University of Reading

Building Energy Management and Occupants' Behaviour

-Intelligent Agents, Modelling Methods and Multi-objective Decision Making Algorithms

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy at the

School of Built Environment

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Lai Jiang

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List of Publications

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Yao, R., Luo, Q., Luo, Z., Jiang, L. and Yang, Y. (2015) An integrated study of urban microclimates in Chongqing, China: historical weather data, transverse measurement and numerical simulation. Sustainable Cities and Society, 14. pp. 187-199. ISSN 2210-6707 doi: 10.1016/j.scs.2014.09.007

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List of Abbreviations

AC	Air-conditioning
ARI	Air-Conditioning and Refrigeration Institute
A-HEM/BEMS	Adaptive Home/Building Energy Management System
ANN	Artificial Neural Network
AMV	Actual Mean Vote
BAS	Building Automation System
BACS	Building Automation and Control System
BEMS	Building Energy Management System
BMS	Building Management System
BRE	Building Research Establishment
BREXBAS	Building Research Expert Building Automation System
Btu	British Thermal Units
C-SVC	C-support Vector Classification
Cf	Contents Factor
EDA	Epistemic-Deontic-Axiologic
ELM	Extreme Learning Machine
EMS	Energy Management System
FCAs	Fuzzy Controller-agents
GDP	Gross Domestic Product
Gf	Glass Factor
HBS	Henley Business School
HVAC	Heating, Ventilation and Air-conditioning
Hw	Window Height
LOOCV	Leave-one-out Cross-validation
MASBO	Multi-agent System for Building Control
MOPSO	Multi-objective Particle Swarm Optimization
MSE	Mean Squared Error
NNEM	Neural Network Evaluation Model
NSGAII	Nondominated Sorting Genetic Algorithm II
PDA	Personal Digital Assistants
PDTC	Personalised Dynamic Thermal Comfort
PID	Proportional–Integral–Derivative

PLC	Power Line Communication
PMV	Predict Mean Vote
PPD	Predicted Percentage Dissatisfied
PPV	Predicted Personal Vote
PSO	Particle Swarm Optimization
RBF	Radial-basis Function
Rw	Room Width
SCME	School of Construction Management and Engineering
SMODIC	Smart Sensor System, Optimum Decision Making System and Intelligent Control System
SVM	Support Vector Machine
SVR	Support Vector Regression
TSV	Thermal Sensation Vote
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
W	Watts
Wf	Wall Factor
WSAN	Wireless Sensor Actuator Network
Ww	Window Width
XML	Extensible Markup Language

Abstract

In the UK, buildings contribute around one third of the energy-related greenhouse gas emissions. Space heating and cooling systems are among the biggest power consumers in buildings. Thus, improvement of energy efficient of HVAC systems will play a significant role in achieving the UK carbon reduction target.

This research aims to develop a novel Building Energy Management System (BEMS) to reduce the energy consumption of the HVAC system while fulfilling occupants' thermal comfort requirements. The proposed system not only considers the occupants' adaptations when making decisions on the set temperature, but also influences occupants' behaviours by providing them with suggestions that help eliminate unnecessary heating and cooling.

Multi-agent technologies are applied to design the BEMS's architecture. The Epistemic-Deontic-Axiologic (EDA) agent model is applied to develop the structure of the agents inside the system. The EDA-based agents select their optimal action plan by considering the occupants' thermal sensations, their behavioural adaptations and the energy consumption of the HVAC system. Each aspect is represented by its relevant objective function. Newly-developed personal thermal sensation models and group-of-people-based thermal sensation models generated by support vector machine based algorithms are applied as objective functions to evaluate the occupants' thermal sensations. Equations calculating heating and cooling loads are used to represent energy consumption objectives. Complexities of adaptive behaviours and confidence of association rules between behaviours and thermal sensations are used to build objective functions of behavioural adaptations. In order to make decisions by considering the above objectives, novel multi-objective decision-making algorithms are developed to help the BEMS system make optimal decisions on HVAC set temperature and suggestions to the occupants. Simulation results prove that the newly-developed BEMS can help the HVAC system reduce energy consumption by up to 10% while fulfilling the occupants' thermal comfort requirements.

Chapter 1 : Introduction

1.1 Background and Research Question

Global warming has become one of the international issues that the world is facing. Scientists have proved this is caused by greenhouse gas emissions (Houghton *et al.*, 1990). To help solve this problem, the United Nations (UN) passed the United Nations Framework Convention on Climate Change (UNFCCC), which proposed tackling the global warming problem by stabilising the greenhouse gas level in the atmosphere (United Nations, 1992). A document published in 2003 shows that the UK government planned to decrease CO_2 emissions by 60% by 2050 on the basis of the emissions level in 1990 (DTI, 2003). The later Climate Change Act passed by the UK parliament in 2008 set the rule that greenhouse gas emissions should be at least 80% less than the emissions level in 1990 (HM Government, 2008). The Chinese government aims to reduce the carbon emission per unit of gross domestic product (GDP) by 40% to 45% before the year 2020 on the basis of the emission level in 2005 (Wang et al., 2011a, Yi et al., 2011).

Buildings have been regarded as one of the major carbon emission sources due to their high levels of energy consumption. It has been reported that, globally, more than 30% of total energy is consumed by buildings and consequently they account for one third of energy-related greenhouse gas emissions (Urge-Vorsatz et al., 2013). The UK government reported that 37% of emissions were produced from heating and powering homes and buildings in 2009 and, in the same report, it is recommended that the emissions from buildings should be around zero by 2050 (HM Government, 2011). In 2015, buildings still contributed 33% of UK greenhouse gas emissions (Committee on Climate Change, 2016). In all developed countries, building energy usage accounts for 20% to 40% of total energy consumption (Perez-Lombard *et al.*, 2008). It has been suggested that a 50% to 90% reduction of building energy consumption should be targeted in the next three decades (Arens et al., 2010). Thus, cutting energy consumption in buildings is a feasible way to decrease carbon emissions caused by them.

Space heating and cooling systems are among the biggest power consumers in buildings (Wu and Noy, 2010). The Heating, Ventilation and Air-conditioning

(HVAC) system contributes around 50% energy consumption in non-domestic buildings (Perez-Lombard et al., 2008). In the UK, 60% of household energy consumption can be attributed to space heating (Palmer and Cooper, 2013). Consequently, efficient control of the HVAC systems in buildings is crucial for energy saving and reaching the 80% greenhouse gas emission reduction target.

On the other hand, providing a comfortable environment is one of the primary purposes of HVAC systems which should not be ignored (Atthajariyakul and Leephakpreeda, 2005). However, such a purpose is not always in accord with the energy saving goal because maintaining the built environment within a comfortable zone is usually energy-consuming. How to deal with the challenge of fulfilling occupants' thermal comfort requirements while achieving energy saving remains a question.

It has been revealed that inappropriate operation of HVAC systems may result in 89% more energy consumption in some built environments (Hong, 2014). Therefore, it is reasonable to control the operation of HVAC systems to avoid unnecessary energy wastage. In modern buildings, the HVAC system can be managed by the Building Energy Management System (BEMS). The energy management system was first developed in the 1970s to monitor and control the operation of HVAC systems. Its control range was later extended to other services such as lighting and alarm systems (Levermore, 2000). Thus the system controls the service plants to provide a comfortable built environment for occupants. Hence, improving the performance of the energy management system is an effective way to promote the energy efficiency of the HVAC system as well as guaranteeing the occupants' comfort.

In order to choose the appropriate settings for the HVAC system, the BEMS needs to understand the thermal comfort requirements from the occupants to whom the HVAC system provides services. The term 'appropriate settings' refers to the targeted environmental conditions generated by the decision-making algorithm in the BEMS system. The relationship between this algorithm and the actuator of the HVAC system is shown in Fig 1.1. The details of how the actuator operates the HVAC hardware to make the indoor environment reach the target, is beyond the scope of this research.

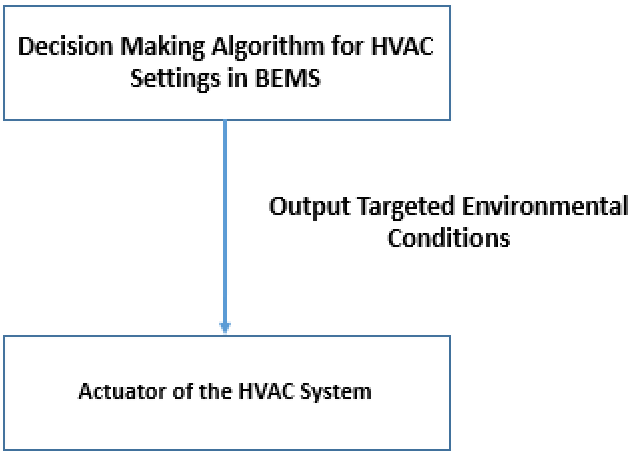


Figure 1.1. Relationship between the Decision-making Algorithm, the Settings of the HVAC system and the Actuator of the HVAC System

The comfort zone is defined by the models and indices proposed by international standards which are used for the 'evaluation of moderate thermal environment' (ISO7730, 2005, ANSI/ASHRAE55-2010, 2010). It has been pointed out that these models and indices in some circumstances do not accurately estimate the thermal sensation of an occupant (Gao and Keshav, 2013, Zhao et al., 2014) or a particular group of people's actual mean vote (AMV) in a certain built environment in real time (Yang et al., 2015). This may cause BEMS to overshoot the settings of the HVAC system, which leads to extra and unnecessary energy consumption while decreasing the comfort level of the occupants. In some situations, a 1℃ room temperature difference will cause 10% energy consumption variation for the HVAC system (Humphreys and Hancock, 2007). One potential solution is that the BEMS system makes decisions for the HVAC system according to occupants' sensation feedback (Moreno et al., 2014) (Erickson and Cerpa, 2012); (Jazizadeh et al., 2014). But how to process and utilise the collected information remains a problem. Once the BEMS understands the needs of the occupants, how to apply the information to decide the HVAC system's settings is another question.

Besides the HVAC system, the impact of the HVAC system's end-users should not be ignored. It is sometimes difficult for an energy management system to decide a set point that will satisfy all the occupants because the algorithm in the system only aims to predict the thermal sensation level in general, regardless of individual differences. To further increase the occupants' thermal comfort level, the solution can be to improve the interaction between the occupants, their personal devices and the BEMS to affect occupants' actions. This solution is based on the adaptive comfort theory: people are not just passively affected by the ambient environment, but actively restore their comfort conditions (Nicol and Humphreys, 2002). In other words, occupants' adaptive behaviours will also change their thermal conditions. Moreover, the occupants' behaviour sometimes directly affects the operation of HVAC systems and their energy consumption. Therefore, people's adaptive behaviours have an effect on both their thermal comfort and energy consumption. So, potentially, it is possible to provide personalised services, such as suggestions to an individual occupant on reactions to their ambient environment in an appropriate way to achieve their thermal comfort sensation, without causing energy wastage. Again, because of individual differences, the suggestions to every occupant should be personalised. How the BEMS decides and provides such suggestions is another question worth looking into.

Finally, it can be found that other than a pure HVAC controller, the BEMS system needs to provide personalised services to all occupants. It collects information from the environment and feedback from occupants, then it feeds forward decisions based on this information to the HVAC system and the occupants. It has already been revealed that the controller in BEMS can be regarded as an agent (Dounis and Caraiscos, 2009), so agent-based technologies can be adapted into the BEMS system development. This research needs to solve the problem concerning how to develop a BEMS, which fits the requirements by using agent-based technologies.

It can be concluded that, in order to reach the energy-saving and the thermal comfort targets, it is reasonable to build up a novel energy management system, which is able to understand the real-time thermal comfort requirements of occupants in the built environment and provide personalised suggestion services to increase the thermal comfort level of each individual who feels uncomfortable.

To build such a system, the following research questions need to be answered.

- How can the energy management system understand occupants' real-time thermal comfort needs in a real building environment?

- How can the energy management system further eliminate the energy wastage of the HVAC system by using information from the occupants and the environment?
- How can the energy management system increase the thermal satisfaction level of occupants whilst avoiding energy wastage by improving the interaction between the buildings and the occupants?
- How to develop an energy management system to take care of the operation of the HVAC system whilst simultaneously addressing the thermal comfort issues of all the occupants?

1.2 Aims and Objectives of the Research

As discussed in the background section, in order to reach the carbon emission reduction objective, it is important to reduce the energy consumption of the HVAC system in buildings. But at the same time, the HVAC system needs to provide a thermally comfortable environment for occupants. Developing a novel energy management system is an effective way to hit both targets, so the main aim of this research is to develop an energy management system to minimise the energy consumption of the HVAC system while satisfying the thermal comfort requirements of the occupants. Such an energy management system fulfils the aim of this research by applying the following method: It chooses the optimal set points for the HVAC plants and it also has the ability to interact with the end-users to provide personalised suggestions on adaptive behaviours. Being guided by the suggestions, each individual can obtain their thermal comfort requirements. The research questions arising from the application of these methods are also demonstrated in the last section. The problems pointed out in the questions can be solved if the developed energy management system obtains the following abilities:

1. Sensing the current environmental conditions in real time
2. Collecting personal factors and occupants’ responses to the current thermal conditions
3. Learning occupants’ thermal comfort preferences
4. Identifying occupants’ adaptive behaviour patterns
5. Calculating the desired set points for the built environment

6. Providing personalised suggestions to the occupants

As shown later in the Literature Review and Research Methodology Chapter, the first and second functions can be realised by the sensor, monitor and human-machine interface hardware, which are not the main focuses of this research. The objectives of this research are as follows:

1. To develop the architecture and identifying the key components, especially the software components, of the energy management system.
2. To develop a modelling method for the system to dynamically predict the personal thermal comfort level for each occupant.
3. To find a method to estimate the thermal sensation level of a group of occupants in the same built environment in real time.
4. To develop a method to numerically analyse and evaluate occupants' behavioural adaptations.
5. To develop optimal decision-making algorithms for the system to decide the set point for the HVAC system.
6. To develop an optimal decision-making algorithm for the system to provide personalised suggestions for the occupants.
7. To integrate the developed models and the decision-making algorithm together into the energy management system architecture and evaluate its performance.

1.3 Applied Research Approaches

In general, the literature review, the experimental method, the questionnaire survey, the statistical analysis, the modelling method and the simulation method are applied in this research to solve the research questions.

The literature review identifies the gap between the existing BEMS research and the BEMS proposed in this research. It also highlights the potential ways to improve the existing BEMS.

In order to enable the BEMS to learn the thermal preferences and behavioural habits of the occupants, both experimental and questionnaire survey research methods were conducted. The experimental field studies were carried out to collect data in real built environments. These studies collected the environmental data from an air-conditioned built environment. The surveys were used to gather the information about the occupants' personal factors as well as their thermal sensations.

The collected data were processed by modelling methods from machine learning and statistical analysis methods from data-mining. The generated model and analysis outcomes allow the system to understand the thermal comfort needs of the occupants and provide the foundations of the decision-making process.

Finally, the simulation method was applied to test the operation process of the developed BEMS and its performance on energy saving and maintaining a thermally-comfortable environment.

1.4 Thesis Structure

The first chapter is this introduction chapter. Following the introduction chapter, the second chapter is the literature review and research methodology chapter in which a comprehensive literature review of the existing building energy management system research is performed. The software and hardware components of the energy management systems are reviewed and their functions summarised. Then the research methodologies for system development, the data collection and data process are discussed.

In the third chapter, the architecture of the multi-agent energy management system is developed. The detailed structures of the personal agent and the local agent are also designed. The chapter realises research objective one.

The fourth chapter develops personal thermal sensation models. The support vector machine algorithm is applied as the modelling method to generate the models. This part of the research fulfils research objective two.

The fifth chapter uses a method based on the personal thermal sensation model and another method based on the support vector machine to develop models to evaluate the thermal sensation level for all the occupants in a built environment. The research concerning objective three is finished in this chapter.

The sixth chapter generates the decision-making algorithms for the personal agent and the local agent in both open-plan and single-occupancy offices. These algorithms are developed particularly for the decision-making process in the proposed energy management system. Objectives five and six are realised in this chapter.

The seventh chapter firstly builds models to simulate the needed cooling and heating loads for an air-conditioned built environment. Then the chapter proposes ways to numerically evaluate how the suggested reactions fit an occupant's usual behaviour patterns. The chapter integrates the models and algorithms developed in previous chapters and above into the agents in the building energy management system. The abilities and the performances of the building energy management system are tested in both single-occupancy and open-plan offices. The chapter completes objectives four and seven.

The eighth chapter concludes the research findings and suggests future research directions.

The structure of this thesis is illustrated in Fig 1.2

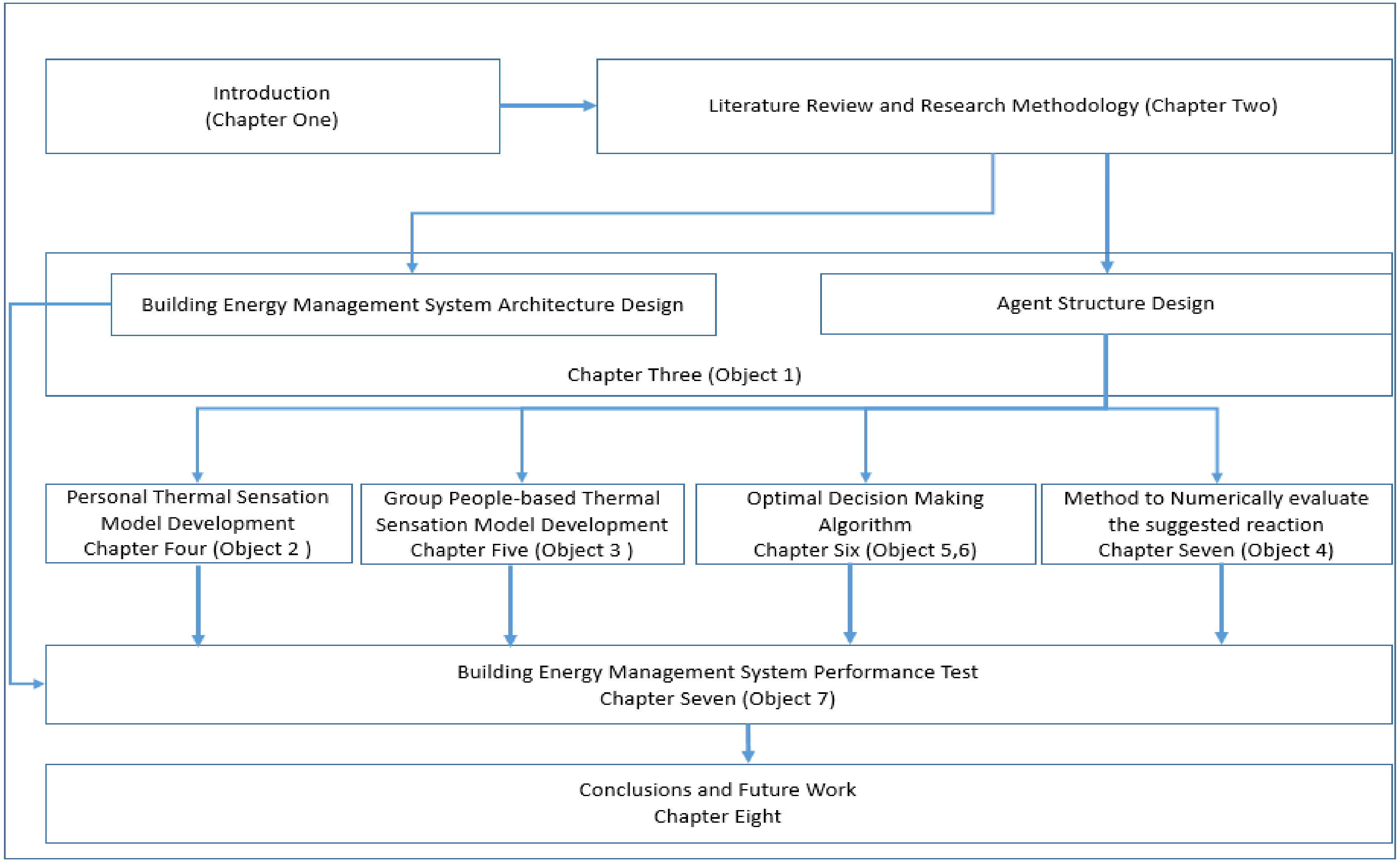


Figure 1.2 The Structure of the Thesis

1.5 Output of the Research

In summary, the innovations made by this research are:

- A novel, multi-agent, BEMS system with agents developed using newly-developed rational agents (Chapter 3).
- A new modelling method to develop the personal thermal sensation models utilising feedback from the occupants (Chapter 4).
- A new modelling method to develop the model estimating the thermal comfort level for a group of people using their feedback (Chapter 5).
- The decision-making algorithms and decision-making process in the new BEMS to make decisions on settings for the HVAC system and personalised suggestions for the occupants (Chapter 6).
- Methods to numerically analyse and process the behavioural adaptations (Chapter 7).

Chapter 2 : Literature Review and Research Methodology

2.1 Literature Review

2.1.1 Building Energy Management Systems

The building energy management system (BEMS) ‘is a computer-controlled system that may be used to monitor and control a building’s power systems including lighting, heating, ventilating and air conditioning’ (Thorpe, 2014). The early version of such systems was introduced into builds in the 1970s to control and monitor the operation of HVAC systems, then the system continued to be upgraded with the advance of electronic technologies and computer science (Levermore, 2000). The objectives of energy management include optimising energy usage as well as decreasing greenhouse gas emissions (Capehart et al., 2008). The system works with HVAC plants to provide a comfortable environment for the occupants. Because of this, in recent years, the system has been regarded as a key component of intelligent buildings, which consider ‘environmental and social needs, and occupants’ well-being’(Clements-Croome, 2014).

The BEMS is found to be a part of the building automation system (BAS), and its functions overlap with the so-called energy management system (EMS), building automation and control system (BACS) and building management system (BMS) (Capehart et al., 2008, Clements-Croome, 2013). For consistency, in this research, the name Building Energy Management System (BEMS) is used.

A traditional BEMS is introduced in Levermore (2000). The system consists of one central station and multiple outstations. The function of the outstation is to control plants using the input from the switch and sensors. For HVAC plants, the control target is defined by a fixed set point represented by an operative temperature. The central station is responsible for running the user software and storing the data about the plants and the buildings for the administrator of the system.

The Building Research Establishment (BRE) developed a BEMS which is used to control the operation of the heating system called ‘Building Research Expert Building Automation System’ (BREXBAS) (Ashworth and Hogg, 2000, Gilmore, 1989). This system is a knowledge-based system, or so-called expert system, which is able to make certain decisions such as determining if the current environment is acceptable and analyses the reason for any current problem (Levermore, 2000). One outstanding point of this system is that it is able to interact with its users about its decisions and advice via a user interface. It has been pointed out that such a system depends on its programmer to pre-set the knowledge into the system and the information provided needs to be interoperated by a professional person such as an experienced energy manager (Scott et al., 1988).

The examples above indicate that these BEMS do not take energy consumption as well as real time occupants' comfort needs into account when controlling the HVAC plants. Abilities of these BEMSs were restricted by their designed function and the technologies they applied. To achieve the goal of energy efficiency and occupant thermal comfort, researchers propose models of new BEMS systems with more functional modules, which are aided by advanced technologies.

Computer technologies, telecommunications and information technologies are applied to upgrade the ability of the BEMS. (Doukas et al., 2007). Based on this idea, in the same literature, a structure of a new BEMS is proposed. Being improved by the suggested technologies, the BEMS integrates a decision making support to achieve a comfortable building environment and efficient energy consumption. In detail, the system contains the following components: indoor and outdoor sensor systems, controllers, decision unit and database. The sensor systems are used to monitor the real time environmental conditions. The decision making model considers requirements from users in the built environment as well as pre-set rules to make decisions for the controller. By applying the decision support model, the BEMS should be able to reduce the energy consumption.

Another BEMS model constructed by a smart sensor system, an optimum decision making system and an intelligent control system (SMODIC) is illustrated in Yao and Zheng (2010). Having been upgraded from the previous BEMS models, the system's decision making relies on accurately estimating occupants' comfort requirements by acquiring their physiological, psychological and behaviour patterns and co-operating with real time environmental data such as temperature, humidity and air velocity. This needed information is collected by sensor networks and human machine interfaces.

With all the information needed, the optimum decision module provides optimised control decisions to the control system to accomplish the best power consumption result. Furthermore, the system is also designed to provide occupants with adaptive behaviour advice in order for them to feel comfortable in their building environment.

These proposed BEMSs provide insight into some of the key elements of the BEMS, including the theoretical basis, the subsystems structure, the input and output of the main system and subsystems and their functions. The insight provides guidance for the BEMS development in this research. Concluded from previous research, an ideal BEMS system should include the following components:

- Sensor Networks
- Human Machine interface
- Decision Making Module
- Actuator
- Data Storage.

By utilising the hardware and software components listed above, the BEMS should realise the following functions:

1. Sensing the current environmental conditions in real time
2. Collecting personal factors and occupants' responses to the current thermal condition
3. Learning occupants' thermal comfort preferences
4. Identifying occupants' adaptive behaviour patterns
5. Calculating the desired set points for the built environment
6. Providing personalised suggestions to the occupants.

Existing attempts to develop the software and hardware components in the BEMS and realise the functions mentioned above are illustrated in the next few sections.

2.1.2 Data collection and Storage Technologies for BEMS

There have been a number of research focuses on effectively collecting information in buildings using advanced sensor technologies. Smart sensor systems are an important subsystem of a building management system to acquire information. Technology developments in the areas of microprocessors, and sensor devices enable sensor networks to have strong information detection and collection abilities. Therefore, sensor networks are applied in many research areas including farming and agriculture etc. (Priyanandhan, 2012, Yu et al., 2013) and have been proven to be ideal for environmental information collection such as temperature monitoring, noise detection and target tracing (Veerasingam *et al*., 2009, Bell and Galatioto, 2013, Dai *et al*., 2013). These functions and abilities are in high demand by building energy management systems. There are many research outcomes in application sensor networks inside buildings. For the indoor environment, it is necessary to use wireless communication technologies to realise the communication between the sensors and other parts of the BEMS. Therefore, the wireless sensor nodes are applied. These nodes can be based on technologies such as WiFi (IEEE 802.11) or Zigbee (IEEE 802.15.4) standard defined by IEEE (Erol-Kantarci and Mouftah, 2010). For example, a wireless sensor network based on the Zigbee standard are recommended to be applied in an energy management system in Wang and Wang (2010). The system is developed to audit energy consumption of home appliances. The sensor network comprises a base station and multiple remote sensors. The remote sensors collect the information from the field then transmit it to the base station, which then forwards the data from the sensors to the main server of BEMS. Based on the test result, the data transmission distance can be as long as 50 meters. Shen et al. (2011) applied Extensible Markup Language (XML) formatted data to solve the connectivity problem between the environmental sensors and the air-conditioner controller. This constructs a heterogeneous system in which different components use different communication standards. The research settled the problem of how these components communicate with each other. Fortino et al. (2012) suggest a building management framework which integrates a network of heterogeneous networks containing wireless sensors as well as actuators. The research demonstrates a very detailed layered design of the network system for both base station and sensor node sides. Supported by the wireless sensor network, the building management framework is claimed to be able to monitor buildings and control the equipment inside (Fortino et al., 2012).

Other sets of research not only apply the sensor network in the BEMS, but also use personal devices as well as databases to further extend the abilities of the system. Personal devices can be employed as media-rich interfaces among users, environment control systems and wireless sensor networks. Clements-Croome (1990) suggests a Sense Diary system to take care of the occupants' well-being in energy efficient buildings. It is proposed that the system utilises the WSN to collect environmental information. Occupants' reactions to the ambient environment are also collected and saved by the system. In the system, mobile phones, personal digital assistants (PDA), PCs and TVs are recommended as media to communicate with the occupants (Mao et al., 2007). Mineno et al. (2010) developed an adaptive home/building energy management system (A-HEM/BEMS). In the research, the sensor network applies both the power line communication (PLC) technology and wireless communication following the Zigbee standard to solve the communication problem caused by distances, obstacles and so on. In a prototype system, the sensor network aims to collect and transmit the information about temperature, humidity, illumination and energy consumption. The PostgreSQL is used to realise the integrated database. Mobile phones and webpages are used to display the information from the system. Similarly, the energy management system proposed in Anastasi et al. (2011) also employed the WSN, the human-machine interface and the database technologies. In this research, WiSensys sensors are applied to fulfil monitoring requirements while the database is being developed by MySQL in the server of the system. Webpages on PCs and interfaces on mobile phones are responsible for the interaction between the system and end users. There are abundant suggestions for realising sensor networks, the human-machine interfaces and the databases in the building energy management systems. Therefore, in this research I will not peruse this in depth.

2.1.3 The Control of HVAC System in BEMS

A number of efforts have been made to develop technologies to control the HVAC system. Calvino et al. (2004) propose a fuzzy proportional–integral–derivative (PID) controller to control HVAC plants. Instead of using a set temperature, this research directly applies PMV value as a control target. A neural network controller is proposed to control the HVAC system (Argiriou et al., 2004). The artificial neural network (ANN) module in the controller is developed from the feed forward back propagation method. ANN technology is also proposed to be used by a model based control method (Marvuglia et al., 2014). In the control method, fixed room air temperatures in summer and winter are used as control targets for the fuzzy logic control unit. A similar control system applied in a hospital is also suggested by Papantoniou et al. (2015). The system applied the fuzzy controller aided by a temperature predicting model developed by ANN. Web-based technologies are introduced into the system. The web page interfaces are responsible for interaction between users and system. Default settings are fixed indoor air temperatures, but they can be overridden by the users.

From the review above, it can be found that technologies such as PID, Fuzzy Logic and ANN are suggested for applications of the controllers/actuators so that either the controllers or the actuators will guide the HVAC plants to meet the set target. On the other hand, the methods used by the BEMS to decide the set point of the HVAC is still under discussion. Some existing systems work with fixed set points and settled schedules. Other systems may adaptively change their set points calculated by a thermal comfort model such as Predict Mean Vote (PMV). The question has been raised: whether the fixed set point or the thermal comfort model reflect the true thermal comfort needs for the group of people that the BEMS provides services to. Furthermore, it is still uncertain how the existing systems deal with individual differences in thermal comfort. In order to provide personalised services, the BEMS should be able to make decisions for each localised environment and individual occupant. The question built up on the previous one is how controllers in the BEMS provide personalised service to every user in the built environment. This complex problem may potentially be solved by agent technologies and multi-agent systems, which are reviewed in the next section.

2.1.4 Applications of Agent based Technologies in the Built Environment

Agent based technologies have been widely applied in the building management and control related research field. The intelligent room developed by the MIT artificial intelligence lab is realised by embedding multiple agents into a built environment (Brooks et al., 1997). With the help of the agents, the intelligent room gains abilities such as speech recognition and machine-occupant interaction in the room etc. The agents used in this intelligent room project are not particularly developed for energy management, but researchers on this project prove that the complex tasks of intelligent building control is better conducted by distributed multiple software agents, not a central controller (Coen, 1997). This research shows the complex problem solving ability of the multi-agent system in the building management area.

Sharples et al. (1999) proposed a multi-agent system, which is called 'Essex IB Model' used inside intelligent buildings. This has been developed to provide assistance to elderly and disabled people. The structure of the agent system is arranged in a distributed way so that one agent is installed per room and all agents are connected via a network. Agents applied in the system are room controller agents based on 'embedded agent' technology. These agents are hardware entities with embedded micro-processors. In general, it is claimed that the system provides a real-time control response on the basis of information continuously learned from the environment and individual occupants rather than using models developed in advance (Hagras et al., 2003b). In this case, the system has the ability to deal with the situation the system developer did not programme into the system in advance. It is also claimed that functions of the agent include taking care of occupants' comfort and energy saving. Later research (Hagras et al., 2003a) indicates that for the embedded agents, the decision making criteria including occupants' thermal comfort preferences can be learnt by the fuzzy logic method supported by a genetic algorithm. This method is from earlier mobile robot research (Hagras et al., 2000). A similar fuzzy logic based method can also be found in the agent based application in Wang et al. (2006). The multi-agent system with hardware agents is applied in the intelligent building's control system, which is called iDorm (Hagras et al., 2004). However, for the embedded agents, some researchers have pointed out that they might not be suitable for a complicated agent platform due to the limit of hardware abilities (Liu et al., 2008).

A multi-agent system used for deciding the settings of indoor thermostats is illustrated in van Breemen and de Vries (2001). In the research, the control problem is regarded as complex, and divided into several sub-problems. In this case, each sub-problem is solved by a controller and the agent is used to support the process of autonomous decision making of a controller. A fixed comfort zone with temperature ranges is used to define if a user is comfortable or not. It is claimed that such a system is able to avoid overshooting by automatically deciding the settings of the thermostats.

Mo (2002) also suggests considering the individual differences in the agent development process, particularly in illumination and thermal comfort aspects. A case study of an illumination control agent is given in the research. Differing from previous research, the multi-agent system contains several categories of agents arranged into different levels. There are ‘occupant agents’ which aim to serve individual occupants, while higher level agents such as ‘operator agents’ focus on the general performances of the buildings. A similar agent hierarchy is applied in later developed multi-agent building management systems. This research also suggests that the agent’s decision making algorithm considers a trade-off among the different comfort aspects and the energy consumption but how to measure the occupants’ comfort level is not clearly indicated in this research.

Davidsson and Boman (2005) also proposed a control system for office buildings aided by a multi-agent system. The objective of the system is to save energy and improve occupants’ thermal comfort. The system applies power lines as communication links between agents and electrical devices such as actuators for lighting and heating. The multi-agent system is also a decentralised system integrated by different types of agents. It contains personal comfort agents for personal preference, room agents for deciding indoor environmental data and environmental parameter agents to control indoor environment (Davidsson and Boman, 1998) (Davidsson and Boman, 2000). However, personal interests such as the preferred temperature is a fixed figure (22 C°) and it is assumed that at 22 C°the thermal comfort satisfaction rate is 100%. This assumption does not correspond with indoor environmental standards such as ASHRAE and ISO7730 or to the adaptive comfort theory.

A multi-agent framework for energy management control is established in Rutishauser et al. (2005). This framework proposes the use of a fuzzy logic controller to manipulate the service plants. Setting decisions are made by fuzzy logic rules, which are generated by an unsupervised online learning method. The research encounters difficulties in testing learning results of comfortable rules with the real thermal comfort data from the occupants because of restrictions brought by the online learning method itself.

A Multi-agent system for Building Control (MASBO) has been proposed and discussed in several research articles (Qiao et al., 2006, Yong et al., 2007, Liu et al., 2008, Liu et al., 2011). This system contains four kinds of agents: the personal agent, the central agent, the local agent, and the monitor and control agent. By applying these agents, the system aims to adaptively change control instructions based on human behaviour and ambient environment changes in order to save energy and meet occupants' well-being (Liu et al., 2008). The MASBO research provides theoretical guidance on how to develop an agent working for building energy management. It is illustrated that the developed agent should have common properties including: 'reactivity, pro-activeness, social ability and persistence' which is defined in Wooldridge (2009) and Qiao et al. (2006). Moreover, an EDA (epistemic, deontic, axiologic) (Filipe and Brito, 2005) agent model is suggested to define the structure of an agent in the building energy management system (Qiao et al., 2006, Liu et al., 2011). In a MASBO based system, to generate the occupants' personal profiles, the system firstly develops a pre-defined fixed profile for general occupants, then adds personal preference values into the range for each occupant (Yong et al., 2007). The MASBO implies the pervasive informatics theory regarding buildings to have complex signs to improve the interaction between the building and occupants (Liu et al., 2011). The prototype design of this system is described in detail in Liu et al. (2011) but the performance of the system needs to be further investigated.

Dounis and Caraiscos (2007) developed fuzzy controller-agents (FCAs) to control the indoor environment, which is based on '3-D fuzzy comfort sets'. The controller takes into account both occupants' comfort and energy saving. The system contains two types of agents: master agents and slave agents. The master agent is responsible for calculating the set point of the controllers while the slave agent works to avoid the conflict among FCAs (Dounis and Caraiscos, 2008). For occupants, thermal comfort, illumination comfort and air-quality are considered and represented by 3-D fuzzy comfort sets (Dounis et al., 2011). The occupants' preference in this research is derived from the PMV index.

Wu and Noy (2010) also suggested a multi-agent based system to reconcile the occupants' well-being and energy consumption in the domestic area. The proposed prototype system model is integrated with a wireless sensor actuator network (WSAN) to collect environmental information. Personal agents are suggested to play an important role in helping the system to fulfil individual requirements. Personal agents estimate people's preferences and behaviours on the basis of the occupants' profiles, generated from both environmental and personal information.

Rogers et al. (2011) propose a home energy management agent to optimise the use of the heating system on behalf of the householder. Their research developed a model which predicts the thermal property of the target house. The agent considers the comfort, carbon emissions and cost of energy to make control decisions. Feedback from the system sent to the occupants contains the cost and carbon emission information.

Yang and Wang (2013b) present a multi-agent system with their own design of agents' algorithms and case studies. The system is also designed to solve conflicts between saving energy and obtaining occupants' satisfaction. Similar to the multi-agent system proposed in Qiao et al. (2006), the system in Yang and Wang (2013b) also incorporates personal agents, local agents and central agents. The central agent controls the local agents who play a significant role as they make decisions for the energy management system. The personal agent is responsible for communicating with the occupants. A Gaussian function is used to express the occupants' thermal comfort. In another paper, authors claim that occupants' behaviour in adjusting the set point of HVAC helped to generate the thermal comfort function (Yang and Wang, 2012a). If the occupants do not actively change the temperature setting, the set point is regarded as the preferred temperature. However, it does not provide a quantitative mathematical derivation or test why the thermal comfort feelings follow such a function. Other research indicates more case studies on how the control agent organises the power distribution for different zones in a built environment (Yang and Wang, 2013a). Earlier research discusses how the local agent makes control decisions (Yang and Wang, 2012b). The agents are developed for and verified by specific case studies, the general structures of components inside the central, local and personal agents are not fully discussed.

A number of research projects have attempted to further extend the ability of multi-agent based building energy management systems by introducing the energy resource side management into the function list of the system (Simoes and Bhattarai, 2011) (Rogers et al., 2012) (Mokhtar et al., 2013) (Mokhtar et al., 2014). The multi-agent energy management system is considered to work with a smart grid (Rogers et al., 2012). It is demonstrated that the electronic grid can be controlled by an electronic agent working with heating/cooling agents and comfort agents (Simoes and Bhattarai, 2011). Alternatively, other renewable sources of power can be managed by a source agent (Mokhtar et al., 2013) (Mokhtar et al., 2014). However, in the above research, the thermal comfort levels of every occupant are represented by one fixed model or even one unchanged set point. The individual differences of occupants are not considered.

