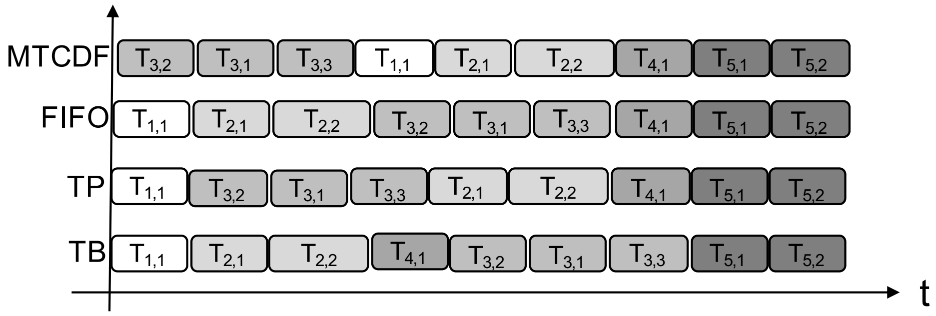


Figure 3-5: Example of scheduling results.

order of execution in the CPS application. Service $= (P_i \prec P_j)$. *We assume that the execution time task* $T_{i,j}$ *inside the platform* P_i *are disordered. In order to meet the highest proportion of successful service execution, the time task sequence within the platform can be adjusted.*

Equation (3.3) is used to calculate the waiting time of the time task. Equation (3.4) for determining whether the time tasks can be executed.

$$W\left(_{i,j}\right) = A_{i,j} + \sum E\left(_{i',j'}\right) \tag{3.3}$$

where i', j' is means the total task before i, j.

$$D\left(_{i,j}\right) \geq W\left(_{i,j}\right) \tag{3.4}$$

$\forall T\left(_{i,j}\right)$ satisfied the Equation (3.4), the service entire time task is executable.

3.2.1 Scheduling Procedure

There are many scheduling algorithms used in various real-time systems. In this subsection, through an example described in Figure 3-5, the performance of three widely used scheduling algorithms, Tree Based (TB), Task Priority (TP), and First In First Out (FIFO) are studied.

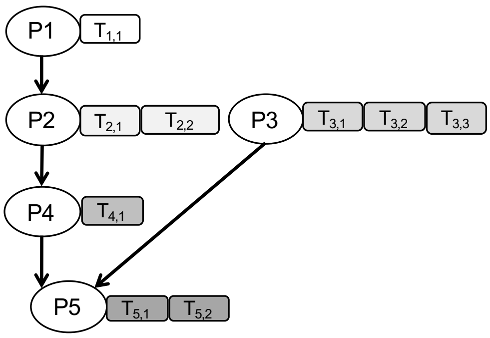
In the case, the lengths of the indivisible fragments in the tasks are shown the execute time length. The parameters of the platform time task are shown in Table 3.1.

Schedules the time task example in Figure 3-6 with the direct way according to the following adjacency matrix in Figure 3-7. Each row corresponds to the starting point, and

Table 3.1: Time task parameters

Platform	$T_{i,j}$	$A_{i,j}$	$E_{i,j}$	$D_{i,j}$
P1	$T_{1,1}$	0	1	5
P2	$T_{2,1}$	1	1	10
	$T_{2,2}$	1	4	10
P3	$T_{3,1}$	0	1	5
	$T_{3,2}$	0	1	1
	$T_{3,3}$	0	1	5
P4	$T_{4,1}$	2	1	10
P5	$T_{5,1}$	3	1	15
	$T_{5,2}$	3	1	15

Figure 3-6: Example of schematic diagram.



each column corresponds to the ending point. For example, $P_1 \prec P_2$, the intersection of the first row and the second column has a value of 1 in the adjacency matrix. Dependency the adjacency matrix, Figure 3-5, Table 3.2 shows that the four scheduling results.

Table 3.2: The scheduling result of example

Algorithm	*Service* Scheduling	$\sum_i^{\forall j} W\left(_{i,j}\right)$	Successful Ratio	Unable to Meet Deadline
TB	$\{P_1 \prec P_2 \prec P_4 \prec P_3 \prec P_5\}$	44	0.6667	$T_{3,1}$, $T_{3,2}$, $T_{3,3}$
TP	$\{P_1 \prec P_3 \prec P_2 \prec P_4 \prec P_5\}$	35	0.8889	$T_{3,2}$
FIFO	$\{P_1 \prec P_2 \prec P_3 \prec P_4 \prec P_5\}$	44	0.6667	$T\ _{3,1}$, $T_{3,2}$, $T_{3,3}$
MTCDF	$\{P_3 \prec P_1 \prec P_2 \prec P_4 \prec P_5\}$	44	1.0000	None

Figure 3-7: Example of adjacency matrix.

$$
\begin{array}{c c}
 & \begin{array}{ccccc} P1 & P2 & P3 & P4 & P5 \end{array} \\
\begin{array}{c} P1 \\ P2 \\ P3 \\ P4 \\ P5 \end{array} &
\begin{bmatrix}
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

3.2.2 Mixed Time Cost and Deadline-First (MTCDF) Algorithm

Dynamic scheduling of tasks in an overloaded real-time system was proposed by [77]. Cheng et al. propose SMT (*satisfiability modulo theories*)-based scheduling method [78]. Lim et al. propose time delay model for smart home [21]. Those pursues to focus on maximizing the total number of tasks that can be completed before their deadlines and time delay model with experiment. In the paper, we propose one navel scheduling algorithm, mixed time cost and deadline first (MTCDF) base the time task database of CPHC framework. This method is used to priorities the scheduling of tasks with a time deadline, and records the computation time.

Some assumptions were applied to the proposed scheduling algorithms, e.g., *1*) The requests for all time tasks for which strict deadlines exist are random; *2*) Time tasks are independent for each platform; *3*) Run-time for each time task is constant and does not vary with time.

According to the time task example, there are two main parts that affect the efficiency of the algorithm. i) The order of execution of the platforms in the same priority situation. ii) The time cost to compute the time task schedule in the deadline-first platform. Such as the scheduling $T_{3,2} \prec T_{3,1} \prec T_{3,3}$.

The relationship between deadline-first and time cost is defined by the following equation:

$$\Gamma_k = \beta \times DF_i + \gamma \times TC_i \tag{3.5}$$

where Γ is means the optimal scheduling index, k is the algorithm, β is the coefficient of deadline-first part, γ is the coefficient of time cost part. $DF_i = \sum_{i=1}^{n} P_i^{deadline}$,

Algorithm 1 Mixed Time Cost and Deadline First (MTCDF)

A *Service* is processing schedule defined by an adjacency matrix $|AJ\,(P_i \prec P_j)|$,P_i,P_j is platform, for all $i, j, k \subseteq N$
$S_{MTCDF} = AJ.\texttt{MTCDFSort}(T_{i,j})$
for all $1 \le i \le n$ **do**
  for all $1 \le j \le n$ **do**
    $sum_i = T_{i,j}^{deadline}$
    sort$(T_{i,j})$ with deadline first
  end for
end for
for all $1 \le i \le n$ **do**
  if $sum_i <= sum_{i+1}.and.P_i.AJ == P_{i+1}.AJ$ **then**
    $S_{k++} = P_i$
  else
    $S_{k++} = P_{i+1}$
  end if
end for
Scheduling list is $S_{MTCDF} = list(S_k, 1 \le k \le n)$

$TC_i = \sum_{j=1}^{m} T_{i,j}^{timecost}$, $i, j, n, m \subseteq N$. The process of schedule synthesis is summarized in Algorithm 1.

3.3 Human Centric Scheduling Based Time Task Model

In most people-centered smart home research, the goal is energy saving and comfort. Human-centered task scheduling focuses on how to achieve human behavior identify and prediction.

The [9] proposed one human-centric framework can make the cyber and physical space behavior awareness, and optimal scheduling based on comfort as well as economy was proposed. This research needs more application and hardware to support it. To identify the human-centric smart home, a framework to model the interaction between a smart home was proposed in [79], so that a smart home can fulfill "comfort + convenience + security" when performing services to interact with its inhabitants. Nevertheless, the above related works mainly deal with how to achieve the sensing and prediction human behavior in smart home system, whereas our work focuses on how to address the hybrid time requirements in CPHS. On the other hand, machine learning and deep learning are widely used in CPS. In previous studies, artificial neural networks (ANNs), decision tree (DT), support vector machines (SVMs) are defined three major machine learning

Table 3.3: Simulation example of time task parameters

ID	Arrival Time	Execution Time	Deadline Time	Priority	Human Centric
1	0	4	21	0	1
2	4	2	17	4	1
3	4	4	15	4	1
4	3	5	25	3	1
5	0	5	30	0	1

approaches for constructing an real time system.

To address the scheduling algorithms of CPHC, considering a scenario exclusively involving of periodic and sporadic tasks, the scheduling can be performed using well-known algorithms like Rate Monotonic (RM) or Earliest Deadline First (EDF). However, their approach is not highly suitable an real-time system (RTS) that uses the machine learning and deep learning approach.

Based on the studies mentioned above, in order to develop the hybrid time requirements of CPHC framework, the CPHC framework should be capable of time and human-centric during operations to change in the system operating conditions. Hence, using a CPHC framework to refine the CPS is an important research issue. In this section, we develop a human centric MTCDF algorithm which is the mixed deadline first, time cost and human centric (MDTH) based the CPHC framework.

3.3.1 Scheduling Procedure

In the following example time task list, there are 5 time tasks with its' the main parameters are shown in Table 3.3. According to this simulation example time task list, FIFO scheduling is $ID_1 \prec ID_5 \prec ID_4 \prec ID_2 \prec ID_3$, EDF scheduling is $ID_1 \prec ID_5 \prec ID_4 \prec ID_3 \prec ID_2$, LLF scheduling is the same as EDF, MDTH scheduling is $ID_3 \prec ID_2 \prec ID_1 \prec ID_4 \prec ID_5$. After scheduling according to different algorithms, as shown in the Fig.3-8. Among them, FIFO, EDF, and LLF have failed tasks. Green block means waiting, black block means execute, yellow block means deadline, red block means failed.

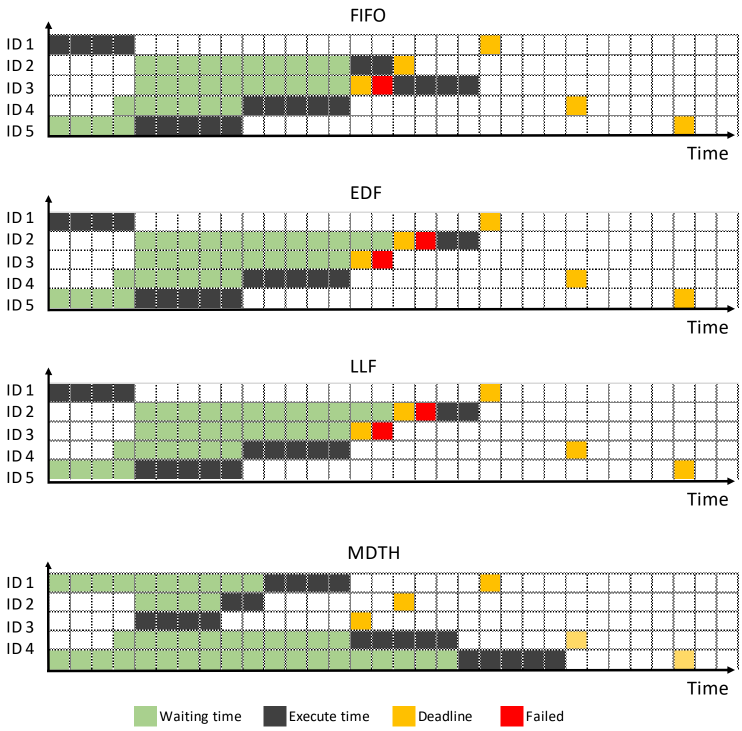


Figure 3-8: Compare different scheduling algorithms with N=5.

3.3.2 Human Centric MTCDF Algorithm

Definition of MDTH

Some assumptions were applied to the proposed scheduling algorithms. (i) The requests for all time tasks for which strict deadlines exist are random; (ii) Time tasks are independent for each other; (iii) Run-time for each time task is constant and does not vary with time.

According to the time task definition, the human-centric value is from the deep learning part of computation model. In this simulation, we use 1 or 0 to distinguish human-centric time task or not. The relationship between deadline-first, time cost and human-centric (MDTH), is defined by the following equation:

$$\Gamma_i = \alpha \times HC_i + \beta \times DF_i + \gamma \times TC_i \tag{3.6}$$

where i is the ith time task, Γ_i is the scheduling value of ith time task. HC_i is the number of human-centric, DF_i is the value of deadline, TC_i is the value of time cost, and α, β, γ is the coefficient with $\alpha + \beta + \gamma = 1$.

Weight of MDTH

In Equation 3.6, there are three weight value α, β, γ of human centric, deadline first, and time cost. The weight value are dynamic results of the experiment of ANN learning results. In the Chapter 5, the best accuracy prediction, the $\alpha = 0.24, \beta = 0.72, \gamma = 0.04$.

3.4 Simulation and Results

3.4.1 MTCDF

In order to evaluate the successful ratio among the TP, TB, FIFO, and MTCDF scheduling algorithms in different λ and service including platforms' number. The input $Service$ is generated according to the adjacency matrix AJ. There is one time task database, with 10 times number of platform random time tasks. The input functions random distribute the time tasks to platform from time task database. Each time task has three parameters, in the Def. (2). For each arrival time $A_{i,j}$ is generated according to Poisson distribution with arriving rate λ to every platform. The simulation parameters and settings in Table 3.4.

Simulation Parameters and Settings

Two scenarios are introduced for time task model: (i)time task scheduling using MTCDF algorithm and (ii) human centric scheduling using MDTH algorithm. Both the MTCDF and the MDTH are according time task model Definition 3.

Successful Ratio

A service is performed by different time tasks of multiple platforms according to the scheduling result. In this simulation, the number of time tasks in the time task database is 10 times the number of platforms, and randomly matched to the platform as the service is generated. The arrival time and deadline of the time task are with the Poisson

Table 3.4: Simulation parameters and settings for MTCDF.

Parameter	**Value**
CPU	Intel Core i7 CPU 2.4GHz
Memory	16GB
Software	C Language Programming
Arrival task	Poisson distribution
Average inter arrival time of task	10ms - 100ms
Simulation loop	20 times

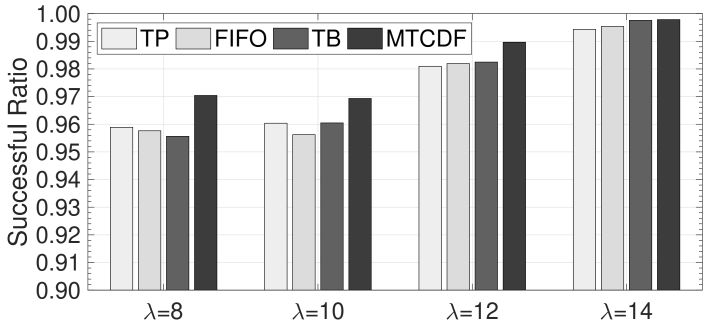


Figure 3-9: Successful ratio with $N = 5$ based on the MTCDF.

distribution. With $\lambda = \{8, 10, 12, 14\}$, the time task number is the the successful ratio and the optimal index Γ_k was observed.

We have measured the effect of successful ratio on different platform number with different λ. As seen from Figure 3-9 , when the λ is changed, the successful ratio are increased. Especially, more MTCDF can improve more successful ratio in the same λ comparing with TP, TB, and FIFO. As Figure 3-10 , we show the successful ratio with 10 platform. In Figure 3-11 , we show the 100 platform. As the result, the successful ratio is over 0.648. And the four scheduling algorithms results are very close.

Optimal Scheduling Index

The optimal scheduling index refers to the more appropriate scheduling was found. We use the min-max normalization method to process the results. In Figure 3-12, Figure 3-13 and Figure 3-14 show the optimal scheduling index Γ with different λ different platform number N. The results show that the optimal scheduling index can give to optimization scheduling results, with meeting the time requirements first and time cost.

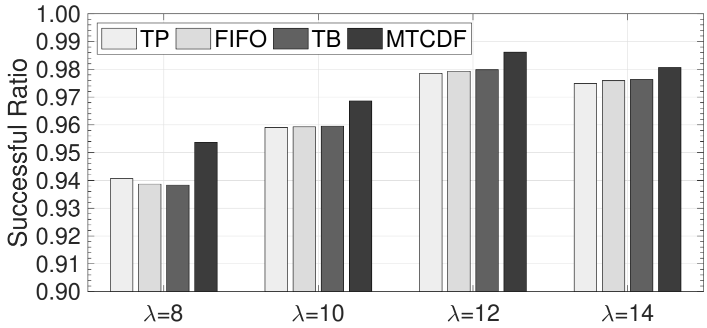


Figure 3-10: Successful ratio with $N = 10$ based on the MTCDF.

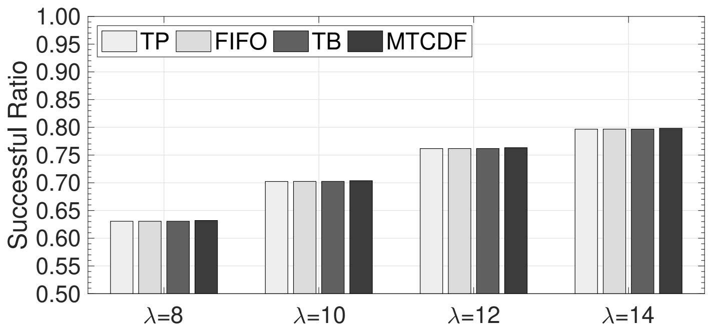


Figure 3-11: Successful ratio with $N = 100$ based on the MTCDF.

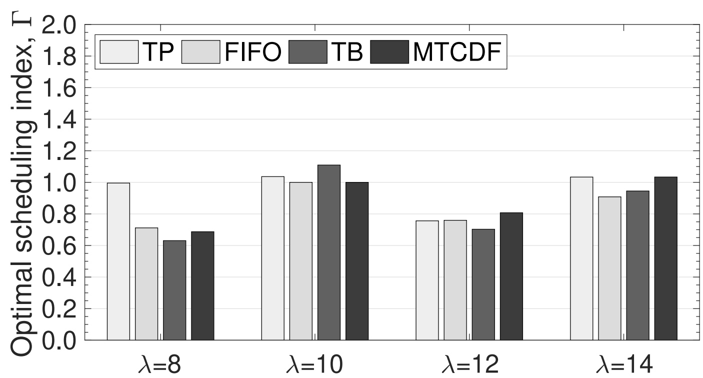


Figure 3-12: Optimal scheduling index Γ with $N = 5$ of MTCDF.

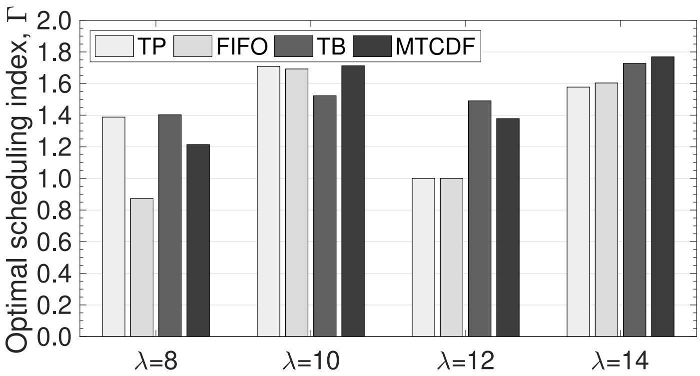


Figure 3-13: Optimal scheduling index Γ with $N = 10$ of MTCDF.

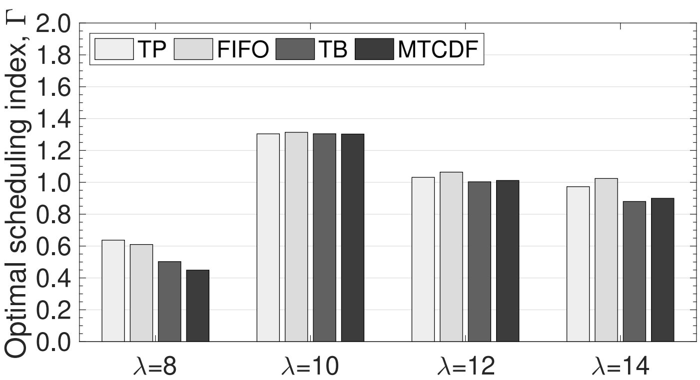


Figure 3-14: Optimal scheduling index Γ with $N = 100$ of MTCDF.

3.4.2 Human Centric MTCDF

We intercepted the air conditioning status change data in iHouse, on August 15, 2016, from 12:30 to 17:30, during that time there was human commands to change the air condition less than 7 times. We can get human as the main body of the environment and also the object of environmental action. In this simulation, we use the human-centric parameter to indicate whether it is a human-centric time task.

In order to evaluate the successful rate among the first in first out (FIFO), earliest deadline first (EDF), least laxity first (LLF), and human centric MTCDF scheduling algorithms, MDTH in different number of time task.

The MDTH simulation results of the scheduling average success rate are shown in the Figure3-15. We processed 20 times for average success ratio calculating. Based on the number of different time tasks number, MDTH can maintain the success ratio of task scheduling, it is average more 0.05 ratio than other algorithms.From the results human centric MTCDF has 100% success ratio in every number of time task. MDTH can

Table 3.5: Simulation parameters and settings for MDTH.

Parameter	**Value**
CPU	Intel Core i7 CPU 2.4GHz
Memory	16GB
Software	C Language Programming
Arrival task	Poisson distribution
Average inter arrival time of task	100ms
Simulation loop	20 times
Number N	5,10,15,20
T_a	Poisson distribution
T_e,T_d	Random number, $T_d > T_a + T_e$
H	Human centric value random from iHouse database
P	Requirement priority, random value

maintain the success ratio of task scheduling, it is average improve 5% success ratio than other algorithms.

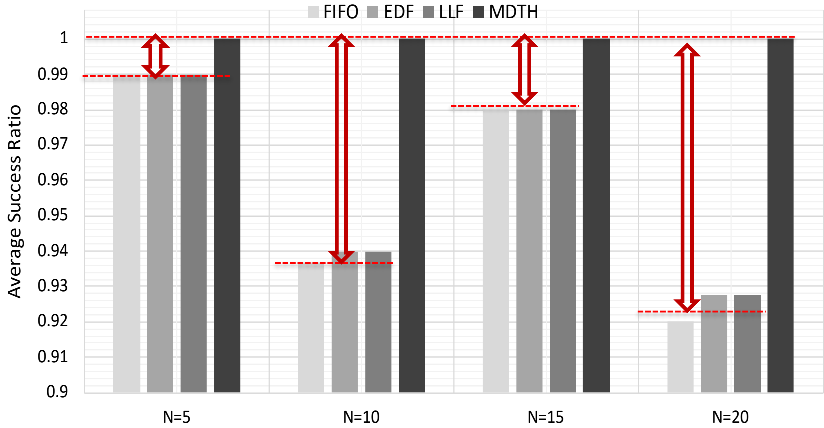


Figure 3-15: Average success ratio with MDTH.