It can be concluded from the existing literature that the key characteristics of BEMS include:

- Application of multi-agent technologies
- Consideration of both thermal comfort and energy consumption
- Consideration of individual thermal preference differences
- Provision of feedback to occupants
- Consideration of adaptive behaviours in the decision making process.

Table 2.1 summarises the features of the reviewed agent modules.

Table 2.1 the Properties of the Existing Agents in Building Management Research Area

Paper	Application of multi-agent technology	Consideration of both thermal comfort and energy consumption	Consideration of individual thermal preference differences	Provision of feedback to occupants	Consideration of adaptive behaviours in the decision making process
(Brooks et al., 1997)	✓				
(Coen, 1997)	✓				
(Davidsson and Boman, 1998)	✓	✓			
(Sharples et al., 1999)	✓	✓	✓		

(Davidsson and Boman, 2000).	✓	✓			
(van Breemen and de Vries, 2001)	✓	✓			
(Mo, 2002)	✓	✓	✓		
(Hagras et al., 2003a)	✓	✓	✓	✓	
(Hagras et al., 2003b)	✓	✓	✓	✓	
(Hagras et al., 2004)	✓	✓	✓	✓	
(Rutishauser et al., 2005).	✓				
(Davidsson and Boman, 2005)	✓	✓			
(Qiao et al., 2006)	✓	✓		✓	
(Yong et al., 2007)	✓	✓	✓	✓	
(Dounis and Caraiscos, 2007)	✓	✓			
(Liu et al., 2008)	✓	✓		✓	
(Dounis and Caraiscos, 2008)	✓	✓			
(Wu and Noy, 2010)	✓	✓	✓	✓	
(Liu et al., 2011)	✓	✓	✓	✓	
(Dounis et al., 2011)	✓	✓			
(Rogers et al., 2011)		✓		✓	
(Simoes and Bhattarai, 2011)	✓	✓			
(Yang and Wang, 2012a)	✓	✓	✓	✓	✓
(Rogers et al., 2012)	✓	✓		✓	

(Mokhtar et al., 2013)	✓	✓			
(Yang and Wang, 2013b)	✓	✓	✓	✓	
(Mokhtar et al., 2014)	✓	✓			

The table illustrates a number of researchers from building management research areas who propose that multi-agent technologies should be applied by the management system. Energy savings and thermal comfort are two key elements that should be considered in the BEM research that were not popularly considered in early research before 2000. To realise human-centralised control, feedback is suggested to be collected from occupants. However, the information provided from the system only contains the environmental information from the sensors and the current decided settings. Very few systems tend to provide advisory information on the energy management system. In some of the research, the users' profiles and comfort models are developed to support the agents' decision making process. But the accuracy of such profiles and models needs to be verified and improved. Few researchers have tried to involve the behavioural adaptations in the decision making process and use them as effective ways of changing the thermal condition for individuals. Moreover, personal behavioural pattern differences are not considered by the agents in the research shown in the above table, so personalised suggestions based on personal preferences and personal behaviour patterns cannot be performed by these agents.

In conclusion, research into building energy management systems has provided scholars with a lot of interest. A novel BEMS still needs to be developed to have all six functions including: sensing environmental parameters in real time, collecting occupants' personal factors and their thermal feelings, learning occupants' thermal comfort preferences, identifying occupants' adaptive behaviour patterns, calculating the desired set points for the built environment and providing the personalised suggestions to the occupants.

Through a comprehensive literature review, it is concluded that the following four functions of the BEMS are still under investigation: learning occupants' thermal comfort preferences, identifying occupants' adaptive behaviour patterns, calculating the desired set points for the built environment and providing the personalised suggestions to the occupants. There is a need to develop personal thermal models and models to estimate all individuals' thermal sensation levels in order to learn the occupants' thermal comfort preferences. The developed models need to be verified and new decision making algorithms are needed to aid the BEMS to make multiple decisions for different HVAC systems and individual people. Finally, on the system level, agent technologies should be applied to integrate all the software and hardware resources in the BEMS, in order that it can be constructed under multi-agent architecture.

2.2 Research Methodology

2.2.1 Research Design

In general, research and design of a novel BEMS falls into to the realm of design science research. Design science research focuses on creating innovative artefacts for solving problems in the real world (Simon, 1996). Therefore design science methodologies are applied in this research. Based on the design process model proposed in Takeda et al. (1990), the research process and relevant research approaches are arranged as the following sequence: firstly a literature review was carried out to identify gaps between the existing BEMS research and the BEMS proposed in this research, then aspects that needed to be improved or re-developed were considered. The literature review of the BEMS is already illustrated in the last section.

Subsequently the research entered the development stage, which involved the whole system structure design, the development of thermal sensation models, the development of behavioural adaptation assessment algorithms and the development of decision making algorithms. Further literature reviews in each sub-area were carried out to illustrate ways of solving the development problems. In order to develop thermal comfort models and behavioural adaptation assessment algorithms, occupants' preferences on thermal comfort and behavioural adaptations needed to be investigated first. In this case, quantitative research approaches were selected to perform the investigation, and were based on three reasons: 1. Occupants thermal sensations are suggested to be collected by the ASHRAE seven-point sensation scale; 2. the relevant environmental and personal conditions are represented in quantitative ways; 3. The decision making algorithms need objectives such as thermal comfort and behavioural adaptation to be inputted in numerical formats. In detail, an experimental field study and questionnaire survey were applied as ways to collect data regarding thermal comfort and behaviours, which were all common methods applied by previous research and international standards (Liu et al., 2012) (Beizaee et al., 2012) (Li et al., 2012) (Indraganti et al., 2013, ISO7730, 2005, ANSI/ASHRAE55-2010, 2010). Because people's personal preferences were considered by the BEMS, a longitudinal experiment and questionnaire survey were carried out in an air-conditioned environment. The collected data were the primary data, which were processed by both the modelling algorithms and the statistical analysis method. To further test the validation of the newly generated modelling method, both primary data and secondary data were used. The secondary data were collected in a controlled environment and they do not contain information regarding occupants' behaviour. Therefore, the secondary data were only processed by the modelling method.

Following the development stage, the novel BEMS were tested in a simulated built environment. Simulation approaches were utilised to generate the building model. Multiple case studies were carried out to test the functionality of the BEMS and its energy saving performances.

The following sections illustrate the procedure of the longitudinal experiment and questionnaire survey, and software and hardware platforms for data process, system development and test. The realisation of the system structure development, modelling, statistical analysis method and simulation algorithm are discussed in detail in the rest of the thesis.

2.2.2 Experiment and Data Collection

The models and algorithms used to describe the occupants' thermal feelings and their behaviours are still under development. These models and algorithms should be developed from environmental data and data from occupants. In this research, both primary data and secondary data were used for modelling. The secondary data were from an international database. They were collected from an experiment carried out in China. The primary data were collected from experiments carried out in the University of Reading in the UK. The experiment built environments are air-conditioned and the detail of the experiment processes and data collections are described in the following sections.

2.2.3 Experiments and Data Collection in Chongqing

A series of experiments were carried out in Chongqing, China from 2008 to 2010 to collect the data concerning the subjects' thermal feelings in a controlled environment. A recent publication (Yang et al., 2015) describes the details of the experiments. The experimental indoor environment was supplied by a heating, ventilation and air conditioning (HVAC) system. During each experiment, the environmental condition settings were different. The parameters including the globe temperature, air temperature, relative humidity and air velocity were recorded by a thermal comfort monitoring station assembled in accordance with the standard ISO 7726-2001(2001). The locations of sensors were 0.6 m above the ground beside the subject. The specifications of the sensors are listed in Table 2.2. Photos of the experiment are shown in Fig 2.1

Figure 2.1 Photos of the Experiment in Chongqing, China (Yang et al., 2015)

Twenty-one healthy people aged between 20-30 years old were involved in the series of experiments. All of them had stayed in Chongqing city for more than two years. One person did not complete the experiment. Each experiment session lasted for 90 minutes for one person. In the first 20 minutes, no data were recorded to enable the subject to become accustomed to the exposed indoor environment, then, his/her thermal comfort sensation was recorded by using a questionnaire survey at 10 min intervals. In the questionnaire, the thermal sensation was measured by the ASHRAE seven-point thermal sensation scale: cold, cool, slightly cool, neutral, slightly warm, warm and hot (ANSI/ASHRAE55-2010, 2010). The ambient environmental parameters were collected every 10 minutes whilst the questionnaire surveys were being completed. During the experiment period, all the subjects were wearing clothes with the same insulation level (0.26 CLO) and were doing work with the same activity level (1.2 MET). The settings of the environmental parameters are illustrated in Table 2.3. All 20 subjects attended up to ten 90-minute experiment sessions. A total of 1199 sets of valid data from these 20 subjects were collected, and have been used for the development and verification of models. The detailed numbers of data sets collected from each subject are depicted in Fig. 2.2. After each experiment, the collected environmental parameters, personal information and the thermal sensation data were stored in a database for further process and analysis.

Table 2.2 Specification of the sensors used in experiments in China (Yang et al., 2015)

Sensor	Air Temperature	Relative humidity	Air velocity	Black-bulb temperature
Valid Range	−25–150 °C	0– 100% RH	0.01–20 m/s	−10–100 °C
Accuracy	±0.1 °C	±2% (15–40%) RH ±1% (40–70%) RH ±0.5% (70–98%) RH	±0.05 m/s(0–0.5 m/s) ±0.1 m/s(0.5–1.5 m/s) 4%(>1.5 m/s)	±0.15 °C

Table 2.3 Range of environmental parameters in the controlled environment

Environmental Parameters	Minimum Value	Maximum Value
$\boldsymbol{T_g}$	24.94 ℃	29.58℃
$\boldsymbol{T_a}$	26.07℃	30.04℃
$\boldsymbol{RH}$	41.5%	80.1%
$\boldsymbol{V_a}$	0.11m/s	0.17m/s

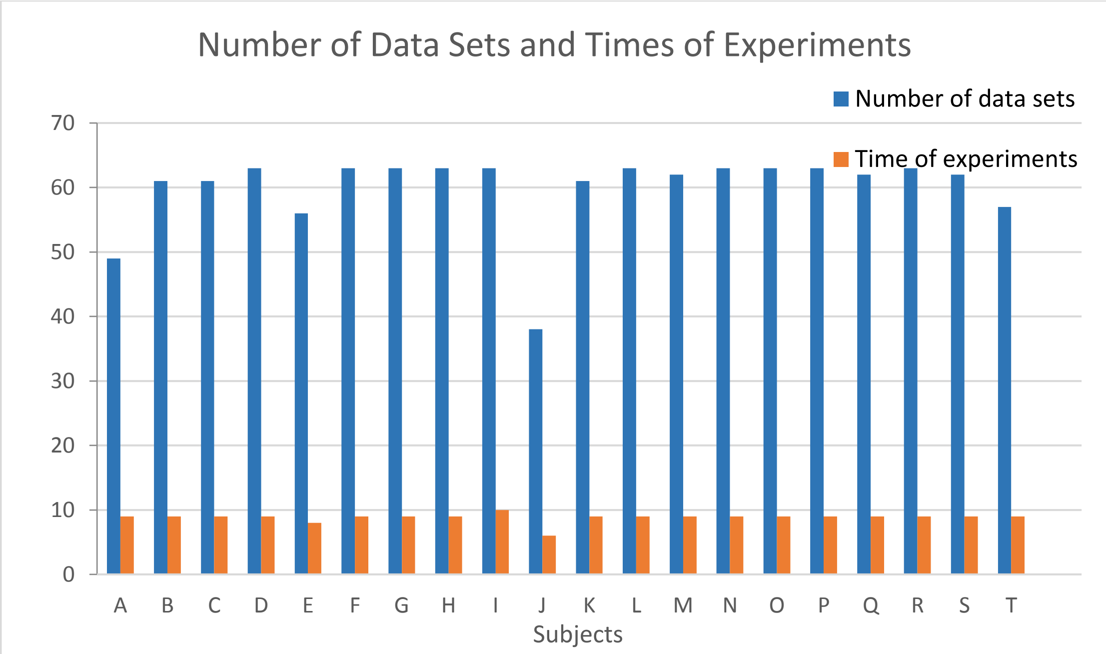


Figure 2.2 Number of data sets collected from each subject and time of experiments in Chongqing

2.2.4 Experiments and Data Collections in Reading

2.2.4.1 General Information about Experiment in Reading

The primary data collection includes physical environmental data, personal factors and occupants' thermal sensation and behavioural data. The experiments were carried out in the University of Reading between the year 2014 and 2015. These experiments were approved by the School of Construction Management and Engineering's (SCME) Research Ethics Committee. These experiments were carried out in air-conditioned spaces.

2.2.4.2 The Introduction of the Air-Conditioned Environment

The air-conditioned environment is located in the Henley Business School (HBS) building on Whiteknights campus, University of Reading. The exterior of the building is illustrated in Fig. 2.3.

Figure 2.3 the HBS building

As shown in Fig 2.3, it is a four storey building. Inside the building, there are classrooms, meeting rooms, offices and rest areas. The major experimental area is located in the ground floor of the building. The occupants of this area are administration staff, academic staff and PhD students. Three open plan office areas with air conditioning were selected as the experimental areas as all the occupants who agreed to take part in the experiment were located in these areas. The air conditioning system operates in these areas from 9:00 to 17:00 all year around except at weekends and university closure days. The recommended set temperature was 23 degrees centigrade for all these areas.

2.2.4.3 The Instruments Used to Collect the Environmental Information

Based on previous research, there are four environmental factors which affect the occupants' thermal comfort. They are air temperature, relative humidity, mean radiant temperature and air velocity. In this experiment, air temperature, relative humidity and air velocity are directly measured. The mean radiant temperature was derived by measured globe temperature. The air temperature and relative humidity were collected by the sensors installed in the environment. The air velocity and the globe temperature were measured by hand-held equipment.

Two types of sensors were used to collect the air temperature and humidity in this research. The first type was: EL-GFX-2+ high accuracy temperature and humidity data logger provided by LASCARE, and the second type was Tinytag ULTRA2 from Gemini Data Loggers.

EL-GFX-2+ Data Logger   Tinytag ULTRA2 data logger

Figure 2.4 Air Temperature and Humidity Sensor

HT30 testo 405-v1

Figure 2.5 Globe Temperature and Air Velocity meters

Globe temperature and the air velocity values were measured by two hand-held instruments. The globe temperature was measured by HT30 provided by EXTECH Instruments. The testo 405-v1 was used to measure the air movement in the experimental environment. The specifications of the sensors and instruments are illustrated in Table 2.4. All of the sensors and instruments were new and were calibrated by the manufacturers.

Table 2.4 the Specification of the Instruments and Dataloggers

Sensor	Valid Range	Accuracy	Vender
EL-GFX-2+	-30°C to +80°C 0% to 100% RH	±0.2 ℃ ± 1.8%	LASCAR electronics
Tinytag ULTRA2	-25°C to +85°C 0% to 95% RH	±0.35 °C ±3.0% RH at 25°C	Gemini Data Loggers
HT30	0°C to +80°C	±2 ℃	EXTECH Instruments
testo 405 V1	0 m/s to 5 m/s	±0.1m/s	testo

2.2.4.4 Software Used to Download the Data

The data recorded by the data loggers were retrieved by using the software provided by the vendors. The data log in the EL-GFX-2+ was read by the software Easylog USB. The Tinytag Explore 4.6 was used to download the data in the Tinytag UTRA2 sensors. The user interfaces of the software are shown in Fig 2.6 and Fig 2.7.

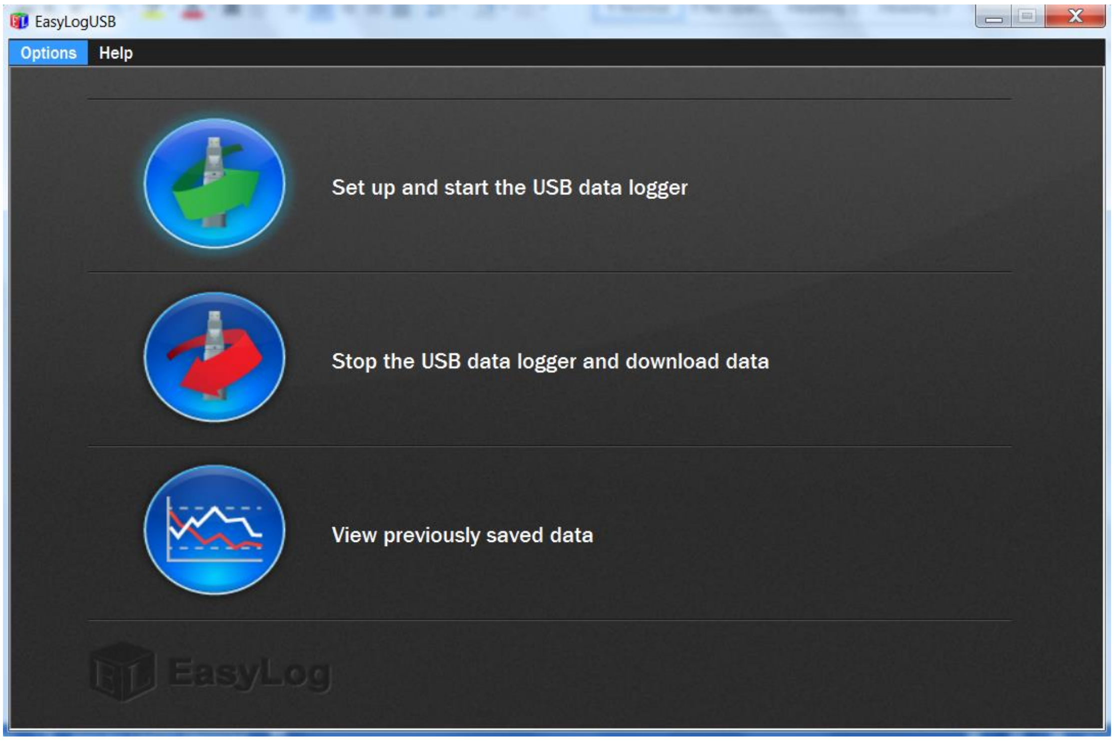


Figure 2.6 The User Interface of Easylog USB

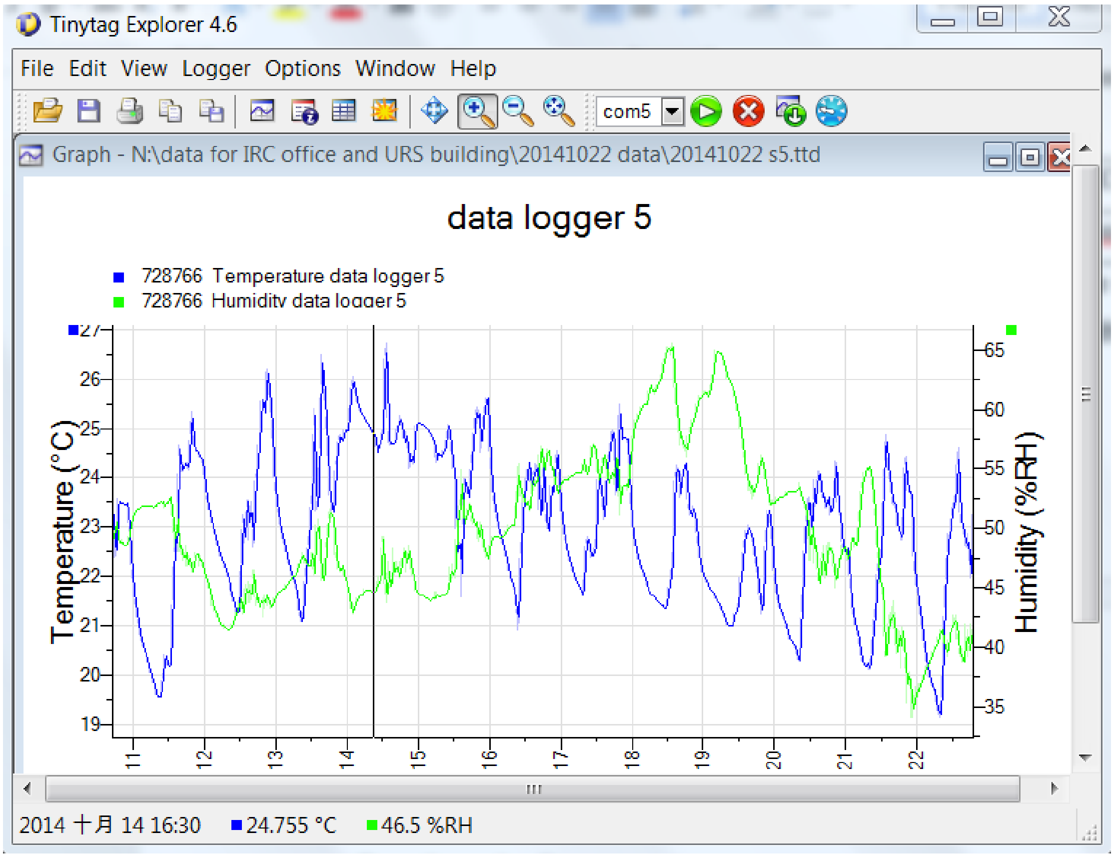


Figure 2.7 The User Interface of Tinytag Explore 4.6

2.2.4.5 Questionnaire Survey

The questionnaire survey was conducted throughout the experimental period to collect data from the subjects from October 2014 until August 2015. Two types of questionnaires were used during the experiment: a general questionnaire and an activity logger. The purpose of the survey was to collect the subjects' personal factors including clothing insulation levels and activity levels, subjects' sensations in the ambient environment and their reactions to the environment. The design of the questions in the questionnaires followed the current international standards: (ISO7730, 2005, ANSI/ASHRAE55-2010, 2010) and referred to previous research (Liu et al., 2012) (Beizaee et al., 2012) (Li et al., 2012) (Indraganti et al., 2013), and my consultation with psychologist Marylin J. Williams.

The general questionnaire firstly asked about the subjects' current activity levels and their clothes. The data on clothes were used to derive the clothing insulation level of occupants. The CLO values of different types of clothes were obtained from the international standards and the published works mentioned above. The effects of office chairs were also considered. Then the occupants were asked to feedback their current sensations concerning their indoor environment, especially their thermal sensations. The thermal sensations were represented by the ASHRAE seven-point thermal sensation scale. In the following section, the subjects were required to report their actions in the previous two hours, which they used to change their thermal sensations. Some information related to their thermal feelings such as how long they stayed in the built environment and what they sensed about the air movement were also collected. Finally, the occupants were asked what their thermal expectations were. If they wanted to change their ambient thermal environment, they were asked to state the methods they were going to use. The data logger focused on occupants' behavioural adaptations. The data logger questionnaire was constructed on an hourly basis. Every hour during the working period, a subject who agreed to fill in the logger was asked to provide feedback. This feedback included his/her thermal sensation and thermal expectation at that time. The subject also needed to provide information on the status of the facilities such as an air-conditioning system. Correspondingly, he/she also needed to report any behavioural adaptation over the previous hour. Samples of questionnaires and data loggers are attached in the appendix.

2.2.4.6 The Experiment Procedure in Reading

The experiment and data collection in the air-conditioned environment in the UK took place from October 2014 to August 2015. Site surveys had been conducted prior to the beginning of the experiment. The purpose of these was to collect the necessary information to design the questionnaire as well as to decide where to install the sensors. During the site survey, some basic physical information about the experiment area was collected. Occupants' commonly used adaptive behaviours relating to thermal comfort were observed during a site survey in the experiment area. All this information was used to generate relevant questions in the questionnaire.

Letters were sent to all the potential candidates in the environment to explain the purpose and scope of the experiment as required. All subjects were volunteers who were ordinary healthy people working in office areas. Consent forms were signed by all the subjects, which were required by the SCME's Research Ethics Committee.

Functions of the sensors and contents of the questionnaires were explained in detail to all of the subjects and other occupants in the experimental area.

By recruiting the subjects for the experiment, the experimental areas in each building were chosen, and three areas in the air-conditioned environment were selected. The experimental areas were labelled as: ACzone 1, ACzone2, and ACzone3. Once the experiment formally began, questionnaire surveys were conducted twice a day, two days a week in each zone, except when the researcher was off campus or when the university was closed. While the subjects were filling in the questionnaires, their ambient environmental conditions were recorded by sensors and hand-held meters. All of the environmental data were collected at points around 0.6m (at the waist level) above ground close to the occupants. The collected environmental data and personal factors followed the specification of the class II data defined in Brager and de Dear (1998), which is suitable to analyse the subjects' comfort influenced by environment as well as their behavioural responses. If a subject agreed to fill in an activity data logger, the logger questionnaire would be given to the subject in advance. The subject completed the questionnaire during working hours when he or she was inside the experimental environment, then the completed logs were collected by the researcher. In total, twelve subjects agreed to attend the experiment, but only six of them finished it. A total number of 247 effective samples were collected from these six subjects. Fig. 2.8 shows the total number of effective samples collected from each subject.

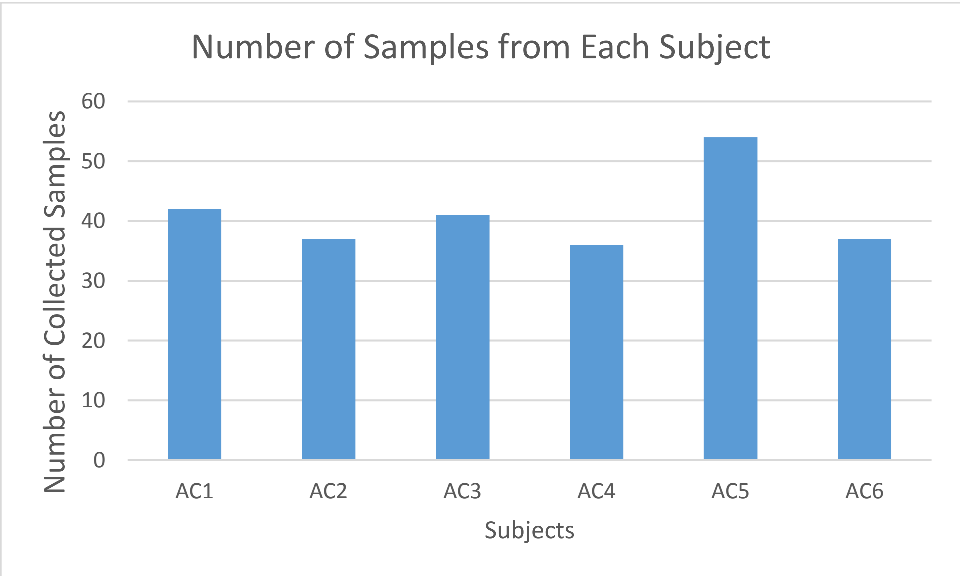


Figure 2.8 Number of samples collected from each subject in Reading

Figure 2.9 Experimental Data Collection in Reading

2.2.5 The Data Process and System Development Platform

The rest of the thesis introduces the system architecture design, agents' components structure design, agents' components' development, simulation and case studies for system performance test. For agents' components' development, the primary data and secondary data are processed by modelling methods and statistical analysis. All these developed models and analysis were realised by a desktop computer. The configuration of the computer is: Intel Core2 Duo CPU 2.33G HZ; 4GB memory; 64-bit Windows 7 operation system. Both the primary data and the secondary data were stored in EXCEL sheets generated by Microsoft EXCEL software. The components of the agent in the BEMS were programmed by the MATLAB software. The programs were stored as *.m format files.

2.3 Summary

The first part of this chapter comprehensively reviews the existing research on BEMS. Based on the review, it can be found that the personal thermal sensation model and models to estimate all individuals' thermal sensation levels need to be investigated. Agent technologies should be applied in the BEMS and the BEMS can be constructed under multi-agent architecture. The second half of this chapter illustrates the research methodology used in this research in detail. The system and agent development are illustrated in detail in the next chapter. The thermal sensation modelling is in Chapter 4 and Chapter 5. The decision making algorithm is in Chapter 6. The statistical analysis, the simulation and case studies are in Chapter 7.

Chapter 3 : A Building Energy Management System Based on the Multi-Agent Approach and EDA Agent Model

3.1 Introduction

Literature reviews reveal that agent-based technologies have been employed to develop energy management systems by a number of researchers. What is an agent? The definition of an agent is 'anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators' (Russell and Norvig, 2010). More specifically, an agent developed by computer hardware and software is 'a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its delegated objectives'(Wooldridge, 2009). An environmental controller can be regarded as an agent (Weiss, 1999), so it is natural to employ agent-based technologies to improve the abilities of the controllers to reach their designed objectives. However, from literature reviews, it can be concluded that, although various agent-based systems have been developed by different researchers for energy management systems, no developed system can realise all the functions required by the BEMS in this research. Hence, the development of a new multi-agent BEMS is necessary.

From the whole system point of view, the main purpose of the agent-based energy management system is avoiding energy wastage; while maximally fulfilling the thermal comfort requirements of every occupant inside the air-conditioned environment. As the comfort requirement for one occupant may be different from another's, the whole energy management problem is complex and difficult to solve using only one controller or agent. In this case, the developed BEMS should be a multi-agent system, which is a system containing more than one agent (Huberman and Clearwater, 1995). However, from the review of agent systems in the last chapter, there are different agent system architectures proposed in the existing research. How to decide on the appropriate system architecture for BEMS in this research remains a question. To develop the multi-agent system, the system architecture should be confirmed first.

Once the BEMS system architecture has been developed, agents inside it need to be designed. It has been suggested that agents in the BEMS are intelligent agents, which is also a ‘rational agent that realises the best possible solutions in a given situation’ (Dounis and Caraiscos, 2009). Research from the artificial intelligence area gives the basic properties or abilities an intelligent agent should have (Wooldridge and Jennings, 1995):

- Autonomy: the agent functions without outside guidance.
- Reactivity: the agent is able to respond to changes in an outside environment.
- Pro-activeness: not only does the agent passively respond to the environmental changes, it actively decides on its actions.
- Social ability: the agent is able to communicate and co-operate with other agents.

Besides all these properties, Nwana (1996) pointed out that the intelligent agent should also have the following abilities: Learning, to be Co-operative and Autonomous.

The concept of the ‘rational agent’ is also from artificial intelligence, which means an agent ‘that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome’ (Russell and Norvig, 2010). Based on this definition, the intelligent agents in the BEMS should be able to make rational decisions based on the given information by using the hardware and software components provided by the system. Already, a number of researchers have developed software and hardware components to realise parts or all of the properties of the intelligent agent (Davidsson and Boman, 1998, Sharples et al., 1999, Dounis and Caraiscos, 2008, Yang and Wang, 2013b). But how to make the agent act rationally in the BEMS by utilising the developed software and hardware requires further work.

In this chapter, the framework of a multi-agent energy management system is proposed. Firstly, the system architecture is designed. Two types of agent: the local agent and the personal agent, should be involved in the multi-agent system based on the system’s requirements. Secondly, the structures of the local agent and the personal agent are developed on the basis of the Epistemic-Deontic-Axiologic (EDA) agent model. These two types of agent work together to enable the energy management system to meet the design purposes. In each agent component, the necessary software or hardware modules are identified to realise the function of the component.

3.2 Literature Reviews on Agent Structure and Rational Agent Development in BEMS

3.2.1 A Review of Multi-Agent System Architecture

In general, the architecture of a multi-agent system and functions of the agent inside the system depend on the problem the system is designed to solve and the methods that can be utilised to obtain a solution. Research from the MIT intelligent room project employed different agents to realise different targets in the built environment (Coen, 1997). In that system, the agents were connected to each other and worked co-operatively (Brooks et al., 1997). For energy management control in buildings, each embedded room agent developed in Sharples et al. (1999) is responsible for controlling one room. They are connected to each other to share information. Functionally, all the room agents are the same, as they face the same control target. The agents applied in the MASBO system developed by (Liu et al., 2008) have different functions. In this system, personal agents serve the occupants; the local agent controls the environment and the central agent provides the services, such as configuring the whole system. In this case, the function of an agent depends on the problems it is facing. It can also be found that the agents in the BEMS system were grouped into different levels by (Dounis and Caraiscos, 2007). In their research, master agents take care of general energy efficiency and comfort issues in the building while slave agents manage subsystems. Similar to the research from (Liu et al., 2008), the system developed by (Yang and Wang, 2013b) also includes personal agents, local agents and central agents. The architecture of the agents is arranged in a hierarchical way with multiple local agents connected to one central agent while a local agent is serving more than one personal agent. The hierarchical architecture is defined because the problems are grouped into different levels. Different agents work at different levels to solve problems within those levels. It can be concluded that the system architecture of the BEMS and the types of agent inside in this research depends on the nature of the problem it is facing and the methods the agents use to solve the problems. Following the guidance provided in Weiss (1999) and Dounis and Caraiscos (2009), in the next few sections the problems within the main research problem is decomposed, first into smaller problems, then a potential problem-solving method is allocated to every agent. Finally, the system architecture is designed.

3.2.2 A Review of Rational Agent Development in BEMS

Literature suggests developing agents in the BEMS by introducing the Epistemic-Deontic-Axiologic (EDA) agent model, which is developed from social psychology theory (Qiao et al., 2006, Yong et al., 2007, Liu et al., 2008). This means that the agent applied in the BEMS is generated by the Epistemic (E) component, the Deontic (D) component and the Axiologic (A) components. The general structure of the EDA agent model is illustrated in Fig. 3.1. Original definitions of EDA are ‘Axiologic - to be disposed in favour or against something in value terms; Epistemic - to adopt a degree of belief or disbelief; Deontic - to be disposed to act in some way’ (Stamper et al., 2000). Please note that it is assumed that all the software and hardware of the BEMS use the same data format, so the input and output information of the agent does not need to be interpreted. Therefore, the perceptive interpreting and output interpreting components are not discussed in the agent structure.

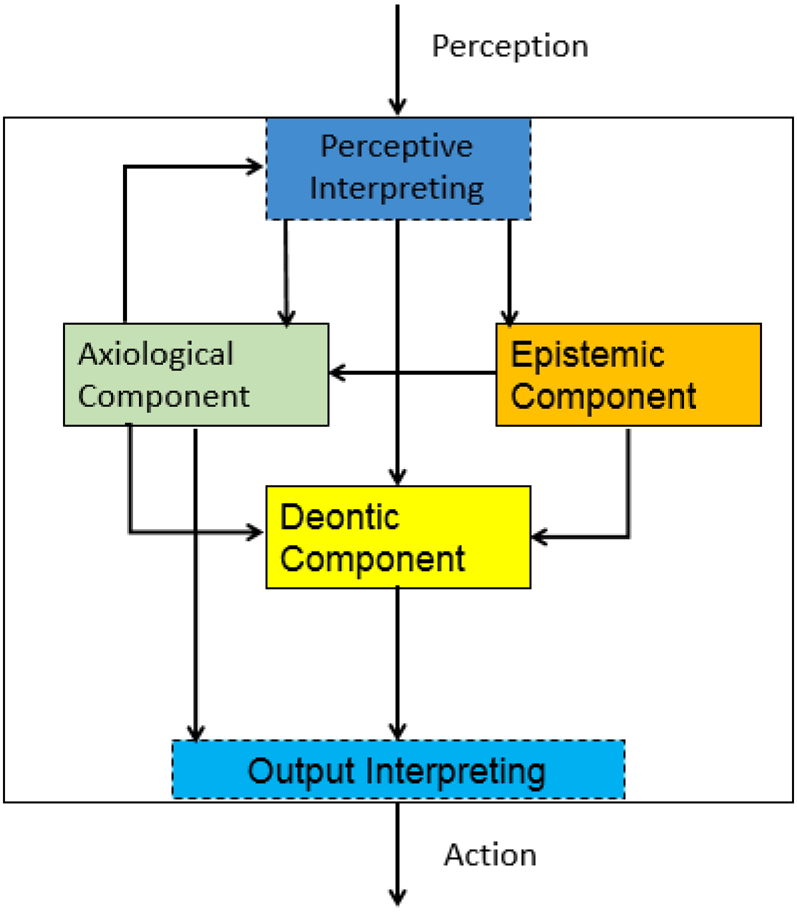


Figure 3.1 Structure of the EDA Agent Model (Liu et al., 2011)

The EDA model only provides the theoretical framework for the components in an intelligent agent. Later research attempts to interpret the framework of components in the EDA model in the BEMS context (Liu et al., 2011). In summary, components in the EDA model-based agent in a BEMS are defined in the following terms in the literature:

- The E-component represents the facts or knowledge the agent believes, including the regulations and occupants' preferences.
- The D-component contains the set of available plans and goals.
- The A-component is an evaluating component. It evaluates the plans in the D-component and chooses the appropriate plan based on the knowledge in the E-component.

This research clarifies the logic between each component in an agent in the BEMS. The ability of the agent that can act rationally depends on the A-component making rational decisions. The same literature claims that it focuses on the development of the D-component in an agent. It is still not clear how to realise all the functions proposed for the E, D and A components by using the software and hardware resources provided in the BEMS. Furthermore, the question of how the agent can make decisions following the rational agent definition is not fully answered. The question can be answered by methods from the artificial intelligence research area and the control research area. Two methods can be found to realise the rationality of the agent. The first one is recommended in Filipe and Fred (2007), which is to make a decision in a deductive way, such as following the Condition-Action rules(Winston, 1992), or, alternatively, to let the expectation of the system be represented by objective functions. From the control theory, the value of objective functions are maximised to realise the optimal decision-making (Russell and Norvig, 2010). Then, the rational agent is realised by maximizing the expectations. Therefore, the A-component is realised by a decision-making module equipped with the decision-making algorithms mentioned above. The detail of the decision-making algorithms is discussed in Chapter 6.

In later sections, following the EDA model, the functions components in agents used in BEMS are investigated. The software and hardware needed to realise these components are decided. How these software and hardware systems operate together following the logic of the E, D and A components to decide the rational actions is also discussed.

3.3 The Architecture of the Multi-Agent System

Literature reviews reveal that in order to decide the architecture of the multi-agent system, the problems the system is going to solve need to be analysed first.

The problem decomposition method helps to determine the categories of the agents applied in the whole system. The main object in this research can be sub-divided into three sub-objects:

1. Avoiding the energy wastage of the HVAC system.
2. Avoiding the energy wastage of personal conditioning appliances (if such instruments are available).
3. Enabling each occupant to acquire a thermally comfortable feeling in the controlled environment.

It is clear that the problems can be categorised into two types. The first type of problem is regarding the HVAC system and the solution to it will affect the whole built environment under investigation and the second type concerns a single occupant. Based on the review, the agent responsible for the operation of the HVAC system is called the local agent. Agents interacting with the end-users are called personal agents. The Introduction Chapter indicates that the methods used by the agents to affect the indoor environment and end-users are:

1. Sending the optimal settings of the HVAC system to the actuator.
2. Making personalised suggestions to the occupants, if necessary.

Thus, the first method is utilised by the local agents. The local agent decides set points and then sends them to the HVAC actuator directly. The suggestions need to be passed to the occupants by personal agents via human/machine interfaces. On the basis of the definitions of types and functions of agents, their positions in the whole system architecture can be defined. The architecture of the multi-agent-based energy management system is illustrated in Fig. 3.2. In the system, the local agent and the personal agents cooperate with human-machine interfaces, sensor network systems and the actuator of the indoor HVAC system.

In this research, the energy management system is assumed to provide services in two scenarios: a single occupancy office and an open-plan office. The proposed personal agent and the local agent are able to realise the management targets in these two environments. Every personal agent is responsible for one occupant. Higher-level agents suggested by other research, such as central agents, which are used to control a whole building or even multiple buildings are not considered here. The development of the components inside the personal agents and local agents are introduced in detail in section 3.4.

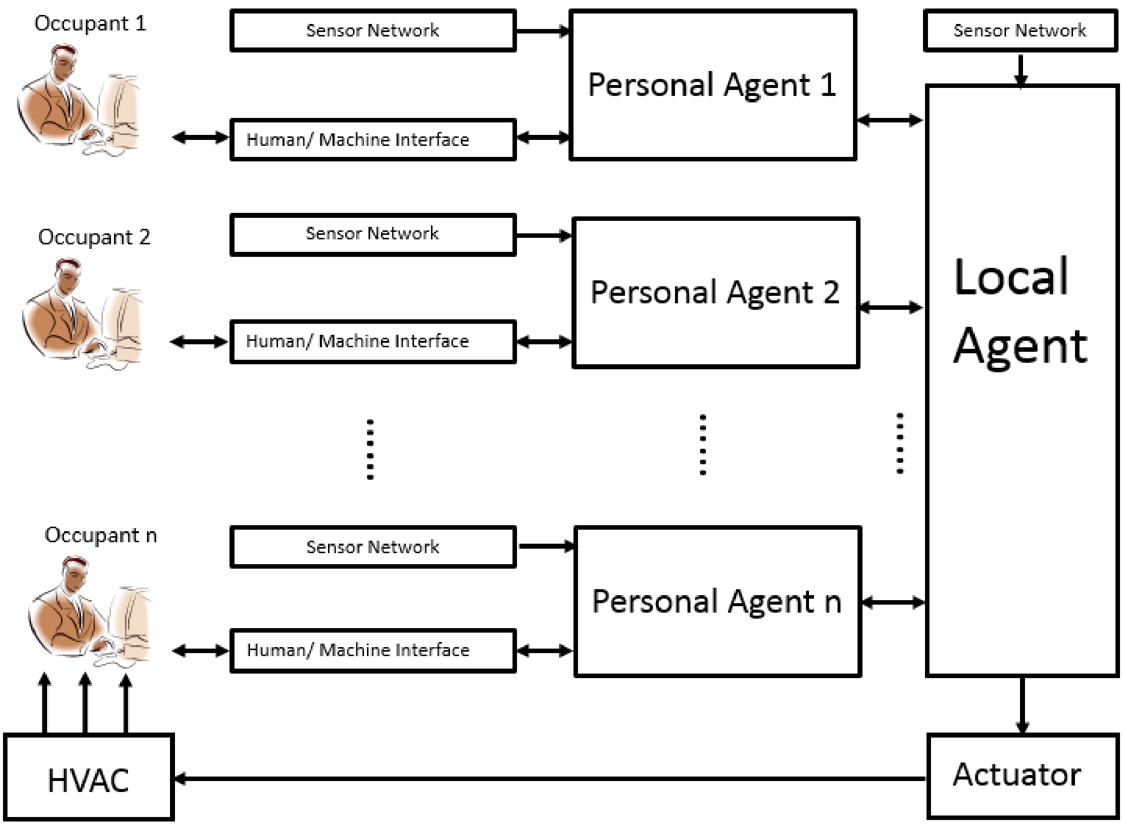


Figure 3.2 The Architecture of the Multi-Agent System

3.4 Development of the Local Agent and Personal Agent

3.4.1 Abilities Needed by the Agents in the BEMS

The literature review concluded that agents in the BEMS should be rational agents. The existing literature only theoretically defined the abilities or properties of an agent. The EDA agent model provides the theoretical framework of an EDA agent, but the EDA model defined components need to be developed in the context of BEMS. The key logic of the EDA-based agent is that it makes decisions using the decision-making module in the A-component-based on the action plans in the D-component and knowledge provided by the E-component. In this case, to define the functions of each component, the aim of the decisions needs to be clarified first, and then the needed information from the E-component can be defined. The decisions from the system have three aspects: deciding the settings for the HVAC system; deciding the suggestion for actions of the occupants, if necessary and deciding the best way to present the personalised suggestions from the system to the occupants. The settings of the HVAC system are decided by the thermal sensations of the occupants and the ambient environment information, the energy consumption of the HVAC and occupants' personal factors. This requires the system to have the following functions: detecting the real-time environmental conditions; gathering the personal factors and thermal sensations and learning the occupants' thermal comfort preferences. Personalised suggestions should be made by considering the occupant's personal thermal sensations and personal behaviour patterns. This requires the agents to have abilities to: learn the occupants' adaptive behaviour patterns, estimate the energy consumption in the built environment, save the collected learnt information and then to make rational decisions.

The environmental information is from the sensor network. The personal information, including personal factors and personal thermal sensations, is collected by human-machine interfaces and then saved in a database. It has already been pointed out that these technical details of these parts of the system are not the main focus of this research. Action plans in the D-component includes the settings of the HVAC system, the adaptive behaviours available and the possible ways of making suggestions for the occupants. The E-components should have abilities to learn the occupants' thermal preferences and their commonly-used behavioural adaptations. It also provides a method to evaluate the energy consumption of the HVAC system.

In the next section, the desired outcomes of local agents and personal agents in both single-occupancy and open-plan offices are illustrated. Then the functions of the components in each agent can be defined.

3.4.2 Functions of Local agents and Personal Agents in an Open-plan Office

As depicted by Fig. 3.2, in an open-plan office with multiple occupants, the local agent decides the HVAC settings. To make such a decision, the D-component in the local agent needs to provide the plans regarding the different settings of the HVAC. The E-component in the local agent needs to provide the information regarding the real-time environmental conditions from the sensors, the method for estimating the energy consumption and the method to evaluate the thermal sensation level. The A-component inside the local agent makes decisions by using the information from the D- and E-components.

If a certain occupant is not satisfied with the current environment settings, his/her personal agent will help the occupant to re-gain his/her neutral feelings by deciding the best adaptive reaction. The decision is based on the occupant's thermal sensation and the environmental information from the local agent. In this case, the E-component in the personal agent receives the environmental information from the local agent, then provides the information with the personal thermal sensation evaluation method to the A-component. The A-component makes decisions based on the information and method from the E-component and action plans from the D-component.

If a personalised suggestion from the personal agent is also needed, the decision is made from the suggestion plans in the D-component, the decision on the occupant's actions and his/her commonly-used behavioural adaptations in the E-component.

3.4.3 Functions of Local agents and Personal Agents in a Single Occupancy Office

In a single occupancy office, the number of occupant personal agents, 'n' in Fig. 3.2, is equal to one. Because there is only one occupant, the thermal sensation assessment method used by the local agent is the one that estimates the thermal sensation of this particular occupant. In this case, the local agent can decide both the set points of the HVAC system and any necessary behavioural adaptations. To make such decisions, the A-component needs the E-component to provide ambient environmental information, the occupant's personal information and the methods for evaluating thermal comfort, energy consumption and behavioural adaptation. The E-component needs to collect the information about environmental conditions and the thermal comfort evaluation method from the personal agent. The D-component in the agent provides the potential plans for the HVAC settings and behavioural adaptations.

However, the suggested actions may not be those the occupant uses most, so the personalised suggestions need to be decided by the personal agent. The A-component in the personal agent needs a method to evaluate the behavioural actions from the E-component. The E-component is also responsible for recording the personal information, such as the occupants' clothing and activity levels, to help the system understand their personal thermal sensation preferences as well as the personal patterns of behavioural adaptation. Similar to the personal agent in the open-plan office, the D-component provides the suggestion plans for the A-component to make decisions. As shown in Fig. 3.2, personal agents interact with the occupants whom they are serving via human-machine interfaces.

In order to realise the functions of the agents and the components, the agent system needs to employ a set of software and hardware modules. These modules and the relationship between them are discussed in the next section.

3.4.4 The Local Agent and Personal Agent based on the EDA model

As discussed above, the functions of both local and personal agents are different when the energy management system faces different environmental scenarios. However, the agent structure remains the same when facing different scenarios. Agents only need to replace some of the supporting software modules used in the E-, D- and A-components to deal with different situations.

The local agent developed by the EDA agent model is illustrated by Fig. 3.3. The knowledge base (E-component) of the agent is constructed using algorithms to generate the methods which evaluate thermal comfort, energy consumption and behavioural adaptations; the real-time information from the sensor network and human-machine interfaces and the stored information from the local database. The decision-making module (A-component) chooses the action plan from the set of available plans (D-component). In a personal occupancy office, the plan contains the HVAC system settings and the reaction suggestions. The thermal sensation model used is the personal thermal sensation model. In an open-plan office, the plan only contains the settings within the HVAC system. The thermal model evaluation method aims to reconcile all the thermal preferences from people in the environment. The local agent makes decisions by considering not only the occupants' thermal preferences but also their adaptive behaviours.

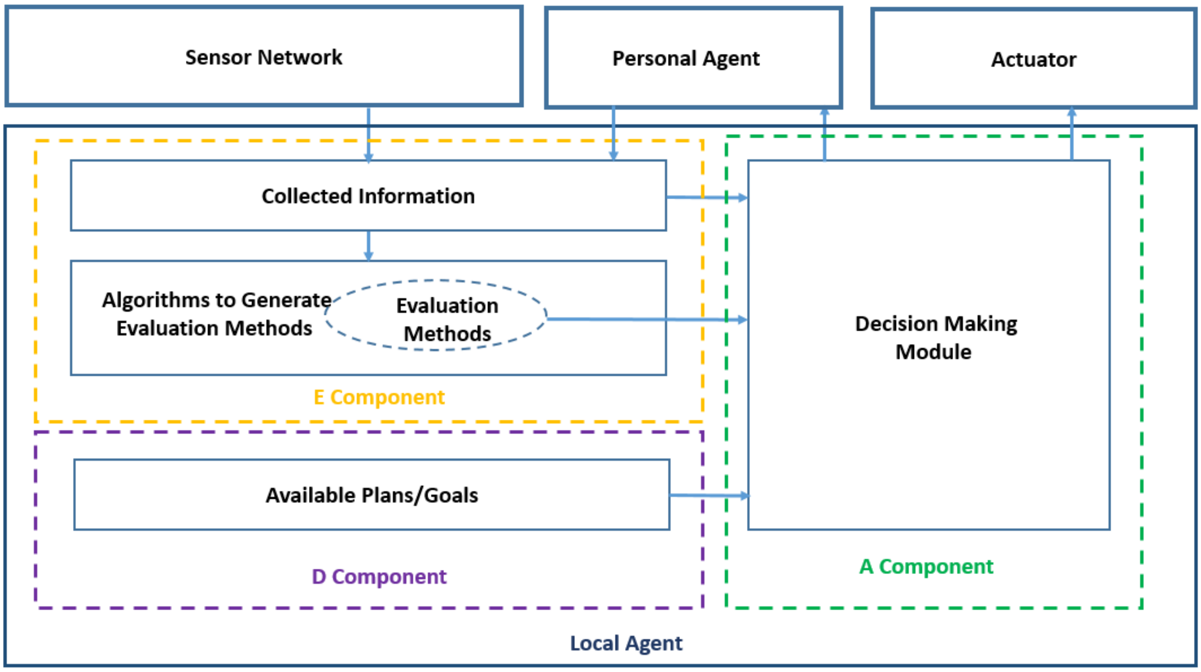


Figure 3.3 Structure of the Local Agent

The personal agent developed by the EDA agent model is illustrated by Fig. 3.4. Similar to the local agent, the knowledge of the personal agent (E-component) is also acquired from the sensor network, database and the modelling algorithm. It also receives the decision information from the local agent. In the single occupancy offices, because the behavioural adaptation is already decided by the local agent, the decision-making module (A-component) only needs to decide how the suggestions from the system should be provided to the occupant. In open-plan offices, the local agent is only responsible for making decisions about HVAC set points. In this case, if the thermal condition of an end-user needs to be improved, the personal agent will use the settings information from the local agent, the personal comfort model, environmental information and personal factors to evaluate the best action he/she can take. The decision is then sent in an appropriate personalised way to the end-user. The decision-making process is different from the one used in the single occupancy scenario. Here, the personal agents not only play an assistant role for the multi-agent-based energy management system as information collectors, and recording/passing channels, but in this research, the personal agent needs to also make decisions.

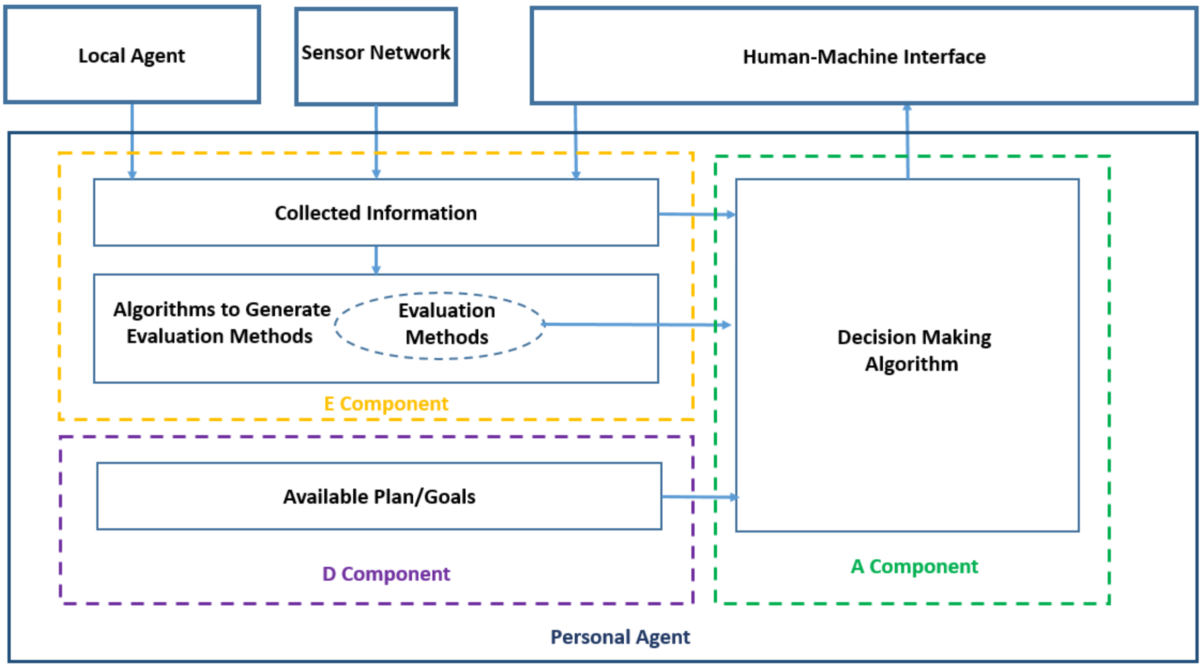


Figure 3.4 Structure of the Personal Agent

Please note that in an energy management system, once the HVAC settings are confirmed, the relevant information is sent to the actuator to operate the HVAC system. The operation of the actuator and the HVAC hardware is outside the scope of this research.

3.5 Summary:

In this chapter, the architecture of a multi-agent energy-management system is developed. The architecture is defined by the nature of the problem the system is going to solve. In the multi-agent system, the structures of the local agent and personal agent are also designed. The functions of these two types of agent are discussed in detail. The agent-building process follows the EDA agent model. By applying the agent model, components of the energy management system are arranged in a regular way. If serving a different user or facing a different environment, the relevant agents only need to update the software or hardware modules inside the component without changing the whole structure of the agent. The developed agents can work autonomously without guidance from end-users. The agents not only react to the environmental changes, but they can also make suggestions to occupants, if needed. The agents have various learning abilities, about occupants thermal comfort preferences for example. The local agents and personal agents work with others to realise the design aims of the system. So the agents in the system are intelligent agents. Most importantly, the EDA agent model guarantees the agents' rationalities. The software and hardware modules needed to support the components in the agents are also discussed. The remainder of this thesis illustrates how to develop some important software modules. The next chapter discusses the algorithm to generate the personal thermal sensation model. The model is used as the objective function to evaluate the occupants' personal thermal sensation levels

Chapter 4 :The Personal Thermal Sensation Model

4.1 Introduction

In the introduction chapter and the literature review section, the necessity of utilising predictive models integrated in the energy management system to forecast the occupants' feelings to guide the operations of an HVAC system has already been indicated. In general, the models enable the HVAC energy management system to understand the current thermal comfort needs of every individual to avoid mismatching the demand and supply of heating and/or cooling, which causes energy wastage. Such models are developed from the occupants' feedback on the thermal conditions (Jazizadeh et al., 2014).

It has also been demonstrated that two types of thermal sensation models are needed by the energy management system to confront different application scenarios. This chapter focuses on the development of personal thermal sensation models. They function in both single occupancy and open plan offices. The HVAC system in a single occupancy office aims to improve the thermal environment around an end-user. It has been suggested that applying thermal sensation models to accurately predict individuals' thermal sensations demands is an effective solution to achieve optimal control of a personalised environmental control system (Gao and Keshav, 2013). Generated personal thermal sensation models directly help the optimal decision-making algorithm in a local agent to calculate the optimised set points of the HVAC or personal conditioning system in a single-occupancy office.

In an open plan office, personal thermal sensation models can be used to predict the real-time individual thermal feelings of an occupant to provide personalised services. They can also be used to generate the thermal sensation model for all the occupants (Yang and Wang, 2013b, Klein et al., 2012). Again, the models will provide solid evidence for the energy management system to decide the optimal indoor thermal conditions for the open plan office. How to use the personal thermal sensation models to generate such a model is discussed in the next chapter.

Therefore, an effective modelling algorithm is required by the energy management system to generate the personal thermal sensation models. In this chapter, the modelling methods of developing personal thermal sensation models are investigated. A novel personal thermal sensation model based on the Support Vector Machine (SVM) algorithm is proposed in this research. The proposed modelling method is used to generate the personal thermal sensation model by using the data collected in China and the UK, and then the performance of each developed model is tested. Applications of the developed models is demonstrated in Chapter 7.

4.2 Related Work

Thermal sensation prediction is essential to indoor thermal environment design, operation and assessment. Methods of prediction have been widely adopted by design standards and guides. For example, the widely applied PMV-PPD index has been adopted by the ASHREA 55 and ISO 7730 standards (ANSI/ASHRAE55-2010, 2010, ISO7730, 2005); the adaptive model using the running mean temperature in the EN15251 standard (Comité Européen de Normalisation, 2007) and the aPMV model integrated in the ‘Chinese evaluation standard for the indoor thermal environment in civil buildings’ (GB/T50785-2012, 2012). However, here is criticism that the thermal sensation predictions recommended by the international standards are not suitable to be directly applied as individual thermal comfort predictors in many conditions (Gao and Keshav, 2013, Zhao et al., 2014). It is argued that these models recommended by the standards are developed for the estimation of the average thermal sensation of a large number of people under certain conditions, which may not be suitable for the situation when significant individual differences of thermal comfort preferences exist (Liu et al., 2007). Recently, developing personal thermal sensation modelling has attracted many researchers’ interest. Table 4.1 lists the most current published papers on the topic and their main characteristics.

Table 4.1 Properties of existing thermal sensation models

Paper	Name	Modelling methods	Is the model accuracy testing presented in the paper?	Do the inputs of the personal thermal sensation models involve all T_a ; $\overline{T_r}$; V_a and RH factors ?	Are outputs of the model directly compared with the real collected TSVs with ASHRAE 7 scales?
(Liu *et al.*, 2007)	Neural Network Evaluation Model (NNEM)	Back Propagation Neural Network	Yes	Yes	No
(Feldmeier and Paradiso, 2010)	N/A	Fisher Discriminant	No	No	No
(Rana *et al.*, 2013)	N/A	Support Vector Regression	Yes	No	Yes
(Gao and Keshav, 2013)	Predicted Personal Vote (PPV) Model	Least Square Regression	Yes	Yes	Yes
(Zhao et al., 2014)	Personalised Dynamic Thermal Comfort (PDTC) Model	Weighted Least Square Estimation	Yes	Yes	Yes
(Yang and Wang, 2013b)	N/A	N/A	No	No	No

From Table 4.1 it can be seen that by applying the Back Propagation (BP) artificial neural network algorithm, Liu et al. (2007) developed a personal thermal sensation model, namely the Neural Network Evaluation Model (NNEM). The NNEM has four input factors: air temperature, air humidity, air velocity and mean radiant temperature; and three types of output: cool, comfortable and warm, which were represented numerically by 0, 0.5 and 1 respectively. The idea of ANN is originally from simulating the way that biological systems process information, and the ANN with n input nodes, one hidden layer and k output is shown as a network in Fig. 4.1 (Bishop, 2006). In the network, a_i is an input factor and o_j is an output prediction. The process of calculating the output of the ANN is as follows (Russell and Norvig, 2010):

The value of a hidden layer node h_j is:

$$h_j = f_1(\sum_{i=1}^{n} a_i \omega_{ij}) \quad (4.1)$$

And the output o_j is:

$$o_j = f_2(\sum_{i=1}^{m} h_i c_{ij}) \quad (4.2)$$

f_1 and f_2 are the activation functions which can be defined by the ANN algorithm developer.

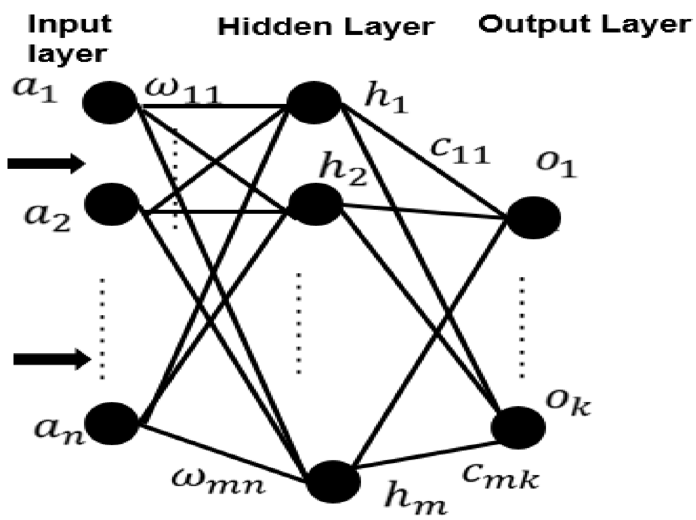


Figure 4.1 ANN structure

The training algorithm of ANN calculates the coefficients such as ω_{ij} and c_{ij} in the network by using 'error backpropagation' technology, whose details can be found in Haykin (1999). Liu et al. (2007) used two case studies to evaluate the performance of the BP artificial neural network modelling algorithm: in the 'fixed clothing and activity' case, the model which has been developed accurately predicted the thermal sensation in all four test samples from a person; in the 'variable clothing and activity' case, the accuracy of the model reached 80% when the model was trained by 20 new samples. Compared to the ASHRAE 7-scale sensations, this model outputs the thermal sensations in less detail.

Feldmeier and Paradiso (2010) developed a model that applied the Fisher Discriminant method to separate different levels of thermal sensation. The algorithm was used to generate models to aid a personalised HVAC controller. Similar to the research (Liu et al., 2007), the thermal sensation information collected from the occupants had only three categories: cold, neutral and warm, then the Fisher Discriminant method calculated the decision boundary between the hot and cold sensations by utilising ambient temperature and humidity as factors. The detail of the Fisher Discriminant method is introduced in Bishop (2006). Assuming that the Fisher Discriminant method is used here to linearly classify a data set which contains two classes of data: class one (C_1) and class two (C_2) and letting the factor vectors $\boldsymbol{x}$ and y represent the class label of the data, the decision boundary of the generated classifier can be written as:

$$y = \boldsymbol{\omega}^{\boldsymbol{T}}\boldsymbol{x} \tag{4.3}$$

The weight vector $\boldsymbol{\omega}$ will be calculated by the following equation:

$$\boldsymbol{\omega} = \boldsymbol{S}_{\boldsymbol{w}}^{-\boldsymbol{1}}(\boldsymbol{T_1} - \boldsymbol{T_2}) \tag{4.4}$$

where $\boldsymbol{T_1}$ is a mean vector of the factor vectors from all class one data samples and $\boldsymbol{T_2}$ is a mean vector of the factor vectors from all class two data samples. Matrix $\boldsymbol{S_w}$ is a within-class covariance matrix, which is given by:

$$\boldsymbol{S_w} = \sum_{\boldsymbol{x}\in\boldsymbol{c1}}(\boldsymbol{x} - \boldsymbol{T_1})(\boldsymbol{x} - \boldsymbol{T_1})^{\boldsymbol{T}} + \sum_{\boldsymbol{x}\in\boldsymbol{c2}}(\boldsymbol{x} - \boldsymbol{T_2})(\boldsymbol{x} - \boldsymbol{T_2})^{\boldsymbol{T}} \tag{4.5}$$

Once $\boldsymbol{\omega}$ is calculated, a particular $\boldsymbol{x_i}$ is submitted into function (4.3), if the outcome is$y_i > 0$, then this data sample belongs to class one, otherwise it is from class two.

Feldmeier and Paradiso (2010) found that the different levels of thermal sensations are separated by linear decision boundaries and the detailed model predicting accuracy is not involved.

The traditional thermal balance theory and the predictive mean vote (PMV) index originally from Fanger's research (Fanger, 1970) were also applied for the personal thermal sensation model development. Gao and Keshav (2013) developed a Predicted Personal Vote (PPV) model, which directly integrated the PMV index into the model structure. The PPV model assumed that the occupants' actual thermal sensation vote could be calculated from the PMV index by adding on a 'personal part'. The personal part was expressed by a multi-dimensional linear function, whose factors include air temperature, mean radiative temperature, air velocity, humidity level, metabolic rate and clothing insulation value. The structure of the model functions of PPV can be found in function (4.6) (Gao and Keshav, 2013).

$$PPV=PMV+C_1X_1+C_2X_1+C_3X_1+C_4X_4 + C_5X_5 + C_6X_6 + C_7 \quad (4.6)$$

In Function (4.6), X_1, X_2, X_3, X_4, X_5 and X_6 represent air temperature, mean radiative temperature, air velocity, relative humidity metabolic rate and clothing insulation value respectively. Gao and Keshav (2013) also noticed that if the sample size is small, the PPV model in equation (4.6) will be simplified to a function of PMV. For both full and simplified formats of the PPV model, the least square regression method was used to calculate the coefficients of the model function. However, the effectiveness of the modelling method may need further investigation, as in the presented work the evaluation process is only expressed by a single case study with 12 training samples and eight testing samples.

Zhao et al. (2014) introduced a Personalised Dynamic Thermal Comfort (PDTC) model, which is similar to the PPV model. They also applied a regression method to estimate the personal coefficients of the model function. The structure of the model functions of PTV are shown in Equation (4.7):

$$PTV=E_0+ E_1X_1+ E_2X_2- E_3(X_3 +X_4) \quad (4.7)$$

In Equation (4.7), E_1 is the coefficient of water vapour pressure; E_2 is the coefficient of air temperature and E_3 is the coefficient of radiant sensible heat loss from skin and the convective sensible heat loss from skin (Zhao et al., 2014). The clothing insulation and activity levels are considered as fixed values in the research.

Yang and Wang (2013b) proposed that an occupant's personal thermal comfort level can be expressed as a 'Gaussian Function' which can be expressed as Function (4.8):

$$\mathrm{CT}_i = e^{-(t-t_{maxi})^2/(2d_i)^2} \tag{4.8}$$

where t_{maxi} means the 'maximum comfort temperature' of occupant i and d_i indicates the tolerance of discomfort of the same occupant. No detailed example provided in the literature explains how to calculate t_{maxi} and d_i from the collected data. Further investigations may be needed to verify why the personal thermal sensation follows such a distribution.

The support vector machine (SVM) algorithm has been utilised in the thermal comfort research area. Megri *et al*. (2005) applied support vector regression (SVR) to develop thermal sensation models. They claims that their research shows the potential of using the SVM to generate the thermal index of a particular small group of people. Rana et al. (2013) applied a similar ϵ-SVM regression method to generate the personal thermal sensation model and verify the feasibility of using 'humidex' as a predictor. The inputs of the personal model developed in this research only include temperature and humidity, or 'humidex', which is calculated from temperature and humidity**.** Megri and Rana both applied the SVM algorithm as a regression tool in their research. More background information about the ϵ-SVM regression method can be found in the next chapter.

Comparing all the research mentioned in this section, a research question has been raised as to whether an SVM-based personal thermal comfort model has a better performance when it takes into account a complete set of environmental factors that affect thermal sensation including temperature, humidity, air velocity and mean radiant temperature. In this research, a modelling method aided by C-support Vector Classification (C-SVC) (Chang and Lin, 2011) is proposed for generating personal thermal sensation models. Being different to the existing thermal comfort modelling methods, this new study attempts to solve the personal thermal sensation modelling using an algorithm that particularly deals with classification problems. Comprehensive boundary decision-making methods are used here rather than directly applying linear boundaries in all cases. The input parameters of the model include the well-accepted key factors of the ambient thermal environment affecting thermal feelings, which include air temperature, mean radiant temperature, air velocity, relative humidity, clothing insulation level and activity level (Fanger, 1970, Olesen, 2000). The outputs of the generated models are expected to closely match the value of the personal thermal sensation vote, which should accord with the ASHRAE seven-point thermal sensation scale. The format of the original thermal sensation data from the questionnaire survey has been retained. A strict evaluation rule is applied: a success prediction will only be declared if the prediction value is exactly the same as the collected true value.

4.3 The Modelling Method and Algorithm

4.1.1 Regarding Personal Thermal Sensation Modelling as a Classification Problem

In this research, the input vectors of the thermal comfort model are the environmental parameters and personal factors, while the outputs are thermal sensations. The personal thermal sensation model functions to ‘map’ the particular thermal conditions with an individual’s thermal sensation. In this case, from a machine-learning prospective, the personal thermal sensation modelling issue can be regarded as a supervised learning problem (Bishop, 2006, Russell and Norvig, 2010). Moreover, in previous research, the occupants’ thermal feelings were collected in the form of thermal sensation votes (TSV) based on the ASHRAE seven-point scale thermal comfort scheme, i.e. cold (-3), cool (-2), slightly cool (-1), neutral (0), slightly warm (1), warm (2) and hot (3) (ANSI/ASHRAE55-2010, 2010). It is logical to maintain the model predictions format to remain consistent with the format of the collected real data. In this case, the model’s thermal sensation predictions should also be expressed using the ASHRAE scale detailed above. That is to say, the values used in a personal thermal sensation model are discrete. These discrete data can be regarded as a label for the different thermal sensation levels. Therefore, referring to the definitions from the machine learning field in Russell and Norvig (2010) and Han et al. (2012), the personal thermal sensation modelling problem can be regarded as a classification problem. Consequently, C-support Vector Classification (C-SVC) is chosen to support the model generation programming, which is a popular tool in solving classification problems.

4.1.2 The Background of the C- SVC Algorithm

SVM is a machine-learning algorithm which was developed into different formulations, and has been applied in various domains and regarded as an effective classification tool (Xi et al., 2007) (Boser et al., 1992, Cortes and Vapnik, 1995, Banados and Espinosa, 2014, Novakovic and Veljovic, 2011, Zhao et al., 2008). The C-SVC classifier is a separator developed by the C-SVC which is able to categorise two types of thermal sensations (Chang and Lin, 2011). The basic classifier generation is illustrated in this section. For machine-learning purposes, the collected data are arranged as input and output pairs. Assume the total number of data sets is N, the input-output pairs can be expressed as ($\bar{u}_i$, y_i); $i = 1,2, \dots N$. The input vector $\bar{u}_i$ contains environment parameters and personal factors. The targeted output y_i only contains one element which is the thermal sensation of the person in the circumstance, which is defined by $\bar{u}_i$. Let $y_i = 1$ represent the thermal sensation class number one and $y_i = -1$ represent thermal sensation class number two.

All sets of the input and output pairs are divided into training sets and test sets. Let the number of training sets be represented by M. During the training process, only training sets are used. The SVM utilises 'maximum margin hyperplane' as the decision boundary to separate two different classes when solving classification problems, and it is the optimal hyperplane that provides the maximum margin between the two classes (Witten *et al.*, 2011). The 'maximum margin hyperplane' is illustrated in Fig. 4.2. Note that this figure only depicts the situation when two classes are linearly separable. In Fig. 4.2, nodes expressed by the same symbol (star or triangle) belong to the same class.

The 'support vectors' are the vectors closest to the decision hyperplane derived from the training set and they define the optimal hyperplane which has the maximum margin (Witten *et al.*, 2011). In Fig.4.2, nodes 1, 2 and 3 are selected as support vectors. The equation of the optimal hyperplane can be expressed as Equation (4.9) (Russell and Norvig, 2010):

$$\bar{\omega}^T \bar{u} + b = 0 \tag{4.9}$$

$\overline{\omega}$ and b are the weight vector and bias respectively, and $\overline{u}$ is an input vector. The mathematical derivation of the C-SVC problem is briefly demonstrated in Function (4.10) to Function (4.16). Further details can be found in the references (Chang and Lin, 2011, Bishop, 2006, Cortes and Vapnik, 1995, Haykin, 1999).

For all the training sets and the maximum-margin hyperplane, the rule represented in Function (4.9) must be obeyed by:

$$\mathrm{y_i}(\overline{\omega}^T\overline{u}_i + b) \geq 1 \tag{4.10}$$

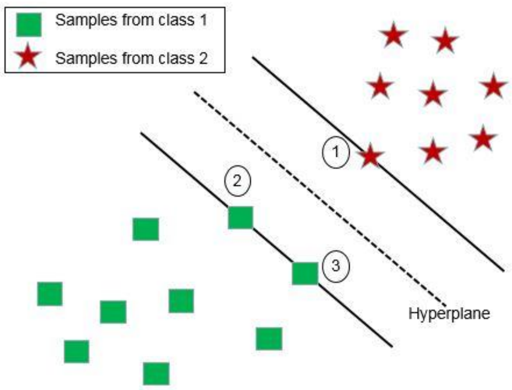


Figure 4.2 Support vectors and hyperplane

It has been proven that finding the maximum margin is equivalent to finding the minimum of the output of the Function (4.11) (Haykin, 1999):

$$\theta(\overline{\omega}) = \frac{1}{2}\overline{\omega}^T \cdot \overline{\omega} \tag{4.11}$$

Function (4.11) satisfies the constraint: $\mathrm{y_i}(\overline{\omega}^T\overline{u}_i + b) \geq 1$; i=1,2,…M.

However, in real-world applications, the training data may be noisy. Furthermore, the data from the two classes may not be linearly separated. So the ‘soft margin hyperplane’ and the ‘kernel trick’ are introduced into the C-SVC algorithm to realise the classifiers in these situations. First, for the soft margin hyperplane, a parameter ξ_i is introduced, then the function to be minimised becomes Function (4.12) (Cortes and Vapnik, 1995, Haykin, 1999):

$$\min_{\overline{\omega},b,\xi} \frac{1}{2} \overline{\omega}^{\mathrm{T}} \cdot \overline{\omega} + \mathrm{C} \sum_{\mathrm{i}=1}^{\mathrm{M}} \xi_{\mathrm{i}} \qquad (4.12)$$

The constraint condition of (4.12) is $\mathrm{y_i}(\overline{\omega}^T \bar{u}_i + b) \geq 1 - \xi_i$; $\xi_i > 0$; i=1,2,…M, and *C* is a user-defined positive figure.

This research employed the 'radial-basis function' (RBF) kernel (Bishop, 2006) for the problem of linearly inseparable cases. The kernel is used to map the input vectors from the original feature space into a higher dimensional space where the cases become linearly separable and the RBF can be expressed as Function (4.13):

$$\mathrm{K}(\bar{\mathrm{u}}_{\mathrm{i}}, \bar{\mathrm{u}}_{\mathrm{j}}) = \mathrm{e}^{-\frac{1}{2\delta^2}\|\bar{\mathrm{u}}_{\mathrm{i}} - \bar{\mathrm{u}}_{\mathrm{j}}\|^2} \qquad (4.13)$$

The problem of finding the maximum-margin hyperplane becomes solving an optimisation problem (Novakovic and Veljovic, 2011), which is expressed in Function (4.12) subject to:

$$\mathrm{y_i}\left(\overline{\omega}^{\mathrm{T}} \overline{\emptyset}(\bar{u}_i) + b\right) \geq 1 - \xi_i; \qquad (4.14)$$

$$\xi_i \geq 0; i = 1,2 \dots . M \qquad (4.15)$$

$\emptyset(\bar{u}_i)$ is from the kernel function:

$$K(\bar{u}_i, \bar{u}_j) = \emptyset(\bar{u}_i)^T \emptyset(\bar{u}_j) \qquad (4.16)$$

The minimisation problem of Function (4.12) can be converted into solving the dual problem expressed in Function (4.17) to Function (4.20)(Chang and Lin, 2011) (Haykin, 1999):

$$\min_{l} \ \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{M} l_i \, l_j y_i y_j \, K(\bar{u}_i, \bar{u}_j) - \sum_{i=1}^{M} l_i \qquad (4.17)$$

subject to:

$$\sum_{i=1}^{M} l_i \, y_i = 0; \qquad (4.18)$$

$$0 \leq l_i \leq C, i = 1,2 \dots . M \qquad (4.19)$$

By finding the optimum solution of Function (4.17) subject to (4.18) and (4.19), let l_{io} and b_o be the optimised coefficients, then the decision function $\mathrm{G}(\bar{u})$ can be expressed as:

$$\mathrm{G}(\bar{u}) = sgn(\sum_1^M y_i l_{io} K(\bar{\mathrm{u}}_i, \bar{u}) + b_o) \qquad (1.20)$$

If an input vector $\bar{x}$ is submitted into Function (1.20), which contains environmental parameters and personal factors, and $\mathrm{G}(\bar{x}) = 1$, this means that the generated classifier predicts the thermal sensation of the subject as being in thermal sensation class number one under the input circumstance.