3.5 Summary

In this section, we address the time task model of CPS. We define a new time task model the CPHC framework. The contributions of the CPHC framework are it reduces the repetition rate of the components and the elements in the same model can be approximated, to enhance the efficiency of computation and control. According to the CPHC framework design principle, we proposed the MTCDF algorithm and MDTH algorithm for computation model scheduling algorithm aiming the human centric CPS scheduling. The simulation results show that the MTCDF and MDTH time task scheduling method can improve service success rate. The CPHC framework can generality of the matching optimal scheduling index for time requirement and task mixed service.

Chapter 4

Personal Thermal Comfort Model for Control Module

4.1 Introduction

An environmental thermal comfort model has previously been quantified based on the Predicted Mean Vote (PMV) and the physical sensors parameters, such as temperature, humidity, and airspeed in the indoor environment. However, first, the relationship between environmental factors and physiology parameters of the model is not well investigated in the smart home domain. Second, the model that is not mainly for an individual human model leads to the failure of the thermal comfort system to fulfill the human's comfort preference. In this section, a CPHC framework is proposed to take advantage of individual personal thermal comfort to improve the human's thermal comfort level while optimizing the energy consumption at the same time. Besides that, the physiology parameter from the heart rate is well-studied, and its correlation with the environmental factors, i.e., PMV, airspeed, temperature, and humidity are deeply investigated to reveal the human thermal comfort level of the existing energy efficient thermal comfort control (EETCC) system in the smart home environment. Experiment results reveal that there is a tight correlation between the environmental factors and the physiology parameter (i.e., heart rate) in the aspect of system operational and human perception. Furthermore, this section also concludes that the current EETCC system is unable to provide the precise need for thermal comfort to the human's preference.

A personal comfort model a new approach to thermal comfort modeling that predicts an individual's thermal comfort response, instead of the average response of a large population. It leverages the Internet of Things and machine learning to learn individuals' comfort requirements directly from the data collected in their everyday environment. In this chapter, we propose a personal thermal comfort prediction model for Smart Homes. The usability of the model is summarized through two cases study, one is that the prediction of the human physiological factor (Heart rate), the other is that the prediction of summer thermal comfort. In the case of heart rate prediction, we used the LSTM deep learning algorithm. In the prediction of personal thermal comfort summer thermal comfort model, we used ANN's neural network prediction algorithm.

4.2 Background and Motivation

4.2.1 Thermal Comfort

Maintaining thermal comfort for humans is one of the key aspects related to the general concept of comfort encountered in human life and activities. Thermal comfort is taken into account, together with visual comfort, acoustic comfort, protection against electromagnetic radiation and air quality, to ensure appropriate quality and sustainability of the living environment. Thermal comfort is described as the state of the mind that expresses satisfaction with its thermal surrounding. Thermal comfort has a wide connotation, also including physiological and psychological aspects, in addition to the ambient characteristics. The implications of thermal comfort in the human activities are increasingly considered in various energy management contexts, together with energy efficiency, environmental impact and economics. In [80] paper, thermal comfort is including the thermal comfort indicators to evaluate, such as assessing thermal comfort is primarily regulated using models based on static heat model transfer equations. P.O. Fanger has been proposed the predicted mean vote/predicted percentage of dissatisfied (PMV/PPD) model in 1970 [28]. This model has been presented by ISO-7730 (2005) [64]. The static thermal models, however, have some limitations. For example, the PMV/PPD model is based on laboratory experiments on adults in highly controlled thermal chambers for a relatively extended period. It is not suitable for different age range of people at home.

Halawa et al. [65] review the studies on adaptive thermal comfort and look critically at the foundation and underlying assumptions of the adaptive model approach and its findings. Craenendonck [66] review the experiments of human thermal comfort in controlled and semi-controlled environments.

Predicted Mean Vote

The PMV thermal comfort model is developed using the fundamental of heat balance and experiment data. A set of correlations is developed from the heat balance equation and experimental data, thus the PMV is formulated as a function of six variables, which includes the air temperature, air velocity, air humidity, clothing resistance, test subject metabolic rate and mean radiant temperature. The meteorological parameters and personal settings of the test subject must be known before calculating the PMV index. The meteorological parameters are air temperature, mean radiant temperature, relative air velocity and the water vapor partial pressure and the personal setting are the clothing insulation, body production of mechanical energy and mechanical work factor.

The PMV index is assessed when the subject is at rest and at the same time exposed for a long period to a constant condition. The equation used to calculate the PMV index is shown in Equation (4.1). The parameters that are required to calculate the PMV index are shown in Equations (4.2 – 4.9).

$$\begin{aligned} PMV = \big(0.303e^{-0.036M} + 0.028\big) \cdot \{&(M - W) \\ &- 3.05 \cdot 10^{-3} \cdot [5733 - 6.99 \cdot (M - W) - P_a] \\ &- 0.42 \cdot [(M - W) - 58.15] \\ &- 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - P_a) \\ &- 0.0014 \cdot M \cdot (34 - T_r) \\ &- 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot \Big[(t_{cl} + 273)^4 - \big(\bar{T}_r + 273\big)^4\Big] \\ &- f_{cl} \cdot h_c \cdot (t_{cl} - T_r) \; \} \end{aligned} \tag{4.1}$$

where

- M is the metabolic rate, in watts per square meter (W/m^2)

- W is the effective mechanical power, in watts per square metre (W/m^2)
- I_{cl} is the human's clothing insulation factor
- f_{cl} is the clothing surface area factor
- t_a is the air temperature
- $\bar{t_r}$ is the mean background radiant temperature
- v_{ar} is the air velocity
- p_a is the humidity level

1. Clothing Surface Radiative Energy

Radiative energy is one of the energy exchanges at the surface of the clothing, which is necessary in order to compute the clothing surface temperature, t_{cl}. The clothing surface radiative energy, R_{clo} is shown in Equation (4.2), where the clothing surface area factor, f_{cl} is calculated in Equation (4.7), clothing surface temperature and mean radiant temperature, t_{cl} and $\bar{T_r}$ are given in $°C$.

$$R_{clo} = 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot \left[(t_{cl} + 273)^4 - \left(\bar{T_r} + 273\right)^4 \right] \tag{4.2}$$

2. Clothing Surface Convection Energy

Convection energy is also one of the energy exchanges at the surface of the clothing, which is necessary in order to compute the clothing surface temperature, t_{cl}. The clothing surface convection energy, C_{clo} is shown in Equation (4.3), where the clothing surface area factor, f_{cl} is calculated in Equation (4.7), the convective heat transfer coefficient, h_c is given in $W/m^2 \cdot K$, clothing surface temperature and room temperature, t_{cl} and T_r are given in $°C$.

$$C_{clo} = f_{cl} \cdot h_c \cdot (t_{cl} - T_r) \tag{4.3}$$

3. Clothing Surface Temperature

The clothing surface temperature is estimated based on the calculated skin temperature and the convective and radiative energy fluxes at the surface of the clothing. The clothing surface temperature is non-linear and the clothing surface temperature is used in determining the convective and radiative energy, thus the equation must be solved numerically until it satisfies the Equation (4.4). The clothing surface temperature in $°C$, t_{cl} is shown in Equation (4.5), where the metabolic rate and effective mechanical power, M and W are given in W/m^2, clothing insulation, I_{cl} is given in $m^2 \cdot K/W$.

$$(R_{clo} \cdot t_{cl}) + (C_{clo} \cdot t_{cl}) = 0 \tag{4.4}$$

$$t_{cl} = 35.7 - 0.028 \cdot (M - W) - I_{cl} \cdot (R_{clo} + C_{clo}) \tag{4.5}$$

4. Convective Heat Transfer Coefficient

The convective heat transfer coefficient is the turbulent heat transfer coefficient between clothing and air. The convective heat transfer coefficient, h_c given in $W/m^2 \cdot K$ is shown in Equation (4.6), where the relative air velocity, v_r is given in m/s.

$$h_c = \begin{cases} 2.38 \cdot |t_{cl} - T_r|^{0.25} & , 2.38 \cdot |t_{cl} - T_r|^{0.25} > 12.1 \cdot \sqrt{v_r} \\ 12.1 \cdot \sqrt{v_r} & , 2.38 \cdot |t_{cl} - T_r|^{0.25} < 12.1 \cdot \sqrt{v_r} \end{cases} \tag{4.6}$$

5. Clothing Surface Area Factor

The clothing surface area factor is defined as the ratio of the clothing surface area to the subject body surface area. The clothing surface area factor, f_{cl} is shown in Equation (4.7).

$$f_{cl} = \begin{cases} 1.00 + 1.290 \cdot I_{cl} & , I_{cl} \leq 0.078\, m^2 \cdot K/W \\ 1.00 + 0.645 \cdot I_{cl} & , I_{cl} > 0.078\, m^2 \cdot K/W \end{cases} \tag{4.7}$$

Besides, the conversion from clothing insulation, clo to $m^2 \cdot K/W$ is $1clo = 155m^2 \cdot K/W$.

6. Mean Radiant Temperature

The mean radian temperature is the average temperature of the wall surrounding the subject. The mean radian temperature, $\bar{T_r}$ in $°C$ can be calculated using Equation

(4.8), where the surface temperature of the wall i in $°C$ and the angle factor between the occupant and surface i, F_{p-i} [81].

$$\bar{T}_r^4 = \sum_{i=1}^{6} T_i^4 \cdot F_{p-i} \tag{4.8}$$

7. Relative Air Velocity

The relative air velocity, v_r given in m/s is shown in Equation (4.9), where a correction factor, C_{air} is multiplied with the outdoor air speed to calculate the relative air velocity.

$$v_r = c_{air} \cdot v_{out} \tag{4.9}$$

Predicted Percentage Dissatisfaction

The PPD thermal comfort model is an extension on the PMV thermal comfort model, where the PMV calculates the thermal sensation while the PPD calculates the percentage of subjects that are dissatisfied with the given thermal conditions. The equation used to calculate the PPD is shown in Equation (4.10). Comfort Criteria: Occupant comfort is achieved when the PMV value is between -0.5 to +0.5. The corresponding predicted percentage of dissatisfied people falls below 10%, as shown in Figure 4-1.

$$PPD = 100 - 95 \cdot e^{\left(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2\right)} \tag{4.10}$$

From Equation (4.10), it is noted the minimum PPD is 5%, where PMV is equal to zero. The minimum PPD is 5% due to the reason that providing an optimal thermal environment for every subject is not possible.

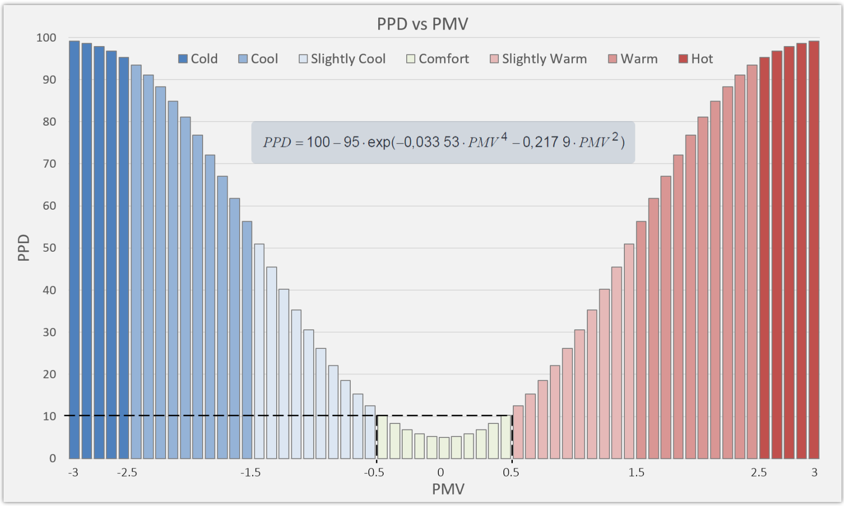


Figure 4-1: PPD against PMV.[1]

Draft Risk

The DR thermal comfort model is categorized as an air velocity model. Draft is known as the undesired local cooling of the body caused by air fluctuation [82]. The DR in metric unit is shown in Equation (4.11), where the local air temperature, $t_{a,l}$ is given in $°C$, the local average air velocity, $\bar{v}_{a,l}$ given in m/s and percentage of local air turbulence intensity, Tu given in %.

$$DR = (34 - t_{a,l}) \cdot (\bar{v}_{a,l} - 0.05)^{0.62} \cdot (0.37 \cdot \bar{v}_{a,l} \cdot Tu + 3.14) \tag{4.11}$$

For conditions, such as $\bar{v}_{a,l} < 0.05\,m/s$, $\bar{v}_{a,l} = 0.05\,m/s$ and $DR > 100\%$, $DR = 100\%$. The $t_{a,l}$ is in the range of $20°C$to $26°C$while the ranges from 10% to 70%. ASHRAE Standard 55-2017 stipulates that the DR must be $< 20\%$.

Stander of Thermal Comfort

Although the PMV/PPD model gives us a way in judging the thermal comfort level, the human's subjective evaluation is essential. In this reserach, we use the ASHRAE 55 [29] to make the subjective evaluation level into seven-level evaluation, as shown in Table 4.1. It contains seven thermal sensation levels: "cold (-3)", "cool (-2)", "slightly

[1] Figure source: https://www.linkedin.com/pulse/role-cfd-evaluating-occupant-thermal-comfort-sandip-jadhav/

cool (-1)", "neutral (0)", "warm (1)", "slightly warm (2)" and "hot(3)", respectively. In [40, 67, 68], the subjective comfort evaluation methods are given in smart homes. This subjective evaluation level is modified as a subjective comfort level (SCL) to be used for the participant to answer their direct thermal sensation via the online questionnaire with the intention to study the difference in between human's subjective thermal comfort and system's thermal comfort level.

Table 4.1: The average human's comfort degree on the 7-point ASHRAE scale

Cold	**Cool**	**Slightly cool**	**Neutral**	**Slightly warm**	**Warm**	**Hot**
-3	-2	-1	0	$+1$	$+2$	$+3$

According to the standard ISO 7730 of the indoor environment comfort index, in summer season (experiment in the Cheaper 4 Section 4.3) the environment temperature is in range of 23 and 28 °C, relative humidity is in range of 30% and 70%, body vertical temperature difference is less than or equal to 3 °C, average wind speed is less than 0.25 m/s. In winter season (experiment in the Cheaper 5 Section 5.5) , the environment temperature is in range of 20 and 24 °C, relative humidity is in range if 30% and 70%. During these specification ranges, a human will feel comfort in indoor environments.

4.2.2 Energy Efficient and Thermal Comfort Control

The energy efficient thermal comfort control (EETCC) algorithm is a supervisory rule-based control controller developed for smart home [83]. The EETCC algorithm is a thermal comfort controller that utilizes the actuator that uses the least energy consumption to maintain thermal comfort in the room. For example, when the outdoor air temperature is lower than the indoor temperature while the intended action is to cool the room, the EETCC algorithm will open the window to allow the cold outdoor air to lower the temperature in the room instead of utilizing the air-conditioner. Besides, the EETCC algorithm uses the states of actuators as different PMV categories to determine which combination of actuators to turn on or off. The PMV, PPD, and DR at every iteration to determine the state of actuators that satisfy the target thermal comfort demand while consuming the least energy. Furthermore, there is a timer in the EETCC algorithm to prevent frequent actuation to reduce the tear and wear of the actuators in the room. Furthermore, there is a timer in the EETCC algorithm to prevent frequent actuation in order to reduce the tear and wear of the actuators in the room. The flowchart and states of the EETCC algorithm are shown in Figure 4-2.

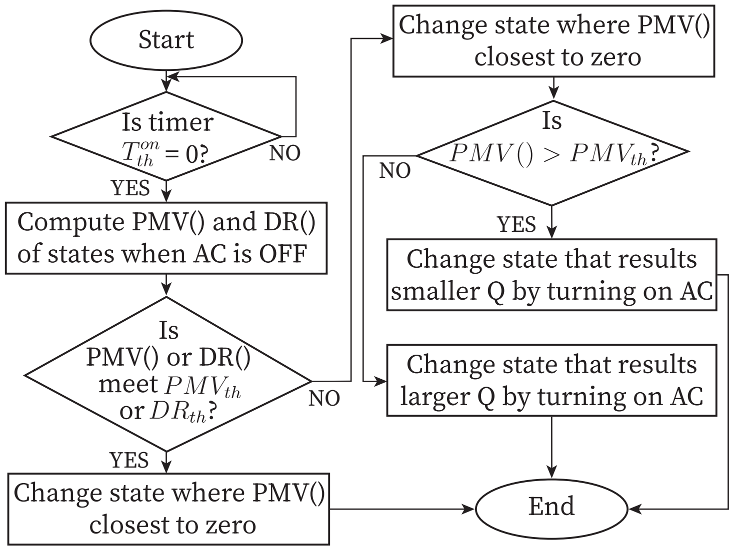


Figure 4-2: Flowchart of EETCC algorithm.

As the experimental smart home, iHouse contain various types of networked sensors and actuators that provides the required feedback parameters and output controls to the proposed temperature controller. In order for the temperature controller to be able to communicate with the networked sensors and actuators in the iHouse, an ECHONET Lite capable system has to be developed to translate the necessary control signals and feedback sensor data to the appropriate formats. The EETCC system mainly provides ECHONET Lite protocol translation, data processing while supporting real time device management and data logging. There are two revisions of the EETCC system that is developed, where the one version is written in C language and the other one version is rewritten in Python language. For this study, the C language version is chosen. Two PMV categories are considered in the EETCC control algorithm, which one is category A: $-1 < PMV < 1$ and another one is category B : $-0.5 \leq PMV \leq 0.5$. Then we considered three different actuators that can be used to control the thermal comfort in the room, which are the air-conditioner, window, and curtain. These three actuators can be categorized into eight different actuation profiles, where each profile is a combination of the actuation state of the actuators in the room. However, only six combinations are implemented. Two of the states are removed from the eight possible combinations as both of the states involves turning on the air-onditioner and opening the window at the same time. These states are not logical as opening the window while cooling or heating the room with an air-conditioner is inefficient as the heat exchanges due to convection between the indoor and outdoor environment would occur and reduce the capability of the air-conditioner to cool or heat the room. Hence, increasing the time taken to cool or heat the room to a certain temperature at the same time will increase the energy usage by the air-conditioner. The remaining six states are shown in Table 4.2. The result of the control state and human thermal comfort will be discussed in Section 4.3.5.

Table 4.2: States of the actuators

State	**Air-conditioner**	**Window**	**Curtain**
S1	0	0	0
S2	0	0	1
S3	0	1	0
S4	0	1	1
S5	1	0	0
S6	1	0	1

0: Off/Close; 1: On/Open

4.2.3 Personal Thermal Comfort Model

There are two parts of thermal comfort, one is physical, other is physiological. One of this research aim is to propose thermal perception comfort model. Kim. J et.al, proposed personal comfort model in [84]. A personal comfort model predicts an individual's thermal comfort response, instead of the average response of a large population. The key characteristics of personal comfort models are that they: (1) take an individual person as the unit of analysis rather than populations or groups of people; (2) use direct feedback from individuals (e.g., thermal sensation, preference, acceptability, pleasure) and additional

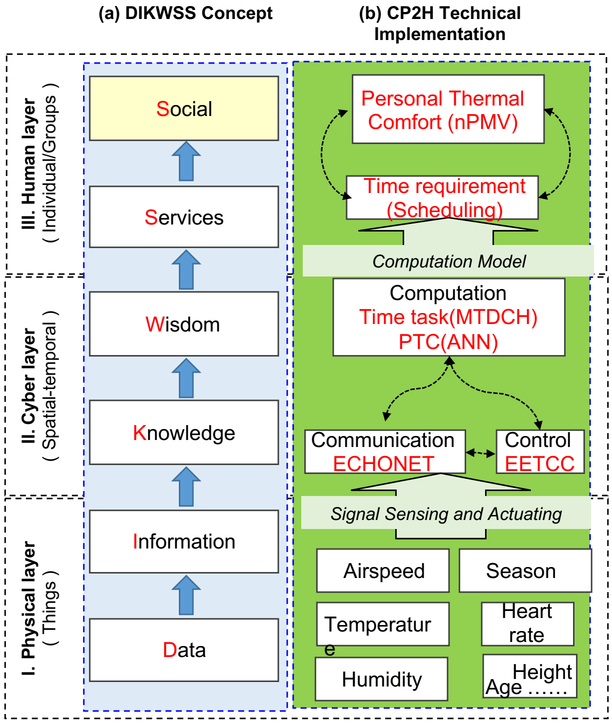


Figure 4-3: Content of the Personal Thermal Comfort model.

relevant data (e.g., personal, environmental, technological), to train a model; (3)prioritize cost-effective and easily-obtainable data; (4) employ a data-driven approach, which allows flexible testing of different modeling methods and potential explanatory variables; and (5) have the capacity to adapt as new data is introduced to the model. In Figure 4-3, the personal thermal comfort model is shown. In the section 2.3.2, the three vertical levels are I. Physical layer, II. Cyber layer, and III. Human layer are mentioned. Personal thermal comfort model is according the DIWKSS layers struct to make the I. Physical layer is included by enviroment sensors data, human heart rate, human age, height, weight and so on. In the II.Cyber layer is included by core algorithms, ECHONET, EETCC and PTC. In the III. Human layer is the model's motivation, like personal thermal comfort $(pPMV)$ in this layer.

Thermal comfort is related to many factors. In this study, the parameters we selected are basic parameters that can be collected and controlled, as follows:

1 Human Parameters

Human parameters mainly include human gender, age, height, and weight. These parameters are slowly changing parameters, that is, time requirements are not strict. Time-critical parameters include changes in the human heart rate and human sub-

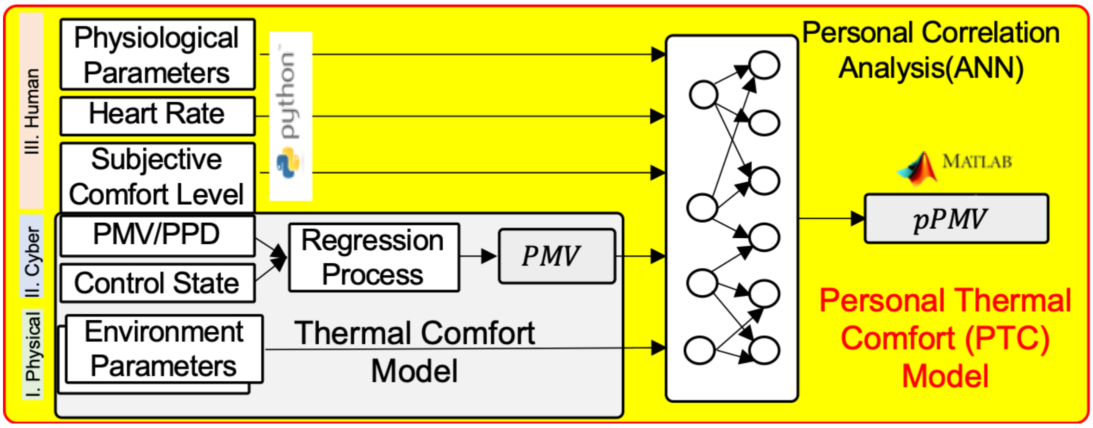


Figure 4-4: Personal Thermal Comfort model.

jective comfort.

2 Physical Parameters

For the physical parameters, we have selected that air conditioning, windows and curtains can be controlled by EETCC. The main parameters are indoor temperature, indoor humidity, and indoor wind speed. The reference parameters are outdoor humidity, outdoor wind speed, and outdoor temperature.

3 Cyber Parameters

The information parameters include PMV and PPD, which are common to international standards. There are also control states that we can change through programming.

The personal thermal comfort model includes human physiological sensor data, human psychological data, environmental data and system calculated data. Make systematic predictions through machine learning.

4.2.4 Motivation

1. Personal Thermal Comfort Parameter and Relationship

   Obtain the human heart rate of ordinary wearable devices, and study its relationship with environmental factors and system factors. This is a prerequisite to ensure that this research can be achieved in smart homes.

2. Human Heart Rate Prediction

   In the smart home environment, when people take off the wearable device, this solution can still predict the heart rate change through human behavior recognition, which will have a direct impact on future Implementation applications.

3. Person Thermal Comfort Prediction
   As the ultimate research goal of this thesis, how can personal thermal comfort in smart homes achieve the synchronization of human physiological and psychological perception and prediction with system regulation.

4.3 Case Study 1: Experiment and Modeling of Personal Thermal Comfort Model

4.3.1 Content and Participants

Consent was obtained from all participants before the subjective questionnaire and the measurements. All involved people agreed to participate in the survey. It should be noted that this study mainly focused on the usage of personal thermal comfort in a real home scenario, that is involved in the use of smart watch to observe the heart rate only. All involved systems were widely used or studied in the real world, and they did not cause any harm to people.

There are 6 participants (2 adult females, 3 adult males and 1 child female), with the adult participants average age, height, weight and BMI of 26.8, 171.0($\pm$2)cm, 64.4($\pm$0.5)kg, 21.72($\pm$0.2)kg/m^2. Detailed physical information about the research participants is shown in table 4.3. All participants had no physical defects, lack of sleep, depression, and other conditions.

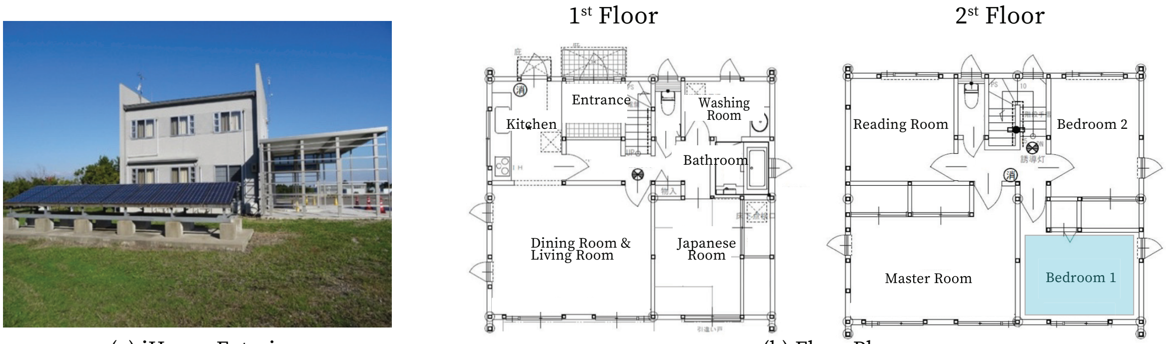
Table 4.3: Brief information of participants

NO.	Gender	Age (y)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Test period	Air temperature ($°C$) Avg.	Humidity (%) Avg.
F1	Female	38	174	59	19.5	May 30	25.2	48.5
						May 31	26.5	45.9
F2	Female	23	154	47	19.8	July 19	25.9	49.6
M1	Male	26	170	56	19.4	May 30	25.2	48.5
						May 31	26.5	45.9
M2	Male	23	175	65	21.2	June 28	27.1	50.9
M3	Male	24	182	95	28.7	June 28	27.1	50.9
C1	Female	8	137	27	14.4	July 21	28.3	51.0

4.3.2 Experimental Environment, iHouse

The iHouse is an advanced experimental and provisioning facility of home network systems that are located in Ishikawa, Japan. The iHouse is a two floor Japanese-styled house consists of 15 rooms as shown in Figure 4-5. This section mainly focuses on the iHouse Bedroom 1, which is shown in Figure 4-6. There are over 300 sensors and actuators in the iHouse and Bedroom 1 alone has more than 20 sensors and actuators. The iHouse Bedroom 1 is chosen as it has a single bed with multiple motorized windows and curtains. Besides, the iHouse Bedroom 1 is also equipped with a Toshiba ECHONET Lite capable split unit air conditioner with a $2.8kW$ rated cooling capacity.

The Bedroom 1 is located on the second floor of the iHouse and has two windows, one facing perfect east and another facing perfect south. The Bedroom 1 is $5.0m$ length, $4.1m$ width, $2.4m$ height. The experiment's implementation is from May to July 2019 in Nomi City, Japan, during this time the average normal highest temperature is 24.7°C, the average normal lowest temperature is 17.7°C. Main sensors and wearable devices are shown in table 4.4. To collect human physiological data, the authors compared several portable wearable and health monitoring devices available in the market, which are popular and common due to powerful functionality, affordable prices, and lightweight features. Considering our requirements on the specification of individual heart rate data, the Apple Watch Series 4 is adopted.



(a) iHouse Exterior (b) Floor Plan

Figure 4-5: iHouse exterior and architectural plan.

Figure 4-6: Badroom 1 of iHouse.

Table 4.4: Brief information on main sensors and wearable device

Type	Name	Range	Parameter
Indoor Temperature Sensor	SHT75 digital sensor	$[-40, 125]$ °C±0.3 °C	14-bits ADC signal processing
Humidity Sensor	SHT75 digital sensor	$[0, 100]\%$ ±1.8%	14-bits ADC signal processing
Wind Speed Sensor	hot-wire anemometer sensor	$[0.015, 5]m/s \pm 0.2\%$	-
Wearable Device	Apple Watch Series 4	$[30, 210]BPM$	64-bit dual-core CPU processor, 16GB capacity

4.3.3 Subjective Comfort Level

In the subjective experience record section, we use random submission and passive submission hybrid mode. The random submission mode is that the participant can submit records online when they feel thermal comfort changing. The passive submission mode is a record provided when the system's physical environment changes, for example, air conditioning is turned off, windows are opened, and the like. The questionnaire uses the Google Forms open-source application to share the web link. Each participant was independently filled in at different terminals (personal computers or personal smartphones), ensuring the accuracy of the experimental results, and removing interference. The questionnaire records by system included: (1) date and time; (2) number of participation; (3) thermal sensation and comfort; Scales of subjective comfort data records example are presented in table 4.5. As shown in Figure 4-7, during the experimental date, 225 individual comfort data records were collected. Summary of the subjective comfort data, which top three are 38.2% Neutral, 20.4% Sightly Cool and 14.7% Sightly Warm.

Table 4.5: Subjective comfort data record structure example

Participation Number	Date and Time	Thermal Sensation	Scale
F1	2019/05/30 10:27:01	Hot	3
M1	2019/06/28 14:05:34	Warm	2

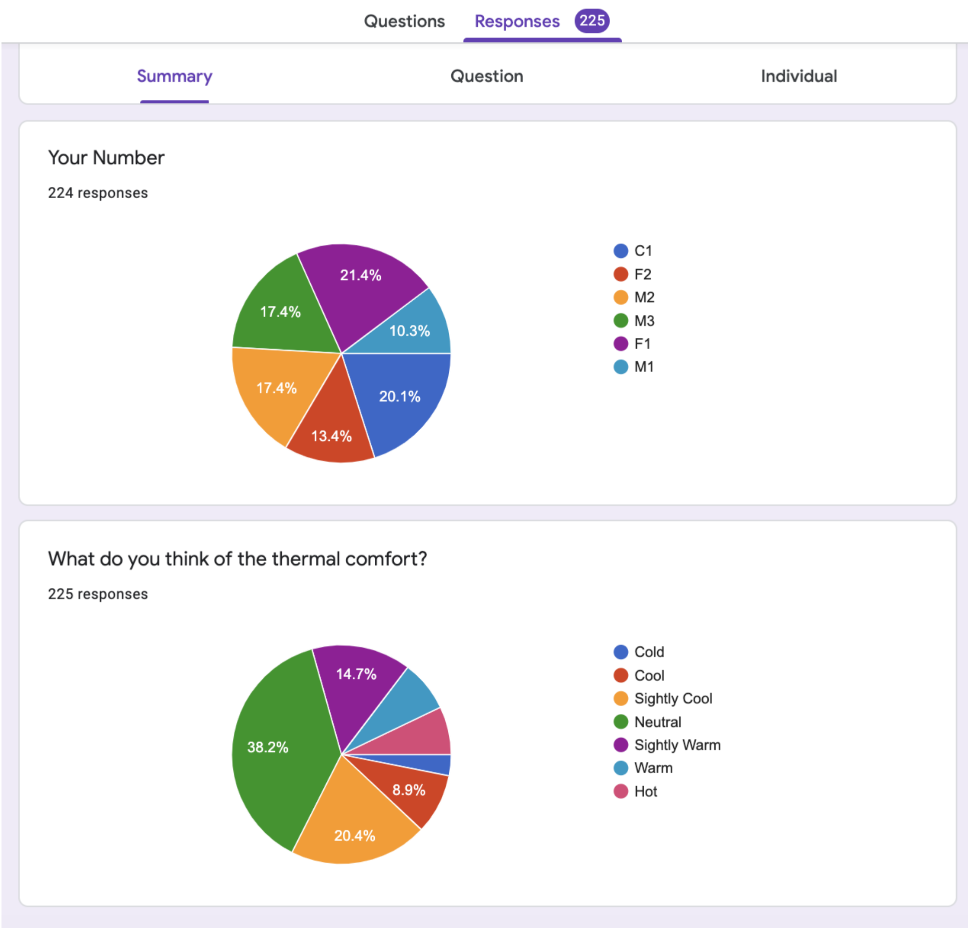


Figure 4-7: Summary of SCL in Google form application.

4.3.4 Experimental Procedure

The experiment was divided into two sets. The first set was two participants who manually adjusted the air-conditioner setting every 30 minutes, automatically recorded the heart rate with a wearable device, and filled in SCL card online during the operation. The second set is based on EETCC's automatic control of the comfort level of the environment. The wearable device automatically records the heart rate, and the subjective comfort is filled in online when the subjective comfort changes. Each collection is divided into two sections, morning session (10:00 AM-11:30 AM) and afternoon session (14:00 PM-16:00 PM), shown in table 4.6. After the end of each session, turn off the air conditioner, close the doors and windows, and let the indoor environment without the system adjustments and human interference.

Six subjects participated in experiments from May to July 2019. Morning and after-

Table 4.6: Experiment sets

Set	Session	Participant	Contents	Total of datasets	Total of samples
Set 1	Morning Afternoon	F1, M1	Air-con is set to 20°C and 25°C alternatively in every 30 minutes Fill the SCL card in every 30 minutes	4	2880
Set 2	Morning Afternoon	F1, F2, M1 M2, M3, C1	Air-con is controlled by EETCC automatically Fill the SCL card in any time	12	8640

noon sessions lasting two hours each were scheduled. It should be noted that participants were volunteers and were aware of the purpose and procedure of data collection. The process defined for the tests requires the users to carry the wearable devices under normal house conditions, and, thus, no particular activity was determined for the tests. Before 30 minutes of every experiment, each participant will be asked to have a rest, like sitting and reading outside of the experimental room to obtain more stable and reliable heart rate. Accordingly, participants were conducting their usual home activities during the tests. These activities are comprised of reading or writing, working on a computer, etc. The indoor and outdoor air temperature, indoor and outdoor relative humidity, indoor and outdoor airspeed were measured continuously by EETCC every 10 seconds.

4.3.5 Results and Discussion

In this section, we divided the experimental results into four parts. The first part is the statistical results of the participants' heart rate collected by the wearable device. The correlation coefficient between the environmental parameters and the participants' heart rate is mentioned in the second part. The third part is about the thermal comfort evaluation of the system compared with the subjective. The fourth part has suggested the relationship between comfort parameters and the control state of the smart home system.

1. Statistical Results

The statistical result of the heart rate with the mode value is 70, the median value is 74, the average value is 75.78, the variance is 104.95, and the standard deviation σ is 10.25. Comparison based on the distribution of different heartbeat data for males and females is shown in Figure 4-8. There are 68.83 % heart rate data records concentrated in the interval of 60–70 and 71–80.

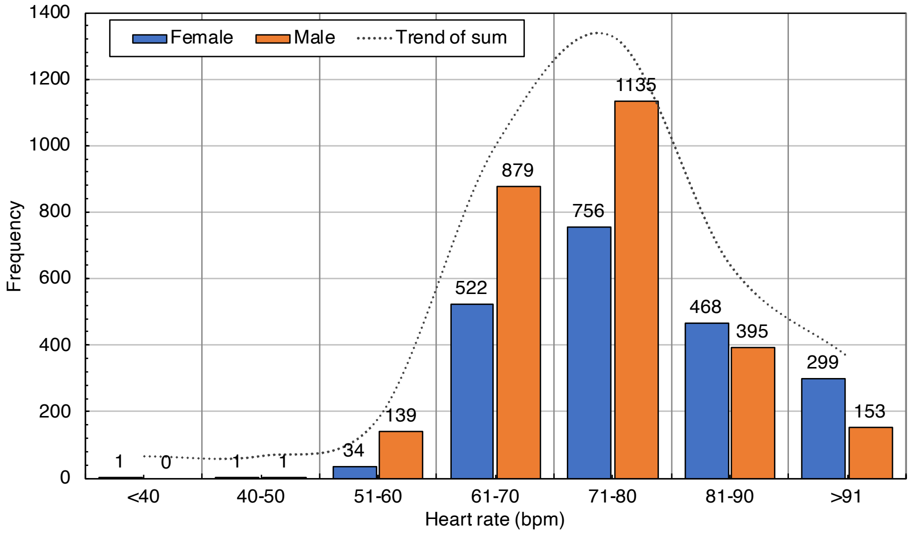


Figure 4-8: Distribution of heart rate.

2. Correlation Co-efficient Between Heart Rate and SCL

The correlation between heart rate and subjective comfort level is tested using Pearson Correlation (r), which is shown in Formula (4.12).

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{4.12}$$

where x is the heart rate and y is SCL.

To analyze the correlation of the two features used (heart rate and SCL). Figure 4-9 shows the scatter plots of these correlations. The total heart rate and SCL correlation value is $r = -0.112$. In warm and hot range, the correlation value is $r = -0.0443$. In slight warm, natural, slight cool range, the correlation value is $r = -0.032$. In cool and cold range, the correlation value is $r = 0.172$. The results indicate a weak correlation between heart rate and SCL, and because of this, the correlation between heart rate and environmental factors is studied.

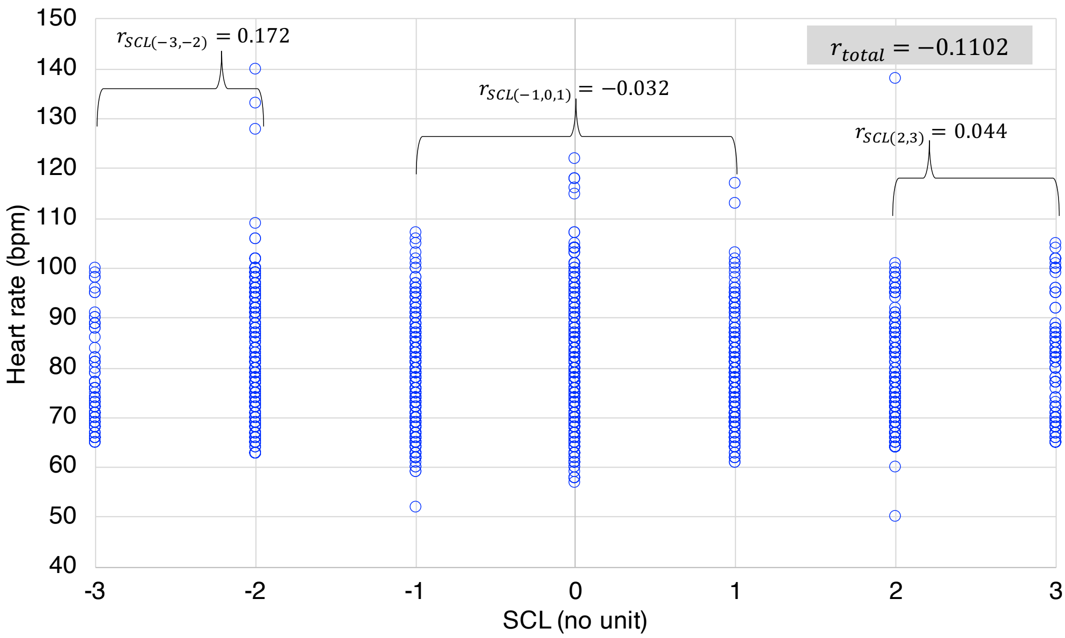


Figure 4-9: The relationship between heart rate and SCL.

3. Correlation Co-efficient among Environment Parameters and Heart Rate

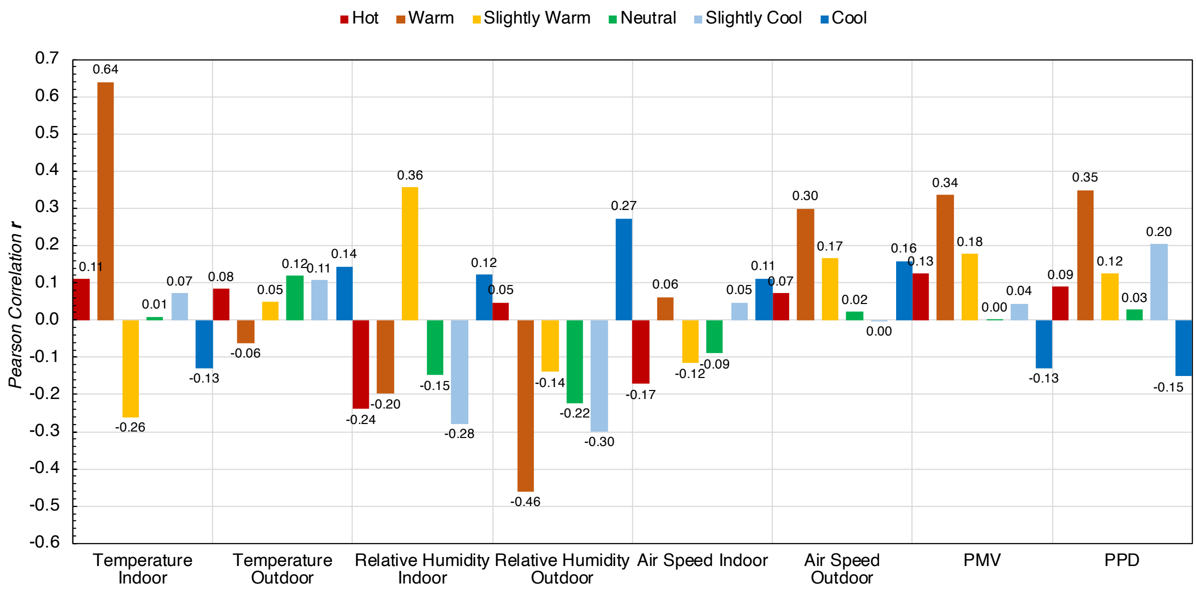
The correlation between heart rate and environmental factors is tested using Pearson Correlation (r), which is shown in Formula (4.12). The results of different subjective comfort levels are shown in Figure 4-10a morning session and Figure 4-10b afternoon session. In Formula (4.12), for heart rate and environmental factors Pearson Correlation analysis with x is the heart rate and y is environment parameters include temperature indoor, temperature outdoor, relative humidity indoor, relative humidity outdoor, air speed indoor, air speed outdoor, PMV, and PPD.

Results are quite revealing in several ways. The morning session is shown in Figure 4-10a, the temperature indoor is most relevant to the heart rate at the warm SCL, and the correlation co-efficient $r = 0.64$. The indoor relative humidity is the most pertinent to the heart rate at the slightly warm SCL, $r = 0.36$. The air speed indoor is the most relevant to the heart rate correlation value $r = 0.30$ at warm the SCL. There is a significant positive correlation between heart rate and indoor parameters under warm SCL. The correlation between heart rate and outdoor environmental parameters is positively correlated with the outdoor temperature at the cold comfort level of $r = 0.14$. Outdoor relative humidity at cold SCL is $r = 0.27$. Outdoor air speed is $r = 0.30$ at warm SCL. Meanwhile, the negative correlation coefficient of outdoor relative humidity is more prominent in the warm SCL; the value of the outdoor relative humidity correlation coefficient is $r = -0.46$.