In this research, there are seven levels of thermal sensations that need to be classified but the classifier described above can only identify two classes at a time. This multi-class classification problem is solved by the 'one against one' method (Knerr *et al.*, 1990), and then multiple classifiers are generated all together to create a complete thermal sensation model for a subject. In this research, the C-SVC algorithm with the 'one against one' method has been realised by using the LIBSVM MATLAB library (Chang and Lin, 2011).

4.4 Data Process and Model Training for Chinese Data

In order to test the accuracy of the C-SVC-based model of the reflection and prediction of personal sensations, experimental data from a series of experiments carried out in Chongqing, China from 2008 to 2010 are used. More details of the data can be found in section 2.24. The data used as training data should not be used again as test data. Therefore, around 50% of each subject's data were used to develop the model and the remaining 50% were used to verify the accuracy of the model. The real numbers of training samples and testing samples of a subject depend on the total amount of valid raw data collected from the experiment. The mean radiant temperature is calculated using Equation (4.21) where T_g is the globe temperature collected on-site (Ferreira *et al.*, 2012).

$$\bar{T_r} = [(T_g + 273)^4 + \frac{1.1 * 10^8 {V_a}^{0.6}}{\epsilon D^{0.4}}(T_g - T_a)]^{0.25} - 273 \qquad (4.21)$$

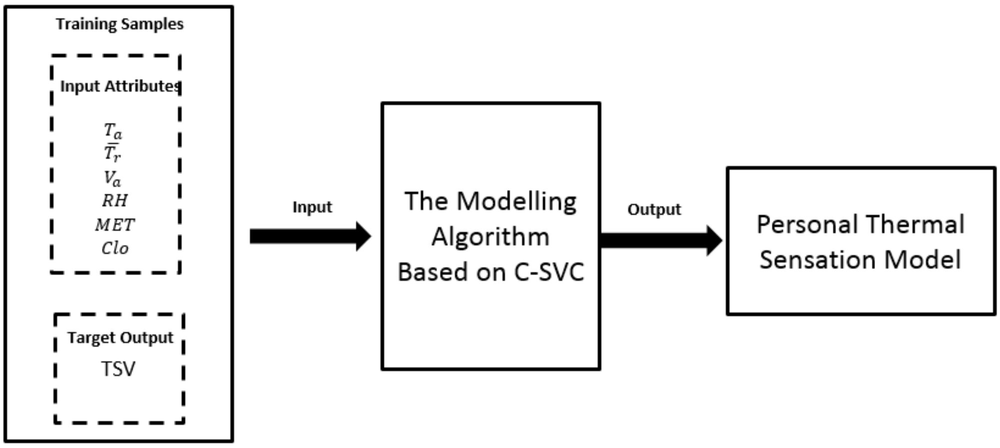


Figure 4.3 Training process of the personal thermal sensation model

Fig.4.3 illustrates the input data structure and the model training process. All the data should be arranged into input and targeted output pairs to fit the C-SVC algorithm. From the figure, it can be seen that the input data required for modelling include: 1) ambient environmental parameters such as $\boldsymbol{T_a}$, $\overline{\boldsymbol{T_r}}$, $\boldsymbol{V_a}$ and $\boldsymbol{RH}$ and personal data such as $\boldsymbol{MET}$ and $\boldsymbol{Clo}$; and 2) a subject's TSV (thermal sensation vote). These data are fed into the modelling algorithm based on the C-SVC and modelled thermal sensations based on the inputted information are then produced. For a subject, only the data collected from the experiments he/she attended were used to develop his/her personal thermal sensation model.

In the development of the modelling algorithm, the LIBSVM library was applied. According to the developer of the library, two parameters: $C \; and \; \gamma$, are used to control the performance of the C-SVC algorithm. Both C and γ are user-defined parameters and optimal pairing C and γ values will improve the C-SVC model quality. The regularisation parameter C controls the trade-off between the trained models' complexity and the errors (Xi et al., 2007, Haykin, 1999) while the parameter γ determines the parameter δ in the RBF kernel Function (4.13), which is defined by Function (4.22) (Chang and Lin, 2011)

$$\gamma = \frac{1}{2\delta^2} \qquad (4.22)$$

In this research, these parameters have been optimally selected by a 'grid-search' method which is recommended by the library developer (Chang and Lin, 2011). It was approved as a reliable method in the existing research (Xi et al., 2007). In the ‘grid-search’ procedure, a series of C and γ values were first calculated separately. Then all the possible combinations of (C, γ) pairs were generated. Based on the performance of the modelling program, both the parameters C and γ were calculated by 2^A where A is from the data range (-4,-3,-2,-1,0,1,2,3,4). The program automatically selects one pair of (C, γ) each time and then applies it to train a model. The performance of the selected (C, γ) was verified by a cross-validation method, which is integrated in the LIBSVM library. A five-fold cross-validation method was programmed. During the validation process, the program split the training sets equally into five subsets then five rounds of the modelling process were performed for each pair of (C, γ). Once a pair was selected, the first round of modelling started. Four subsets of data were used to train the model and the remaining part was used to validate the performance. The validation result of the model generated in this round was then saved. During the next round of modelling for the same pair of (C, γ), the program used another subset as validation data set and repeated the training and validation process. It then saved the validation result again. The same process would be iterated five times until all the subsets had been used once as validation data sets. All five saved test results were averaged and the average value was used to represent the performance of the modelling program with the selected (C, γ). In the end, the selected model was the one developed by the combination of C and γ giving the best validated performance. If more than one (C, γ) pair reached the best performance, the program would select the pair that was validated last in the whole validation process. Fig.4.4 depicts the performance of different (C, γ) pairs during the model training process for subject B. It can be found that multiple (C, γ) pairs have the same performance with validation results reaching 100% accuracy, so after the training process, the chosen (C, γ) pair was (16, 16), which is illustrated as the point Z in Fig.4.4.

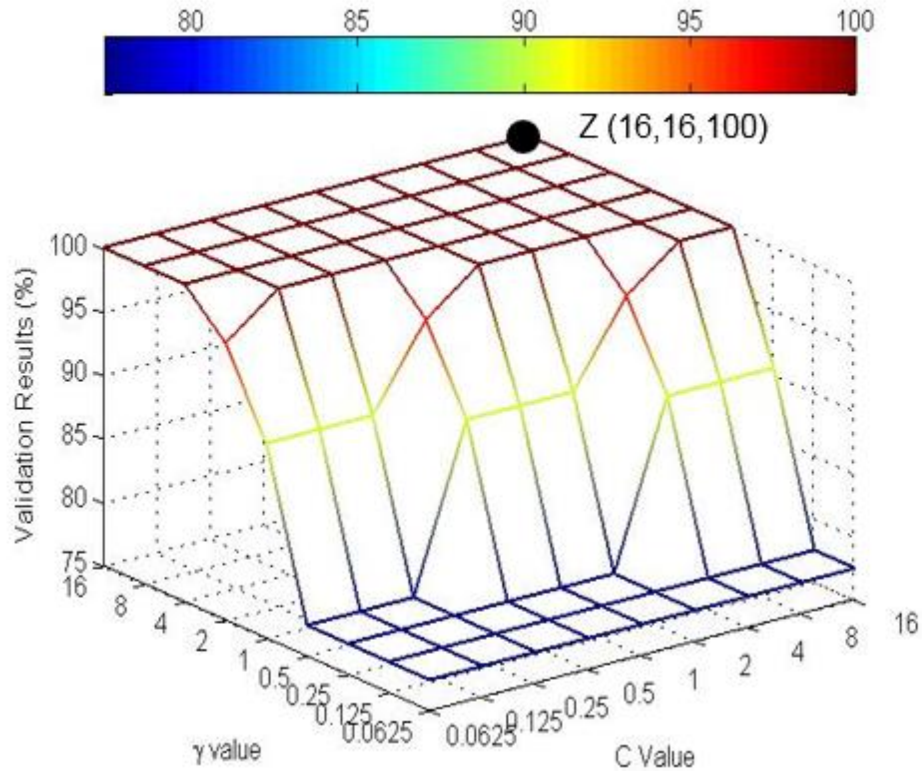


Figure 4.4 Performance of different (C, γ) pairs

Because of the property of the LIBSVM library, the input data of the C-SVC algorithm are re-scaled into the range [0,1]. The re-scale method is defined by the following equation (Kai-Biao et al., 2014):

$$z = (z_{max} - z_{min}) * \frac{y - y_{min}}{y_{max} - y_{min}} + y_{min} \tag{4.23}$$

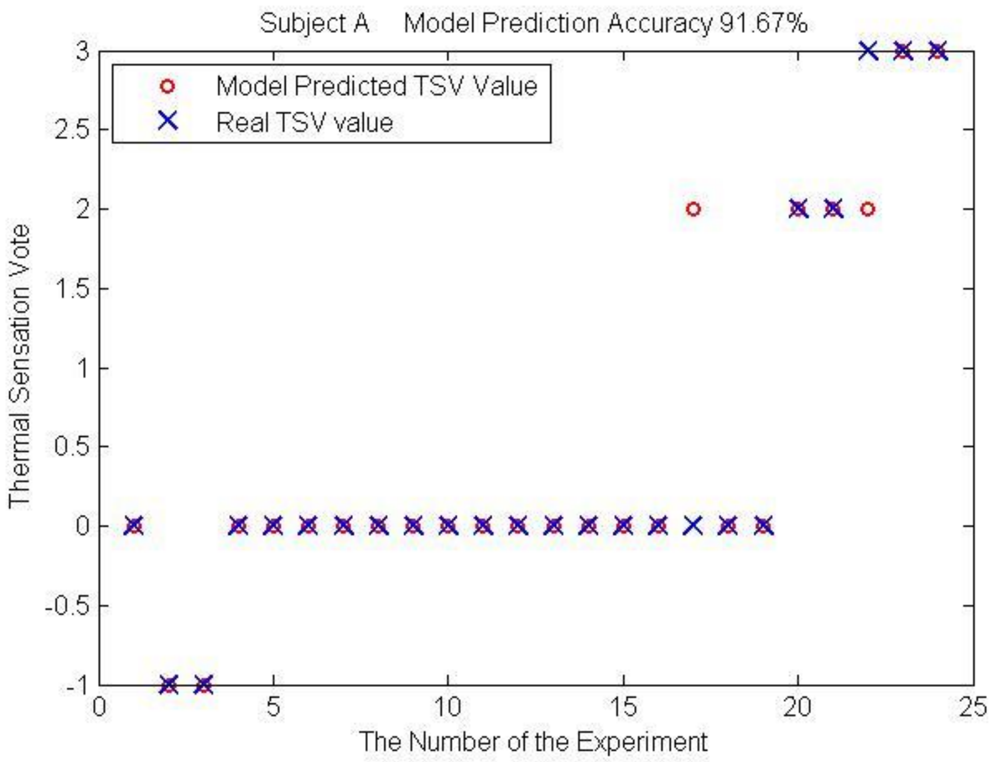
In Equation (4.23), z is the re-scaled data while y is the original data. The z_{max} and z_{min} are the target upper and lower limit of the re-scaled data set separately. The elements having maximum and minimum values in the original set are represented by y_{max} and y_{min}.

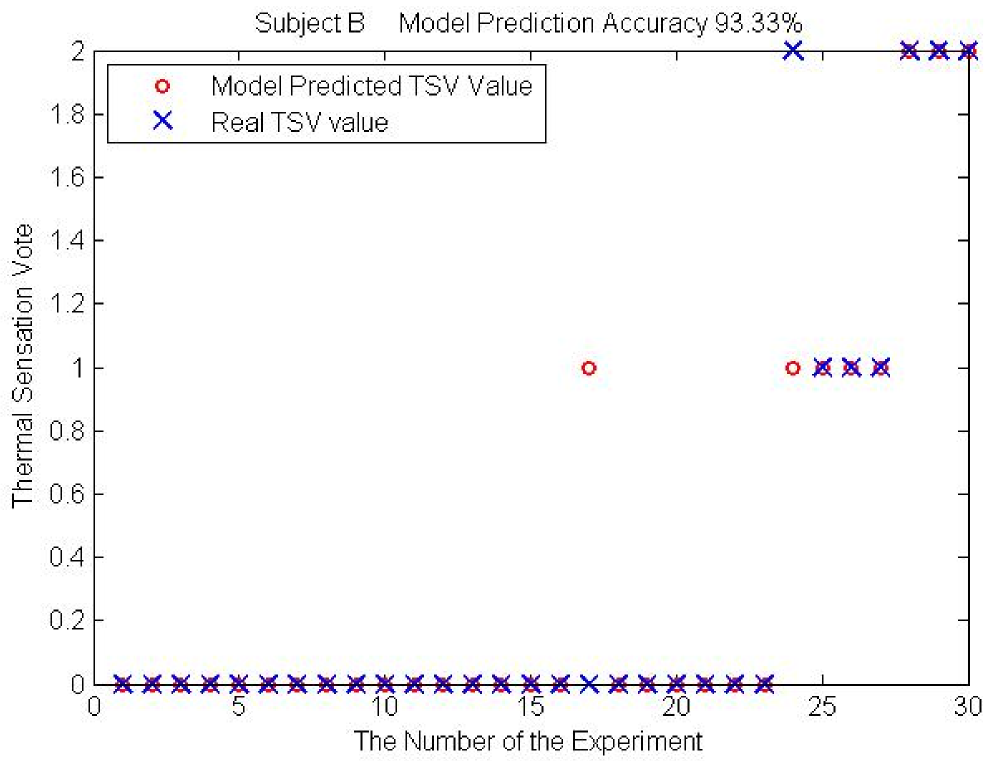
4.5 Verifications of the Model for Chinese Subjects

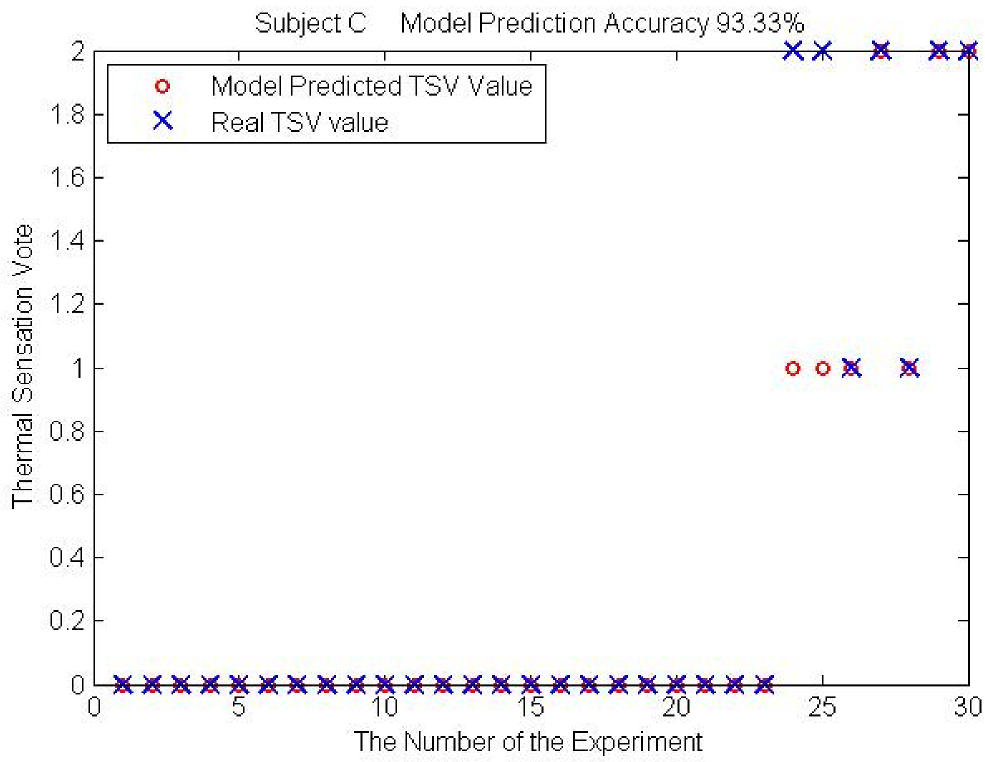
The developed individual thermal sensation model was verified using the test samples. In the test samples, the attributes $\boldsymbol{T_a}$, $\boldsymbol{\overline{T_r}}$, $\boldsymbol{V_a}$, $\boldsymbol{RH}$, $\boldsymbol{MET}$ and $\boldsymbol{Clo}$ were used as the inputs of the personal thermal sensation models. The models' predictions were compared with the actual TSV data collected from the experiment. If, under the same environmental and personal conditions, a model's prediction was equal to the actual TSV data, then the prediction would be regarded as a correct prediction. The performance of a model is expressed by the model's prediction accuracy rate, which is calculated by Equation (4.24) (Chang and Lin, 2011).

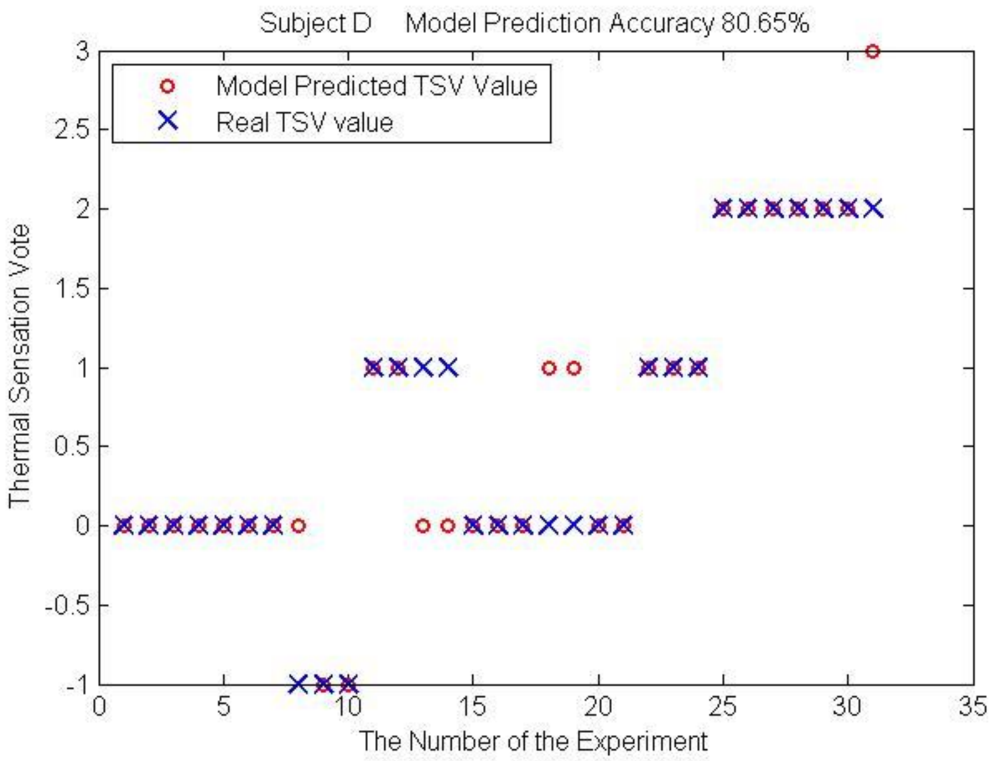
$$\text{Prediction Accuracy Rate} = \text{The Number of Correct Predictions / Total Number of Test Samples} \tag{4.24}$$

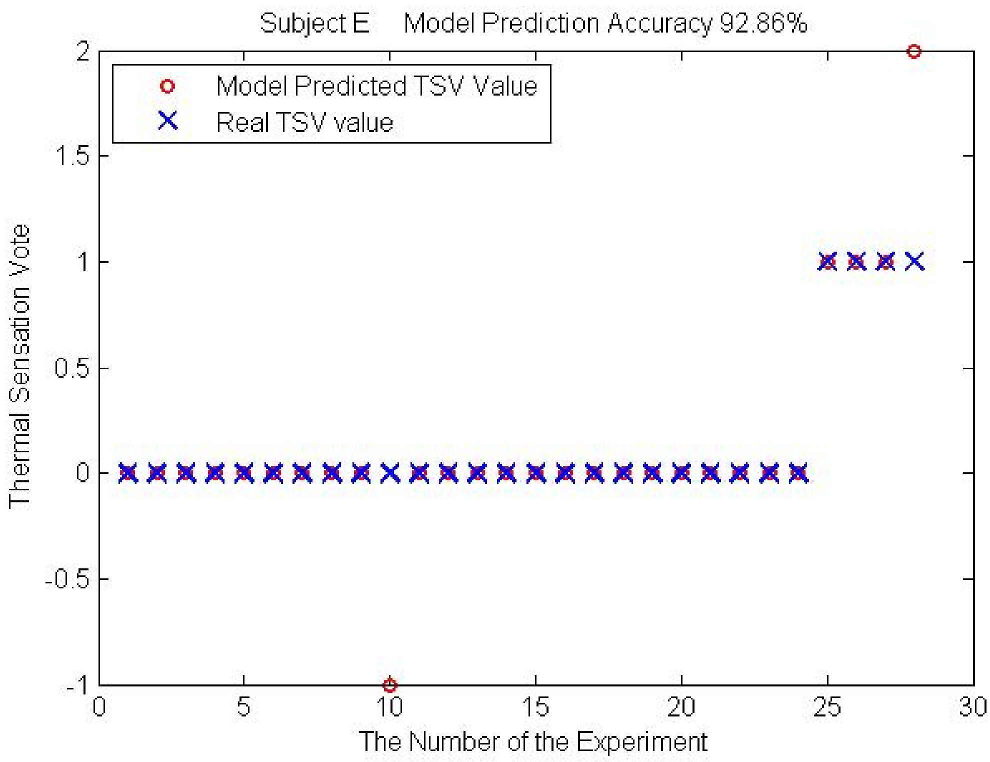
Fig. 4.5 depicts the results of two series of experiments, which test the performance of two individual models for two subjects. The X axis presents the number of the experiment while The Y axis shows the TSV values. The crosses in the figure are the TSV values predicted by C-SVC-based personal thermal sensation models, and the circles represent the actual TSV data collected from the subjects. In the figure, the cross covering the circle means the model makes a correct prediction.


Subject A   Model Prediction Accuracy 91.67%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

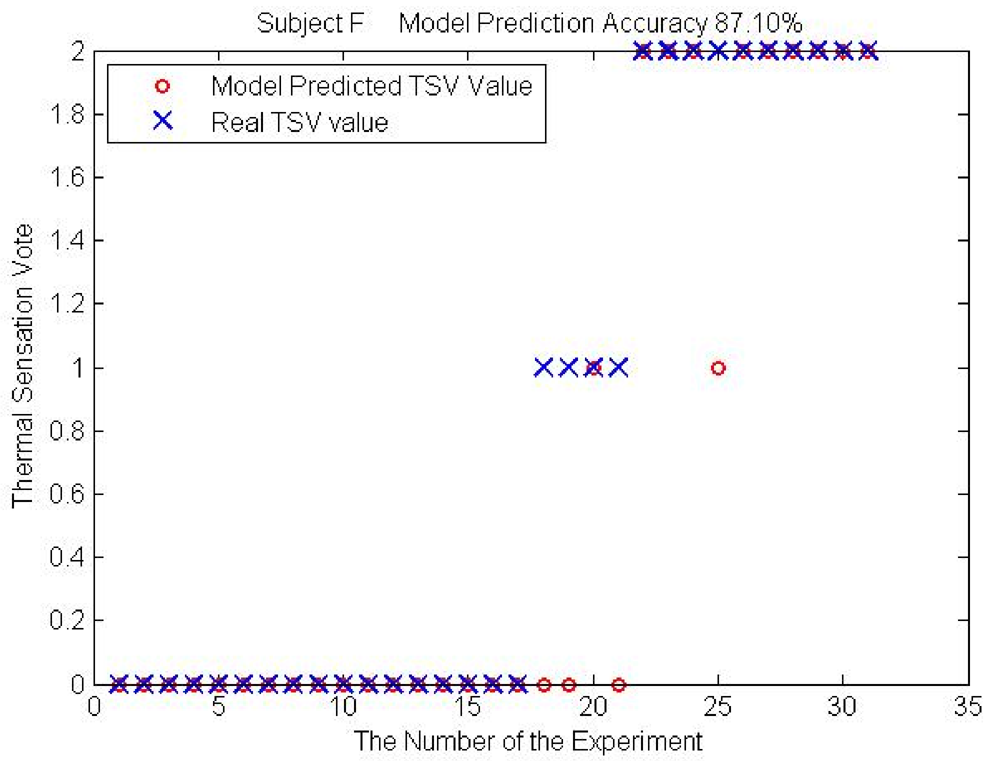

Subject B   Model Prediction Accuracy 93.33%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment


Subject C Model Prediction Accuracy 93.33%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

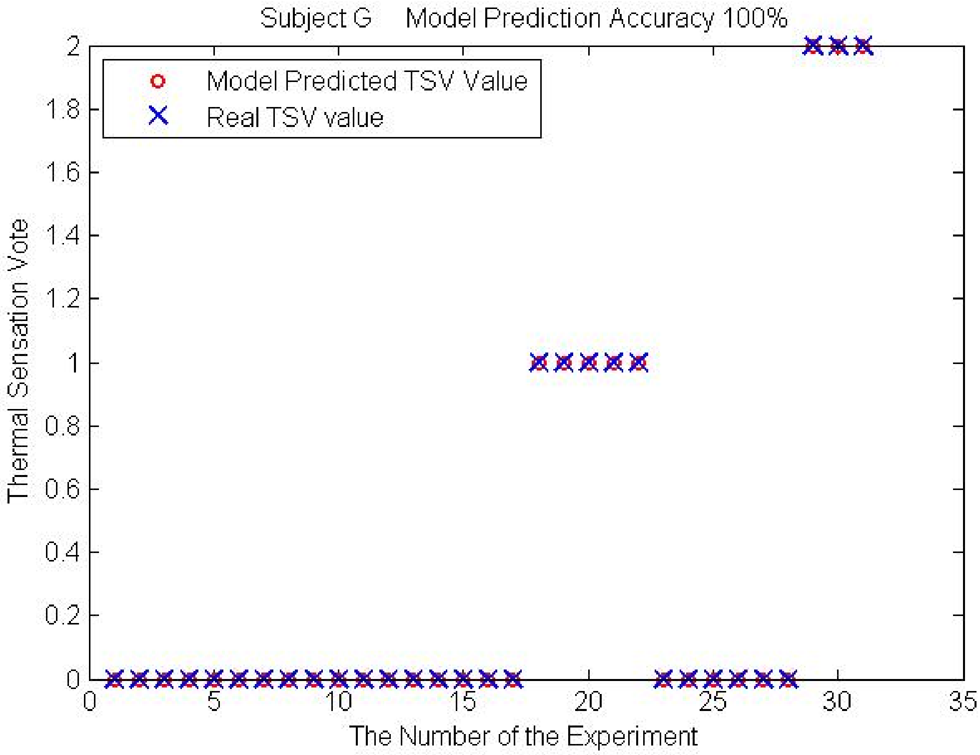

Subject D Model Prediction Accuracy 80.65%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment



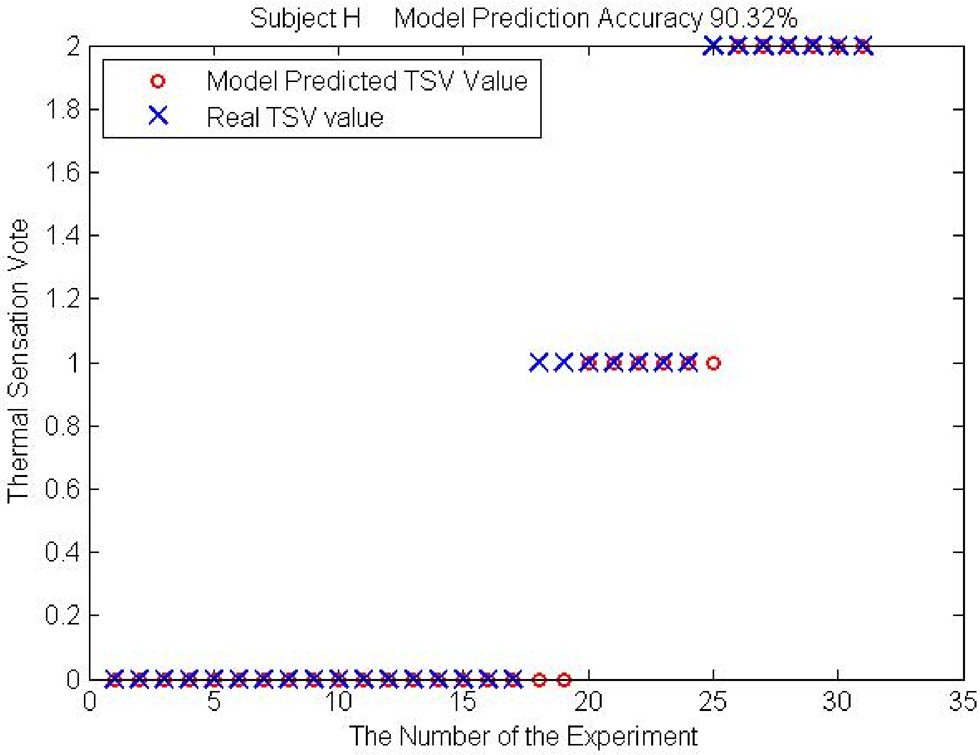
Subject E Model Prediction Accuracy 92.86%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
2
1.5
1
0.5
0
-0.5
-1
0
5
10
15
20
25
30



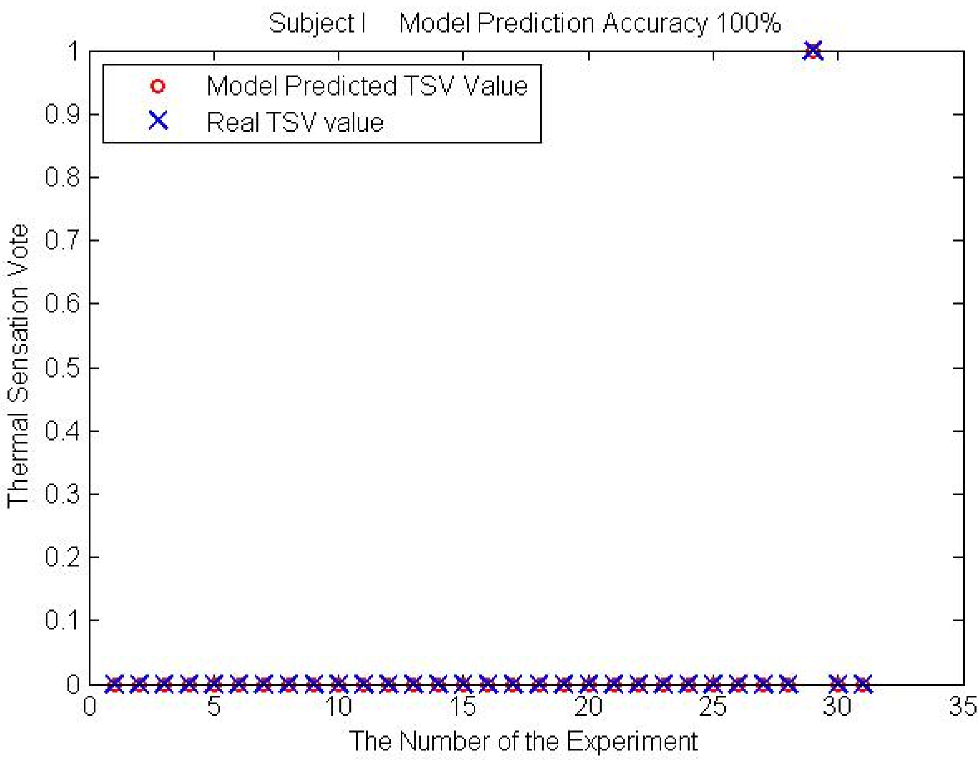
Subject F Model Prediction Accuracy 87.10%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
5
10
15
20
25
30
35



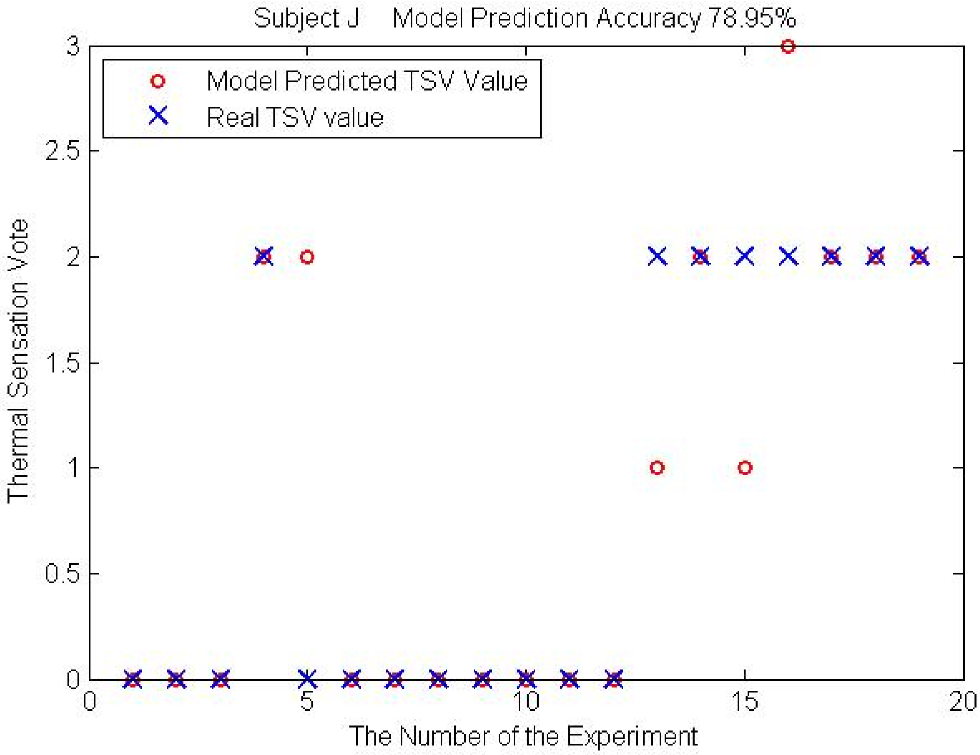
Subject G Model Prediction Accuracy 100%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
5
10
15
20
25
30
35



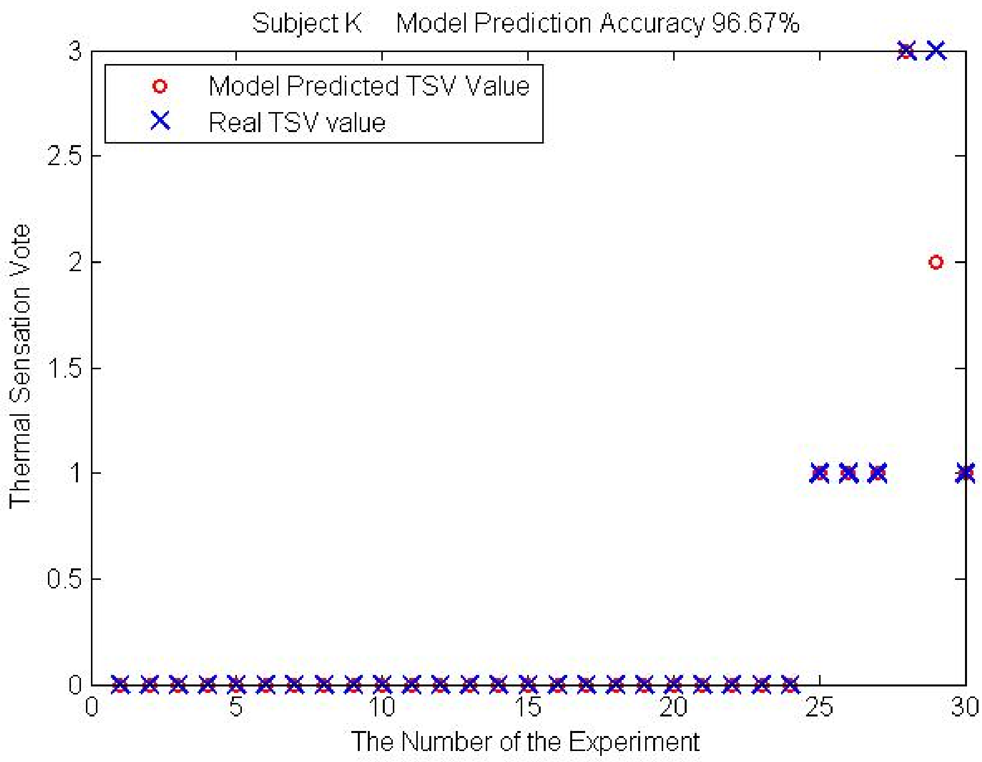
Subject H Model Prediction Accuracy 90.32%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
5
10
15
20
25
30
35