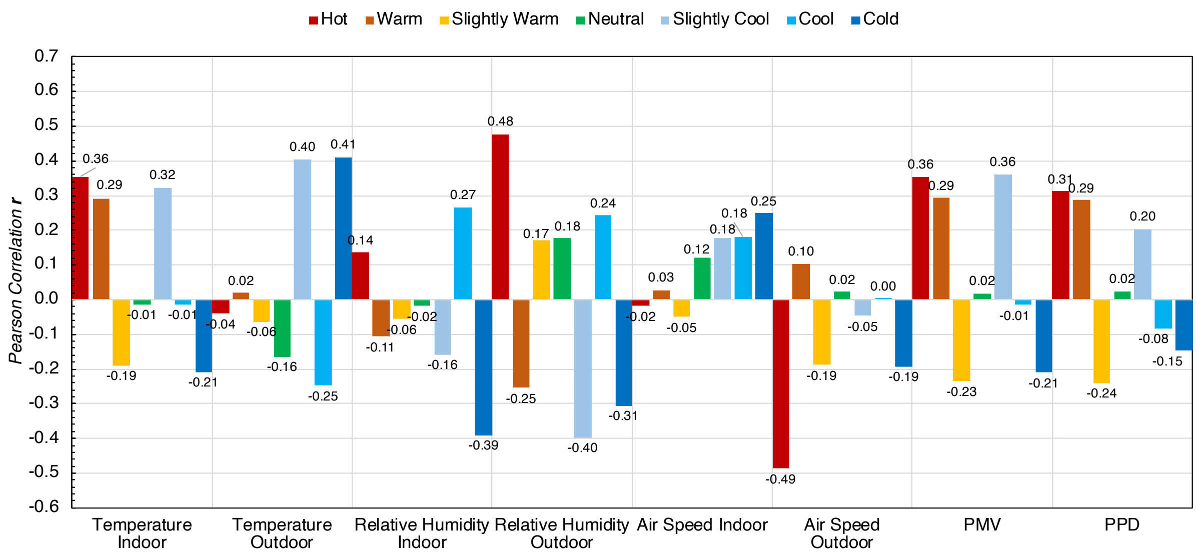
Turning now to the experimental results on the afternoon session, shown in Figure 4-10b. The indoor environmental parameters were more prominent under different subjective comfort levels. The correlation coefficient between indoor temperature and heart rate is $r = 0.36$ at hot SCL. The indoor relative humidity and heart rate correlation coefficient is $r = 0.27$ at cool SCL. Indoor air speed correlation with the heart rate is $r = 0.25$ at cold SCL. On the other hand, the outdoor parameters correlation of temperature is $r = 0.41$ at cold SCL, relative humidity was $r = 0.48$ at warm SCL, outdoor air speed is $r = 0.10$ at warm SCL, and $r = -0.49$ at hot SCL.

4. Personal Thermal Comfort Individual Differences

It can be seen from the Figure 4-11 that there is a significant difference in the comfort zone of the 6 participants have obvious differences in the relationship between indoor temperature and relative humidity in the comfort zone. Although in the same day experiment, under the same room temperature and humidity, there are still differences, for example, M2 and M3.



(a) In the morning



(b) In the afternoon

Figure 4-10: Average *Pearson Correlation r* between the environmental parameters and heart rate.

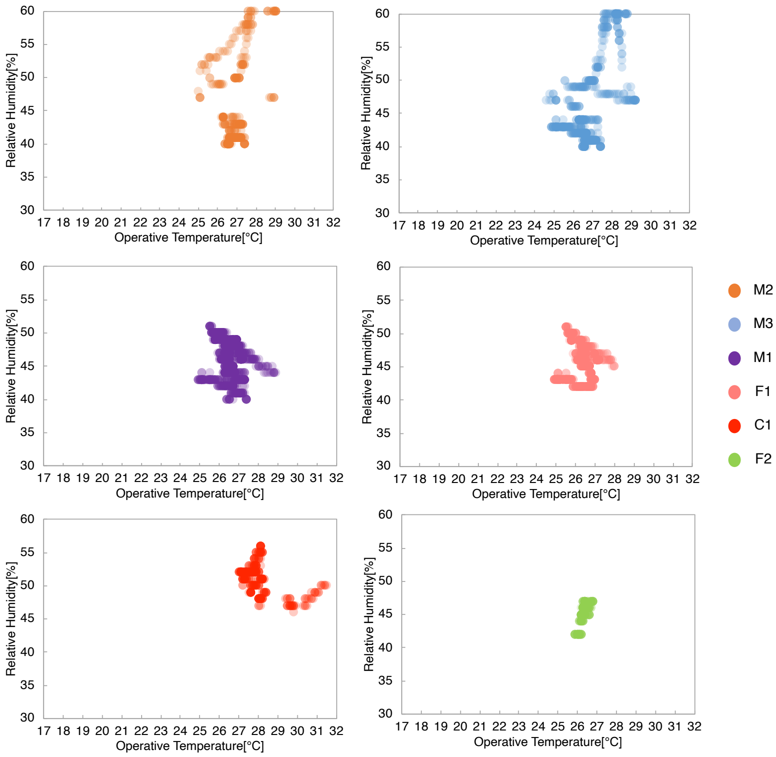
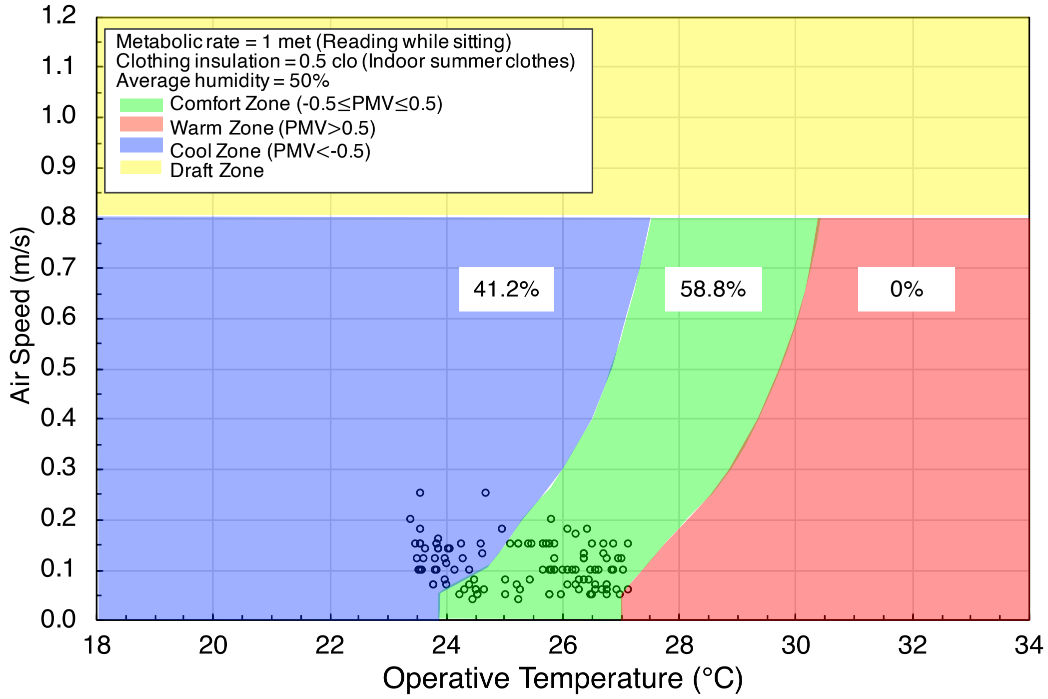


Figure 4-11: Personal thermal comfort individual differences.

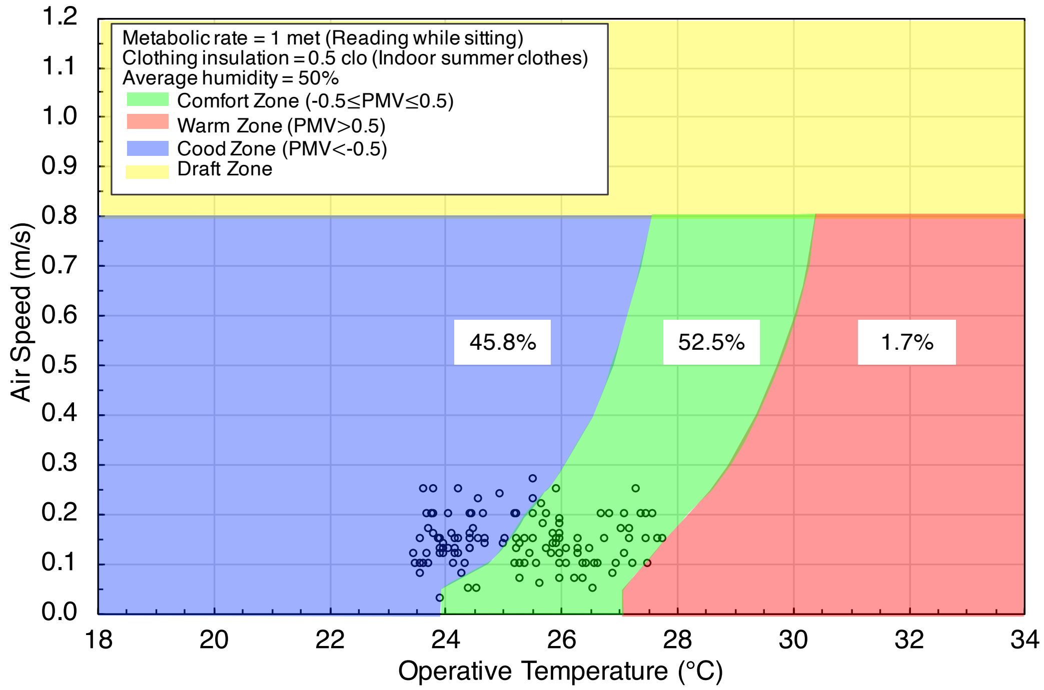
5. Thermal Comfort Assessment

Referring to Berkeley's research results in [85], we define proximate comfort zone, cool zone, and warm zone in this paper's results shown figures. In experiment Set 1, the setting of the air-conditioner is controlled by the participants. Participants set the air-conditioner temperature to 20 or 25 °C, and changed every 30 min. During the time, participants recorded the subjective comfort information.The results that PMV represents air speed against operative temperature without EETCC are shown in Figure 4-12a,b. In the morning session, PMV is 58.8% in the comfort zone, 41.2% in the cool zone, and 0% in the warm zone. In the afternoon session, the PMV is 52.5% in the comfort zone, 45.8% in the cool zone, and 1.7% in the warm zone.

In experiment Set 2, indoor temperature and air speed data were automatically recorded by EETCC. Based on Berkeley's calculation comfort zone, we set the clothing insulation as indoor summer clothes, metabolic rate is reading while sitting, and the average relative humidity is 50%, and then draw the comfort zone as shown in Figure 4-13a and 4-13b. The comfort zone is highlighted in green color, where its PMV value is between -0.5 and 0.5. The warm zone and cool zone are emphasized in blue color and red color. The draft



(a) In the morning



(b) In the afternoon

Figure 4-12: PMV represents air speed against operative temperature without EETCC.

zone is shown up in yellow color.

The morning session result is shown in Figure 4-13a. There is 64% PMV value in comfort zone, 34.5% in the warm zone, and 1.5% in cool zone. In the afternoon shown in Figure 4-13b, the PMV value in the comfort zone is 67.8%, 32% in the warm zone, and 0.2% in cool zone. There is no PMV value in the draft zone, whether in the morning or afternoon.

From Figure 4-14, we can see that relative frequency in different SCL scale. In the neutral range, there is 41.4% in the morning and 66.6% in the afternoon. Average the slightly cool, cool, and cold SCL scale in the cool zone, there are 12.3% in the morning and 11.7% in the afternoon. For the warm zone with average, the slightly warm, warm, and hot SCL value, which are 46.3% in the morning and 21.8% in the afternoon.

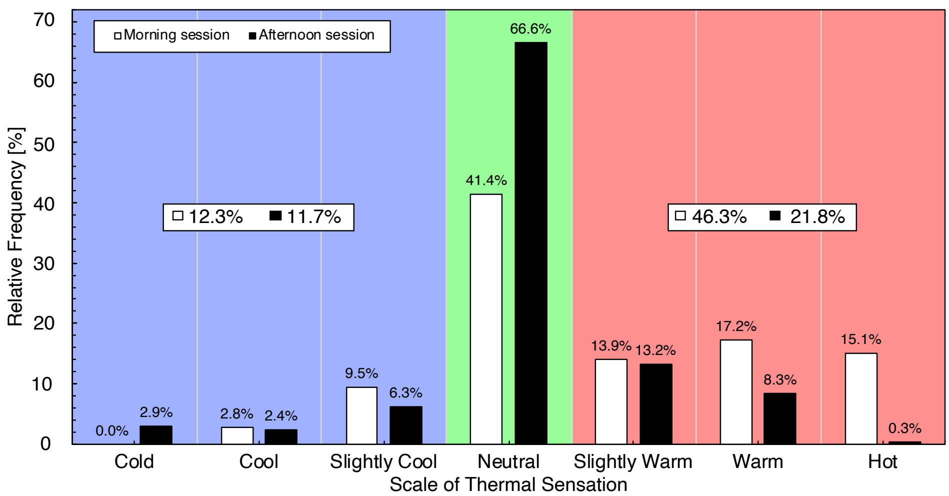
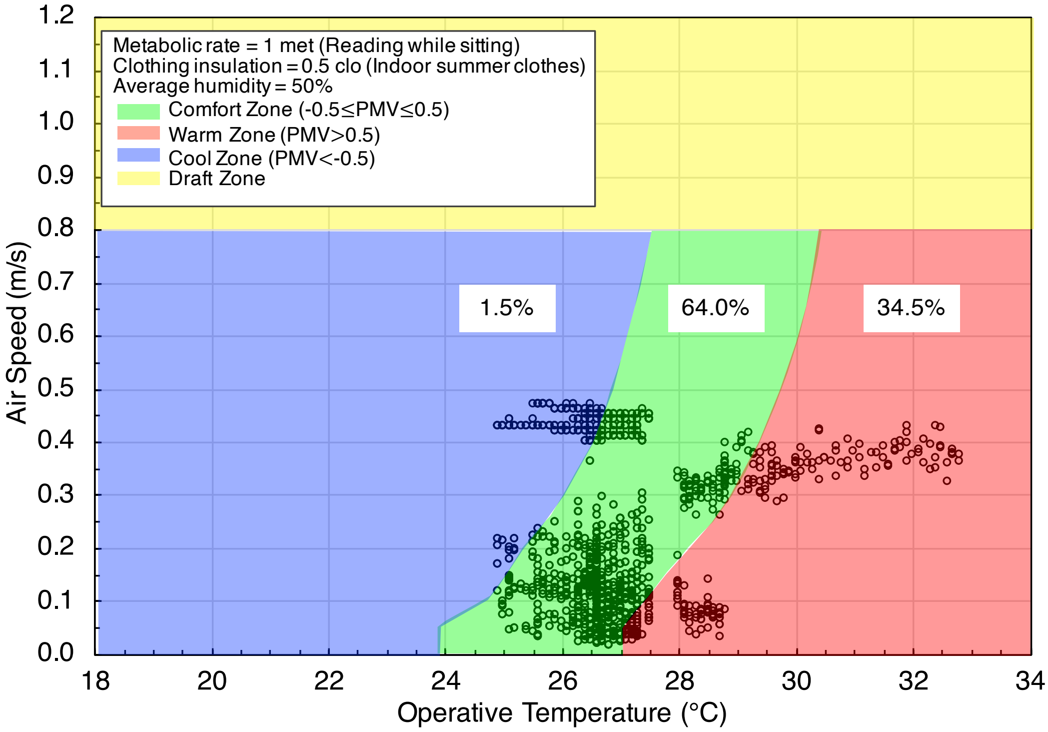


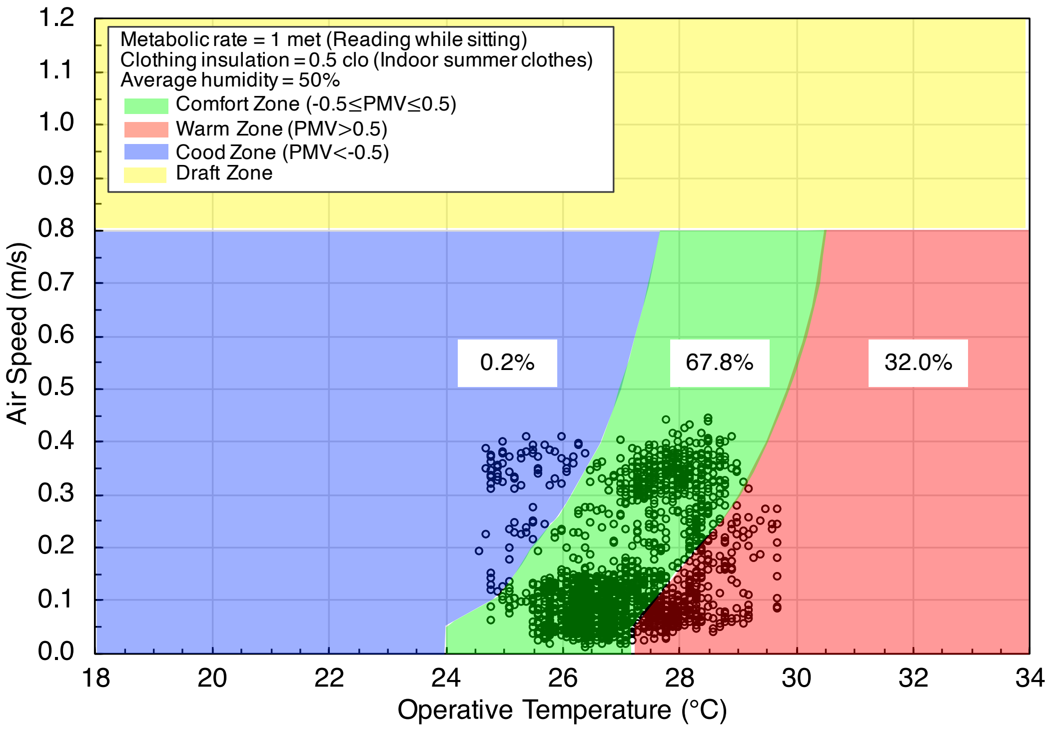
Figure 4-14: Subjective Comfort Level (SCL) represents air speed against operative temperature.

6. Control State and Thermal Comfort

To consider the difference between thermal comfort and thermal sensations in different indoor temperatures scale, the average thermal comfort data is shown in Figure 4-15a,b. The gray zone indicates the PMV values between -1 and 1. The yellow zone indicates the PMV values between -0.5 and 0.5. In Figure 4-15a, the morning session, the average thermal comfort is greater than 1 when the indoor temperature is greater than 28.5 °C and the indoor temperature in the range from 27.5 to 28.4 °C. Each scale of the thermal sensation is unevenly distributed. The indoor temperature scale from 25.5 to 26.4 °C and



(a) In the morning



(b) In the afternoon

Figure 4-13: PMV represents air speed against operative temperature with EETCC.

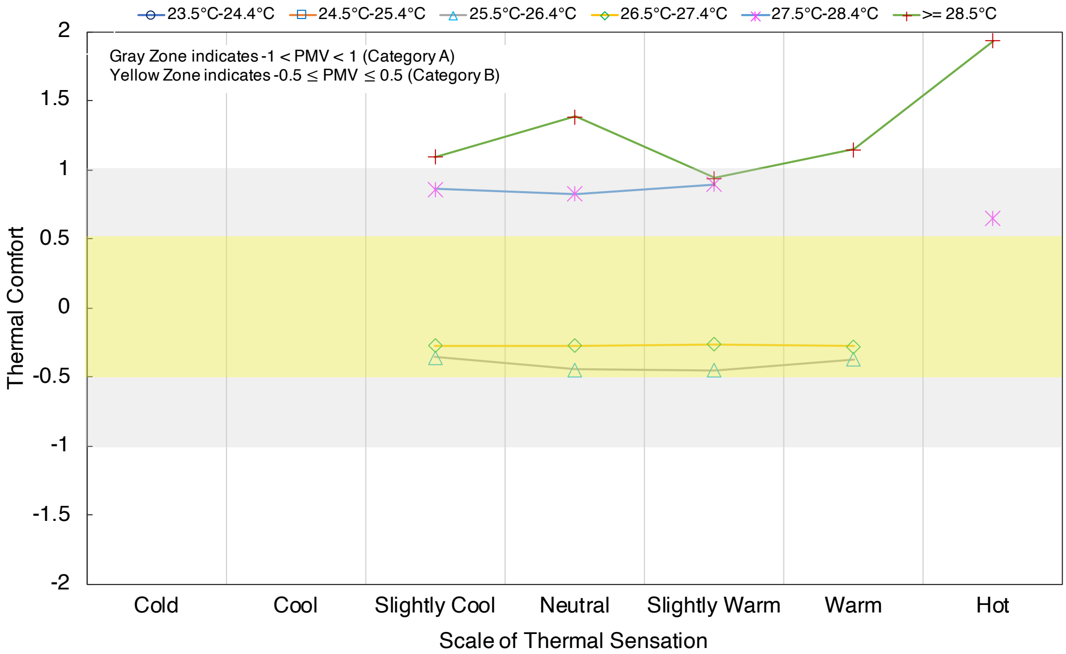
scale from 26.5 to 27.4 °C, those two scales are in thermal comfort yellow zone in thermal sensation scales in Slightly Cool, Neutral, Slightly Warm and Warm. In Figure 4-15b the afternoon session, the indoor temperature scale from 25.5 to 26.4 $°C$ in thermal comfort yellow zone with the thermal sensation from Cold to Hot.

According to the definition of the previous Section 4.2.2, total of control states is six. In Figure 4-16a,b, we show the relationship between the control state and PMV and SCL with time continues. The gray zone indicates the PMV values between -1 and 1. The yellow zone indicates the PMV values between -0.5 and 0.5. The blue line is the highest frequency control state. The black line is the highest frequency PMV value. The red line is the highest frequency SCL value from the six participators.

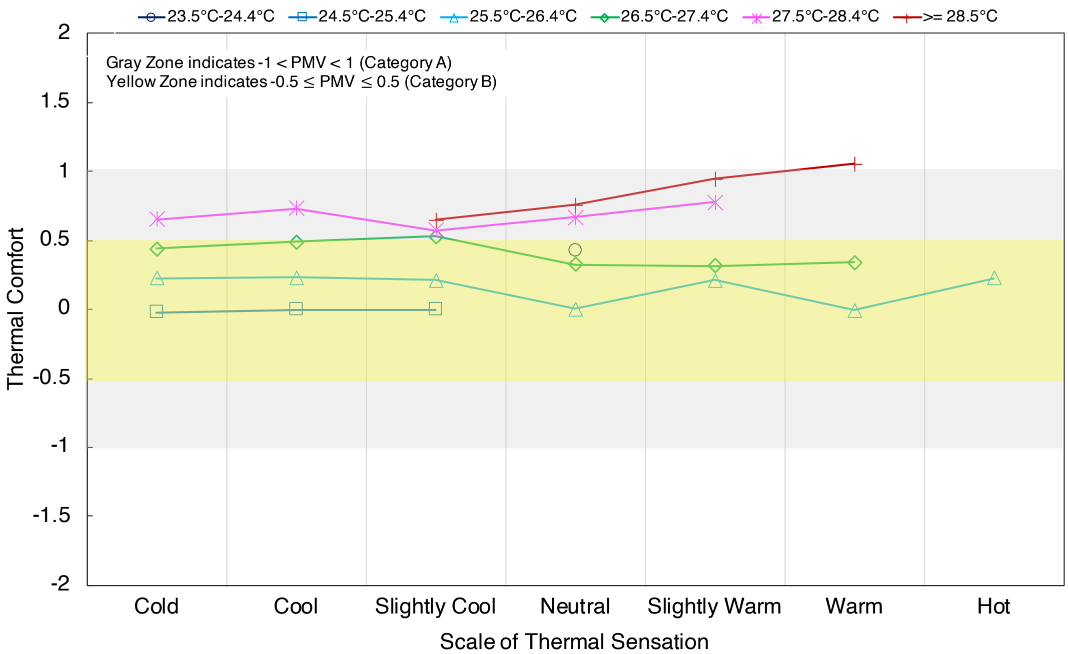
Discussion

Our studies concluded that the correlation between single heart rate and environmental parameters in the smart home. The results show that the human heart rate has more association with indoor temperature, indoor relative humidity, and indoor air speed in the warm zone (including slightly warm, warm) in the morning. The reason for this phenomenon is that the air-conditioner is turned on in the morning to adjust the temperature. The indoor temperature at this time has a specific outdoor temperature and no ventilation. This phenomenon changed in the afternoon, and the heart rate in the afternoon was shown more correlation to the indoor temperature, indoor relative humidity, and air speed in the cold zone. This is because EETCC has achieved proper comfort in the room after adjustment in the morning. When entering the experimental scene in the afternoon, the starting value of comfort is closer to subjective comfort. Our results suggest a possibility that is achieving system thermal comfort in a short period or maintaining system thermal comfort over a long period has a crucial role in producing human thermal comfort adjustment of the heart rate reference system.