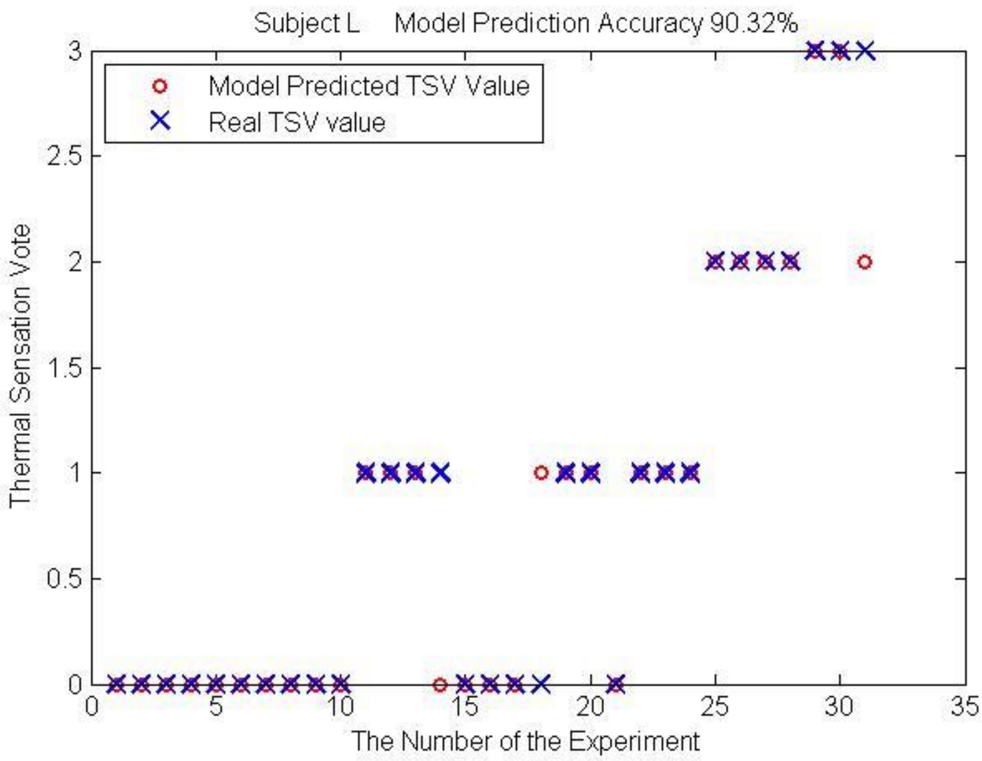


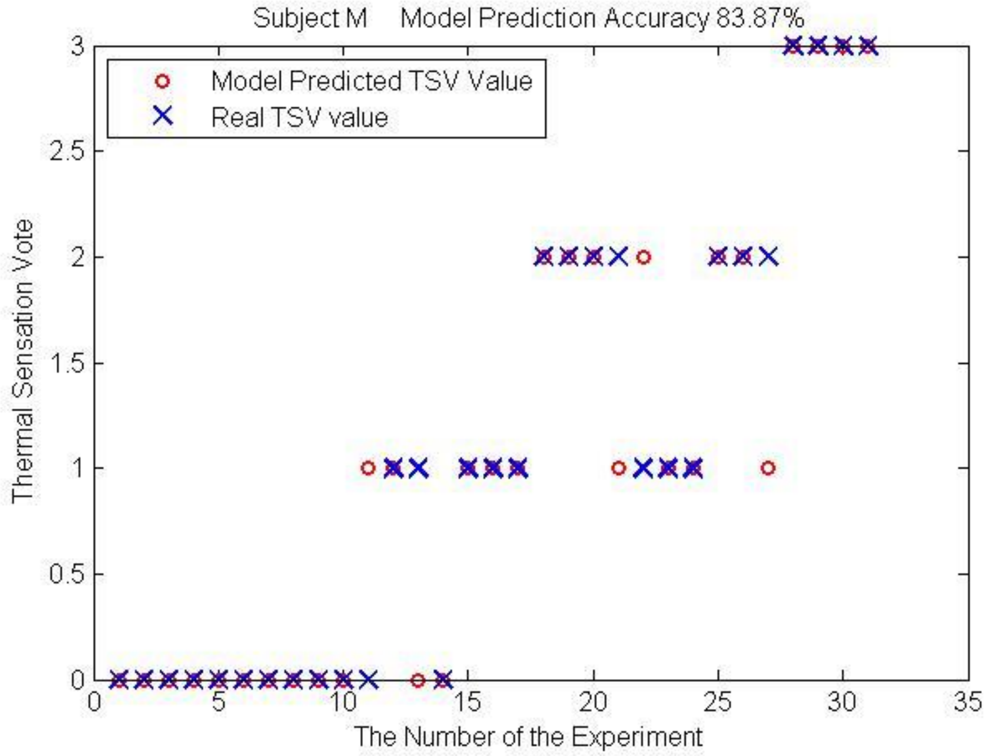
Subject I Model Prediction Accuracy 100%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

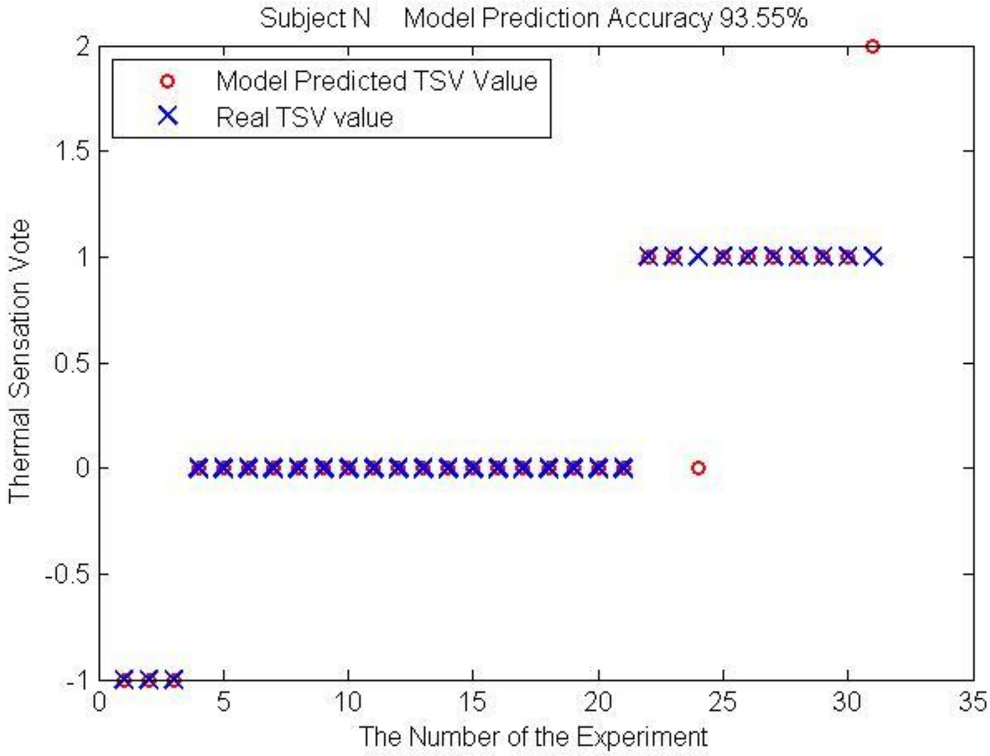


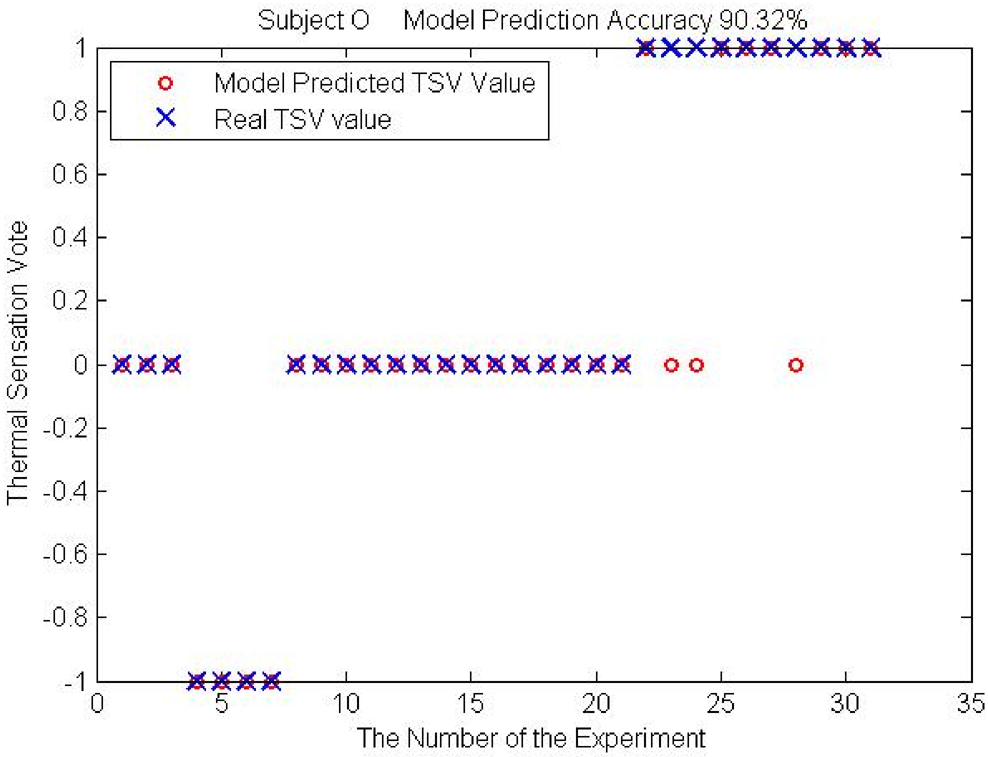
Subject J Model Prediction Accuracy 78.95%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

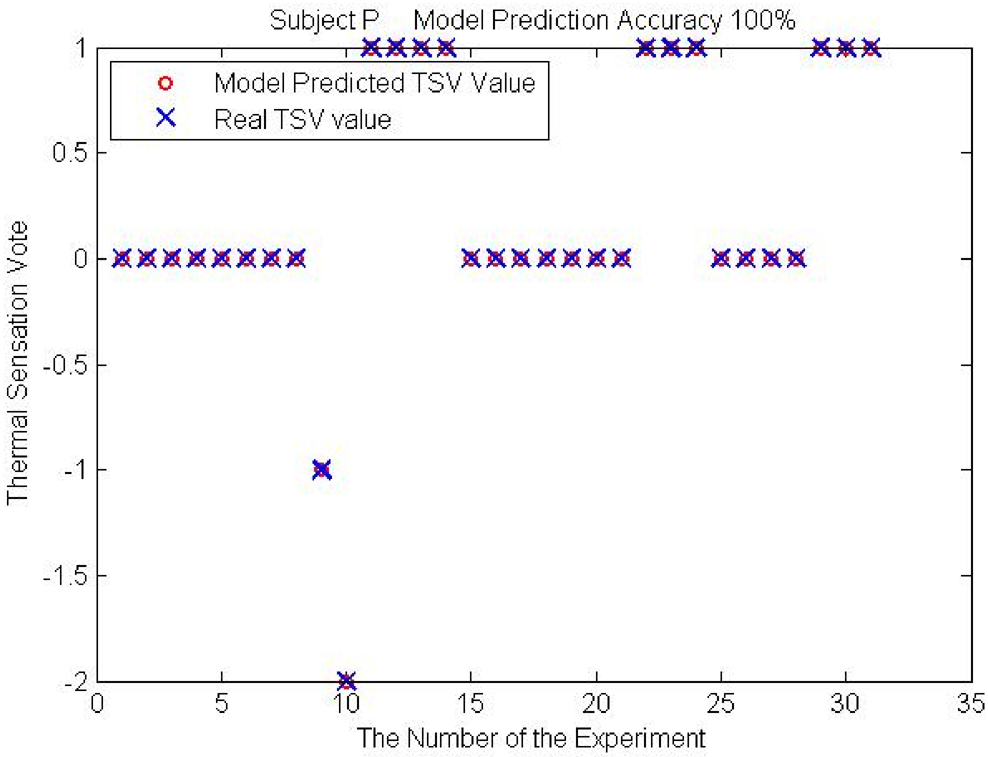

Subject K   Model Prediction Accuracy 96.67%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

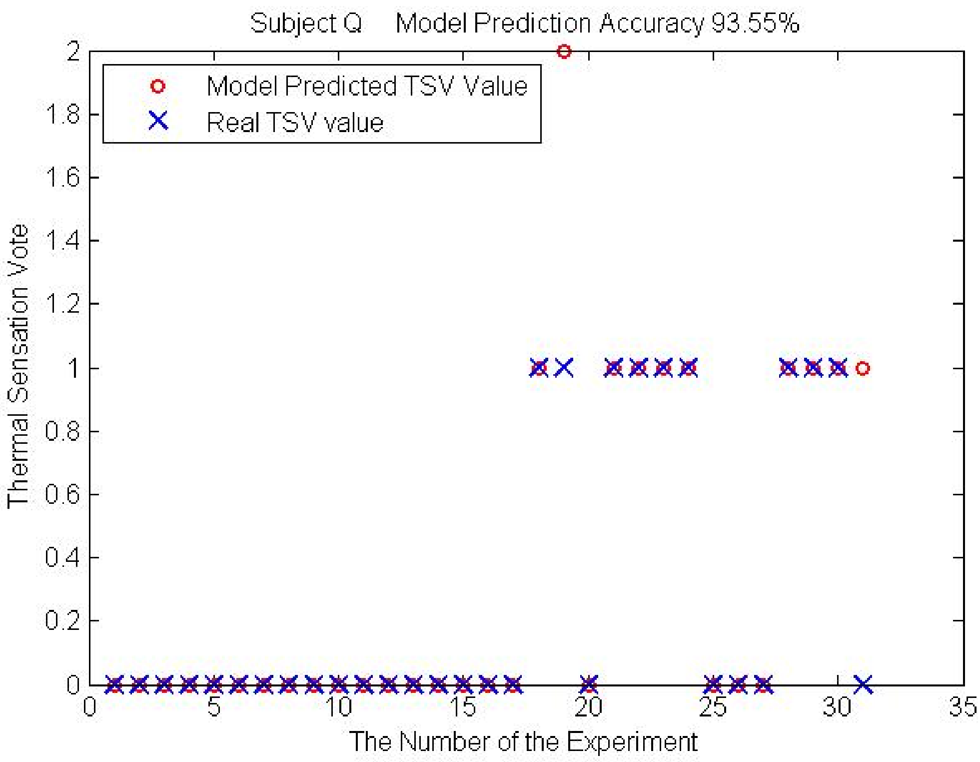

Subject L   Model Prediction Accuracy 90.32%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment

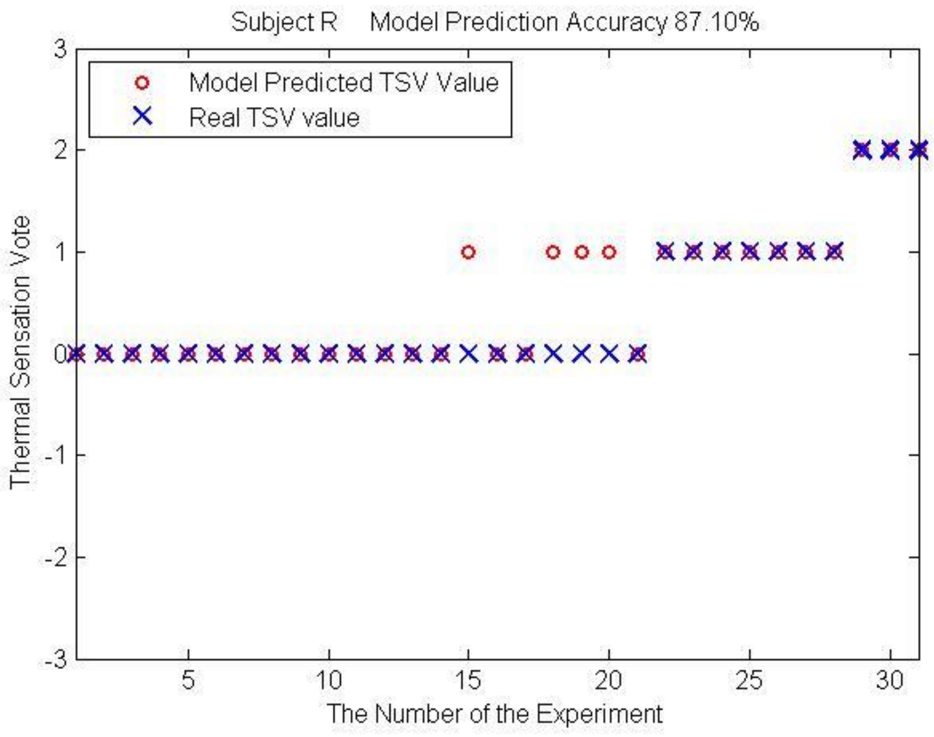

Subject M   Model Prediction Accuracy 83.87%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment


Subject N   Model Prediction Accuracy 93.55%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment


Subject O Model Prediction Accuracy 90.32%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
5
10
15
20
25
30
35


Subject P Model Prediction Accuracy 100%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
1
0.5
0
-0.5
-1
-1.5
-2
0
5
10
15
20
25
30
35


Subject Q Model Prediction Accuracy 93.55%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5
10
15
20
25
30
35


Subject R Model Prediction Accuracy 87.10%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
-3
-2
-1
0
1
2
3
5
10
15
20
25
30

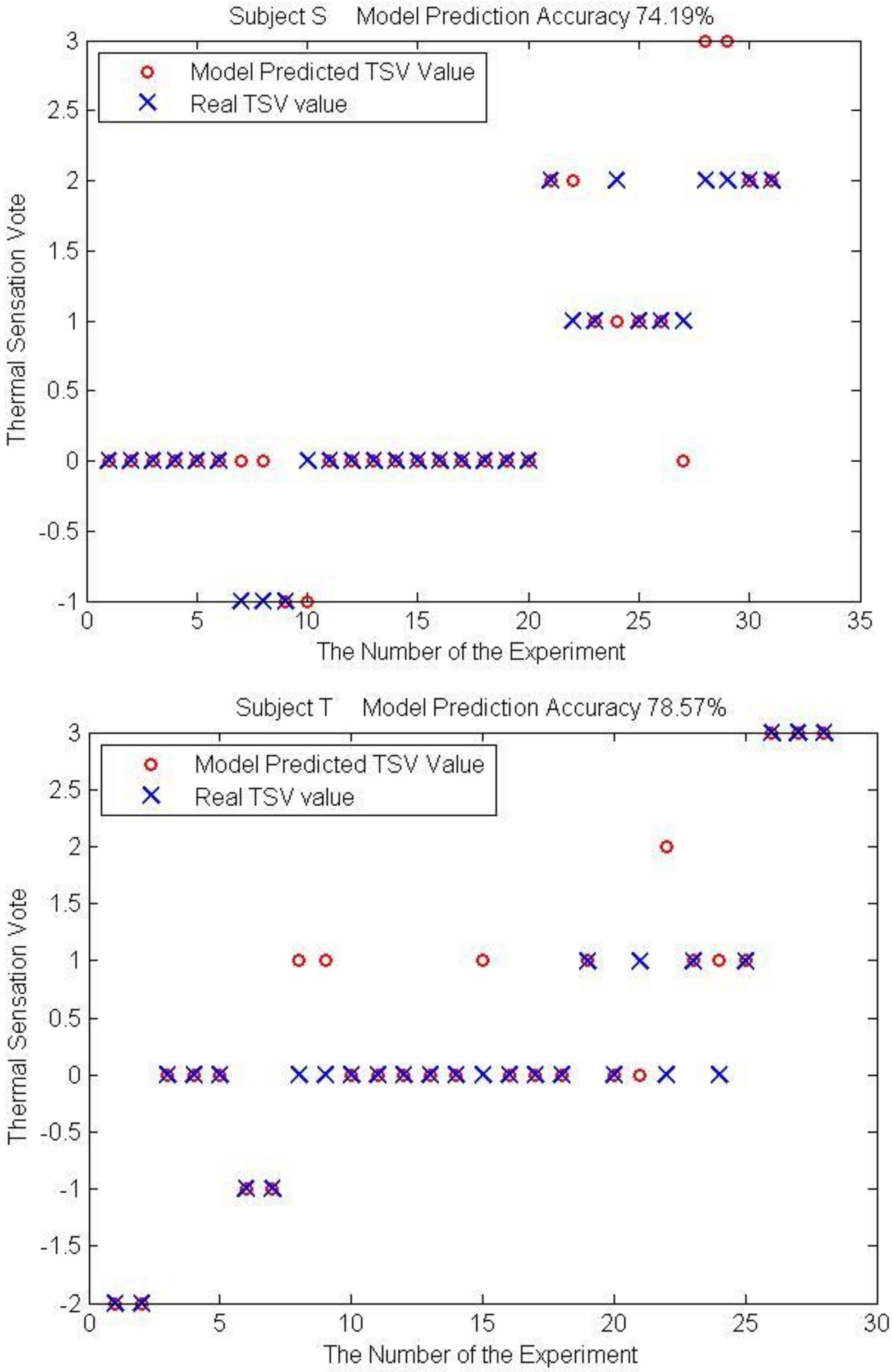


Figure 4.5 Models predicted TSV vs. subjects' actual TSV for Chinese Subjects

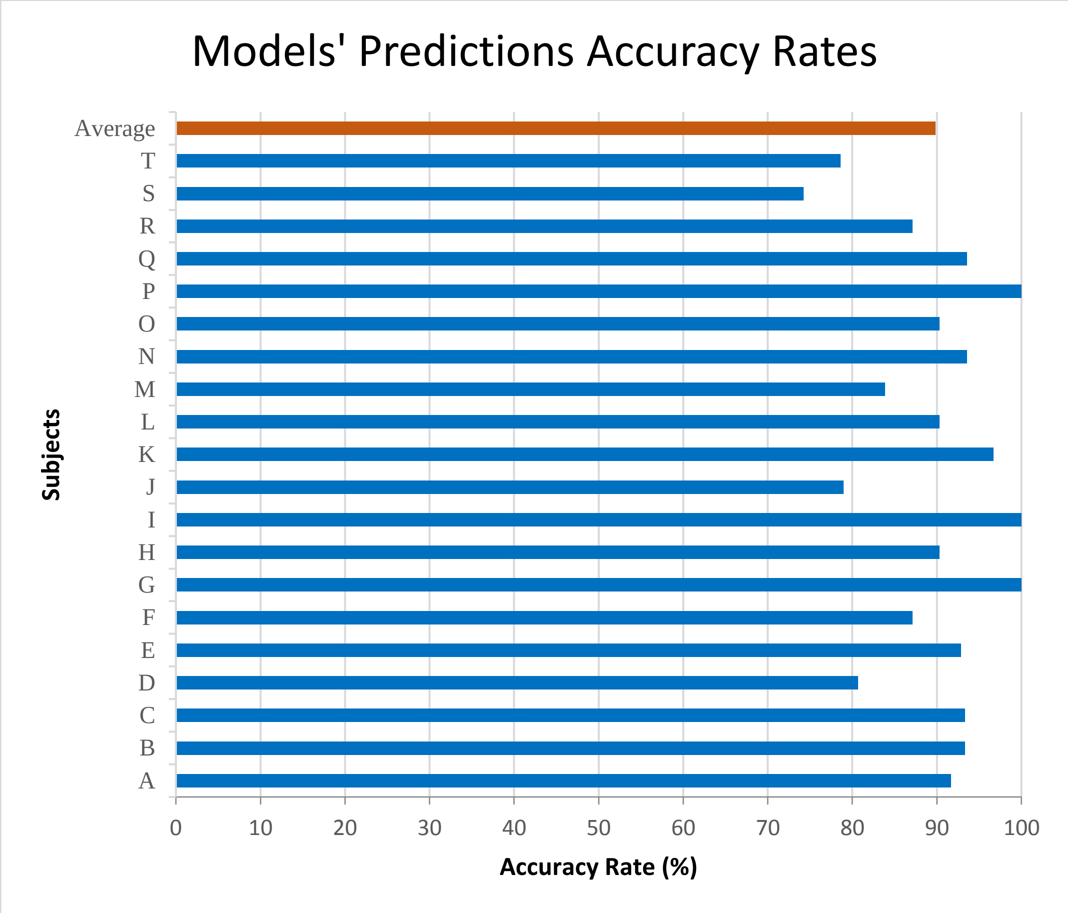


Figure 4.6 Model's prediction accuracy rates for Chinese Subjects

Fig. 4.6 shows the accuracy rate of the predicted models for 20 subjects. From the figure, it can be seen that the average prediction accuracy is 89.82%. 17 out of 20 subjects' individual thermal sensation models have an accuracy rate higher than 80%.

4.6 Comparison Studies

In order to further verify the performance of the personal thermal sensation models based on the C-SVC algorithm, a comparative study is presented. Using the same sets of data, the individuals' thermal sensations were calculated by using the PMV and C-SVC methods.

According to the literature (Rana et al., 2013), if the value of the difference between PMV and the occupant's TSV is less than or equal to 0.5, then the prediction using PMV is regarded as accurate. The accuracy rate of PMV prediction was calculated according to Equation (4.24). Fig. 4.7 depicts the mean values of the accuracy rate of the PMV index and the C-SVC-generated personal thermal sensation models. It can be seen that the average accuracy rate of the personal thermal sensation models (89.82%) is significantly higher than that obtained from the PMV model (49.71%).

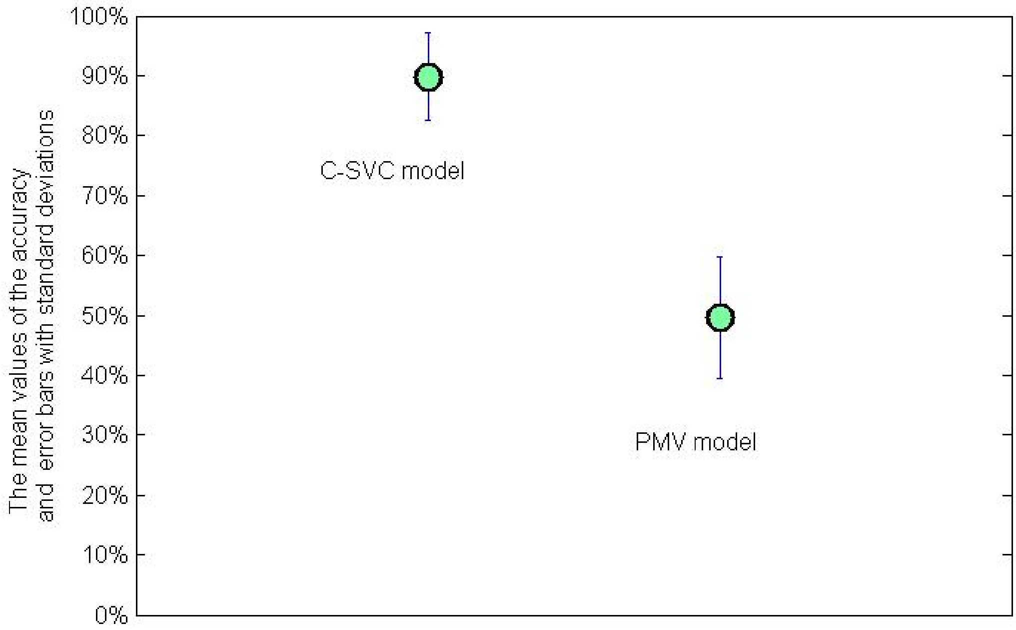
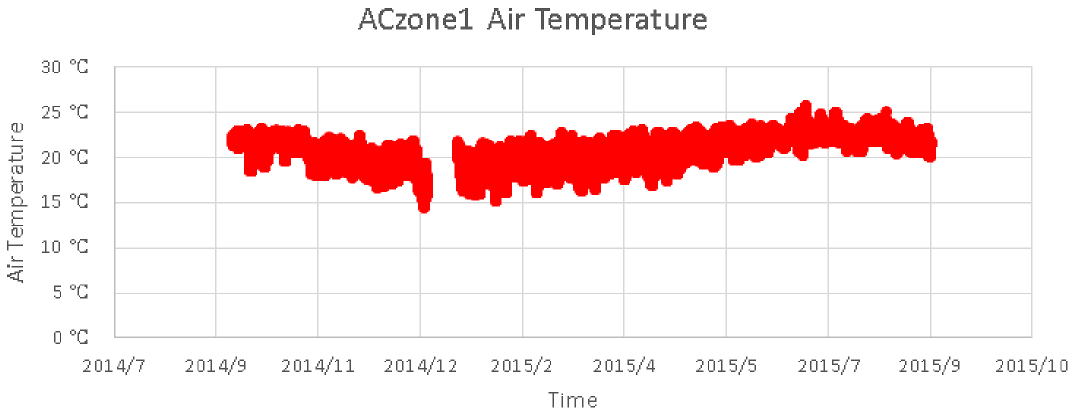


Figure 4.7 Mean accuracy of PMV and C-SVC based models

4.7 The Data Process and Model Training for UK data

The experiment and data collection in the air-conditioning (AC) environment in the UK took place from Oct 2014 to August 2015. The detail of the data collections is illustrated in Section 2.2.5. The air temperature and relative humidity values detected by the data loggers are shown in Fig 4.8, Fig 4.9 and Fig 4.10. The 'gap' within the data in Fig 4.8 and Fig 4.9 was caused by the data logger running out of battery during periods when the researcher was outside the university such as Christmas holidays. During these periods the questionnaire surveys were not conducted, so the experiment was unaffected by the batteries drying out. Some statistical outcomes of the temperature and humidity values are displayed in Table 4.2. It shows that the air temperature range in air-conditioning zones varied from 13.57℃ to 27.16℃.



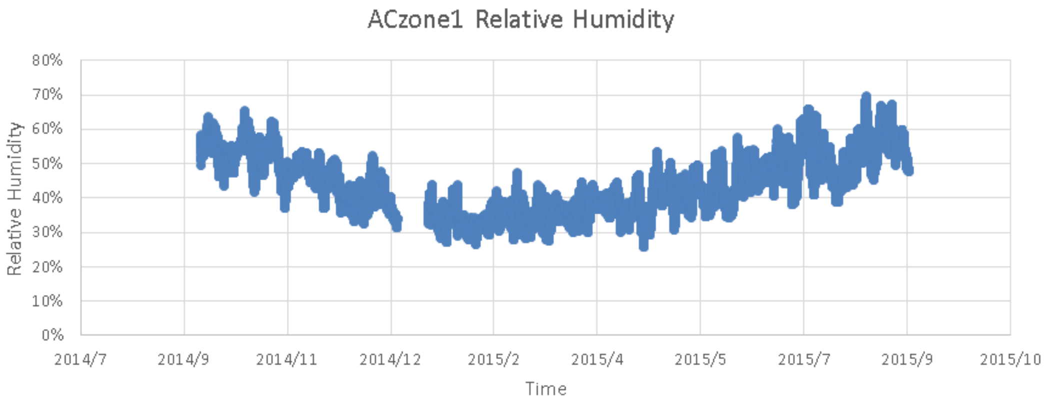
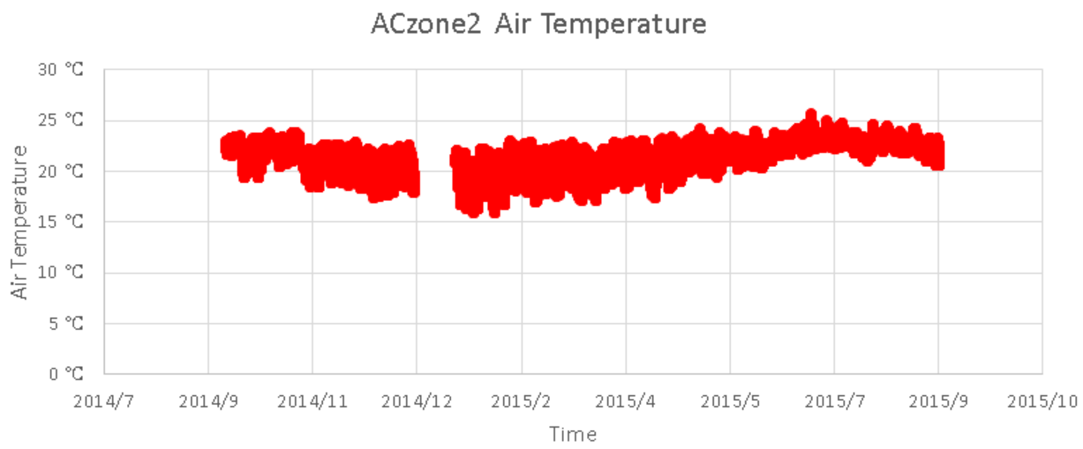


Figure 4.8 Air Temperature and Relative Humidity in ACzone 1



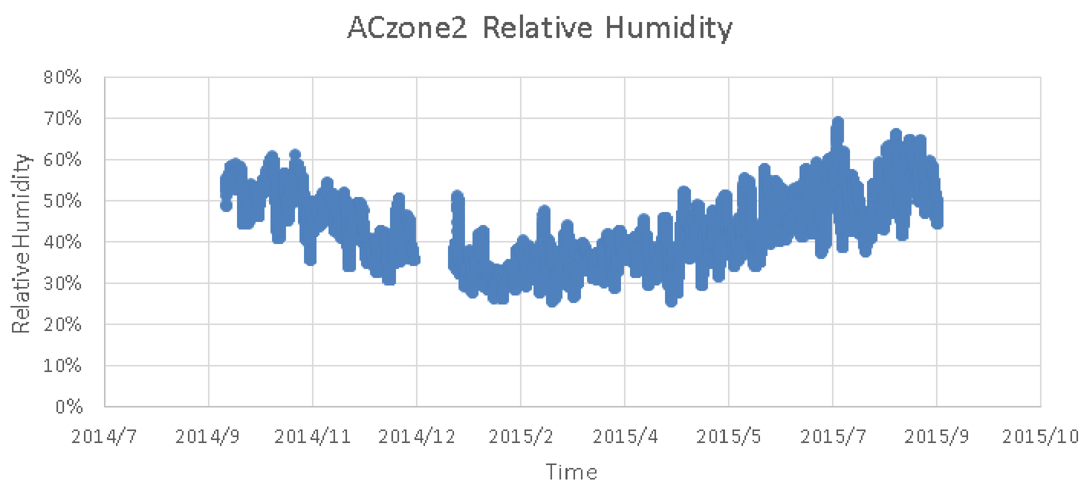
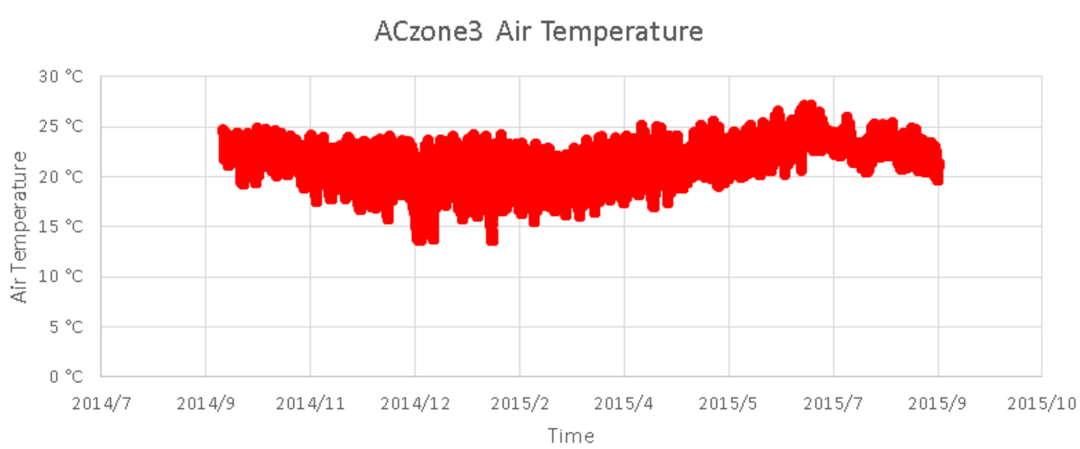


Figure 4.9 Air Temperature and Relative Humidity in ACzone 2



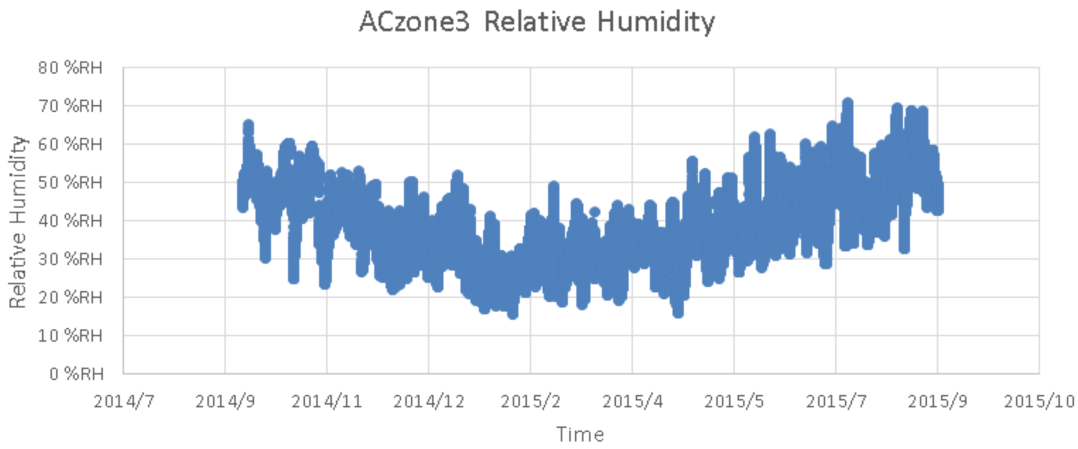


Figure 4.10 Air Temperature and Relative Humidity in ACzone 3

Table 4.2 the general air temperature and relative humidity condition of the air-conditioned space

	ACzone 1	ACzone 2	ACzone 3
Maximum Temperature	25.7℃	25.6℃	27.16℃
Minimum Temperature	14.4℃	15.8℃	13.57℃
Average Temperature	20.74℃	21.23℃	21.08℃
Maximum RH	69.4%	69.1%	70.9%
Minimum RH	25.5%	25.6%	15.6%
Average RH	43.47%	42.85%	39.40%

Table 4.3 Measured Environmental Parameters and Personal Factors in air-conditioned areas

AC Areas	MET	CLO	Air Temperature	Relative Humidity	Air Velocity	Globe Temperature

Maximum Value	1.2	1.27	25.8℃	65.8%	0.23	25.7℃
Minimum Value	1	0.47	19.2℃	17.6%	0.01	20.4℃
Average Value	1.03	0.81	22.49℃	38.2%	0.08	22.87℃

In total, twelve subjects agreed to attend the experiment. Six of them finished it. A total number of 247 effective samples were collected from these six subjects. The distribution of thermal sensation votes are depicted in Fig. 4.11. The picture shows that, in general, the thermal sensation votes are not balanced in a way that subjects tend to feel ‘slightly cool’ or even colder more frequently than they feel ‘slightly warm’ or even hotter. By a deep inspection of the data, it can also be found that only on a few occasions did the subjects tend to feel ‘warm’, ‘slightly warm’ and ‘cool’. In all the samples, only 3.24% of the votes’ values are negative two; 1.62% of votes’ values are positive two; and 7.69% of the votes’ values are one. It is interesting to see that no one reported that they felt ‘cold’ or ‘hot’ during the entire experimental period. On more than half of the occasions (63.56%), the subjects selected ‘neutral’ to describe their thermal sensation feelings at that time. The properties of the data cause some difficulties when the using the C-SVC algorithm to develop the personal thermal sensation models for these subjects. First, the models’ predictions will not contain the negative three and positive three as the training samples do not contain these two classes of feelings. The sample sizes for the ‘warm’, ‘slightly warm’ and ‘cool’ classes for some occupants are too small for the algorithm to develop a model which is able to successfully separate these types of feelings. In this case, a simplified version of the thermal sensation models is developed. Based on the structure of the selected data, the simplified version aims to categorise the thermal sensation into two types: the first type of sensation is feeling ‘slightly cold’ or colder; the second type is feeling ‘neutral’ or warmer. It is meaningful to develop the simplified model since the occupants in the environment rarely feel ‘warm’ or even ‘slightly warm’. The outcomes will help the energy management system to make decisions on whether the occupants will feel cold or not. The application of this type of model is demonstrated in Chapter 7.