Furthermore, the use of EETCC can significantly improve the human thermal comfort level. For example, in Section 4.3.5, the comfort zone ratio increased by an average of 10.25% under the control of EETCC in the morning session and the afternoon session. However, the presence of the warm zone increased by an average of 32.4%, and the present of cool zone decreased by 42.65%. This is because the first principle of EETCC is energy

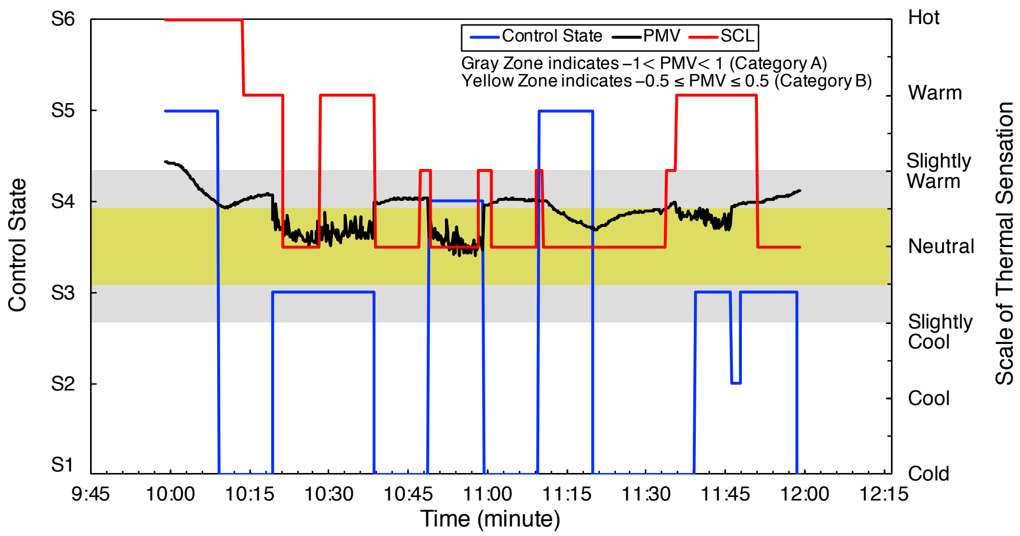


(a) In the morning

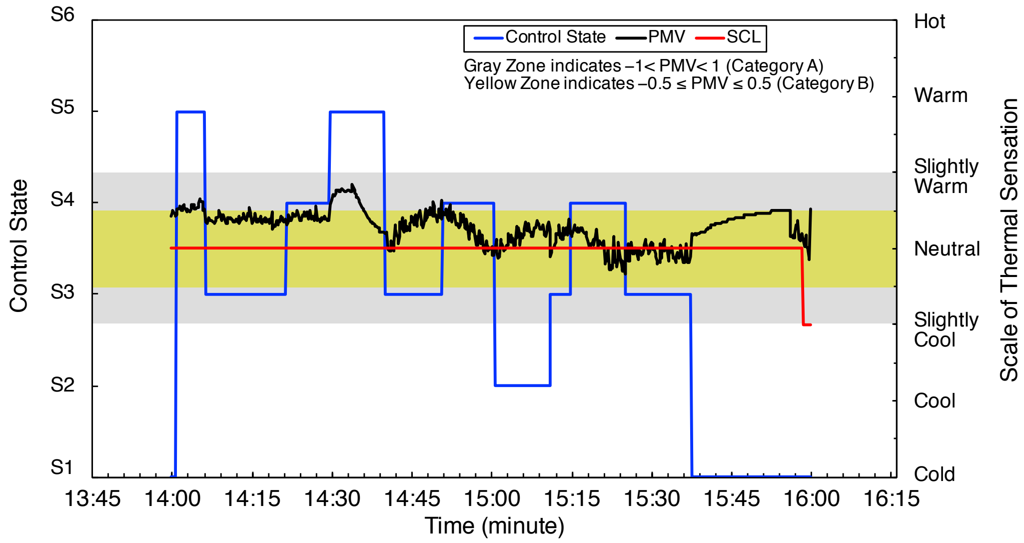


(b) In the afternoon

Figure 4-15: Thermal sensation and thermal comfort at different indoor air temperatures.



(a) In the morning



(b) In the afternoon

Figure 4-16: Control state, PMV, and SCL.

efficiency. The data collected from the environmental sensors is calculated, and if it is within the system's comfort zone, the existing controller state is maintained unchanged.

From the control state and thermal comfort result in Section 4.3.5, although the EETCC well performs the control strategy of system comfort, the human thermal comfort still is not considered. From the analysis of the result shown in Figure 4-16b, the average thermal comfort is in a stable state, the state change can be avoided, and the previous state can achieve the double demand of the human thermal comfort and the energy efficient to the maximum extent.

4.4 Case Study 2: Simulation Verification of Personal Thermal Comfort Model

4.4.1 Artificial Neural Networks

Artificial Neural Networks for PTC model

Artificial neural networks (ANN) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge of cats, for example, that they have fur, tails, whiskers and cat-like faces. Instead, they automatically generate identifying characteristics from the examples that they process.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it.

In ANN implementations, the "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts

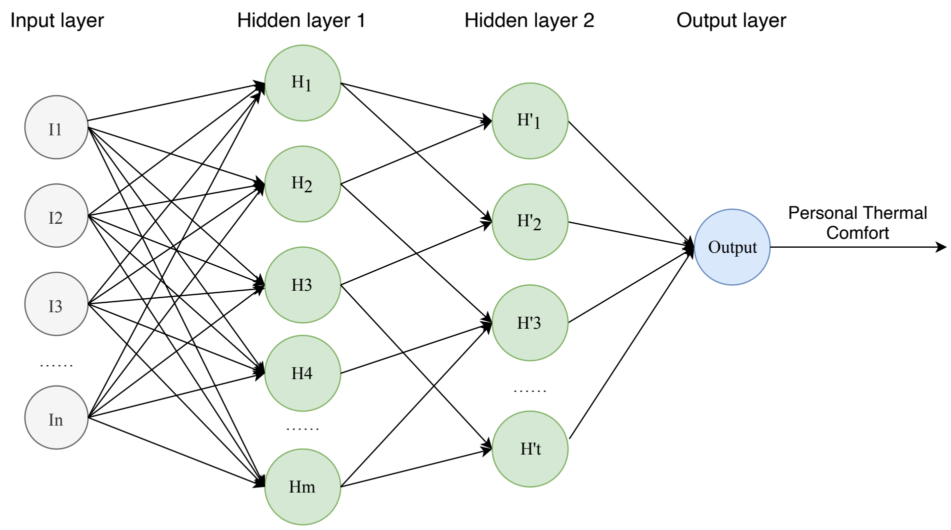


Figure 4-17: Structure diagram of neural network with two hidden layers for PTC model.

as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

The original goal of the ANN approach was to solve problems in the same way that a human brain would. However, over time, attention moved to performing specific tasks, leading to deviations from biology. ANNs have been used on a variety of tasks, including computer vision, speech recognition, machine translation, social network filtering, playing board and video games, medical diagnosis and even in activities that have traditionally been considered as reserved to humans, like painting.

Two-layer Feed-Forward Network

Feedforward neural networks are simple in structure and widely used, and can approximate arbitrary continuous functions and square integrable functions with arbitrary precision. Moreover, any finite training sample set can be accurately realized. From a system perspective, the feedforward network is a static non-linear mapping. Through complex mapping of simple non-linear processing units, complex non-linear processing capabilities can be obtained. From a computational point of view. Lack of rich dynamics. Most feed-forward networks are learning networks, and their classification capabilities and pattern recognition capabilities are generally stronger than feedback networks.

A single-layer feedforward neural network is the simplest type of artificial neural network. It contains only one output layer, and the value of the nodes on the output layer (output value) is directly obtained by multiplying the input value by the weight value. Take one of the elements for discussion, and the transformation relationship from input to output are in Equation 4.13 and Equation 4.14.

$$S_j = \sum_{i=1}^{n} w_{ji} x_i - \theta_j \tag{4.13}$$

$$y_j = f(s_j) = \begin{cases} 1 & s_j \geq 0 \\ 0 & s_j < 0 \end{cases} \tag{4.14}$$

where $x = [x_1, x_2, \cdots, x_n]^T$ is the input feature vector, w_{ji} is the connection weight x_i to y_j, and the output y_j $(j = 1, 2, \cdots, m)$ is the classification result according to different features.

Multilayer feedforward neural network. A single computational layer perception can only solve linearly separable problems, while a large number of classification problems are linearly inseparable. An effective way to overcome this limitation of the single-computing layer perceptron is to introduce a hidden layer (the number of hidden layers can be greater than or equal to 1) between the input layer and the output layer as the "internal representation" of the input mode. It becomes a multi (computation) layer perception. Because multi-layer feed-forward networks are often trained with error back-propagation algorithms, people often refer to multi-layer feed-forward networks directly as BP (Back Propagation) networks. There is one input layer, one or more hidden layers in the middle, and one output layer. The relationship between input and output transformation in a multi-layer perception network is are in Equation 4.15 and Equation 4.16.

$$S_i^{(q)} = \sum_{j=0}^{n_{q-1}} w_{ij}^{(q)} x_j^{(q-1)}, \left(x_0^{(q-1)} = \theta_i^{(q)}, w_{i0}^{(q-1)} = -1 \right) \tag{4.15}$$

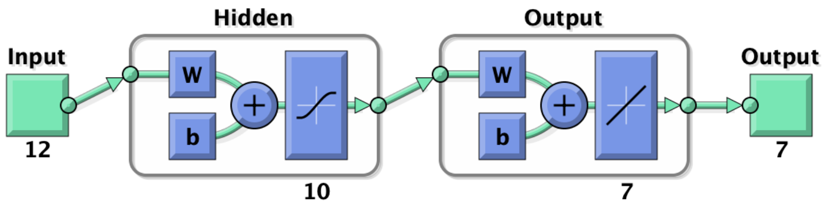


Figure 4-18: BP neural network implementation process.

$$x_i^{(q)} = f\left(s_i^{(q)}\right) = \begin{cases} 1, & s_i^{(q)} \geq 0 \\ -1, & s_i^{(q)} < 0 \end{cases} \tag{4.16}$$

wherr $i = 1, 2, \cdots, n_q; j = 1, 2, \cdots, n_{q-1}; q = 1, 2, \cdots, Q$.

The specific implementation process of the BP neural network is shown in Figure 4-18. The training samples marked in the figure include the input value and the corresponding expected output value. The specific learning steps of the BP algorithm are as follows: i) the training network is used to train the neural network multiple times, ii) at the same time, the weights and thresholds in the network are adjusted continuously to reduce the error between the expected value and the output value. The BP neural network algorithm is mainly divided into two parts, the first part is the forward transmission, and the second part is error backward transmission. BP neural network information forward transfer process: The sample data values are processed by the input layer, hidden layer, and output layer of the neural network in sequence, that is, the input data are obtained through hidden layer processing, the output layer to obtain. In the forward part of the data information, the weights in the network are always fixed, and neurons in the same layer only work for the next layer of the network.

4.4.2 Methodology

BP Neural Network Design

Step of BP neural network structure design.

Step 1: Select the number of neurons in the input and output layers.

From the PMV thermal comfort model in this section, we know that there are 12 factors that can affect the PMV value. It is determined that the number of neurons in the input layer of the BP neural network is 12, and the input value of the input layer are the indoor air temperature, indoor airspeed, relative humidity, human heart rate, age, gender, height, weight, BMI, SCL, PPD, and control state. There is one neuron in the output layer, which is the $pPMV$ value.

Step 2: Determine the number of hidden layers.

There can be single hidden layer and multiple hidden layers in BP neural network, and as the number of layers increases, the accuracy of the algorithm will increase. The output value error is reduced. However, in this case, the network in the BP algorithm will become more complicated, the required training time will increase, and the stability will decrease. Therefore, the number of hidden layers should be selected according to actual needs, and the pros and cons should be fully considered. At the same time, according to the literature [3], when the number of hidden layers is 2, most of the nonlinear relationships can be mapped. Therefore, this paper uses a two-layer hidden layer feed-forward neural network structure.

Step 3: Determine the number of hidden neurons.

Selecting the number of neurons in the hidden layer of the neural network is a key step in the success of network training. If the number of hidden layer neurons is too small, its training is equivalent to no effect; if the number of hidden layer neurons is just enough, although the neural network will be trained, the algorithm performance will be poor and there is no fault tolerance; if the number of hidden layer neurons is Too much, the network training time will be very long, which may cause the algorithm to converge difficultly, learn meaningless information, and make it impossible to update the new model. The simplest method for selecting the number of neurons in the hidden layer can use the trial and error method. The neural network is sequentially trained by building the number of neurons in the hidden layer, and the error of the output value of the neural network is considered. At the same time, the reliability of the neural network structure is comprehensively considered. This method is adopted. Finally, you can find the most suitable number of neurons. But this trial-and-error method requires constantly changing the number of nodes and constantly retraining the neural network, which requires a lot of time to complete. Therefore, the selection of the number of hidden layer neurons can be based on the following empirical Equation 4.17:

$$n' = \sqrt{n+m} + a \tag{4.17}$$

In the formula: n is the number of input neuron nodes; m is the number of output neuron nodes; $a = [1, 10]$ is constant, according to the above formula and supplemented by experimental proof, the number of hidden layer neurons 10 is selected.

Simulation Settings

To evaluate the performance of PTC predication model shown in the Figure 4-17, a summer season simulation is conducted based on the plant modeled in the previous section. The outdoor temperature sna solar radiation on 15th August 2013 (Summer). The simulation is based on an actual bedroom in the iHouse and simulated on Simulink R2019a. Besides, the simulation is performed on a MacBook Pro with Intel Core i7 processor at 3.1 GHz and 16 GB. The room model parameters and settings that are used in the simulation are tabulated in Chapter 4 Table 4.7.

In this simulation, there are two types of prediction, one is Subjective Comfort Level (7 classes), other is $pPMV$ used to control the EETCC in Table 4.8. A_i is i participation's age,$G_i = \{0, 1\}$ is i participation's gender, 0 is male 1 is female,H_i is i participation's height,W_i is i participation's weight, HR_i^t is i participation's t time heart rate (bpm), BMI is i participation's BMI value, T_{in} is indoor temperature, AS_{in} is indoor airspeed, RH_{in} is indoor relative humidity, CS is the control state of EETCC in Table 4.2.

4.4.3 Result

1.Subjective Comfort

As table 4.8 shown, input layer 12×6795 data, output 7×6795 data. The percentage correct classification is 77.5%, the percentage incorrect classification is 22.5%. The confusion matrix is shown in Figure 4-19.

Table 4.7: Simulation parameters and settings.

Parameter	**Value**
Volume of room ($L \times W \times H$), V_{room}	$5.005 \times 4.095\ times 2.4m^3$
Air volume flow rate, CFM	$300ft^3/min$
Minimum cooling load of HVAC, u_{min}	$5kW$
Maximum cooling load of HVAC, u_{max}	$6.3kW$
Coefficient of performance, COP	3.44
Solar transmittance of window type 1, g_{w1}	0.79
Solar transmittance of window type 2, g_{w2}	0.41

Table 4.8: A brief information of PTC predication model simulation setting

Type of prediction	**Input Layer**	**Output Layer**
SCL	$A_i, G_i = \{0,1\}, H_i^t, W_i, HR_i^t, BMI$ $T_{in}, AS_{in}, RH_{in}, PMV, PPD, CS$	$\{-3,-2,-1,0,1,2,3\}$
$pPMV$	$A_i, G_i = \{0,1\}, H_i, W_i, HR_i^t, BMI$ $T_{in}, AS_{in}, RH_{in}, PMV, PPD, CS$	$pPMV \sqsubseteq \mathbb{R}$

2. $pPMV$

$pPMV$ prediction result is shown in Figure 4-20 for every participation. R1 is a test simulation participation information like male, 43 years old, 175cm, 60kg, and usually heart rate is measured by Apple Watch S4. From the Figure 4-21, $pPMV$ are average 55% in the Category B, and EETCC has 42%. Figure 4-22 shows the total 6 participation's $pPMV$ in 24 hours, and one test participation's $pPMV$.

3. Energy Consumption

The total air conditioner electricity consumption for EETCC and EETCC/PTC is computed and plotted according to their respective seasons as shown in Figure 4-23. For reference tracking scenario, the air conditioner electricity consumption by EETCC/PTC is lower than EETCC by 0.1% respectively.

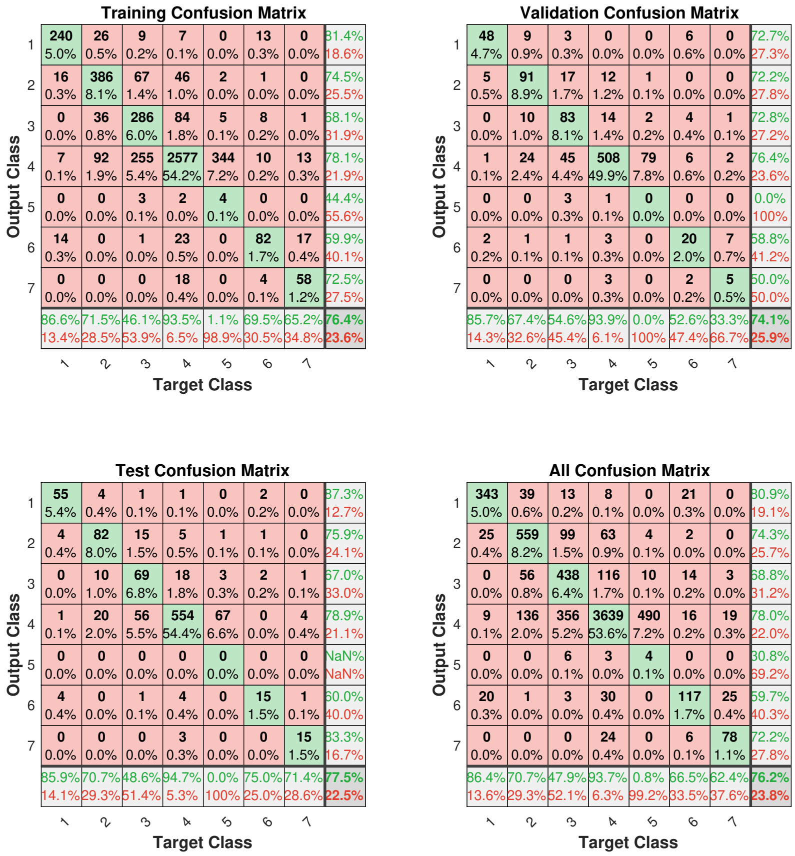


Figure 4-19: Confusion matrix of subjective comfort level.

4.5 Summary

Based on the studies on personal thermal comfort in this chapter, several conclusions can be drawn. Creating the environmental thermal comfort model for the indoor environments should not be the ultimate goal for the thermal comfort services in the smart homes. Personal thermal comfort that comprises of the subjective thermal level of human and thermal comfort level of system is more suitable for the individual human. Indeed, the thermal comfort control systems are beneficially operating to well-fit to the human's comfort preference with the guaranteed indoor air quality for healthcare smart home environments. This chapter has also introduced the CPHC framework, which consists of the generic of personal thermal comfort model and EETCC system.

Experiment results reveal that there is a tight correlation between the environmental factors and the physiology parameter (i.e., heart rate) in human thermal comfort.

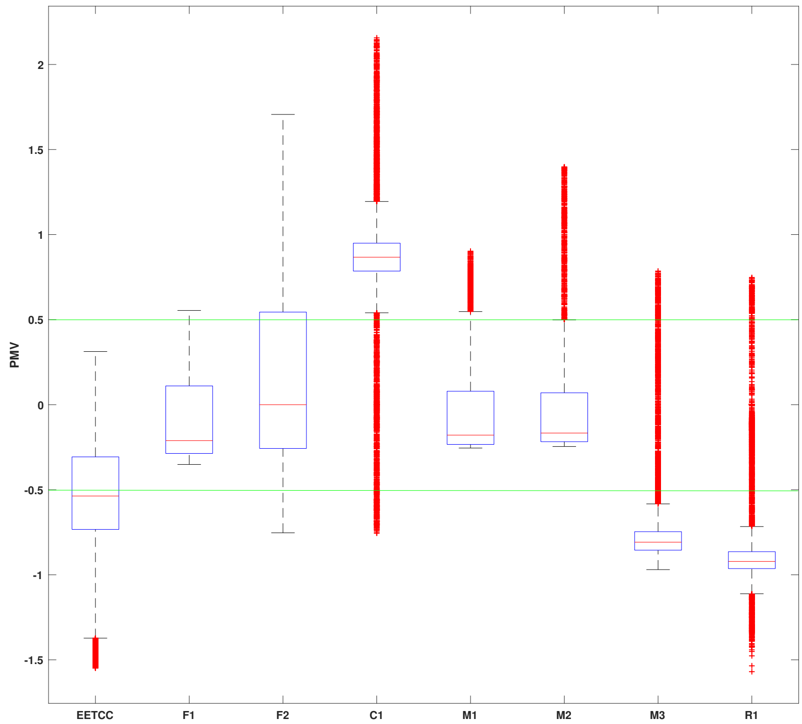


Figure 4-20: PTC prediction $pPMV$ box plot.