In order to develop this simplified version of models, the training and testing targets in the samples need to be re-arranged. The thermal feelings ‘neutral’, ‘slightly warm’ and ‘warm’ are regrouped into one class which is labelled ‘zero’. In contrast, the thermal feelings ‘slightly cool’ and ‘cool’ are labelled as ‘negative one’.

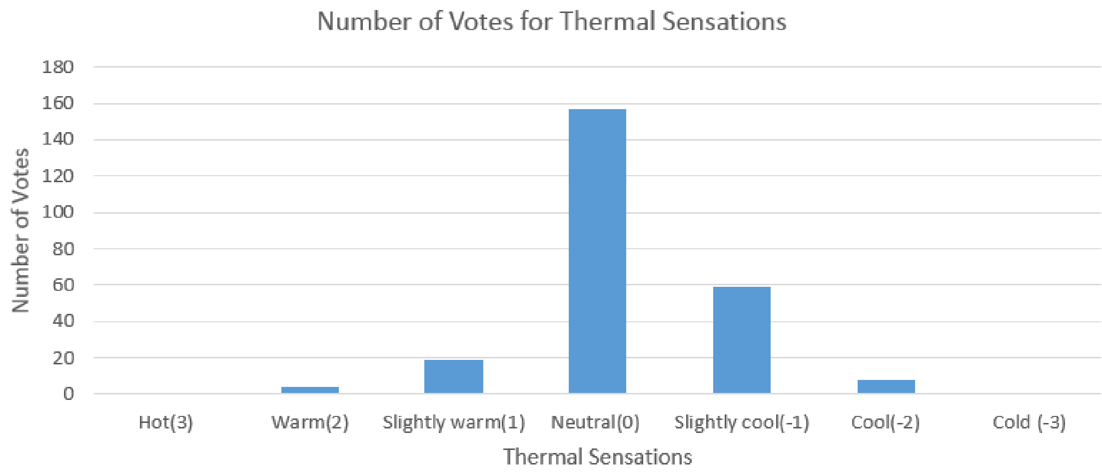


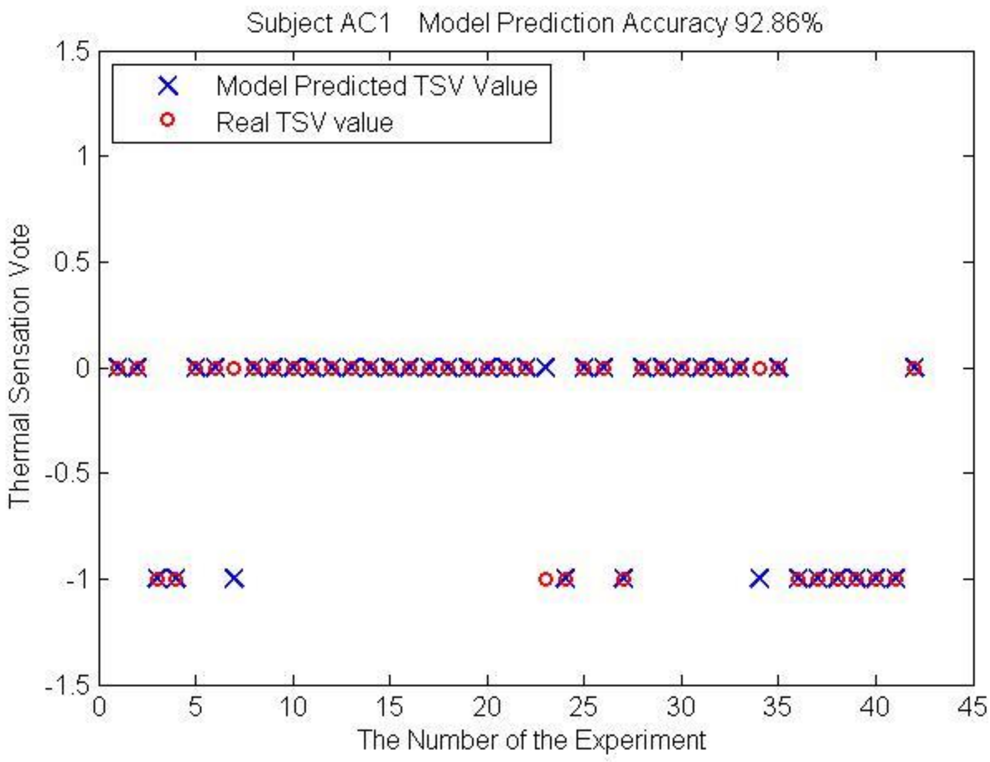
Figure 4.11 Distribution of the votes from the AC environment in the UK

Another issue of the data collected in the UK is that for each subject, the average sample size (41.17 per subject) is around 18 samples smaller than the average sample size of data collected in China (59.95 per subject). Fig. 2.8 shows the total number of effective samples collected from each subject. From the experiences learnt from the modelling process in China and previous research (Rana et al., 2013), around 30 training samples are needed to successfully generate the personal thermal sensation models. For some subjects, if 30 samples are used as the training sample, less than 25% of the data are left as testing data. It is difficult to decide the training group and testing sample group because of the limit of the total sample size. In this case, the leave-one-out cross-validation (LOOCV) method is used to verify the modelling ability of the C-SVC algorithm for the UK data.

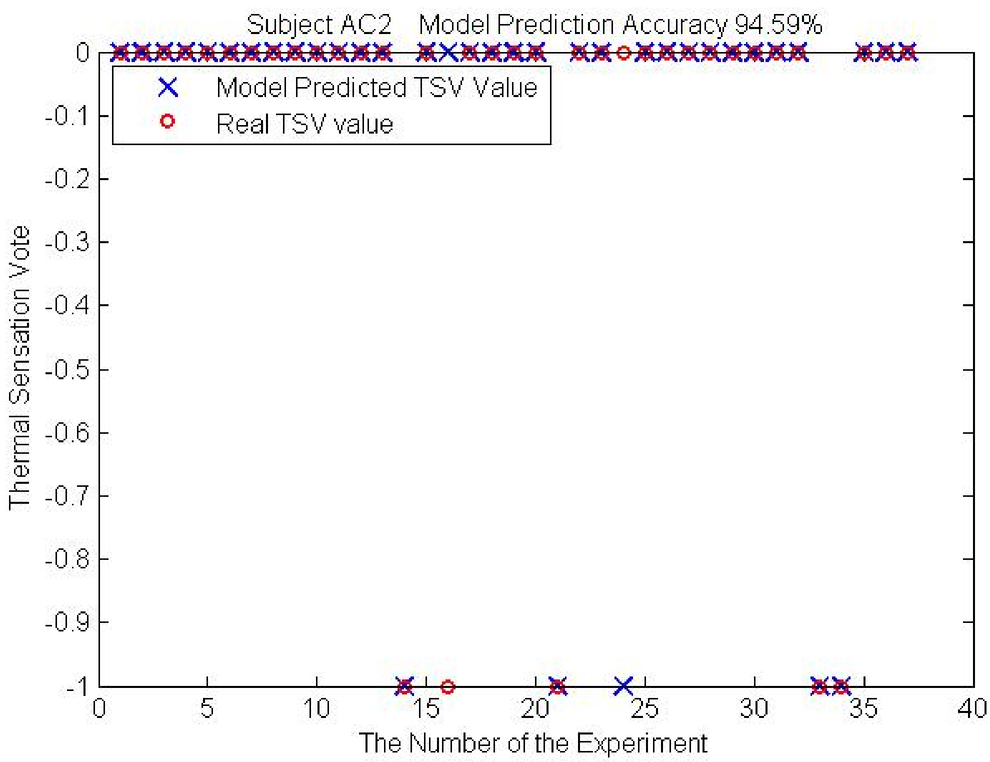
The LOOCV method is actually a type of k-fold cross-validation method, which is used to estimate the performance of the modelling method (Cawley, 2006). The general idea of this method is to leave one sample as the test sample while using the rest of the samples as training samples in every interaction of validation, then the process will be repeated n times until all of the samples become the test sample once and the performance of the modelling method is estimated by the prediction outcomes from all interactions (Russell and Norvig, 2010) (Han et al., 2012). This method is applied when the overall number of samples is limited as it maximally utilises the available data samples (Hopgood, 2000, Bishop, 2006). When generating the models for the decision-making algorithm, all of the effective samples are used as the training samples to guarantee that the performances of the generated models are equivalent to the validation outcomes.

Fig 4.12 depicts the performance of the models for subjects AC1, AC2, AC3, AC4, and AC5. The statistics of the accuracy rates for these five subjects are recorded in Fig.4.13. It should be noted that based on testing outcomes, the modelling algorithm gains a better performance when choosing a linear kernel instead of the RBF kernel when generating the model for user AC2, so the linear kernel instead of the RBF kernel is selected for the subjects. In Fig. 4.13, the average accuracy of the C-SVC developed models is 85.71%. In contrast, the average prediction accuracy of the PMV model for these five subjects is 68.9%.

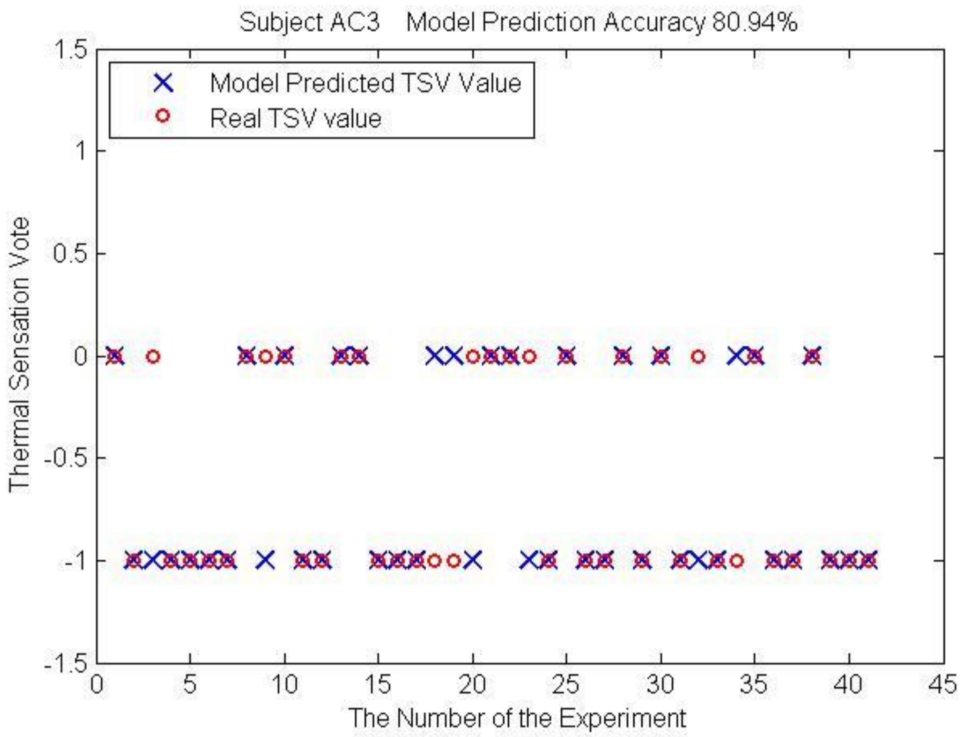
The situation for subject AC6 is special. During the whole experiment period, the reported thermal sensations from the subject are always ‘neutral’. It indicates that this subject has a wide range of thermal comfort zones. The accuracy of the developed model for the subject is 100% because the training and testing samples all belong to one class. It seems that as long as the thermal conditions are within the range of the conditions collected from the field study, the subject’s thermal feeling will be neutral. This special case is not involved in the performance statistics depicted in Fig 4.13.

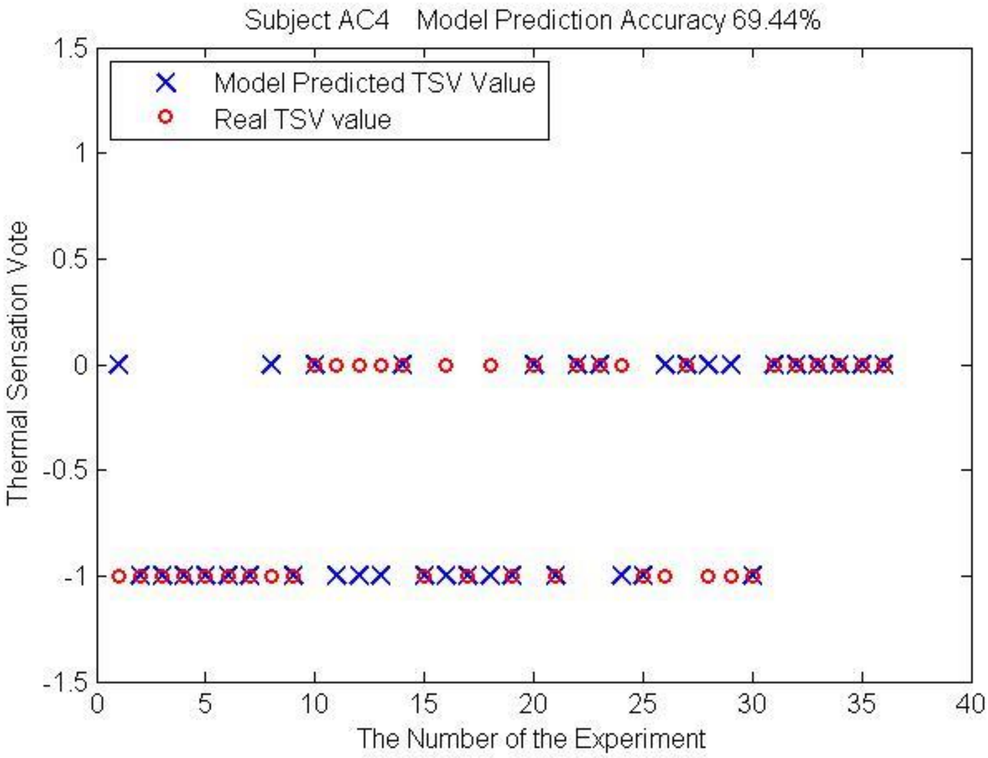


Subject AC1   Model Prediction Accuracy 92.86%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
1.5
1
0.5
0
-0.5
-1
-1.5
0
5
10
15
20
25
30
35
40
45



Subject AC2   Model Prediction Accuracy 94.59%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
-1
0
5
10
15
20
25
30
35
40


Subject AC3 Model Prediction Accuracy 80.94%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
1.5
1
0.5
0
-0.5
-1
-1.5
0
5
10
15
20
25
30
35
40
45


Subject AC4 Model Prediction Accuracy 69.44%
Model Predicted TSV Value
Real TSV value
Thermal Sensation Vote
The Number of the Experiment
1.5
1
0.5
0
-0.5
-1
-1.5
0
5
10
15
20
25
30
35
40

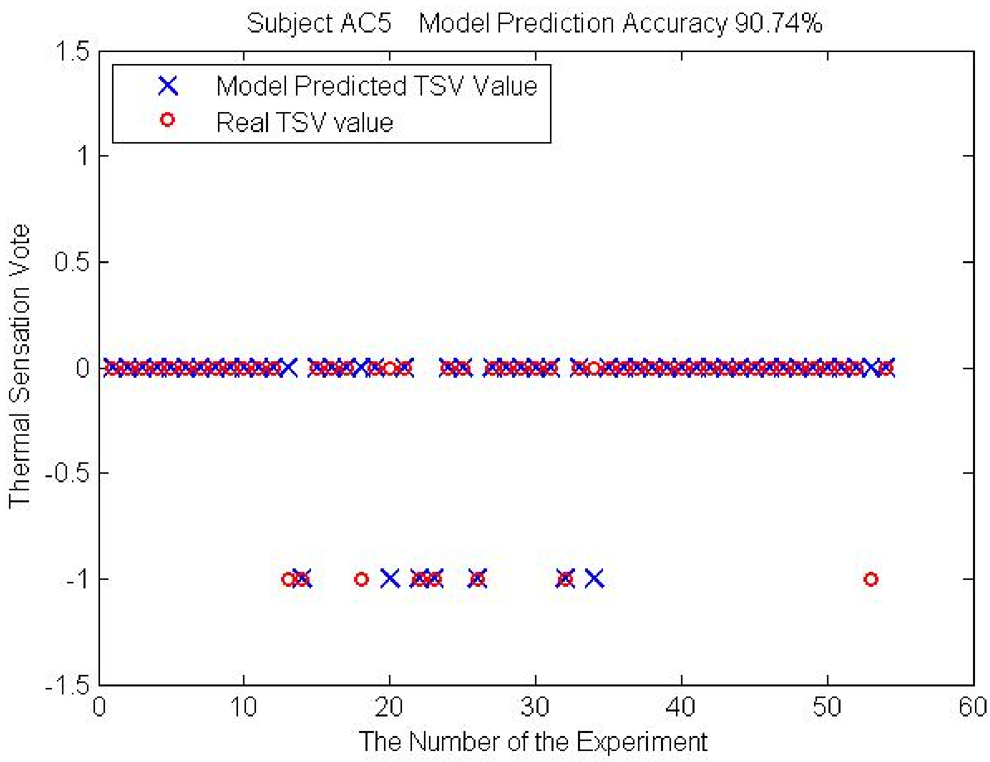


Figure 4.12 Models predicted TSV vs. subjects' actual TSV for UK subjects

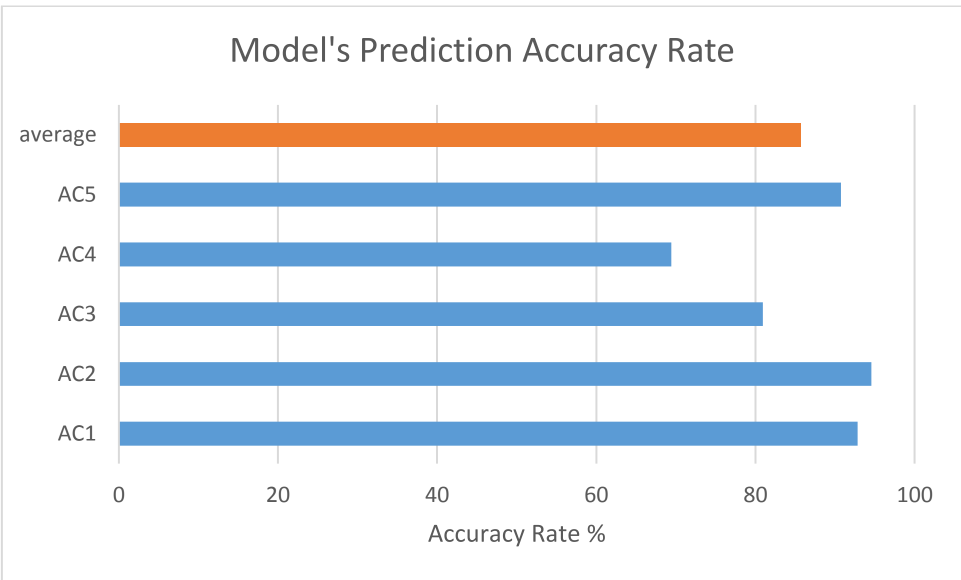


Figure 4.13 Model's prediction accuracy rates (UK Data)

For subjects AC1 and AC3, the experiment results indicate that models outputting more detailed results can be developed. The developed models target the occupants' real sensation votes without any simplification. Similar to the data process procedure for the Chinese data, the target output follows the ASHRAE seven-point thermal sensation scale. The performance of the developed models is shown in Fig 4.14 and Fig 4.15 separately. The validation outcomes indicate that the prediction accuracies of the developed models are higher than 70%.

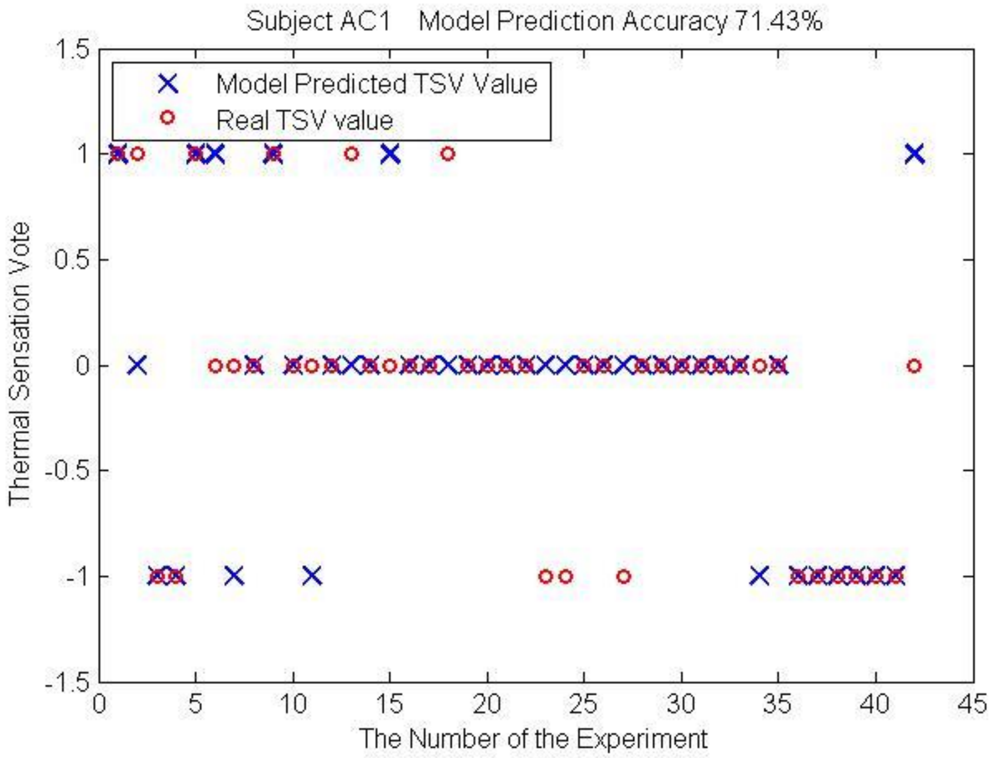


Figure 4.14 Model Predicted Thermal Sensation Level vs. subjects' actual TSV for subjects AC1 (ASHRAE Seven Point-scale)

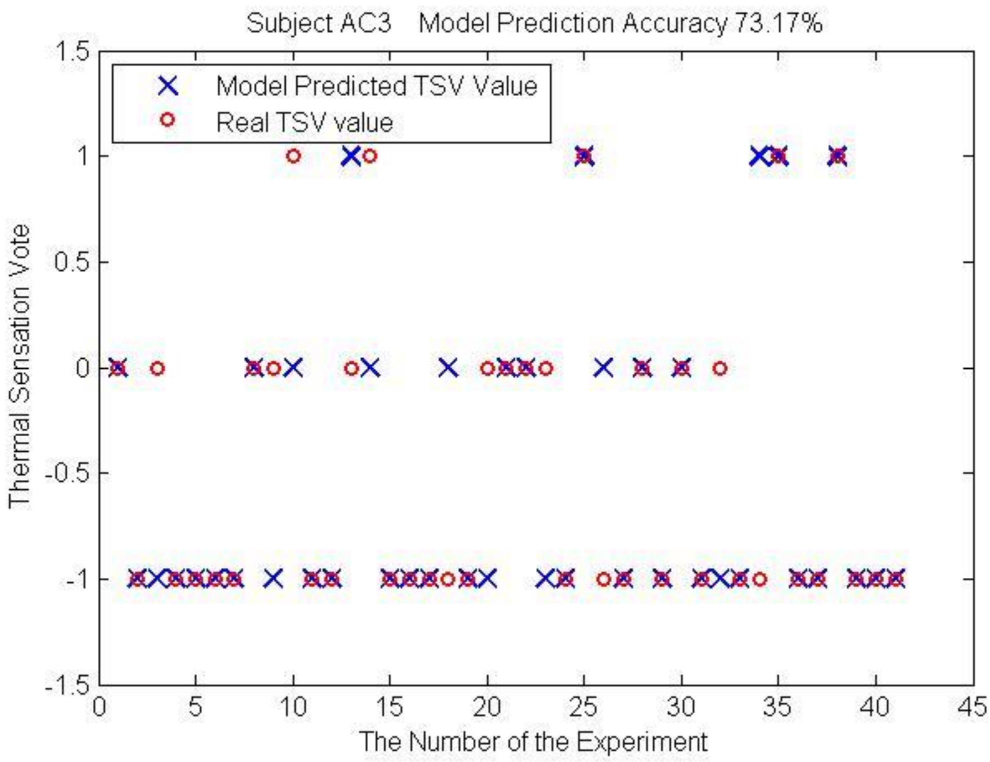


Figure 4.15 Model predicted Thermal Sensation Level vs. subjects' actual TSV for subjects AC3 (ASHRAE Seven Point-scale)

4.8 Summary

This chapter presents a C-SVC method of modelling personal thermal sensations. The modelling method has been verified using the experimental data collected in an HVAC-supplied indoor environment with real thermal sensation votes from twenty subjects in China and six subjects in the UK. For the Chinese subjects, the developed model aimed to directly reflect the thermal sensation level without any simplification assumption. The average rate of prediction accuracy of these models is above 89%. For UK subjects, because of the data structure, simplified output targets were set; however, the model prediction accuracy exceeded 85%. The results of this study indicate that the modelling problem can be regarded as a classification problem in the context of machine learning. The developed models can realistically reflect the occupant's thermal sensation and expectation. It is argued that people's thermal sensation could vary from season to season; the C-SVC algorithm can be re-developed on a seasonal basis in order to fully reflect the dynamic adaptation of humans.

Ideally, the method will be used in an energy management system to control HVAC system operations in the built environment. The system embeds the C-SVC algorithm to perform personal thermal sensation modelling using the stored data sets and to predict thermal sensations. Once the model has been trained and verified, the thermal sensation information will be predicted. With the help of the modelling algorithm and the developed model, the decision-making scheme of the energy management system will be able to calculate the set points for the HVAC system controller while providing personalised services to each individual occupant by understanding his/her thermal demands. Being guided by detailed thermal information, the energy management system may be able to save energy while improving the thermal conditions for occupants under certain circumstances. The applications of the C-SVC method based models are illustrated in Chapter 7.

Chapter 5 : Developing a Thermal Comfort Model for a Group of People in an Air-Conditioned Office

5.1 Introduction

In an open-plan office, the space is usually occupied by a number of people, whose thermal sensation could vary from one person to another. The question is how the HVAC system can satisfy the majority of the occupants. To solve this issue, there is a need to understand the occupants' thermal expectations and provide the most acceptable operational guidance to the system.

It is commonly accepted that individuals have different thermal sensations and thus expectations. The temperature setting in an open-plan office could be challenging as, if it is not properly determined, it could lead to individuals' thermal dissatisfaction and energy wastage. Therefore, it is necessary that the BEMS in this research employs the thermal sensation models based on a group of people to predict the thermal comfort level of a particular group in real-time. A realistic estimation of the actual thermal sensations of the group of people is essential to the energy management of buildings because, in the context of improving thermal comfort while achieving energy efficiency, an incorrect estimation could lead to thermal discomfort and/or energy wastage. For example, 1℃ environmental temperature difference may lead to 10% energy usage variations for HVAC systems (Humphreys and Hancock, 2007). However, the modelling method to generate the model for the thermal sensation of a group of people is still under investigation.

The aim of this chapter is to develop a thermal comfort model for a group of people that the HVAC system is serving and to provide information to the energy management system for an optimal control. In this chapter, the modelling methods, which generate the models to help the HVAC system to make decisions on its set points are reviewed. Then, the support vector regression (SVR) method is selected to generate the model for the thermal sensation of a group of people. The performances of models generated by the SVR method are verified by the data collected from the experimental studies.

5.2 **Literature Review**

The ASHRAE 55 and ISO7730 standards adopt the PMV/PPD (predict mean vote/predicted percentage dissatisfied) index to define the thermal comfort conditions (ANSI/ASHRAE55-2010, 2010, ISO7730, 2005). The PMV index is based on a physical heat balance model and its predictions are derived from four environmental parameters: air temperature, mean radiant temperature, relative humidity and air velocity and two personal parameters: clothing and activity level (Fanger, 1970) (Olesen, 2000). The PMV/PPD index has been widely applied to estimate occupants' thermal sensations in order to provide control guidelines for HVAC systems (Calvino et al., 2004, Hwang and Shu, 2011, Hornod et al., 2012, Cigler et al., 2012). However, a number of researchers revealed that the PMV/PPD index may not accurately reflect the occupants' actual thermal sensations in certain air-conditioned environments (de Dear and Fountain, 1995, Karyono, 1995, Humphreys and Nicol, 2002, Indraganti et al., 2013). This may be caused by the PMV index being unable to consider occupants' adaptions to the environment (Nicol and Humphreys, 2002).

Besides the physical model, a type of method to generate a thermal sensation model for a group of people by first of all understanding the thermal sensation from each individual, then estimating the overall thermal comfort level of the whole group of people can be calculated from the individuals' predictions. The simplest model of this type assumes all the people in the same environment have the same temperature preferences (Davidsson and Boman, 2005). To consider the individual differences, the individuals' thermal comfort levels can be predicted by individual thermal comfort models. The research from (Yang and Wang, 2013b) assumes that an occupant's thermal comfort levels can be expressed as a 'Gaussian Function' in which the mean value is the 'maximum comfort temperature'. The overall comfort level of a group of people is derived from a function that calculates the mean value of the weighted sum of all the individual comfort levels. It can be found that this method uses zone temperature as the only input factor of the personal comfort models. The validation of the model's predictions is not fully discussed in this paper.

People's thermal sensation models can also be directly developed from the environmental data, personal data and thermal sensation votes collected from the field study without generating individuals' thermal sensation models first. A regression-based modelling method is used to match the input factors, such as environmental factors and personal factors, with the thermal sensations, which are the model's outputs. One research study concluded that regression modelling methods are based on the black box theory (Kariminia et al., 2016), which is specified in Yao et al. (2009). The regression-algorithm-based modelling scheme tends to propose the structure of the thermal comfort model equations with undefined coefficients first, then it uses the regression method to decide the coefficients' values (de Dear and Brager, 1998) (McCartney and Nicol, 2002, Yao et al., 2009, Singh et al., 2011, Yang et al., 2015, Harimi et al., 2015). The models generated by these researchers are all used to estimate the thermal sensation of a large number of people, not for a particular group of people.

Modelling methods based on machine learning are also applied for the development of a thermal comfort model for a group of people. The Extreme Learning Machine (ELM) is used to develop models to predict the thermal sensations of outdoor subjects (Kariminia *et al*., 2016). For indoor naturally-ventilated environments, an Artificial Neural Network (ANN) is suggested to develop people's thermal sensation models (Li *et al*., 2012). It is interesting to see that ANN and support vector regression (SVR) have also been applied to developed models to approximate PMV values in a built environment (Megri et al., 2005, Ferreira et al., 2012, Castilla et al., 2013). In these studies, PMV values are regarded as people's true thermal sensation levels. It has been discussed that PMV sometimes may not accurately assess people's thermal sensations, but the above research proves that by using a group of people's thermal sensation vote values to replace the PMV values, the machine learning algorithm is technically able to generate the model for the thermal sensation of this group of people. Compared to the traditional regression method, machine-learning-based algorithms do not need to formulate the model function in advance.

From the review, it can be found that there are two types of method potentially able to generate a model for the thermal sensation of a group of people. The first method is applying the personal thermal sensation models. Then, the mean thermal sensation votes are calculated from the outcomes of the predictions from the personal thermal sensation models. The second method applies the modelling method based on machine learning technologies.

In this chapter, both the methods are used to develop a model for the thermal sensation of a group of people. In the first method, the personal thermal sensation models have been introduced in Chapter 4. In the second method, the SVR algorithm is applied to generate the model. The models are generated and tested using the data collected from the experimental studies.

5.3 Research Method

5.3.1 Group-of-People-based Thermal Sensation Model Developed using Personal Thermal Sensation Models

This section introduces the method which generates the model for the thermal sensation of a group of people from personal thermal sensation models. For brevity, this modelling method is called the personal-model-based method. Fig. 5.1 is the diagram which illustrates the modelling process for this method. Assuming that n subjects in the built environment are labelled from AC1 to ACn. The developed personal thermal sensation model for subject ACi is represented by 'Personal Thermal Sensation Model ACi', i= 1,2,…n. The input parameters include four environmental parameters and two personal factors.

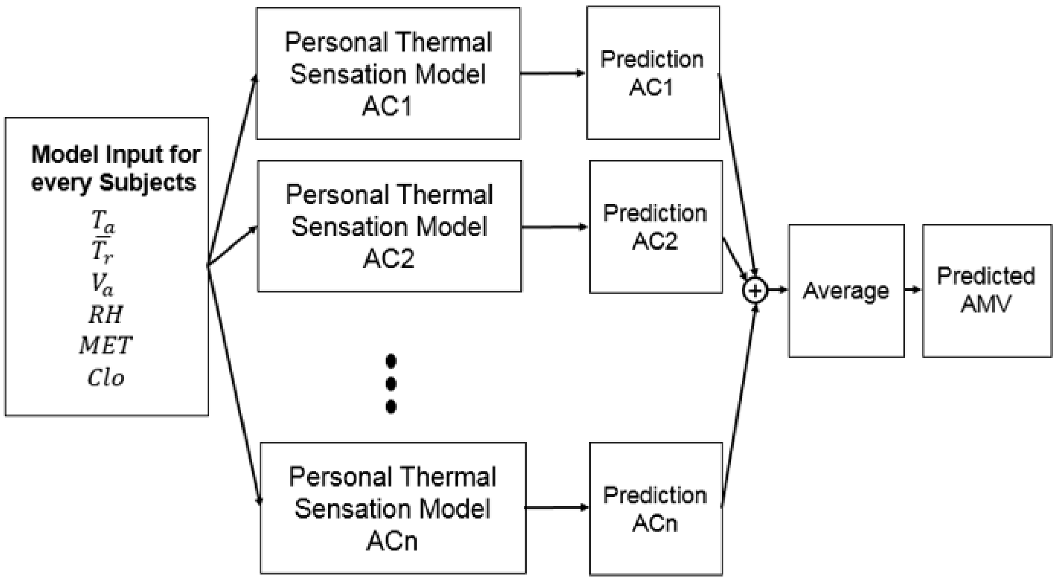


Figure 5.1 The Prediction Process of the Model Developed by Method One

It is assumed that all occupants' thermal sensations are equally important. Let PACi represent the output of the personal thermal sensation model ACi. The predicted actual mean vote (AMV) can be expressed as:

$$AMV = \frac{1}{n}\sum_{i=1}^{n} PACi \qquad (5.1)$$

5.3.2 The Group-of-People-based Thermal Sensation Model Based on the SVR Algorithm

5.3.2.1 SVR Algorithm

The second method directly derives the thermal sensation model based on the SVR algorithm from the real thermal sensation votes of a group of people along with personal factors and environmental data collected from the field study. SVR is a modelling method from machine learning. Differing from the C-SVC method introduced in Chapter 4, it is a regression algorithm based on the support vector machine, which has been used for developing regression models by a number of researchers (Li et al., 2009, Edwards et al., 2012, Jain et al., 2014).

The introduction of the basic principle of SVR can be found in Vapnik (1999) and Haykin (1999), which is included in this section from formula 5.2 to formula 5.16. Assuming the total number of data sets is N, the input-output pairs can be expressed as ($\bar{u}_i$, y_i); $i = 1,2, \ldots N$. Let M be the total number of training samples. The input vector $\bar{u}_i$ contains environmental parameters and personal factors. The targeted output y_i only contains one element, which is the thermal sensation value under the circumstance, which is defined by $\bar{u}_i$. Let z_i represent the output value of the developed regression model when the input vector is $\bar{u}_i$. By considering the kernel function defined in equation (4.16), the relationship between the output and the input pair can be expressed as:

$$z_i = \bar{\omega}^T \emptyset(\bar{u}_i) + b \qquad (5.2)$$

The ϵ-insensitive loss function $L_{f\epsilon}$ can be expressed as (Vapnik, 1999):

$$L_{f\epsilon}(y,z) = \begin{cases} |y-z| - \epsilon, & when\ |y-z| \geq \epsilon \\ 0, & otherwise \end{cases} \qquad (5.3)$$

The relationship between $y - z$ and $L_{f\epsilon}$ is depicted in Fig. 5.2. Then, the problem the regression algorithm needs to solve is minimising the empirical risk ER:

$$ER = (\textstyle\sum_{i=1}^{M} L_{f\epsilon}(y_i, z_i))/M \qquad (5.4)$$

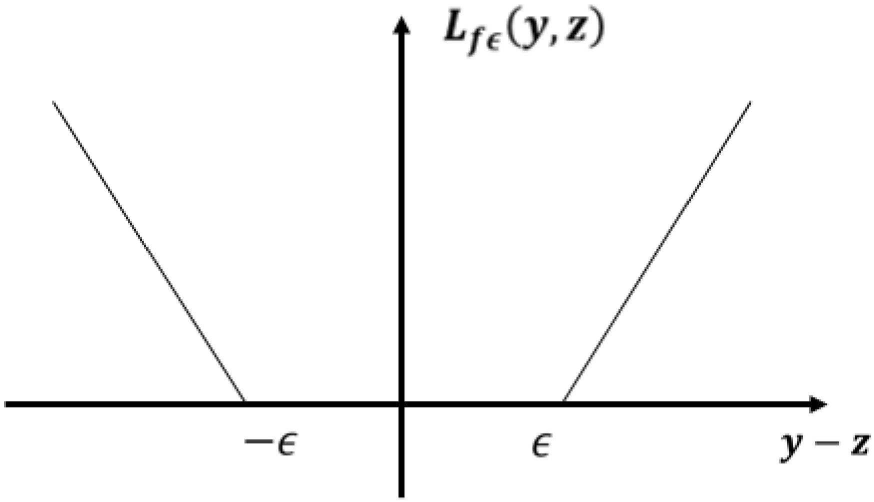


Figure 5.2 ϵ-insensitive loss function (Haykin, 1999)

The ϵ-insensitive loss function can be reformed by introducing positive slack variables which are defined as in Xi et al. (2007):

$$L_{f\epsilon}(y,z) = \xi_i + \xi_i'; \quad (5.5)$$

$$\begin{cases} \xi_i = \mathrm{z_i} - \mathrm{y_i} > 0;\ \xi_i' = 0; when\ \mathrm{z_i} - \mathrm{y_i} > \epsilon \\ \xi_i' = \mathrm{y_i} - \mathrm{z_i} > 0;\ \xi_i' = 0; when\ \mathrm{y_i} - \mathrm{z_i} > \epsilon \\ \xi_i = \xi_i' = 0 \quad\quad\quad otherwise \end{cases} \quad (5.6)$$

Then the minimising problem can be converted into:

$$\min_{\bar{\omega},b,\xi,\xi'} \frac{1}{2}\bar{\omega}^{\mathrm{T}} \cdot \bar{\omega} + \mathrm{C}\sum_{\mathrm{i=1}}^{\mathrm{M}} \xi_i + \mathrm{C}\sum_{\mathrm{i=1}}^{\mathrm{M}} \xi_i' \quad (5.7)$$

Subject to is $\bar{\omega}^T\varphi(\bar{u}_i) + b - \mathrm{y_i} \leq \epsilon + \xi_i$ (5.8)

$$\mathrm{y_i} - \bar{\omega}^T\varphi(\bar{u}_i) - b \geq \epsilon + \xi_i' \quad (5.9)$$

$$\xi_i \geq 0;\ i = 1,2,\dots,M \quad (5.10)$$

$$\xi_i' \geq 0; i = 1,2,\dots,M \quad (5.11)$$

C is a positive regularization parameter. By defining the Lagrangian function, the dual problem of the regression problem is (Megri *et al*., 2005, Rana *et al*., 2013):

$$\max_{l,l'} -\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}(l_i - l_i')\,(l_j - l_j')\,K(\bar{u}_i,\bar{u}_j) - \epsilon\sum_{i=1}^{M}(l_i + l_i') + \sum_{i=1}^{M}\mathrm{y_i}(l_i - l_i')$$

(5.12)

Subject to: $\sum_{i=1}^{M}(l_i - l_i') = 0$ (5.13)

$$0 \leq l_i \leq C, i = 1,2,\dots M \quad (5.14)$$

$$0 \leq l_i' \leq C, i = 1,2, \ldots M \qquad (5.15)$$

In Formula 5.13, l_i and l_j' are Lagrangian multipliers. Finally, the output regression function can be expressed as:

$$\mathrm{H}(\bar{u}) = \sum_{i=1}^{M}(-l_{io} + l_{io}')K(\bar{\mathrm{u}}_i, \bar{u}) + b_o \qquad (5.16)$$

In this research, the ϵ-support vector regression (ϵ-SVR) tool, which is provided by the LibSVM library for Matlab software (Chang and Lin, 2011), is used to realise the SVR algorithm described above.