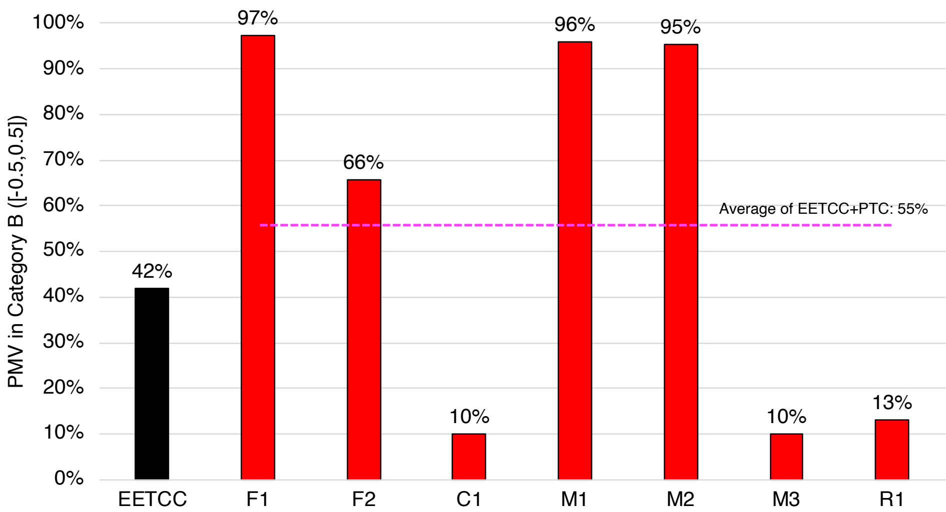


Figure 4-21: Compare the percentage of PMV in Category B.

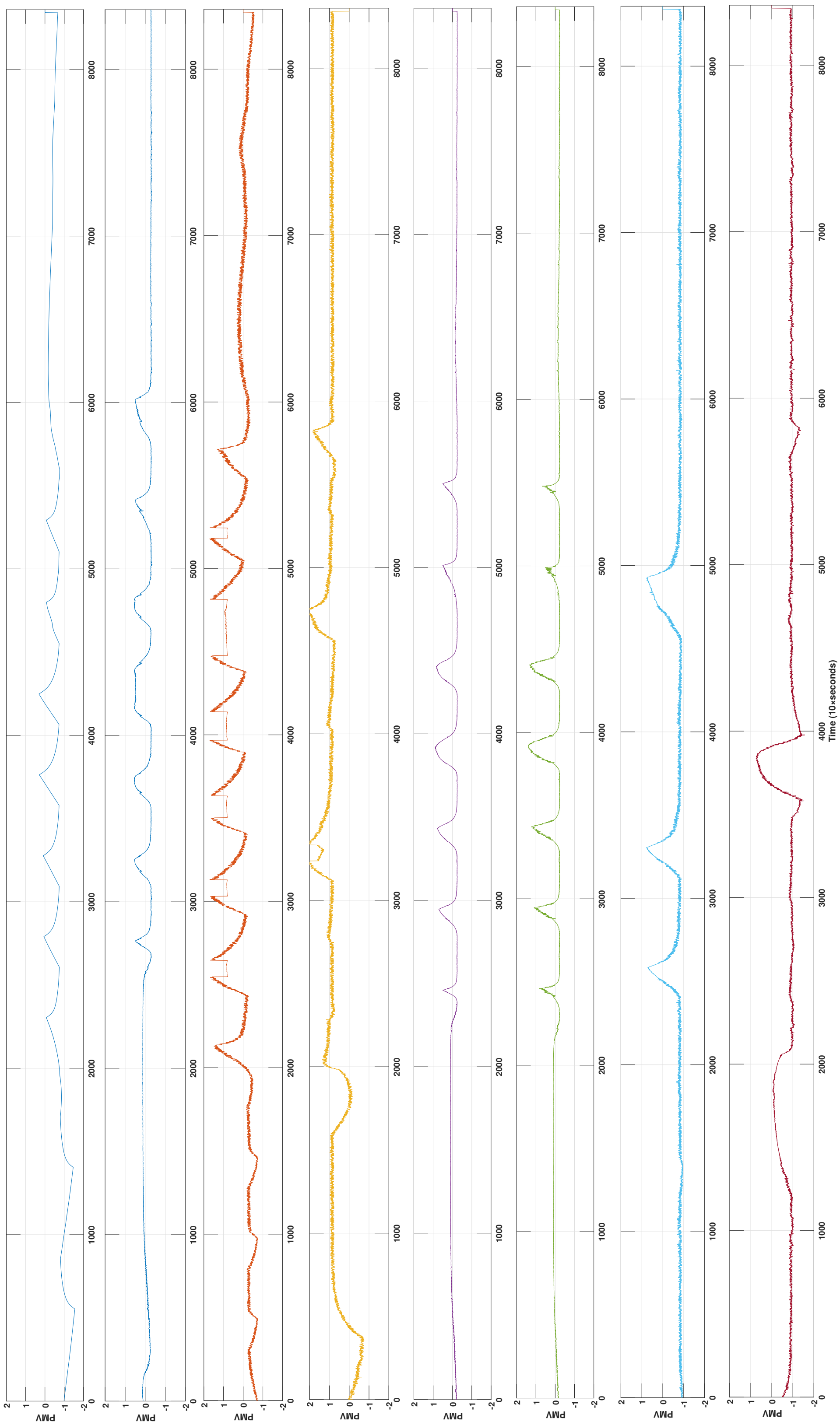


Figure 4-22: Simulation $pPMV$ in 24 Hours.

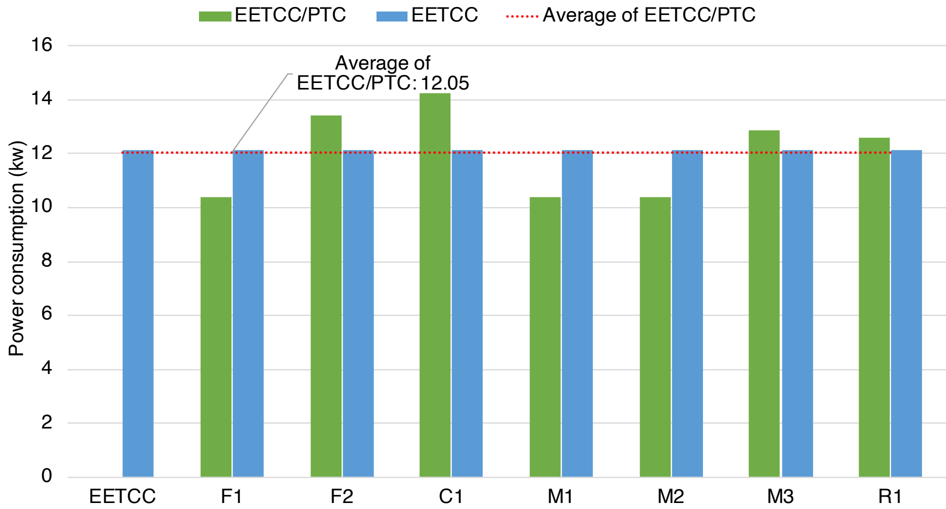


Figure 4-23: Energy consumption.

Through this experiment, this paper also can conclude that the current EETCC system is unable to provide the precise need of thermal comfort to the human's preference. However, the experiment results discover that the relationship between the human thermal comfort and the physiological parameters that we can obtain data from conventional wearable devices has a tied correlation, and this gives a better understanding of a novel solution underlying the thermal comfort for automation control in smart homes.

In this chapter, we first propose a personal comfort prediction model based on machine learning theory. On this basis, personal comfort prediction (Neural Network) without wearable devices were completed. In case 2 study,through MATLAB's EETCC simulation platform, the prediction of personal comfort is completed, and the prediction result of subjective comfort level and the prediction of $pPMV$ are obtained. The prediction of $pPMV$ will be realized in the Chapter 5.

Chapter 5

Implementation of Cyber-Physical Human Centric System for Smart Homes

5.1 Introduction

In previous work [86], we proposed the Cyber-Physical Human Centric System (CPHCS) to system and human requirement studied on human thermal comfort that comprises of the subjective thermal level of the human and thermal comfort level of the system was more suitable for the individual human. The results reveal that the current EETCC system is unable to provide the precise need for thermal comfort to the human's preference. However, the experiment results discover that the relationship between the human thermal comfort and the physiological parameters that we can obtain data from conventional wearable devices has a tied correlation, and this gives a better understanding of a novel solution underlying the thermal comfort for automation control.

In this section, the objective is to introduce the personal thermal comfort (PTC) prediction model to take the personal thermal comfort to improve the residents thermal comfort level while optimizing the energy consumption at the same time using the Artificial Neural Networks (ANN). The proposed personal thermal comfort predication model for CPHCS is also an extension of the EETCC/PTC with the human thermal comfort model, which can be measured by using the smart wearable device. Our contributions in this paper are:

- A significant part of this research is to use the commercial smart wearable devices as the measurement device incorporated with the other sensors and actuators to build and propose the generic CPHCS framework;
- Besides the environmental factors, the physiology parameter from the heart rate is well-studied with the environmental factors, i.e., PMV, air speed, temperature, and humidity are deeply investigated to reveal the personal thermal comfort using the EETCC/PTC prediction control in the smart home environment;

The organization of this paper is as follows. In Section 2, the background about Cyber-Physical Home System, Cyber–Physical Human Centric framework, personal thermal comfort, and ANN will be discussed. In Section 3,describes the implementation model, experiment setup and procedure. In Section 4, experiment results and discussion are provided. Section 6 summarizes the paper and provide some conclusions.

5.2 Background

5.2.1 Artificial Neural Networks for PTC

The use of Artificial Neural Networks (ANNs) in various applications related to energy management in buildings has been increasing significantly over the recent years.

Feed-forward ANNs are direct input-to-output connection computing structures capable of approximating a smooth function with arbitrary accuracy provided sufficient neurons are used. These features are the means to achieve the requirements stated above. The feed-forward ANN direct input-to-output structure provides the constant execution time, their ability to approximate non-linear functions provide the capability of approximating the PMV function. The accuracy of the approximation is related to the number of neurons used in the ANN hidden layer(s), which in turn is linearly related to the execution time. Consequently, the problem consists of finding the appropriate trade-off between the PMV approximation accuracy and the CPHS thermal performance.

In all cases, the approach taken was not the best for personal thermal comfort prediction control applications although this was the main motivation. In this section, it is shown that by following a novel and more appropriate approach, it is possible to select the desired compromise between PMV accuracy and CPHS thermal performance with a common wearable device collecting the human heart rate. The processing of ANN for EETCC/PTC model shown in Figure 5-1.

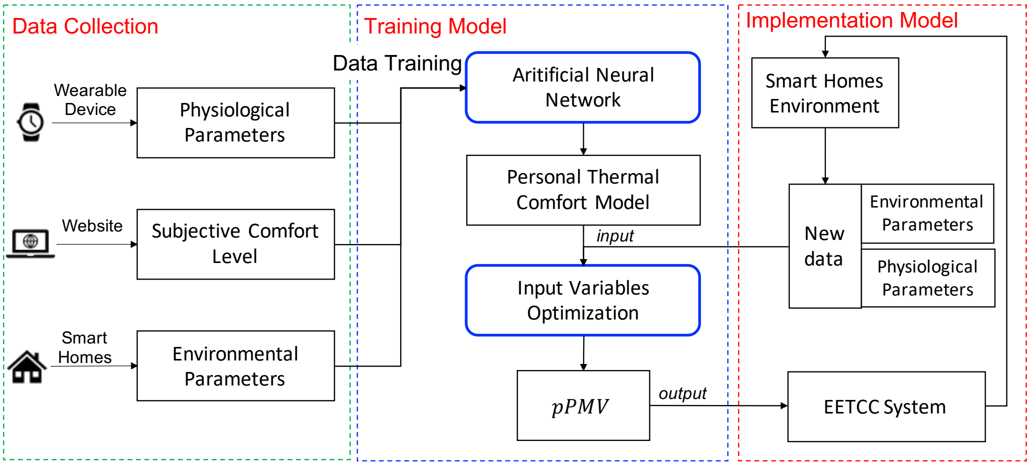


Figure 5-1: The processing of ANN for EETCC/PTC.

5.2.2 EETCC/PTC Control Algorithm

Simulation with MATLAB/Simulink Tool Box and MATLA/Deep Learning Tool Box in iHouse are conducted. The work flow for the neural network design process has seven primary steps.The Deep Learning Toolbox software uses the network object to store all of the information that defines a neural network. After a neural network has been created, it needs to be configured and then trained. Configuration involves arranging the network so that it is compatible with the problem you want to solve, as defined by sample data. After the network has been configured, the adjustable network parameters (called weights and biases) need to be tuned, so that the network performance is optimized. This tuning process is referred to as training the network. Configuration and training require that the network be provided with example data. This topic shows how to format the data for presentation to the network. It also explains network configuration and the two forms of network training: incremental training and batch training. For this section, we use the Algorithm 2 to define the PTC predication work flow.

1 Collect data

2 Create the network,Create Neural Network Object

Algorithm 2 Personal Thermal Comfort Predication based on ANN

Setting $input$, $output$
Setting $Tr = 70\% of(input, output)$, $V = 15\%(input, output)$,$Te = 15\%(input, output)$
Setting net
for all Tr **do**
    $net.function$
end for
for all V **do**
    $output = net.function(V)$
end for
for all Te **do**
    $output = net.function(Te)$
end for
return $net.function$

3 Configure the network — Configure Shallow Neural Network Inputs and Outputs

4 Initialize the weights and biases

5 Train the network — Neural Network Training Concepts

6 Validate the network

7 Use the network

5.3 Design and Modelling of CPHCF-based PTC Model

5.3.1 Implementation Model

The Cyber-Physical Human Centric system implementation architecture is shown in Figure 5-2, which is comprised of four main components: (i) EETCC controller; (ii) communication protocol; (iii) plant and (iv) Personal Thermal Comfort (PTC) Model. The plant simulated in this paper is the iHouse Bedroom 1 and experiment participators (Heart Rate). Modeling of the PTC is discussed while networking components are excluded in this section.

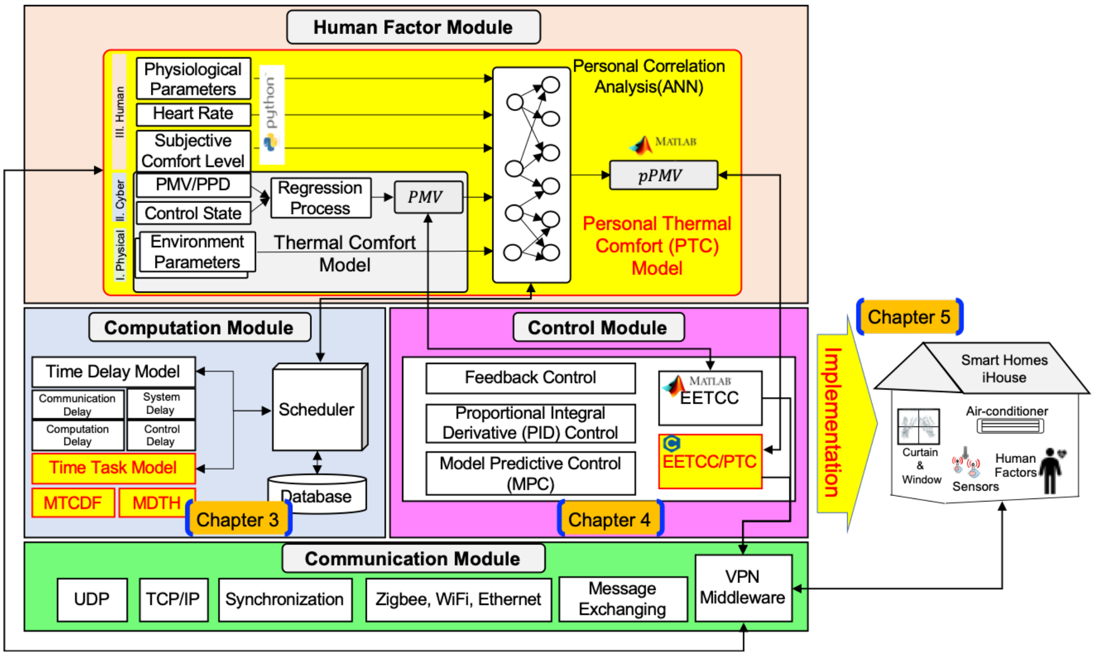


Figure 5-2: Cyber-Physical Human Centric System implementation architecture.

The EETCC implementation architecture is shown in Figure 5-3. The EETCC/PTC implementation architecture is shown in Figure 5-4.

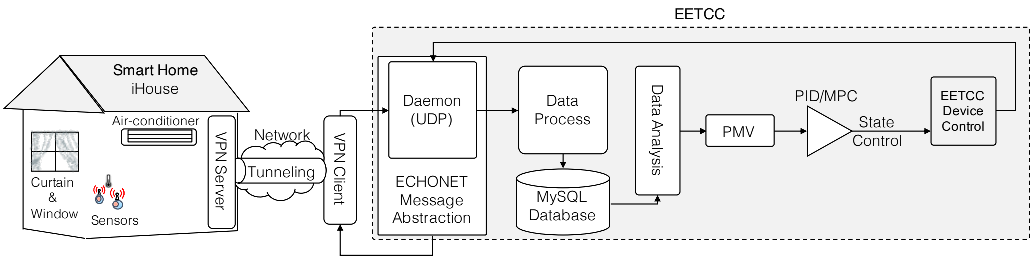


Figure 5-3: The EETCC implementation model architecture.

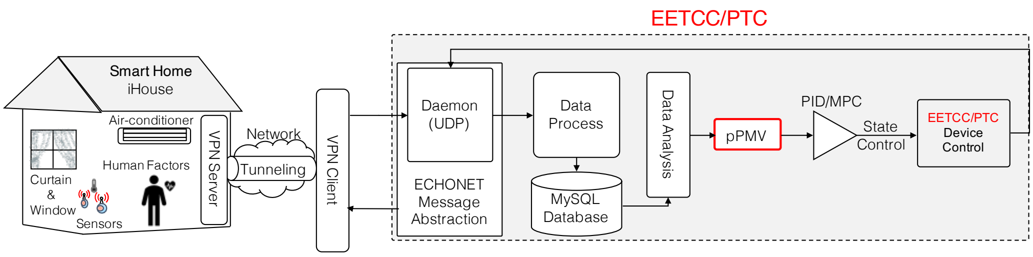


Figure 5-4: The EETCC/PTC implementation model architecture.

Table 5.1: A brief information of EETCC/PTC predication model training

	Input Layer	Output Layer
Human Factors	Heart Rate, SCL	
	Age, Gender, Weight, Height, BMI	
Environment Factors	Indoor Temperature,	
	Indoor Humidity,	$pPMV$
	Indoor Airspeed	
System Factors	PPD, Control State	

5.3.2 EETCC/PTC Control

To develop a new prediction model for personal thermal comfort, this paper first collected data on the thermal environment, thermal sensations (Subjective Comfort Level), and human factors (Heart rate) using EETCC and wearable device (Apple Watch) in iHouse. Subsequently, we built and trained a novel artificial neural network (ANN) model using the collected data. Finally, the ANN models were used to predict a personal thermal comfort environment settings.

For training the two-layer feed-forward network with sigmoid hidden neurons and linear output neurons, the data is divided in the ratio 70%:15%:15% for training, validation and testing data sets, respectively. All computations are performed using the computing application $MATLAB^{®}$ (ver. R2019a). The training settings and the obtained optimal training parameters are summarized in Table 5.1. Total three types 12 parameters are chosen. The log-sigmoid function is used as the activation function for all hidden neurons. A back-propagation method namely, Levenberg-Marquardt algorithm is employed for the learning of the parameters.

5.4 Heart Rate Prediction and Analysis

Heart rate is the speed of the heartbeat measured by the number of contractions beats of the heart per minute (bpm). The heart rate can vary according to the body's physical needs, including the need to absorb oxygen and excrete carbon dioxide. It is usually equal or close to the pulse measured at any peripheral point. Activities that can provoke change include physical exercise, sleep, anxiety, stress, illness, and ingestion of drugs.

Heart rate prediction is considered for three reasons.

- The first reason is that the heart rate is the personal factor using a common wearable device to collect the data. A heart rate monitor or ECG/EEG can be used to get a more accurate heart rate measurement. Recently, wearable technology is improved by ubiquitous computing and wearable computers. IoT (Internet of Things) makes wearable devices pervasive by incorporating it into daily life. There are rising types of smart wearable devices, at the same time, a growing number of data types can be measured.

- The second reason is that the heart rate can be predicted in different human daily activities using the deep learning algorithm. Predicting the heart rate, it will solve the problem that the people who do not want to wear the common wearable device when they are at home. The activity of daily living (ADL) prediction has yielded many results with deep learning sensor data and ECHONET Lite data in the smart home environment. People spend half of their time at home. Whether the home is comfortable or not directly affects people's moods.

- The third reason is the heart rate changed in different thermal environments personalized. Liu. etc, proposed in [87] analyzes human heart rate variability (HRV) at different thermal comfort levels and discusses the mechanism of human thermal comfort. The results indicate that sympathetic activity plays an important role in subjects' thermal discomfort and the LF/HF ratio may be used as an indicator for human thermal comfort.

In this section, aiming to take off the wearable device living activity in the smart home, we proposed a new method to predict the heart rate (HR) with the deep learning of the information obtained from ECHONET Lite data and sensor data combination labels of ADL. All the experiments are done in the Ubiquitous Computing Systems laboratory of the Nara Institute of Science and Technology (NAIST).

5.4.1 Related Works

PPG (Photoplethysmography) is used to give the BVP (blood volume pulse) signal shown in the bottom graph (red signal on gray background) below. The PPG is mainly used to identify the heart rate of the person wearing the sensor. Heart rate is computed by detecting peaks (beats) from the PPG and computing the lengths of the intervals between adjacent beats. The inter-beat-interval (IBI) timing is used to estimate the instantaneous heart rate as well as to estimate average heart rate over multiple beats.

Heart rate and Human Sensation

Barrios, L. in [88] propose to increase thermal comfort by automatically monitoring the inhabitants' satisfaction with the thermal environment using commodity hardware targeting energy savings, and publish detailed temperature and heart-rate data of seven users of the system to the community.

Heart rate is the speed of the heartbeat measured by the number of contractions (beats) of the heart per minute (bpm). The heart rate can vary according to the body's physical needs, including the need to absorb oxygen and excrete carbon dioxide. It is usually equal or close to the pulse measured at any peripheral point. Activities that can provoke change include physical exercise, sleep, anxiety, stress, illness, and ingestion of drugs. There are some define about heart rate:

- High Frequency power (HF): frequency activity in the 0.15 - 0.40Hz range (green in the above chart)
- Low Frequency power (LF): frequency activity in the 0.04 - 0.15Hz range (yellow in the above chart)
- LF/HF Ratio: A ratio of Low Frequency to High Frequency. Some consider this indicative of Sympathetic to Parasympathetic Autonomic Balance, but that is controversial. Please see this article and this article for more information.