5.3.2.2 The Modelling Process based on SVR

The modelling process based on method two is illustrated in Fig. 5.3. The inputs of the modelling algorithm are environmental factors, personal factors and occupants' thermal sensation votes collected from the field study. The developed MATLAB program will automatically collect the input data from the database and input them into the modelling algorithm, then save the developed thermal sensation models.

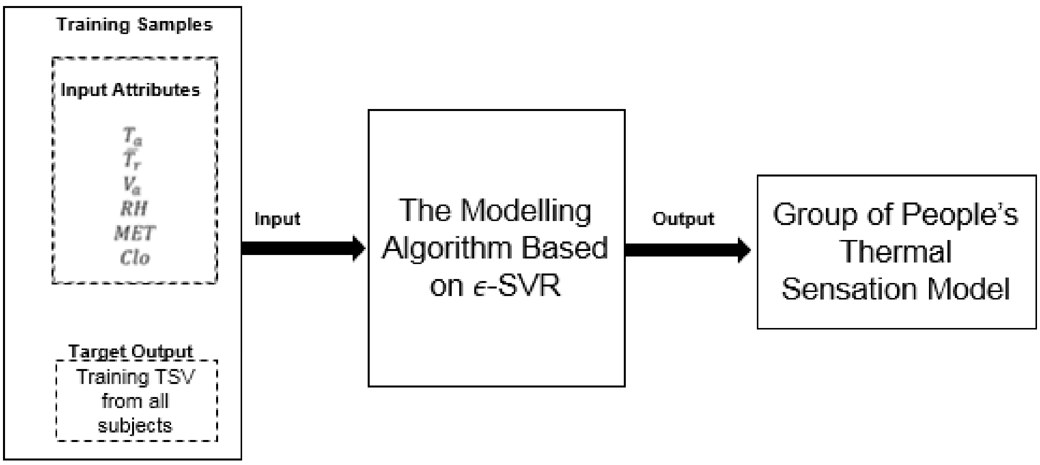


Figure 5.3 The Modelling Process Based on the SVR algorithm

5.3.2.3 SVR-developed Model's Prediction Process

The model prediction process of the model developed from modelling method two is depicted in Fig. 5.4. Unlike the model developed by method one, the SVR algorithm developed a model to directly output the predicted AMV values.

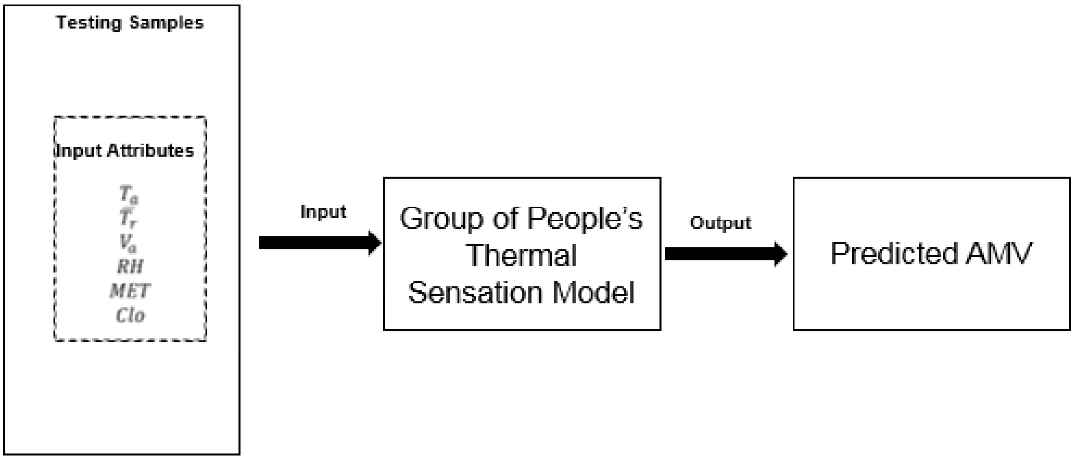


Figure 5.4 The Prediction Process of the Model Developed by the SVR algorithm

5.4 Verification of the Developed Models

5.4.1 Data Used for Training and Testing

In this section, the performance of both modelling methods is discussed. There are two sets of data available for model development: data collected from the 20 subjects in the controlled environment in Chongqing, China, and the data collected from the six subjects in the air-conditioned office at the University of Reading, UK. The data from China and the UK are named as data set one and data set two for short. The data structure and data collection process have already been introduced in Chapter 2.

5.4.2 Thermal Comfort Models Developed from Data Set One

Firstly, the personal-model-based method is used to develop a thermal comfort model from data set one. Section 5.3.1 illustrates that key elements of the method are the developed personal thermal comfort models and the personal thermal sensation models for 20 Chinese subjects, as discussed in section 4.5. These models have already been developed and verified in Chapter 4. The predictions of the developed models are processed by the procedure shown in Fig. 5.1. The mean value of all the predictions from the personal models is regarded as the outcome of the thermal sensation model.

In Chapter 4, it is explained that data set one is divided into two parts. The first part is the training data, which is used to generate the personal thermal sensation models. The second part is used for test purposes. In this chapter, the same testing data can be used again to evaluate the performance of the developed group-of-people-based thermal sensation models. As the predicted target is the actual mean vote (AMV), the bin method is applied here to calculate the value of the actual mean thermal sensation vote. The bin method is used for similar purposes in previous research (de Dear and Brager, 1998, Yang et al., 2015). The method here is realised by the average of the predicted values and the corresponding real sensation values in a range of 0.5 of an ASHRAE scale unit. The fit between the average predicted thermal sensation values and the AMVs is illustrated in Fig. 5.5.

LibSVM developers have applied the mean squared error (MSE) to evaluate the performance of the developed regression models, which is defined in Chang and Lin (2011):

$$\text{MSE}=\frac{1}{M}\sum_{i=1}^{M}(z_i - a_i)^2 \qquad (5.17)$$

In Equation 5.17, z_i is the model predicted value and a_i is the Thermal Sensation Votes collected from the experiment. A smaller value of the MSE means a higher accuracy rate for the model.

In this research, the mean square error (MSE) is used to indicate the accuracy of models. The MSE of the predictions from the group-of-people-based thermal sensation models developed by the personal-model-based algorithm is 0.1149 and it is smaller than that obtained by the PMV model which is 0.4126. This means the performance of the generated model is better than the performance of PMV.

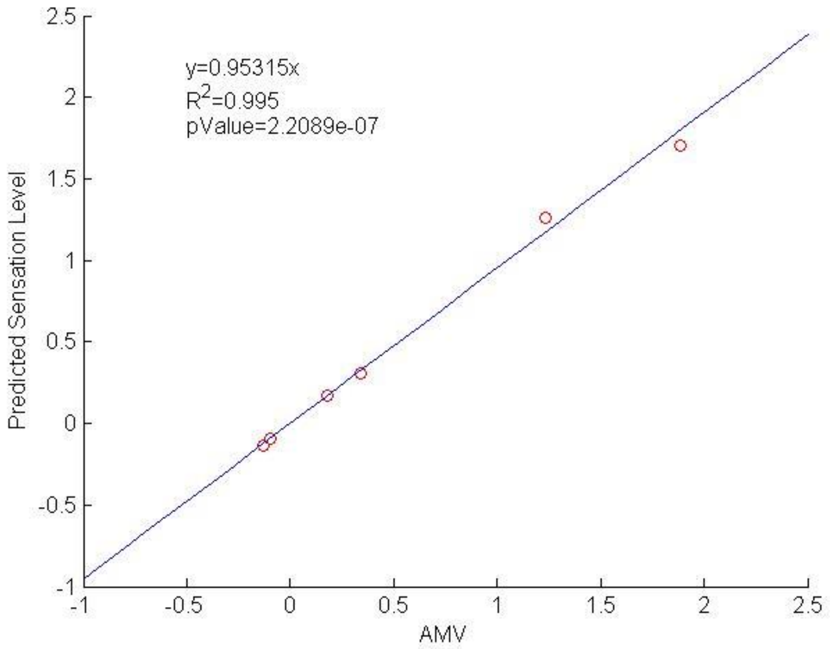


Figure 5.5 The Fit between AMV and Model-predicted Values (Personal-Model-Based Method, Data Set One. Test Data)

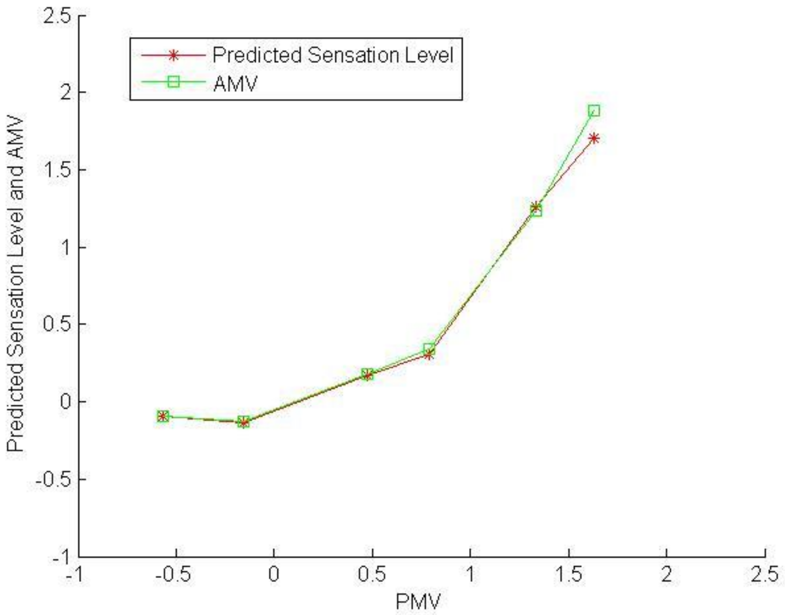


Figure 5.6 Model-predicted Values and AMV against PMV (Personal-Model-Based Method, Data Set One, Test Data)

The developed model is further verified following a process similar to the one proposed in Schumann et al. (2010). The absolute differences between the binned predicted values and the AMV is calculated. It is suggested that the difference between the Model-predicted Values and the occupants' actual mean thermal sensation votes should be smaller or equal to 0.25 (Humphreys and Nicol, 2002). Fig.

5.6 shows the relationship between the predictions and the actual values. The absolute differences between the predictions and the actual mean values are illustrated in Table 5.1. All of the differences are smaller than 0.25.

Table 5.1 The Absolute Error of the Predictions (Personal-Model-Based Method, Data Set One)

AMV Point	One	Two	three	four	Five	six
Absolute Difference	0	0.0062	0.0094	0.0303	0.0323	0.1765

The SVR method is also applied to develop the group people-based thermal sensation model. The model training process is illustrated in Section 5.3.2. The model is generated by the training data set. The linear kernel, polynomial kernel, radial basis function (RBF) kernel and the sigmoid kernel can be chosen to realise Formula 5.2. The developed models' predictions are tested by the test data set. The targeted AMV values are also calculated by using the bin method described above. In order to compare with the target AMV, the model-predicted results are also binned using the same bin method. Fig. 5.7, Fig. 5.9, Fig. 5.11 and Fig. 5.13 show the fit between the predictions of SVR-based models with a linear kernel, polynomial kernel, radial basis function (RBF) kernel and sigmoid kernel predictions and the AMV values. Fig. 5.8, Fig. 5.10, Fig. 5.12 and Fig. 5.14 depict the relationship between the binned predating values and the AMV against the PMV. These pictures illustrate that models developed from different kernels give different performances.

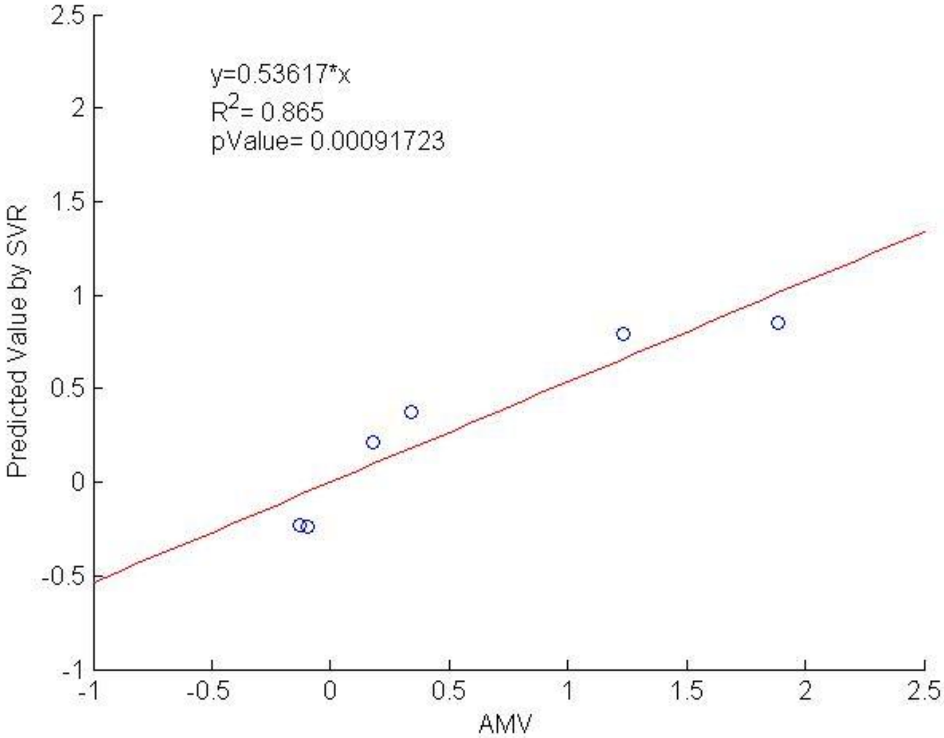


Figure 5.7 The Fit between AMV and Model-Predicted Values (SVR Method with Linear Kernel, Data Set One Test Data)

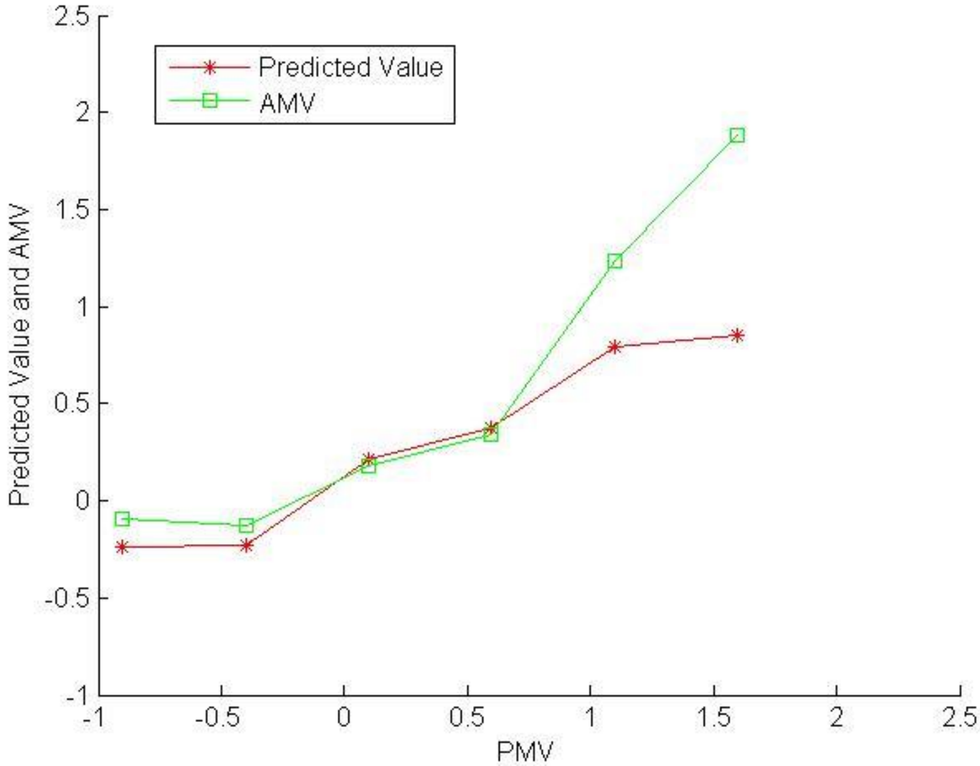


Figure 5.8 AMV and Model-predicted Values aginst PMV (SVR Method with Linear Kernel, Data Set One Test Data)

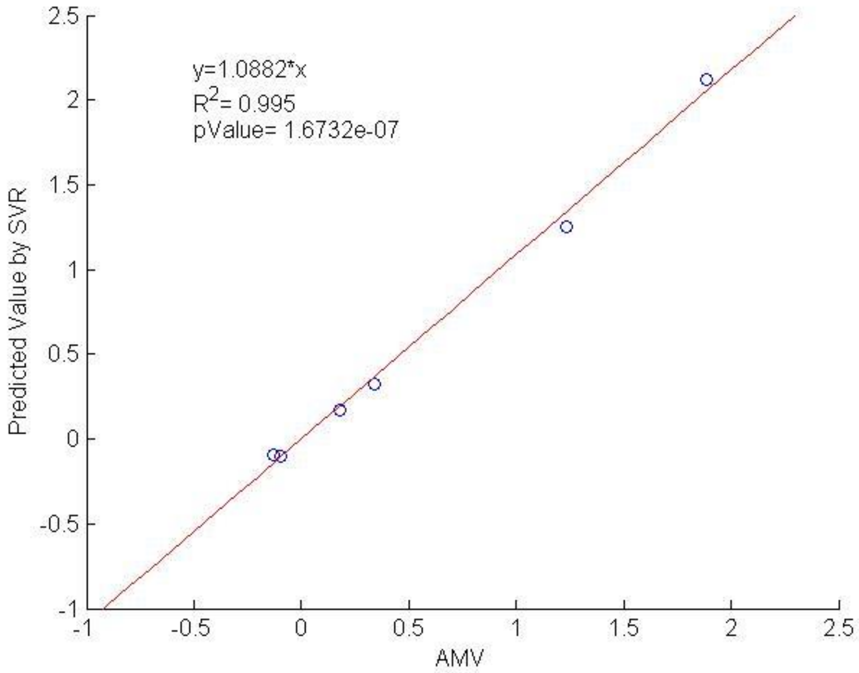


Figure 5.9 The Fit between AMV and Model-Predicted Values (SVR Method with Polynomial Kernel, Data Set One Test Data)

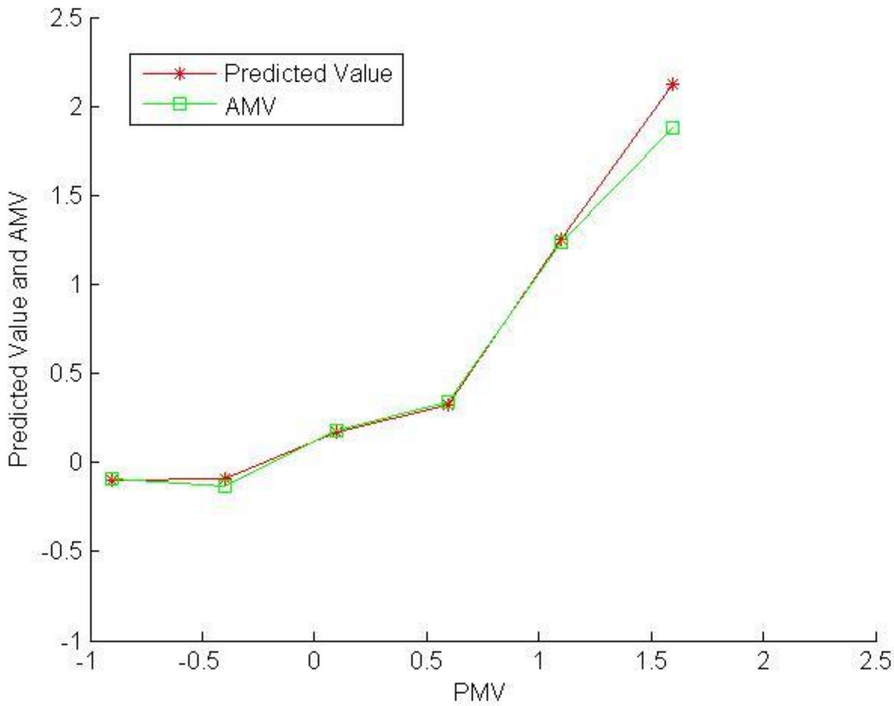


Figure 5.10 AMV and Model-Predicted Values aginst PMV (SVR Method with Polynomial Kernel, Data Set One Test Data)

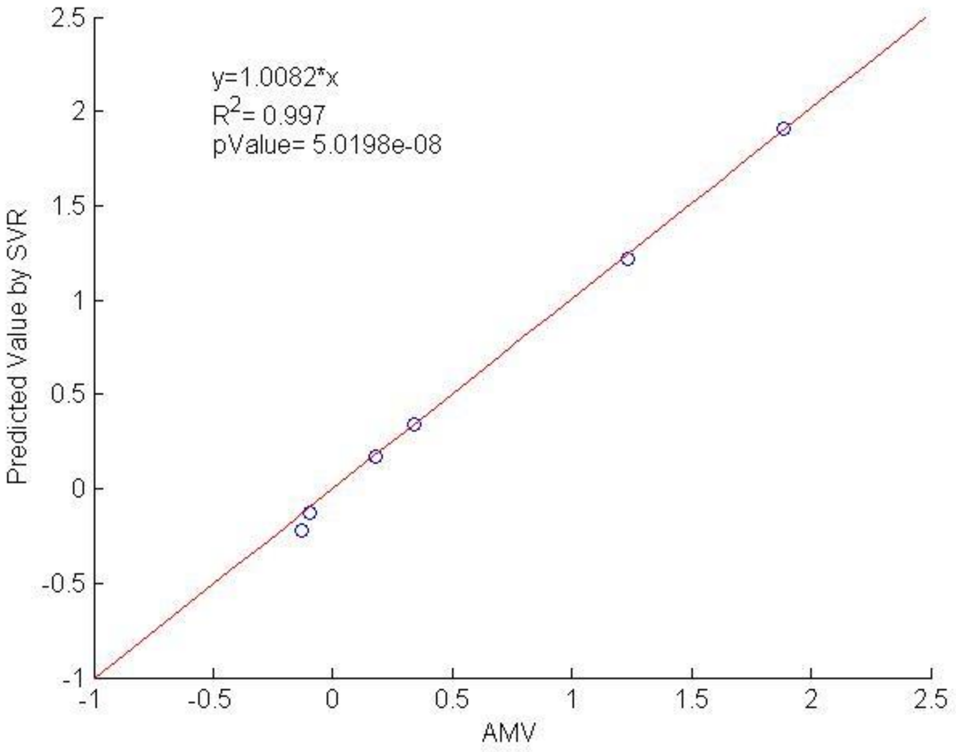


Figure 5.11 The Fit between AMV and Model-predicted Values (Method Two with RBF Kernel, Data Set One Test Data)

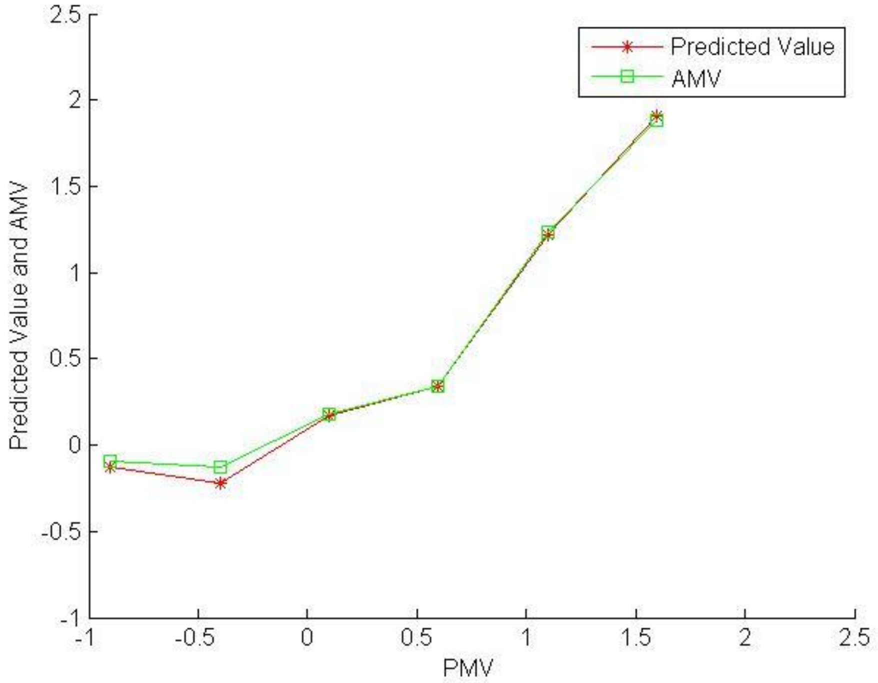


Figure 5.12 AMV and Model-predicted Values aginst PMV (Method Two with RBF Kernel, Data Set One Test Data)

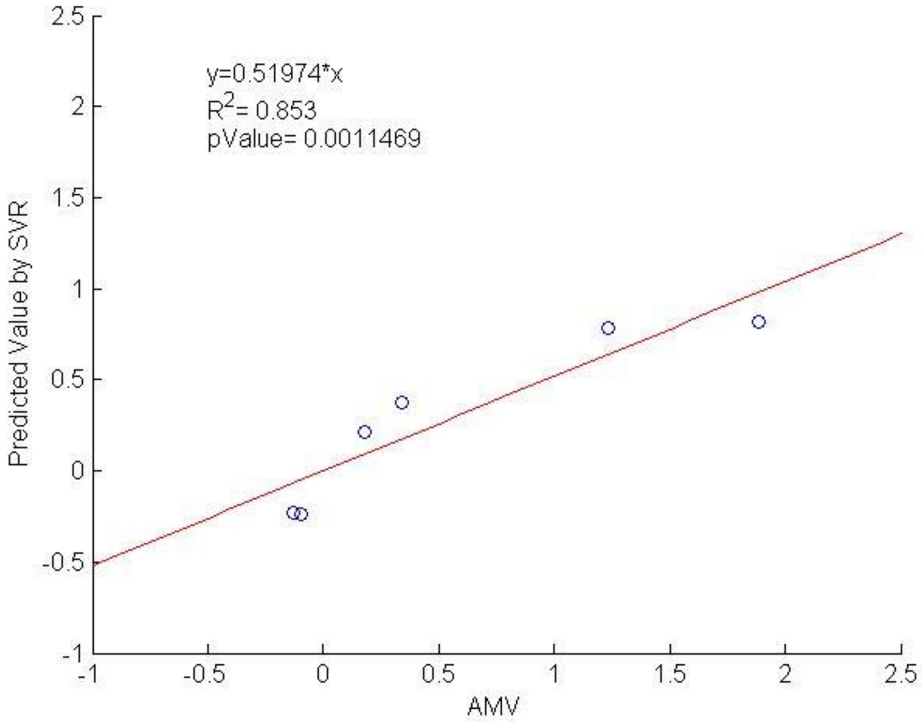


Figure 5.13 The Fit between AMV and Model-predicted Values (Method Two with Sigmoid Kernel, Data Set One Test Data)

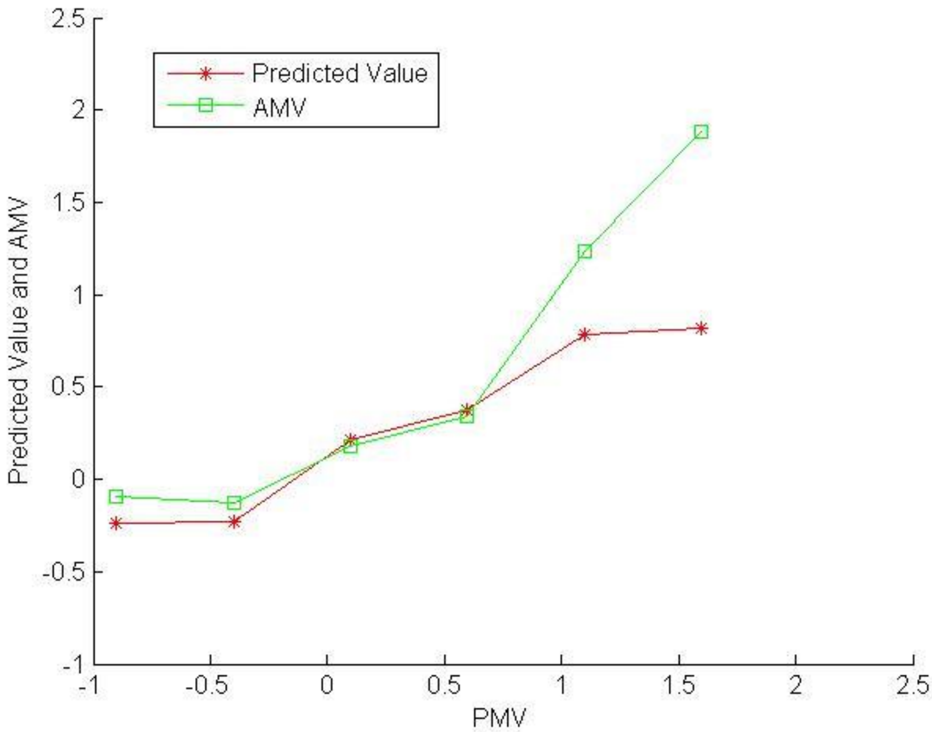


Figure 5.14 AMV and Model-predicted Values aginst PMV (Method Two with Sigmoid Kernel, Data Set One Test Data)

Table 5.2 illustrates MSE values of predictions from the SVR method with four types of kernels. Compared with the performance of the PMV index, which has an MSE of 0.4210, the performances of SVR with a linear kernel and a sigmoid kernel are even worse than the performance of PMV. In contrast, the performances of the polynomial kernel and RBF kernel are better than that of PMV. It can be found that the RBF kernel gives the best testing results among all the kernels. In this case, SVR with RBF kernel is selected as the modelling method for data set one when applying method two. Table 5.3 illustrates the absolute error of the predictions by using the method. It also can be concluded that it is necessary to perform kernel selection before the SVR-based model is developed.

Table 5.2 MSE Values of SVR Models with Different Kernels (Data Set One)

Kernel Name	Linear	polynomial	RBF	sigmoid
MSE Values	0.4449	0.2851	0.2831	0.4538

Table 5.3 The Absolute Error of the Predictions (SVR with RBF Kernel, Data Set One)

AMV Point	One	two	three	four	five	six
Absolute Error	0.0336	0.0912	0.0076	0.0038	0.0128	0.0232

5.4.3 Thermal Comfort Models using Data Set Two

The testing results from the last section prove that both the personal-model-based method and the SVR method are capable of developing thermal sensation models for a group of people in the same environment. In this section, only the SVR algorithm is used to develop the group-of-people-based thermal sensation model from data set two. The main reason is because of the limit of the training samples, the personal thermal sensation models developed from data set two, are simplified models. For some of the occupants, the personal model only predicts if they are feeling cold or not. In this case, being integrated with the personal thermal sensation models, the developed group-of-people-based thermal sensation model cannot replicate the group's thermal feelings in warm conditions. As a result, performances presented here are only the ones from the models developed by the SVR algorithm by using data set two.

As discussed in the last section, besides the other parameters, the kernel function affects the accuracy of the models developed by the SVR algorithm. So, for data set two, firstly the performances of the different kernel functions are compared. Similar to the process carried out for data set one, half of the data in data set two are used as the training sample and the remainder is used as testing samples. The SVR-based models are generated with different kernels by using the training data set, then the models are tested by the test data set. The predicted outcomes and the collected thermal sensation vote data from test samples are processed by the same bin method as the one used in section 5.4.2. The performances of all four kernel functions are depicted in Fig. 5.15, Fig. 5.16, Fig. 5.17, Fig. 5.18, Fig. 5.19, Fig. 5.20, Fig. 5.21 and Fig. 5.22.