Daily Living Activity Recognition and Predication

In previous work [90], daily living activity recognition method is proposed by using ECHONET Lite-ready. The proposed method utilizes information from appliances and motion sensors attached to them as features and recognizes ADLs through machine learning. To evaluate the proposed method, we collected data in smart-home tested while

[1]Figure Source: [89]

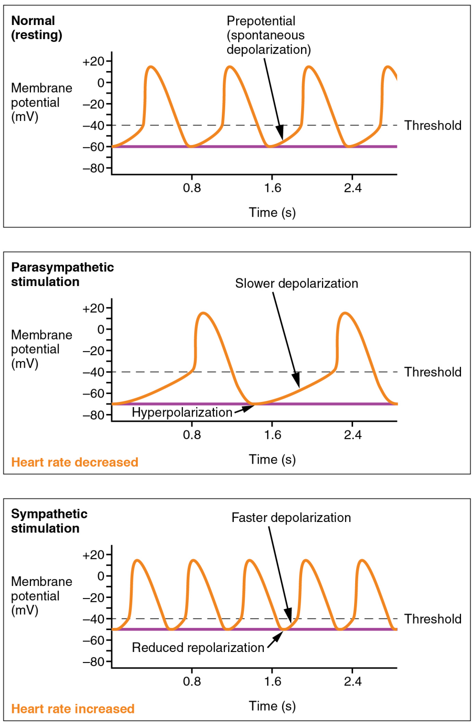


Figure 5-5: Effects of Parasympathetic and Sympathetic Stimulation on Normal Sinus Rhythm.[1]

several participants are living there. As a result, the proposed method achieved about 68% classification accuracy for 9 different activities.

In[91], daily living activity predication using smart-home data, which is in order to be able to learn in time series, activity prediction was performed by analytically method using LSTM (Long Short Term Memory) which is one of Deep Learning algorithms. As a result, it was confirmed that behavioral occurrence timing classification was reproduced in some behaviors such as meals. In this method, we thought that we can learn more correctly by simplifying classification of behavior occurrence timing. As a result, almost all the actions were able to confirm the improvement of recall.

5.4.2 Methodology

1. Heart rate of ADL

In this experiment, we use the wearable equipment to measure the experimenter's heart rate when they stay in the smart-home. The frequency of the experimenter's heart rate is known by statistics, as shown in the Figure 5-6. There are more than 50 % heart rate

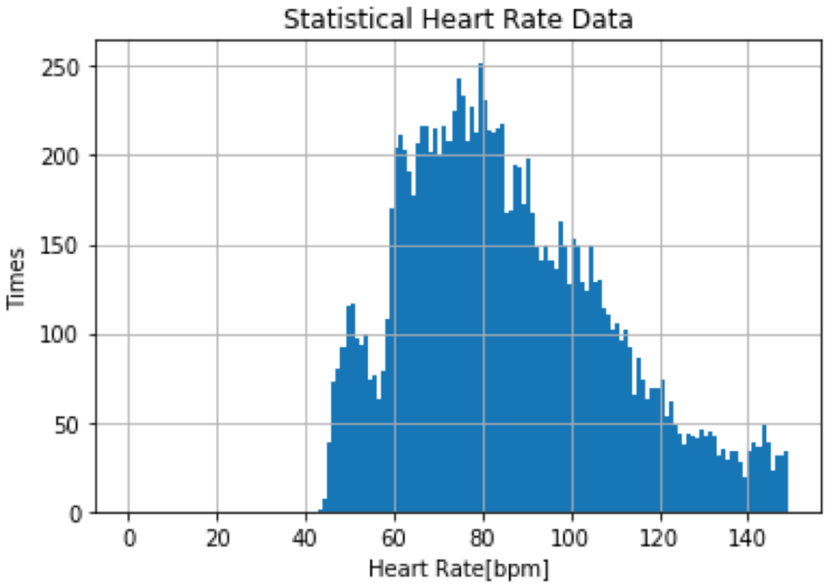


Figure 5-6: Statistical heart rate data.

is from 60 *bpm* to 100 *bpm*.

According to the heart rate reserve (called HRR) shows the exercise intensity assuming that heart rate at rest state is 0 % and the maximum heart rate is 100 %. And is calculated by Karvonen's formula described as Eq.(5.1). In Eq.(5.1), HR_m, HR_{rest}, and AGE, denote the measured heart rate, the heart rate at rest, and the user's age, respectively, and is defined as

$$HRR = \frac{HR_m - HR_{rest}}{220 - AGE - HR_{rest}} \times 100 \tag{5.1}$$

In this experiment, we choose the 80 bpm as the rest heart rate. And classified the heart rate is two class, one is more than 80 bpm, another is lower than 80 *bpm*.

2. Instructions to participants

There are 5 participants in this experiment, 3 male and 2 female. They average age is 23.6. Every participant lived in smart-home 3 days. Their basis information is shown in Table.1. During the experiment date, the participant should use the wearable equipment with normal living activity, like as watching TV, cooking, sleeping and so on.

Table 5.2: Participants information

ID	Date	Gender	Age
FA321FFC	2018/8/13-8/16	Female	26
152DF976	2018/8/16-8/20	Male	24
B8F7D7A3	2018/8/20-8/22	Male	23
2CAA336A	2018/8/25-8/28	Male	23
EBD2AC01	2018/8/28-8/31	Female	22

3. LSTM

Long short-term memory (LSTM) units are units of a recurrent neural network (RNN). An RNN composed of LSTM units is often called an LSTM network. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series.

In this experiment, we use the 17 activity labels and HR value as the input layer. We used the classified method to do the drop layer. At last, we got the HR high class or low class as the output layer.

5.4.3 Result

The purpose of this experiment was to predict heartbeat data divided into two categories through behavioral labels and heartbeat data. We selected 13 days of measurement data as the data input, where the time accuracy of the measurement is seconds. The total amount of these data is 481,585. 80 % of these data are training data and 20 % are test data. In order to better accomplish the goal of this article, in the learning process, the data record with zero heart rate is removed. A zero heart rate data means that the tester is not in the room at this time.

After the ten epochs, the accuracy is 0.9837, which is shown in Figure 5-7.

Figure 5-8 shows the results of all test sets and prediction sets. 1 means high heart rate

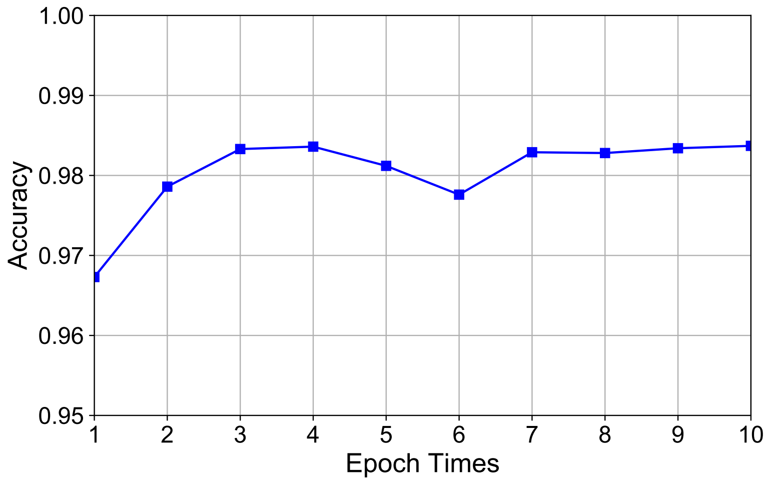


Figure 5-7: Accuracy with epoch 10 times.

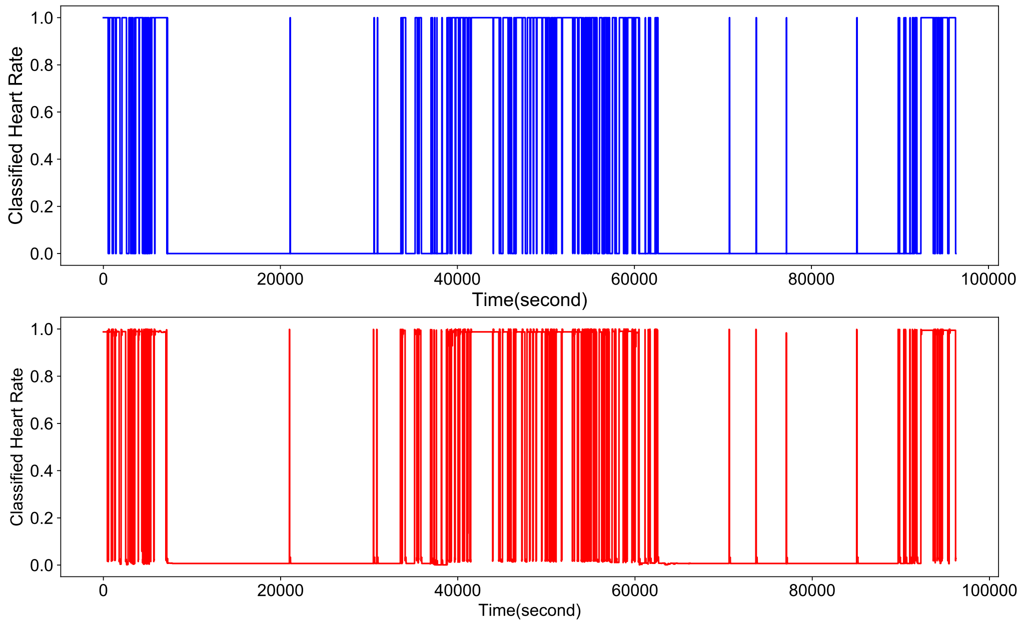


Figure 5-8: Compare classification to predict heart rate and measure heart rate.

on the vertical axis, 0 is low heart rate. Figure 5-9 illustrates the comparison between the test set and the prediction set over an hour. Figure 5-10 shows the comparison between the test set and the prediction set in 10 minutes.

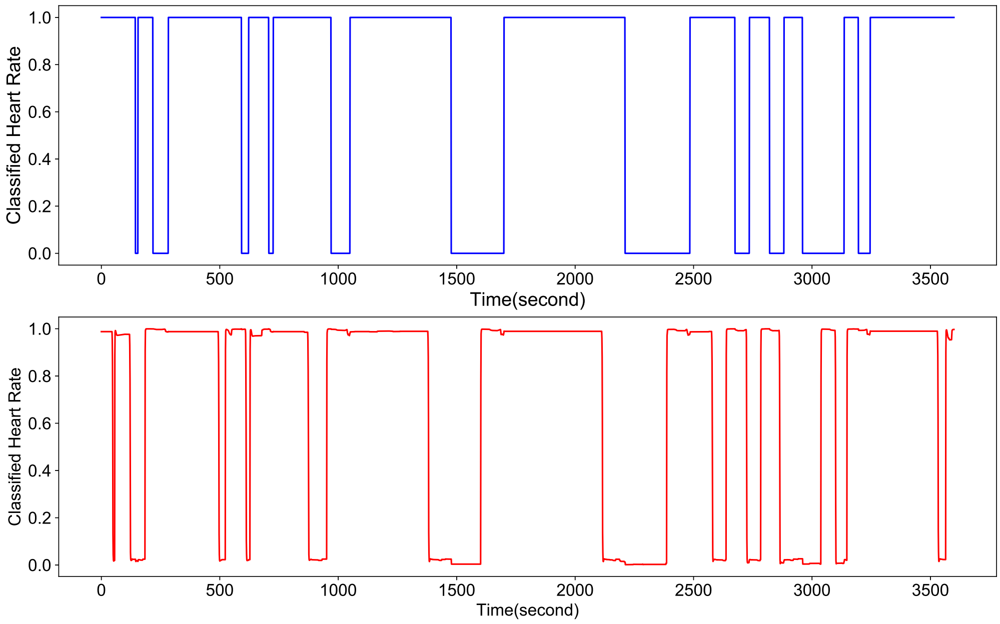


Figure 5-9: Heart rate predation in one hour

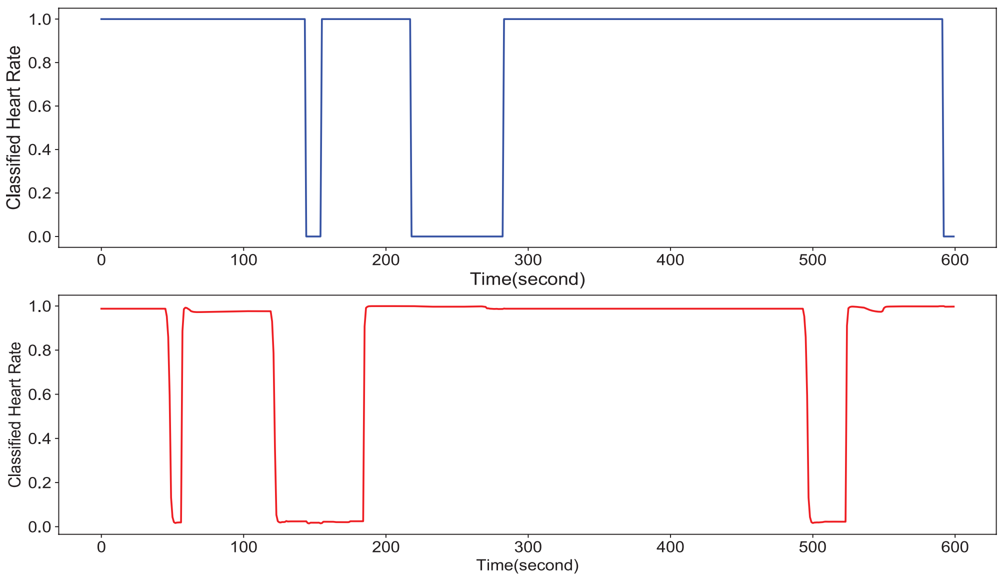


Figure 5-10: Heart rate predation in 10 minutes.

Table 5.3: Brief information of participants

NO.	Gender	Age (y)	Height (cm)	Weight (kg)	BMI (kg/m^2)
F1	Female	38	174	60	20.8
F2	Female	24	155	48	19.9
F3	Female	26	165	51	19.0
F4	Female	26	170	56	19.4
Female	*Average*	*28.8*	*163*	*52.8*	*20.1*
M1	Male	27	171	60	20.1
M2	Male	43	175	65	21.2
M3	Male	23	168	58	20.6
M4	Male	27	172	72	24.3
M5	Male	25	173	60	20.8
M6	Male	24	176	66	21.3
Male	*Average*	*28.2*	*172.5*	*63.5*	*21.4*
Total	*Average*	*28.4*	*168.7*	*59.2*	*20.9*

5.5 Personal Thermal Comfort Prediction and Analysis

5.5.1 Human Subjects

There were ten participants (four female adults, six male adults), with the adult participants average age, height, weight and BMI of 28.4, 168.7 ($\pm$2) cm, 59.2 ($\pm$0.5) kg, 20.9 ($\pm$0.2) kg/m^2. Detailed physical information about the research participants is shown in Table 5.3. All participants had no physical defects, lack of sleep, depression, and other conditions.

5.5.2 Environment and Main Sensors

We chose iHouse the second-floor Bedroom 1 as this experiment environment. Bedroom 1 was 5.0m length, 4.1m width, 2.4m height. There were two windows, and one curtain in Bedroom 1 which could be controlled. Main sensors and wearable devices are shown in the fellow. To collect human physiological data, the authors compared several portable wearable and health monitoring devices available in the market, which were popular and

Table 5.4: Brief step of experiment

Step	Time	Content
1	30 min	Preparation Time
2	60 min	EETCC control the HVAC, Apple Watch collect data
3	30 min	Participant rest. Using the data training the EETCC/PTC model
4	60 min	EETCC/PTC control the HVAC

common due to powerful functionality, affordable prices, and lightweight features. Considering our requirements on the specification of individual heart rate data, the Apple Watch Series 4 was adopted. The main sensors in Table 4.4.

5.5.3 Procedure

Ten subjects participated in experiments from January to February 2020. Morning and afternoon sessions lasting three hours each were scheduled. Each participant was asked to arrive at iHouse, the experimental building, 30 min before starting the experiment. In the first 15 min, the participant took the wearable device for adapting to the comfort and usability of wearable devices. At that same time, we told the participant about the experimental considerations and experimental processing and requirements. During the next 15 minutes, the participant was guided in the experimental room to have a rest with sitting or reading before starting the experiment and recording the data. Furthermore, the participants were conducting their usual home activities during the tests. These activities were comprised of reading or writing, working on a computer, etc. The indoor and outdoor air temperature, indoor and outdoor relative humidity, indoor and outdoor airspeed were measured continuously every 10 seconds. Table **??** is the step for the morning session and afternoon session, and there is one hour for rest and lunch for each participant. The more information in Table 5.4 and Figure 5-11.

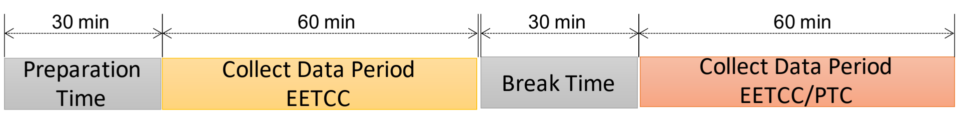


Figure 5-11: The step of procedure.

5.5.4 Results and Analysis

1. Dataset Overview

A total of 32640 data samples of the EETCC/PTC models input-output parameters are experimentally collected, that the 8640 samples are collected for analyzing the P correlation about the different factors in [86] and using those data samples as the first model training data. For data format and data validity reason, there are almost 19000 data sets to do ANN prediction learning. The more information in Table 5.5.

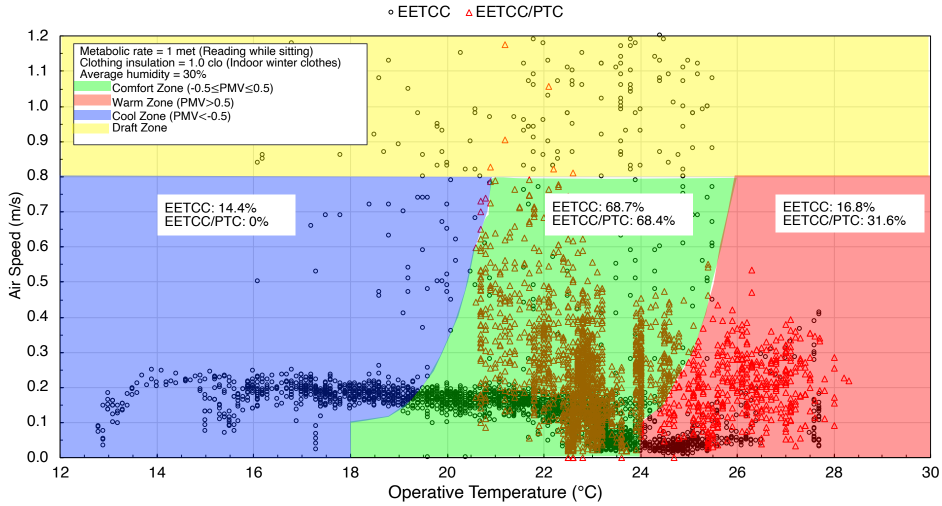
Table 5.5: Experiment data sets

Set	Season	Participant	Contents	Total of datasets	Total of samples
Part 1	Summer	6	Air-con is controlled by EETCC automatically Fill the SCL card in any time	12	8640
Part 2	Winter	10	Air-con is controlled by EETCC automatically Fill the SCL card in any time	20	12000
Part 3	Winter	10	Air-con is controlled by EETCC/PTC automatically Fill the SCL card in any time	20	12000

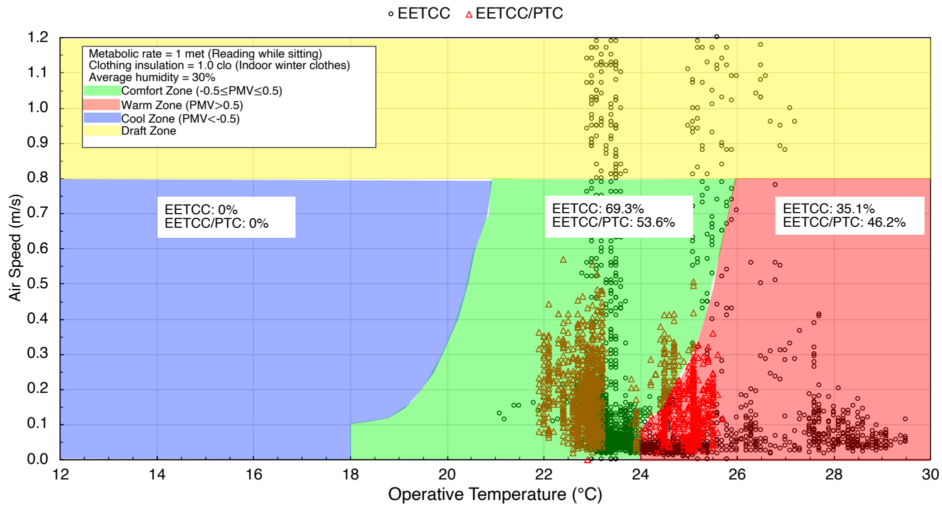
2. System Thermal Sensation

From the results, the indoor temperature and wind speed data are automatically recorded by EETCC (C Programming) and EETCC/PTC(MATLAB Programming). Based on Berkeley's calculation comfort zone, we set the clothing insulation as indoor winter clothes (clo=1.0), metabolic rate is reading while sitting (1 met), and the average relative humidity is 30%, and then draw the comfort zone as shown in Figure 5-12. The comfort zone is highlighted in green color, where its PMV value is between -0.5 and 0.5. The warm zone and cool zone are emphasized in blue color and red color. The draft zone is shown up in yellow color.

The morning session result is shown in Figure 5-12 (a). The EETCC/PTC is made the 68.4% in comfort zone, 31.6% in the warm zone, and 0% in cool zone. The EETCC is made the 68.7% in comfort zone, 16.8% in the warm zone, and 14.4% in cool zone. In the afternoon shown in Figure 5-12 (b), The EETCC/PTC is made the 53.6% in comfort zone and 46.2% in the warm zone. The EETCC is made the 69.3% in comfort zone, 35.1% in the warm zone. There is no PMV value in cool zone.



(a) Morning Session



(b) Afternoon Session

Figure 5-12: PMV represents airspeed against operative temperature with EETCC and EETCC/PTC.

From Figure 5-13, we can see that relative frequency in different SCL scale. In the neutral range, the EETCC/PTC model is more 23% than the EETCC model in the morning session, and more 25.2% in the afternoon. The experimental season is in winter. People prefer thermal environment from the perspective of psychological needs, so they are more satisfied with the thermal comfort adjustment of EETCC/PTC predication model and more suitable with personal thermal comfort needs.

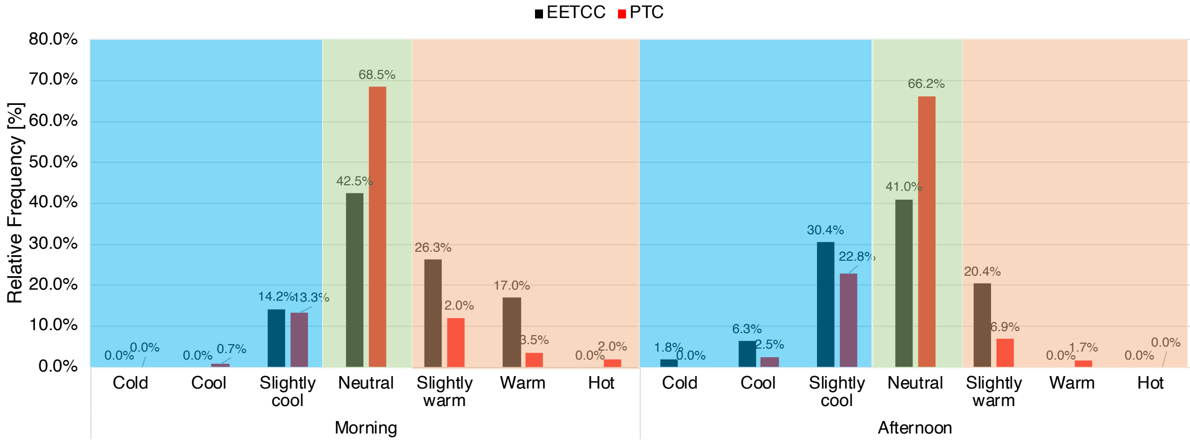


Figure 5-13: Subjective Comfort Level of the EETCC model and the EETCC/PTC model.

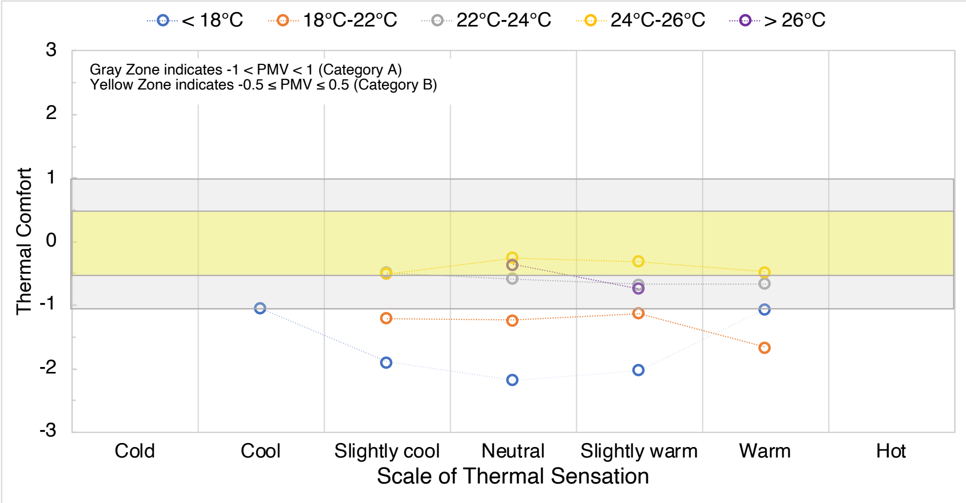
3. Subjective Thermal Sensation

During the experimental date, 671 individual comfort data records were collected. Summary of the subjective comfort data, which top three are 44.9% Neutral, 26.1% Sightly Cool and 16.4% Sightly Warm. Neutral part is improve 6.7% than without PTC.

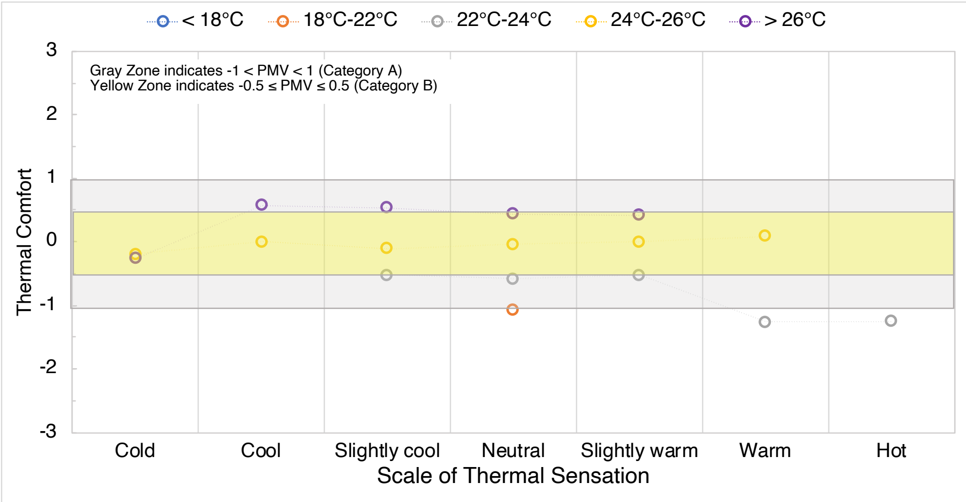
To consider the difference between thermal comfort and thermal sensations in different indoor temperatures scale, the average thermal comfort data is shown in Figure 5-14a and Figure 5-14b. The gray zone indicates the PMV values between -1 and 1. The yellow zone indicates the PMV values between -0.5 and 0.5.

In Figure 5-14a, the morning session, there are no thermal sensation in cold and hot in any temperature scales. The indoor temperature scale from 22°C to 24°C, scale from 24°C to 26°C those two scales are in thermal comfort yellow zone in thermal sensation scales in Slightly Cool, Neutral, Slightly Warm and Warm. The indoor temperature scale $>$ 26°C are in neutral and slightly warm in the yellow zone and gray zone.

In Figure 5-14b the afternoon session, the indoor temperature scale from 24 to 26°C in thermal comfort yellow zone with the thermal sensation from Cold to Warm. The indoor temperature scale from 26°C in thermal comfort yellow zone with the thermal sensation in neutral and slightly warm in the yellow zone.

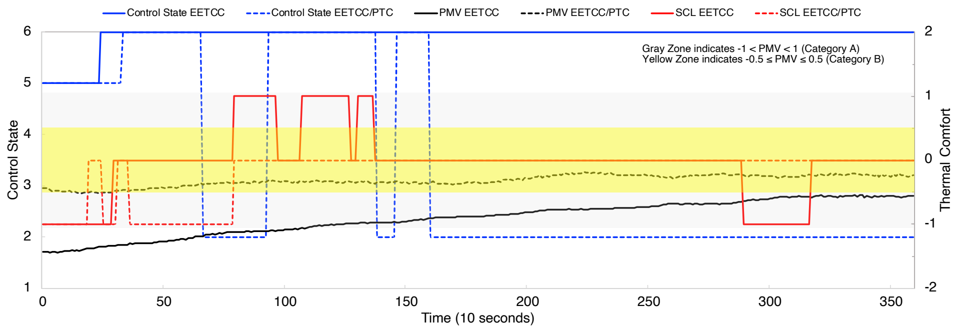


(a) In the morning

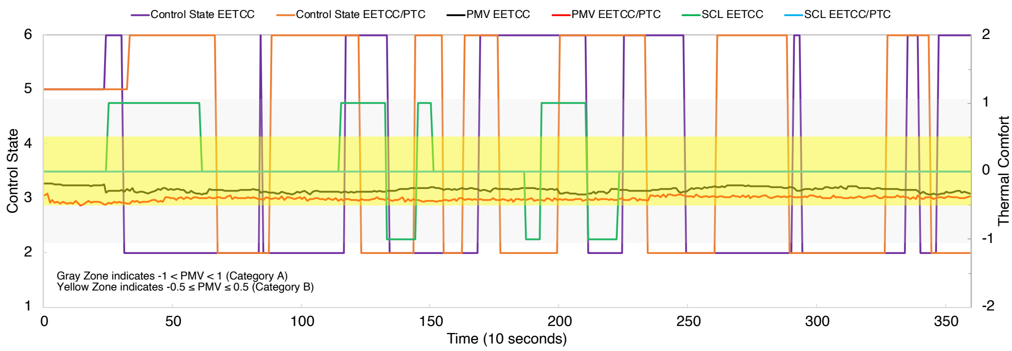


(b) In the afternoon

Figure 5-14: Thermal sensation and thermal comfort.



(a) In the morning



(b) In the afternoon

Figure 5-15: Control state and PMV changes.

4. Control State

There are a total of six control states of EETCC control states definition. In Figure 5-15a and Figure 5-15b, we show the relationship between the control state and PMV and SCL with time continues. The gray zone indicates the PMV values between -1 and 1. The yellow zone indicates the PMV values between -0.5 and 0.5. The highest frequency control state of EETCC and EETCC/PTC in blue line. The black line is the highest frequency PMV value. The red line is the highest frequency SCL value from the six participators.

In the morning session, shown in Figure 5-14a, the EETCC/PTC has less control state changing with high performance (more cover by yellow zone) in PMV and SCL. In the afternoon session, shown in Figure 5-14b, the EETCC and EETCC/PTC change the control state frequency even their PMV value both in the yellow zone.

5. Energy Consumption

This subsection focuses on the energy consumption of control strategies by EETCC and EETCC/PTC that are implementation in this paper. The energy consumption of HVAC is given by

$$E_{aircond} = \frac{1}{COP} \int_{t_{start}}^{t_{end}} |Q_{aricond}(t)|\, dt \tag{5.2}$$

where COP is the coefficient of performance, t_{start} and t_{end} is the start and end time of the implementation, $Q_{aricond}$ is heat gain due to air conditioner. Figure 5-16 shows that power consumption in winter implementation. Comparing the EETCC and EETCC/PTC model to cost the energy consumption in average, the EETCC/PTC model is less 30.5%.

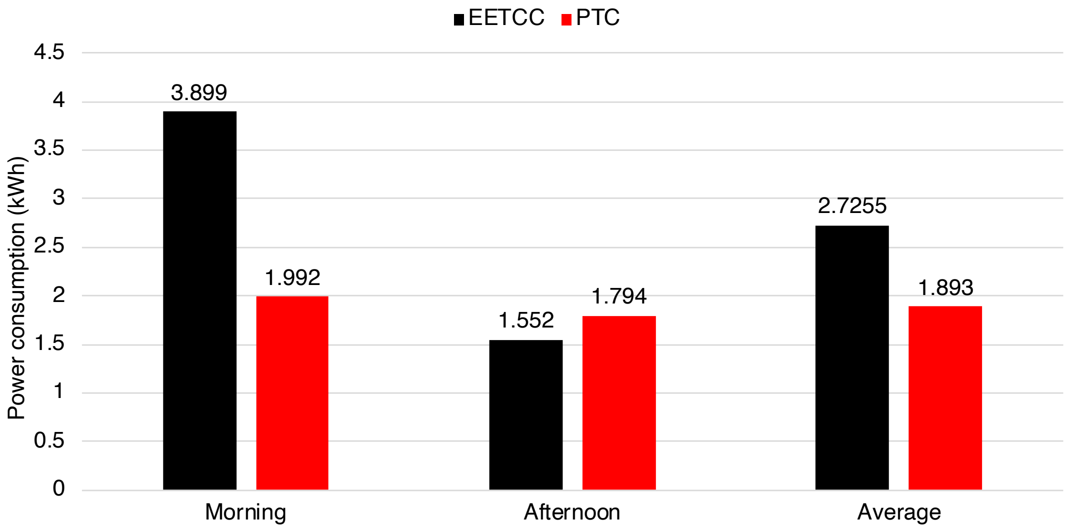


Figure 5-16: Comparison between multiple controller energy consumption for winter.

5.6 Discussions

5.6.1 Prediction Performance of Personal Thermal Comfort Model

There are 21 times training done in this experiment shown in the Figure 5-17. The highest accuracy in the afternoon on 4th February, the value is 0.99702. The best regression plot is shown in Figure 5-18.

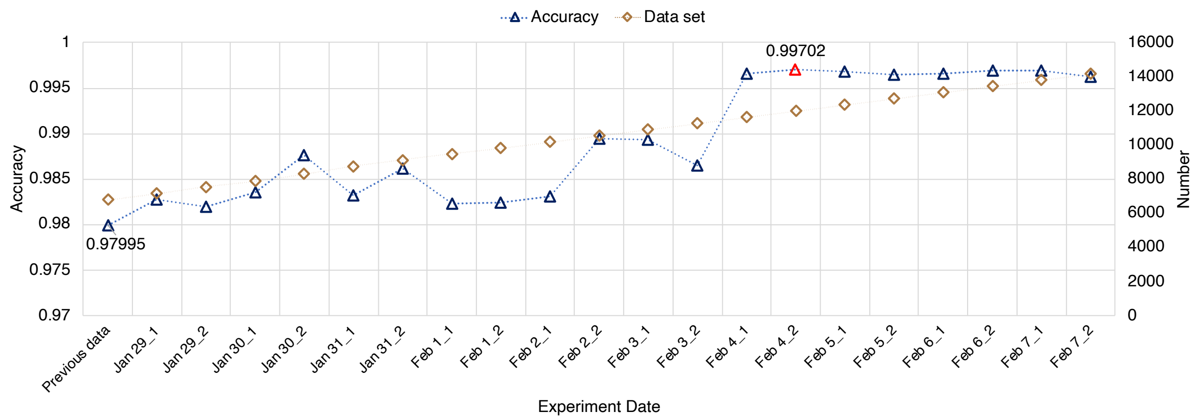


Figure 5-17: Performance of the EETCC/PTC model.

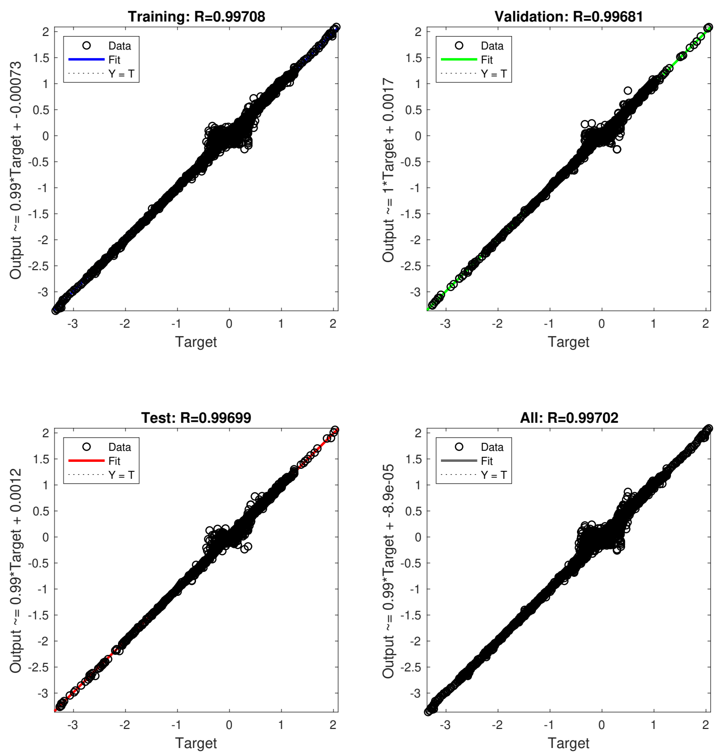


Figure 5-18: The best regression plots of the $pPMV$ based EETCC/PTC.

5.6.2 Heart Rate and Personal Thermal Comfort

With the development of IoT technology, wearable devices have been deeply applied to life. General wearable devices can measure heart rate. Heart rate is also an important parameter to characterize personalize. This paper uses the heart rate as an experiment of human physiological parameters, which is related to thermal comfort. The predictions made using neural network algorithms have also made necessary preparations and research work for removing the wearable device in the smart home environment in the future.

5.7 Summary

A significant part of this research is to use the commercial smart wearable devices as the measurement device incorporated with the other sensors and actuators to build and propose the generic CPHCS framework.

Besides the environmental factors, the physiology parameter from the heart rate is well-studied with the environmental factors, i.e., PMV, air speed, temperature, and humidity are deeply investigated to reveal the personal thermal comfort using the EETCC/PTC prediction control in the smart home environment.

This chapter discussed the heart rate prediction. Heart rate prediction for those people who do not to wear the Apple Watch in home, then it should be discussed. And the experiment are done in NAIST, there are 5 person's 13 days data are collected. The heart rate are classed in two classes, high and low. The prediction results accuracy is 0.9837.

10 persons data are collected and analyzed, and EETCC/PTC shows improvement in terms of the thermal sensation as well as the energy consumption.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This dissertation involves proposing the Personal Thermal Comfort Model for Cyber-Physical Human Centric Framework in Smart Homes. In order to achieve this research goal, the dissertation mainly proposes a CPHC framework based on CPS systems. To extend the CPS to CPHCS, there are three main problems should be solved, the first problem is computation problem that time delay model that it cannot handle the scheduling of multi-platform tasks with inconsistent time requirements, nor can it handle the personalized needs of human. For aiming the CPHC framework different time requirement scheduling computation problem, time task model and MTCDF, MDTH algorithms for human centric scheduling are proposed and simulated. Moreover, I also consider the control problem of personal thermal comfort. The experiments correlation of the human heart rate and environment factors with EETCC control of six participants is implemented in summer 2019. And the simulation of the personal thermal comfort model, there are two case studies included, one is heart rate prediction in different human activity with five participants in the smart home NAIST in summer 2018, other is personal thermal comfort with EETCC/PTC prediction model. At last, implementation of personal thermal comfort for ten participants in iHouse by comparing EETCC and EETCC/PTC in winter 2019. As it is stated, the improve personal thermal comfort level is a primary research area that needs to be solved. The future smart homes should be dynamic and self-motivated with communication between CPHS and human. Embedding intelligence in the form of

CPHC in smart homes to meet the challenges of improved personality, reliability, security, efficiency and system dynamics is a challenging task.

The next generation smart society also called human-centric society, is high intelligence and interaction with communication, computation, and control with the physical world, the cyber world and human. According to the overall trends, CPHC is an interdisciplinary technology that incorporates fixed centralized and CPS and deep interaction with humans organized by applications with the latest developments and novelties. This proposed research can help the development of human centric applications in the smart home environment and give better solutions for inhabitants who are seeking thermal comfort satisfaction with low cost. The following specific contributions are made to advancing the state of the art in this area.

The essential task of personal thermal comfort is to keep the balance between system and human requirement. This dissertation is progressed by the following steps:

1. This dissertation presents some key technologies for the personal thermal comfort model for the cyber-physical human cenrtic framework, especially in smart homes. To propose the high-performance human centric CPS, we analyzed the CPHC framework architecture. Follow the framework, we introduced three components of the framework, which are computation, communication, and control module. At last, the time task model and personal thermal comfort are proposed as this dissertation motivation.

2. We address the time task model of CPS. We define a new time task model for the CPHC framework. The contributions of the CPHC framework are it reduces the repetition rate of the components and the elements in the same model can be approximated, to enhance the efficiency of computation and control. According to the CPHC framework design principle, we proposed the MTCDF algorithm and MDTH algorithm for computation model scheduling algorithm aiming the human centric CPS scheduling. The simulation results show that the MTCDF and MDTH time task scheduling method can improve the service success ratio. The CPHC framework can generality of the matching optimal scheduling index for time requirement and task mixed service.

3. Based on the studies on personal thermal comfort in this chapter, several conclusions

can be drawn. Creating the environmental thermal comfort model for the indoor environments should not be the ultimate goal for the thermal comfort services in smart homes. Personal thermal comfort that comprises of the subjective thermal level of human and thermal comfort level of system is more suitable for the individual human. Indeed, the thermal comfort control systems are beneficially operating to well-fit to the human's comfort preference with the guaranteed indoor air quality for healthcare smart home environments. The CPHC framework, which consists of the generic personal thermal comfort model and EETCC system.

4. Personal thermal comfort parameters research. There are three layers of factors in the CPHC framework, human layer, cyber layer, and physical layer. I choose the heart rate, age, gender, weight, height, and BMI parameters as the human layer's parameters. For choosing the heart rate, I have two reasons, one is the heart rate is easily collected by common IoT wearable devices. The other reason is the heart rate has a relationship with human's thermal comfort and human activities. For physical factors, I consider the indoor environment factors that we can using smart homes system to collect data and control. In this dissertation, the indoor temperature, indoor humidity, indoor air-speed are considered.

5. Experiment results reveal that there is a tight correlation between the environmental factors and the physiology parameter (i.e., heart rate) in human thermal comfort. Through this experiment, this paper also can conclude that the current EETCC system is unable to provide the precise need for thermal comfort to the human's preference. However, the experiment results discover that the relationship between the human thermal comfort and the physiological parameters that we can obtain data from conventional wearable devices has a tied correlation, and this gives a better understanding of a novel solution underlying the thermal comfort for automation control in smart homes.

6. A personal comfort prediction model is proposed under the machine learning theory. On this basis, two case studies based on the prediction of heart rate (LSTM) and personal comfort prediction (Neural Network) without wearable devices were completed.

From this contribution, we achieved three apparent implementation simulation.

- Case 1, we built a new model to predict the heart rate based on daily living activity in smart homes. In order to evaluate the accuracy of the prediction, the experiments with 5 participants were conducted. The results showed that our model could predict the heart rate with 0.9837 accuracies in two classes. This research work can be extended to predict human body data such as heart rate in the future without using wearable devices in a smart home environment.
- case 2, through Matlab's EETCC simulation platform, the prediction of personal comfort is completed, and the prediction result of subjective comfort level and the prediction of nPMV are obtained.

6. Summarizes the implementation details of the EETCC/PTC in a smart home environment using the ANN approach. Implementation is carried out under winter seasons to evaluate the performance and advantages of predictive capabilities in the domain of personal thermal comfort control. Results showed improvement in both thermal comfort and energy minimization.

6.2 Directions and Future Works

This section discusses future research directions for Cyber-Physical Human Centric System in smart home environments. With the best of my knowledge, this research contributes to the issues of system design and implementation effort for the CPHC framework personal thermal comfort system, the experiments for the system validation, and optimal control problems for large scale systems. However, there have still many things to improve:

- There are many factors that affect personal thermal comfort. At present, in this dissertation, 12 factors in 3 layers are studied . In future work, I hope to expand the depth of research on the influence of complex factors such as human body temperature, human activity, light environment, etc;
- Heart rate predicting, aiming the future needs when a person go back to home and do not want to wear the wearable device at home;

- Personal thermal comfort is currently only applicable to a single person, and multiple people need to gradually carry out research in future work;
- The MDTH algorithm should be improved in mulit-person, this will make the system very complexion in the future;
- The execution time of each component obtained by the computation module is not complete. The execution time and status of the components in the system need to be further improved;

Considering the present research, further research will be address not only personal thermal comfort but also the multiple personal thermal comforts such as every member of the whole house. Since the thermal comfort of human wish will be more complex, the stability, computation, and optimization problems of the deep interaction will become the critical problems that need to solve out. By solving these problems, I will consider the personal thermal comfort for more factors of environment and human physical and psychological factors such as lighting factors effect for smart home, office buildings, school classroom, and so on.

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