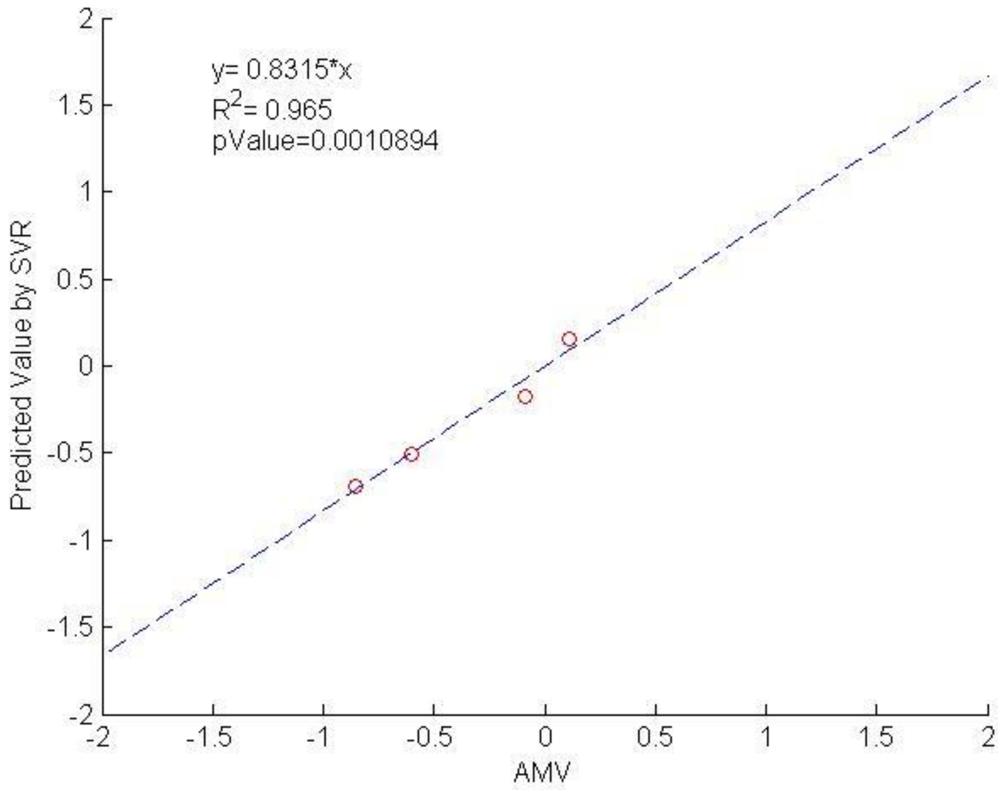


Figure 5.15 The Fit between AMV and Model-predicted Values (SVR Method with Linear Kernel, Data Set Two Test Data)

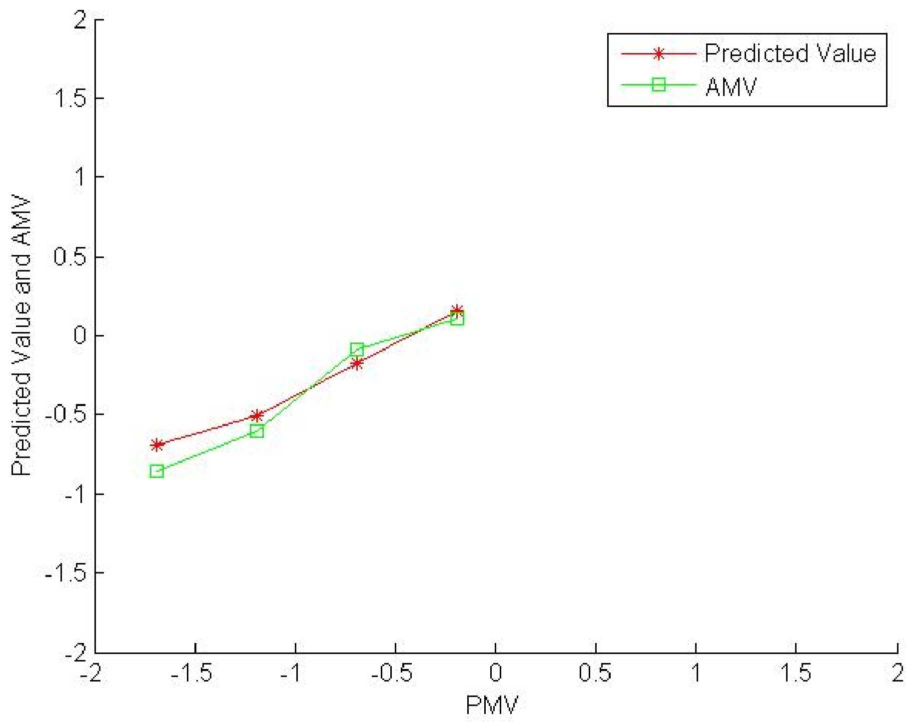


Figure 5.16 AMV and Model-predicted Values aginst PMV (SVR Method with Linear Kernel, Data Set Two Test Data)

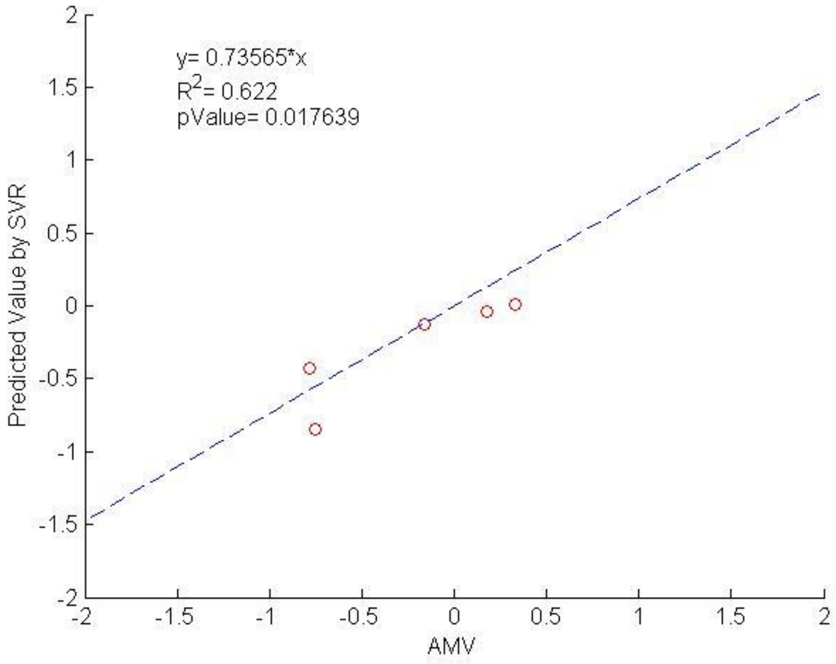


Figure 5.17 The Fit between AMV and Model-predicted Values (SVR Method with Polynomial Kernel, Data Set Two Test Data)

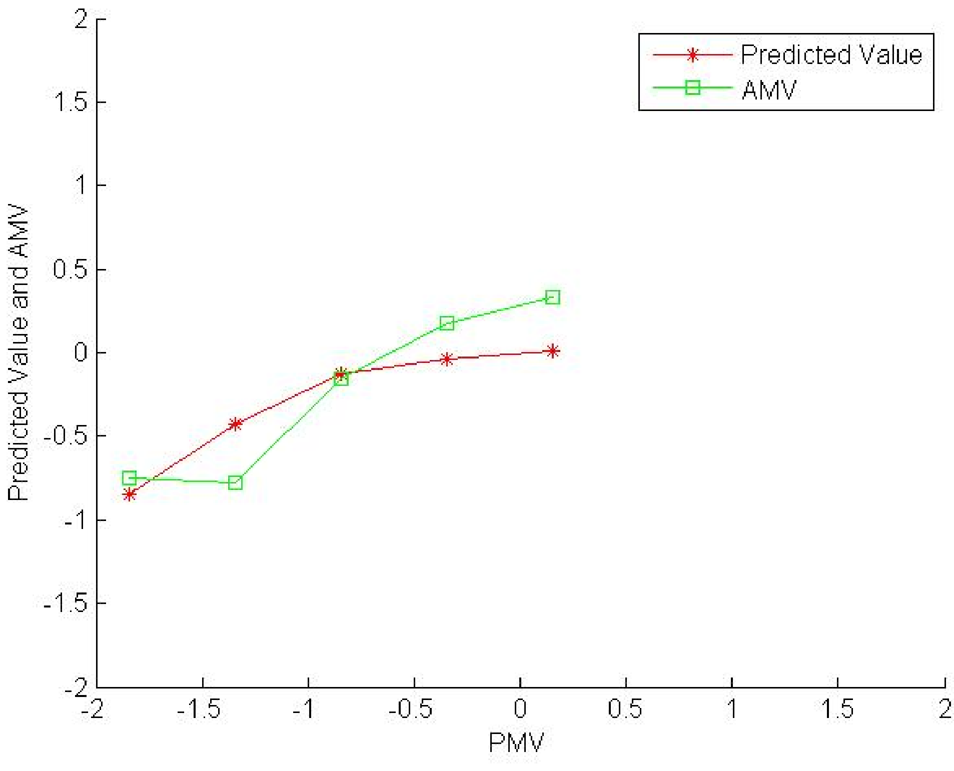


Figure 5.18 AMV and Model-predicted Values aginst PMV (SVR Method with Polynomial Kernel, Data Set Two Test Data)

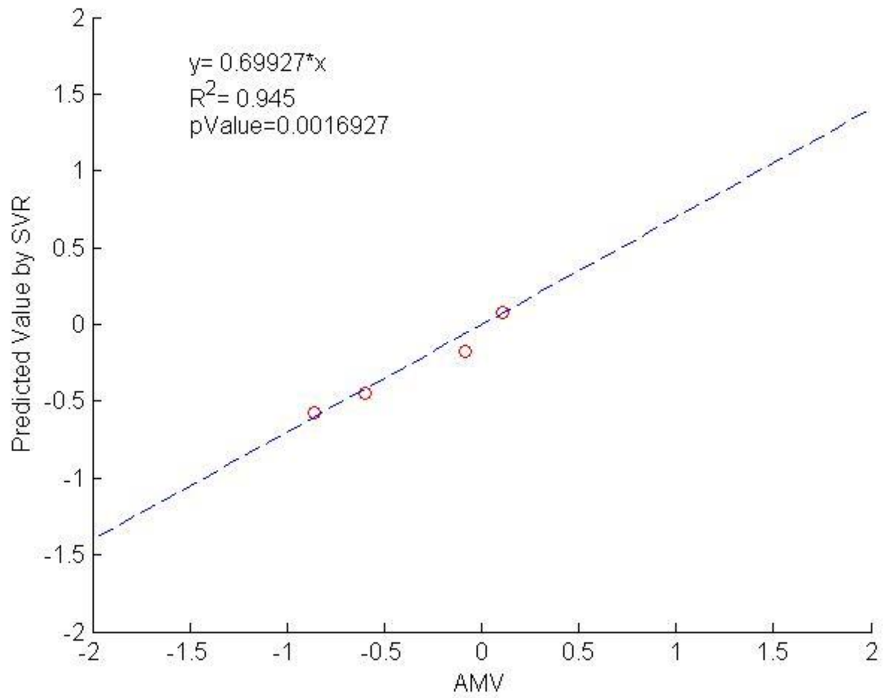


Figure 5.19 The Fit between AMV and Model-predicted Values (SVR Method with RBF Kernel, Data Set Two Test Data)

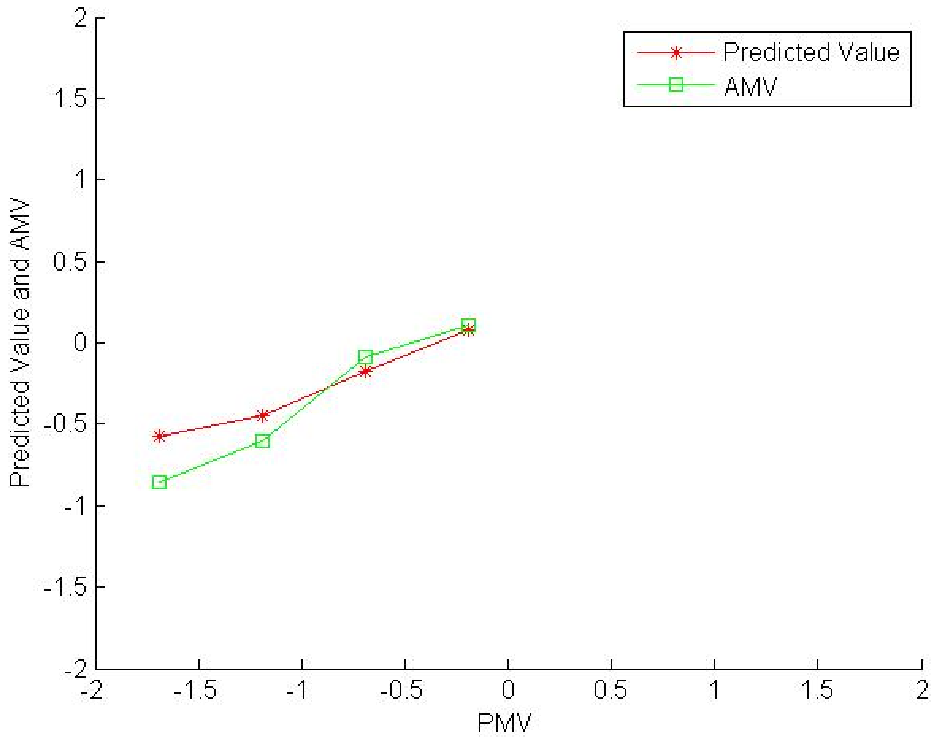


Figure 5.20 AMV and Model-predicted Values aginst PMV (SVR Method with RBF Kernel, Data Set Two Test Data)

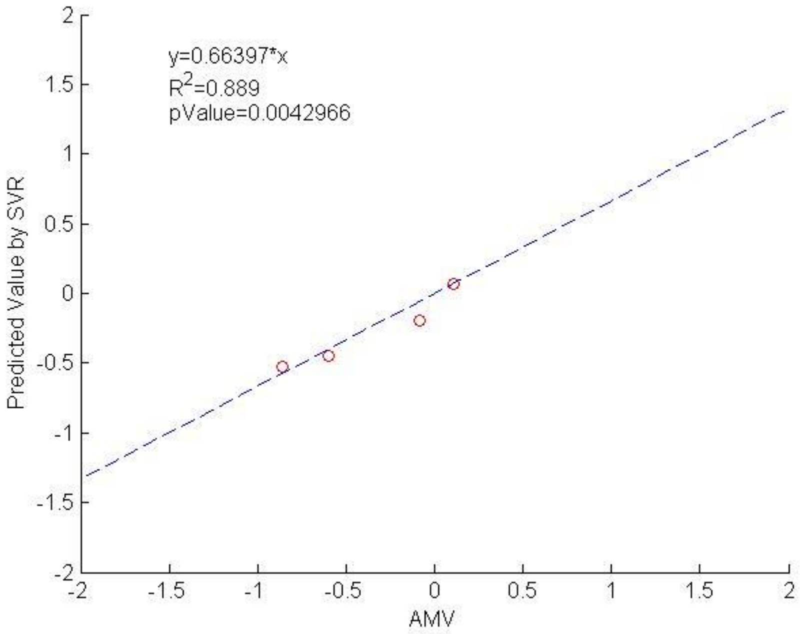


Figure 5.21 The Fit between AMV and Model-predicted Values (SVR method with Sigmoid Kernel, Data Set Two Test Data)

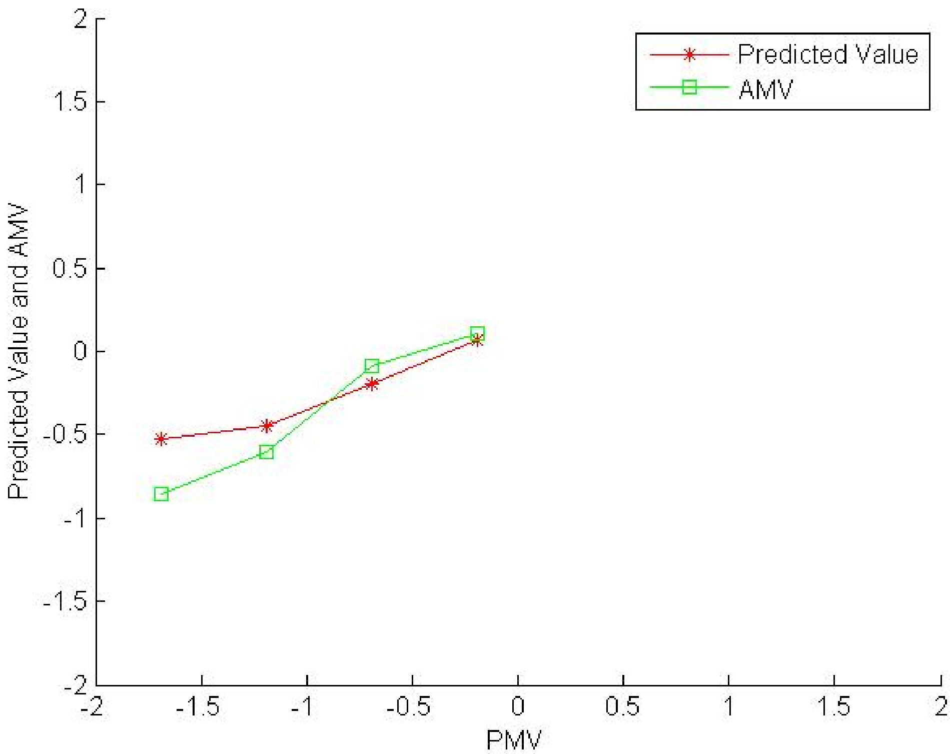


Figure 5.22 AMV and Model-predicted Values aginst PMV (SVR Method with Sigmoid Kernel, Data Set Two Test Data)

The MSE of the predicted values from the SVR-developed model based on different kernel selections is illustrated in Table 5.4. It can be found that, for data set two, the linear kernel gives the best performance. The performance of the RBF kernel is located in second place.

Table 5.4 MSE Values of SVR Models with Different Kernels (training data set from Data Set Two)

Kernel Name	**Linear**	**Polynomial**	**RBF**	**Sigmoid**
MSE	**0.2827**	**0.3509**	**0.2880**	**0.3104**

As stated in Chapter 4, because of a smaller sample size, all of the data are considered for using as training samples to guarantee the performance of the developed model. The training data from data set two only contains half of the data. The performances of the models generated by the training data may not fully reflect the performance of the model generated by all the data. Therefore, the LOOCV method is used here to verify the performance of the model developed using the entire data set. Because the test result already indicates that the Linear kernel and RBF give better performances, only the model developed by the Linear and RBF kernel are validated. The performances of the developed models are illustrated in Fig. 5.23, Fig. 5.24, Fig. 5.25 and Fig. 5.26.

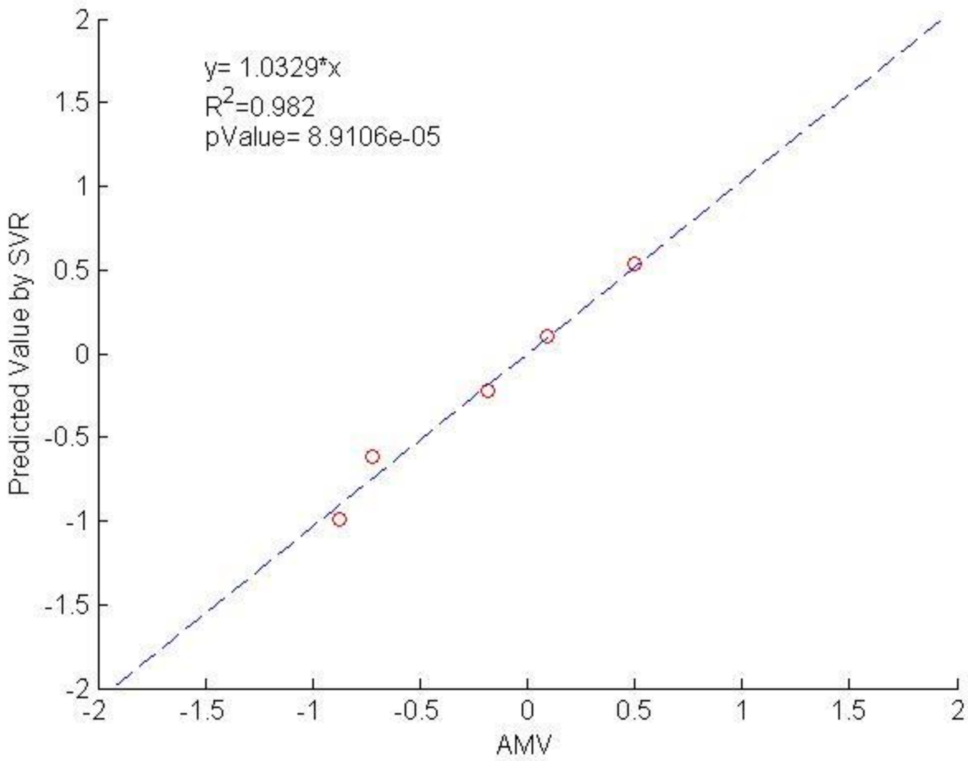


Figure 5.23 The Fit between AMV and Model-predicted Values (SVR Method with Linear Kernel, LOOCV, Data Set Two)

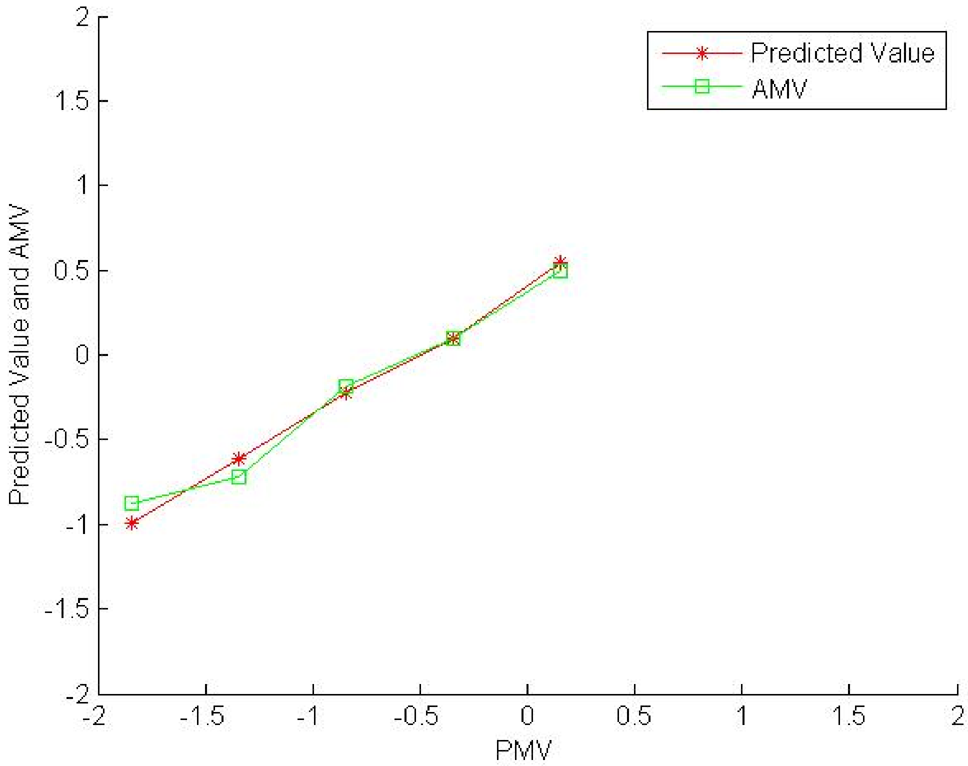


Figure 5.24 AMV and Model-predicted Values aginst PMV (SVR Method with Linear Kernel, LOOCV, Data Set Two)

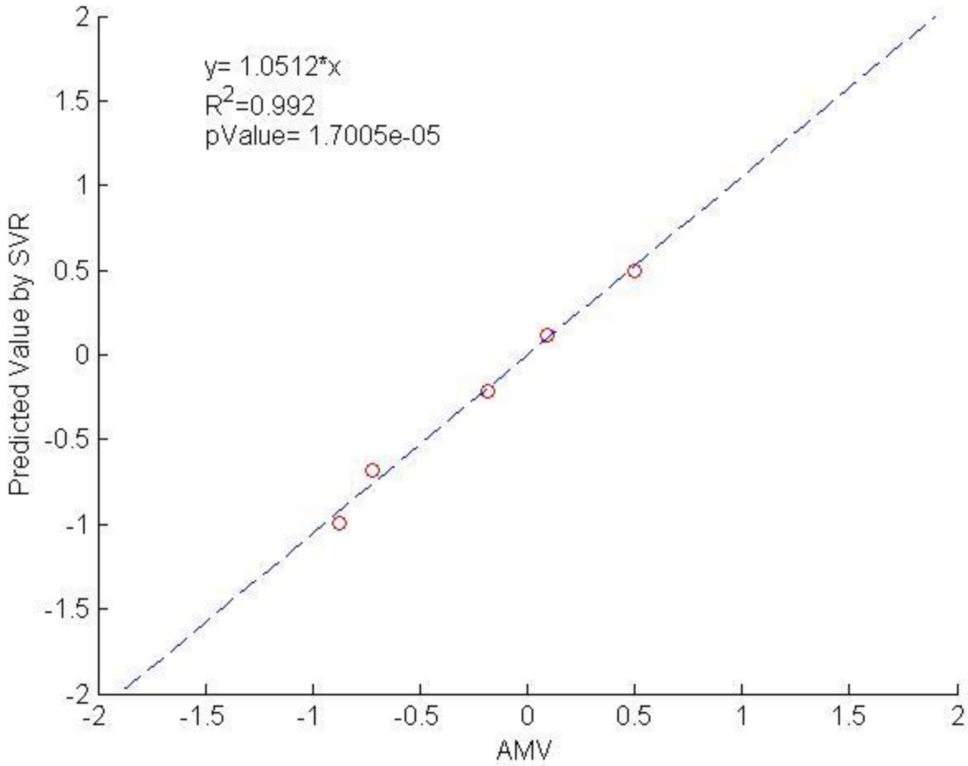


Figure 5.25 The Fit between AMV and Model-predicted Values (SVR Method with RBF Kernel, LOOCV, Data Set Two)

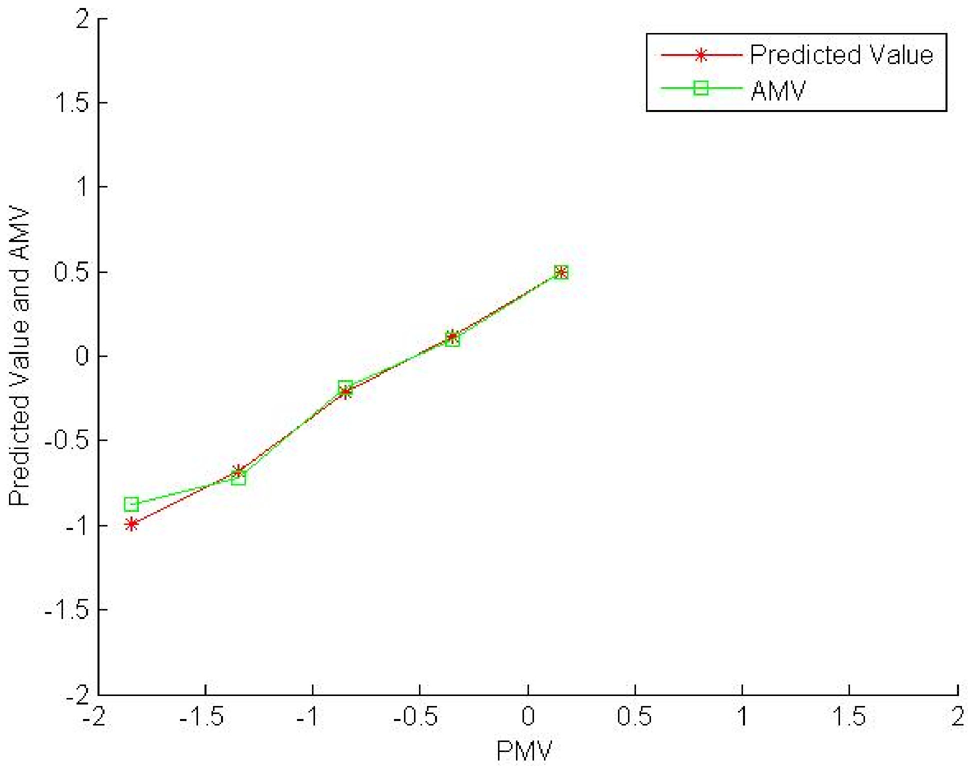


Figure 5.26 AMV and Model-predicted Values aginst PMV (SVR Method with RBF Kernel, LOOCV, Data Set Two)

The MSE values of models developed by the linear kernel and the RBF kernel are 0.3165 and 0.3492 respectively. The performances of these two kernels indicate that the linear kernel has the best performance. The absolute error of the model developed by the linear kernel is shown in Table 5.5. In this case, the SVR algorithm with the linear kernel function is chosen to generate the group-of-people-based thermal sensation model for the group of people in an air-conditioned environment in UK. When generating the model, all of the data collected from the air-conditioned environment in the UK are used.

Table 5.5 The Absolute Error of the Predictions (SVR with Linear Kernel, Data Set Two)

AMV Point	one	two	three	four	five
Absolute Error	0.1160	0.1072	0.0370	0.0059	0.0407

5.4.4 The Thermal Comfort Zone Derived from Data Set Two

By applying the group of people's thermal sensation model developed in Section 5.4.3, the thermal comfort zone of this group of people is calculated and displayed in Fig. 5.27. The assumptions of the environmental conditions and the personal factors are shown in Table 5.6.

Table 5.6 The Comfort Zone Conditions

Air Velocity	MET	CLO
0.06	1	1

In Fig. 5.27, the green area is the comfort zone recommended by the ASHRAE standard (ANSI/ASHRAE55-2010, 2010). The comfort zone is within the range that the PMV is smaller than, or equal to, 0.5 while being bigger than, or equal to, -0.5. A similar results can be obtained by using the on-line tool developed by the Centre for the Built Environment, University of California Berkeley (Tyler et al., 2013). The red area is the thermal comfort zone predicted by the group of peoples' thermal comfort model developed in this research. The boundary on the left-hand side is drawn by the environmental conditions that make the average thermal sensation equal to -0.5. The right hand boundary is drawn by the temperature and levels that make the mean vote equal to 0.5. The comfort area is drawn within the range of relative humidity between 60% and 20%, because most of the data collected from the field study are within the area. The Fig.5.27 shows that this group of people will accept an operative temperature which is lower than the one calculated by the PMV method.

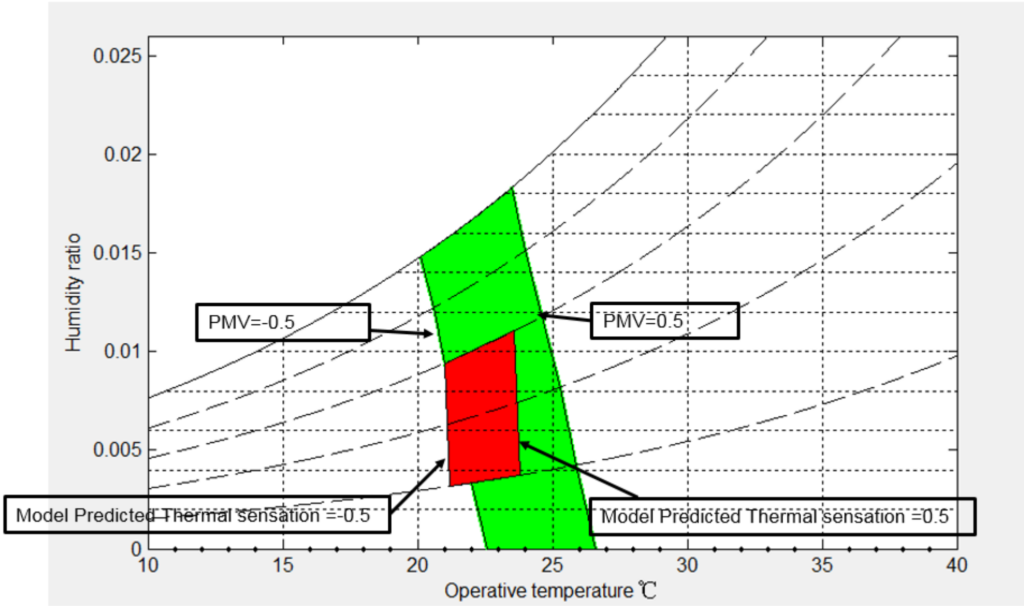


Figure 5.27 The Comfort Zone developed by the PMV model and the SVR Developed Model

5.5 Summary

In this chapter, the personal-model-based method and the SVR method are used to generate the group-of-people-based thermal sensation model. Both the data collected in air-conditioned environments in China and the UK are used to generate and test the generated model. The test results show the models developed by both methods from the data fit the requirement. The results also show that the generated model has a better performance than the PMV index. Then, the SVR method is also used to generate the group-of-people-based thermal sensation model from the data collected in the UK. This generated model is integrated into the BEMS in Chapter 7.

Chapter 6 : Decision-making Algorithms Based on the Lexicographic Method, the ϵ-constraint Method, the Grid Search Method and Condition-Action Rules

6.1 Introduction

The decision-making algorithm is the key element of the A-component in the EDA agent model. It is responsible for the selection of the best action plan stored in the D-component for the agent in a certain situation, which is defined by the knowledge from the E-component during the decision-making process.

The main goal for the energy management system discussed here is to achieve energy efficiency as well as occupant thermal comfort. The potential action plans of an end-user in the D-component could be compromised by either or both types of following action: The first type of action is changing the set points of the HVAC system; The second type of action involves providing suggestions to occupants on adaptive behaviours besides adjusting the temperature set point in order to satisfy their thermal comfort. The decisions are made based on the occupants' thermal comfort preferences, the energy consumption of the HVAC system and the properties of the adaptive behaviours themselves, such as the difficulties in performing certain adaptive behaviours. This information is provided by the E-component. Once an action plan is selected, the system may also need to choose a personalised way to present behavioural suggestions to the occupants since the actions suggested may not be the most usual behaviours that they perform.

This chapter firstly reviews the existing decision-making algorithms applied in building management systems and identifies their deficiencies. Based on the critical analysis of existing decision-making algorithms, novel decision-making algorithms for both local and personal agents in the BEMS in open-plan office environments and single-occupancy offices are proposed and developed. The chapter reveals that the choice of action plans for the HVAC system and the occupants is a multi-criteria decision-making problem. The Lexicographic Method, the ϵ-constraint Method and the Grid Search Method are used to form the solution methods. When choosing ways of making suggestions, the Condition-Action Rules are used to support the decision-making process.

6.2 Literature Review

In this research, the targeted goal is to satisfy the occupant's thermal comfort whilst achieving energy efficiency by optimised energy management and occupant adaptive actions. Therefore, there are three criteria the decision-making algorithm needs to consider, namely 1) thermal sensation; 2) energy consumption and 3) adaptive actions. This decision-making problem is a multi-criteria decision-making problem (Yao and Zheng, 2010, Hamalainen and Mantysaari, 2002). The optimised decision is based on the outcome of the applied optimisation algorithm. The process of multi-criteria decision-making can be called multi-criteria optimisation or multi-objective optimisation (Seo and Sakawa, 1988). Because the criteria are represented by objective functions, for consistency, this research use the term multi-objective optimisation throughout.

It can be found that three types of multi-objective optimisation method are applied in the search related to buildings. The first type of commonly-used method to solve multi-objective optimisation problems is to aggregate the different objective functions into one objective function, then these problems can be solved by the methods which are used to solve single-objective problems (Hopgood, 2000). When applying the method in the building energy-management research area, the method is sometimes faces objectives of reducing the energy consumption whilst maximising the occupants' thermal comfort satisfaction, which forms a bi-objective problem. Different ways are used to aggregate these two objectives together. It is suggested that occupants' discomfort level should be measured by a 'discomfort cost' function, whose cost is then added to the energy cost function to create a new function (Mozer, 1998). In this case, the original bi-objective problem becomes a single-objective problem. The solution that gives the minimum value in the total cost function is equivalent to the solution to the original bi-objective problem. Other than directly adding objective functions together, the weighted sum method multiplies a weighting with each objective function and then adds them together to form a single-objective function (Marler and Arora, 2004). It is suggested that the discomfort and energy costs should each be weighted prior to being added together (Mo, 2002).

May-Ostendorp et al. (2011) generated a single objective function by adding a penalty term, which includes the thermal discomfort effects, to the energy consumption formula. The authors pointed out that the weight coefficient of the penalty term equivalent is 0.05 while the coefficient of energy consumption in their research was one. The Particle Swarm Optimization (PSO) is applied to solve the generated single-objective problem. The weighted sum method is also applied to solve the problem with more than two objectives. For instance, the method is used to develop a general discomfort function which represents three comfort aspects: thermal comfort, visual comfort and air quality comfort (Wang et al., 2011b). The literature above reveals some drawbacks to aggregating objective functions. It is difficult to generalise the definition of the 'discomfort cost', as different people in different situations may have different 'discomfort cost' functions. Furthermore, how to decide the weightings of the different components in the function formulated using the weighted sum method remains a problem. Different weightings lead to different decision outcomes.

Shaikh et al. (2014) pointed out that another method other than the weighted sum method could be used to solve the multi-objective optimisation problem. Instead of looking for ways of forming a single-objective function then finding the single solution directly, the method aims to find all the 'trade-offs' between the objectives first. This means the method attempts to search for the Pareto optimality set, which are 'non-dominated solutions'. The Pareto optimality defines 'a state of affairs in which resources are distributed such that it is not possible to improve a single individual without also causing at least one other individual to become worse off than before the change' (Boukhadra et al., 2015). It can be found that the Nondominated Sorting Genetic Algorithm II (NSGAII) and the multi-objective particle swarm optimization (MOPSO) method are applied to find the Pareto optimal solutions, when the decision-making algorithm tries to reconcile the conflicting objectives of energy saving and fulfilling comfort requirements (Yang and Wang, 2012b, Yu et al., 2015, Yang and Wang, 2013b). This method can also be used to solve the problems with more than two objective functions. Klein et al. (2012) attempted to search for the trade-offs between the thermal comfort objective, the energy saving objectives and the scheduling convenience objective. However, it has already been pointed out that a multi-objective optimisation problem is not fully solved when the Pareto-optimality sets are calculated, as the most preferred solution still needs to be selected from the Pareto optimal solutions by using additional information (Doumpos and Grigoroudis, 2013, Burke and Kendall, 2005). How to make the final decision to choose one preferred solution from the Pareto optimal solutions is still under discussion. Therefore, additional efforts may be needed to make the final decision once the methods, such as NSGAII, provide outcomes.

Zhao et al. (2014) used the 'constrained optimisation formulation' method to calculate the optimal set point in an air-conditioned environment when considering the thermal comfort and energy consumption aspects. This is the third type of method in the literature. In this research, the main objective function is the energy consumption represented by the heating/cooling load whilst the acceptable thermal comfort range serves as a constraint. In general, this method converts one objective into a constraint to the other objective and then solves the constrained single-objective problem to obtain the solution to the original problem. It can be noticed that the local optima problem may be faced when solving the transferred problem. The 'constrained optimisation formulation' method is equivalent to the so-called ϵ-constraint method described in the literature (Marler and Arora, 2004, Mavrotas, 2009, Aghaei et al., 2011). For consistency, the method is named the ϵ-constraint method throughout the rest of this thesis. The solutions from the ϵ-constraint method can be regarded as the final solutions for the decision-making without further processing, so no further efforts are needed. It can be found that the method is also used to settle a multi-objective decision-making problem with three objectives, which involves thermal comfort objectives, air-quality comfort objectives and energy-saving objectives in multiple zones (Hurtado et al., 2013). But the application of the method needs further discussion, as can be seen in the paper, when facing a multi-objective problem having more than two objectives, the weighted sum method is involved to reduce the total number of objectives prior to the ϵ-constraint method selecting the function solution. Again, the weightings are manually defined. Moreover, when converting objective functions into constraints, the numerical boundaries of the constraints also need to be manually defined first, then algorithms can be applied to solve the constraint optimisation problem. It may be difficult for decision makers to pre-define boundaries for some of the objectives.

In order to overcome drawbacks in the existing multi-objective optimisation methods, the Lexicographic method is introduced into decision-making algorithm co-operating with the ϵ-constraint method to solve the multi-objective optimisation problem. The Lexicographic method does not need to manually define the boundary of the constraints. It is also not necessary to involve the weight coefficient in the calculation procedure. The optimisation outcomes can be regarded as final decisions without further processing. Therefore, the Lexicographic method is applied when the number of objectives needing to be considered in a problem is more than two. The ϵ-constraint method is applied when the number of objectives is two and the objectives can be transformed into a constraint. The grid search method is applied to solve the transferred single-objective problems, as this method is suitable to solve such problems and can effectively avoid the local optima problem. The details of these methods are illustrated in the next section.

6.3 Development of Decision-making Algorithms

6.3.1 A Mathematical Description of the Multi-objective Optimisation Problem

The multi-objective optimisation problem can be generally described by function (6.1) (Marler and Arora, 2004, Seo and Sakawa, 1988, Hamalainen and Mantysaari, 2002):

$$\underset{\boldsymbol{x}\in S}{\text{minimize}}\ \boldsymbol{F}(\boldsymbol{x}) = (f_1(\boldsymbol{x}), f_1(\boldsymbol{x}), \dots f_k(\boldsymbol{x}))^T \qquad (6.1)$$

Subject to: $g_j(\boldsymbol{x}) \leq 0, j = 1,2,\dots,\mathrm{m}$

$$h_i(\boldsymbol{x}) = 0, i = 1,2,\dots,\mathrm{n}$$

where $\boldsymbol{x}$ is a vector of decision variables.

S is the feasible set of decision variables (also called the feasible decision space). $f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots f_k(\boldsymbol{x})$ are k objective functions, where k≥2. $g_j(\boldsymbol{x})$ and $h_i(\boldsymbol{x})$ represent equality and inequality constraints. The symbols ‘m’ and ‘n’ denote the numbers of these constraints respectively.

In general, the objective functions of the energy consumption, thermal comfort and behavioural adaptations are expressed as $f_e, f_c\ and\ f_b$ respectively. Every built environment has its own $f_e, f_c\ and\ f_b$ functions.

6.3.2 Multi-objective Optimisation Methods

6.3.2.1 Lexicographic method

The lexicographic method arranges the objective functions into a sequence and solves them one at a time (Stanimirovic, 2012). The word ‘lexicographic’ refers to the way in which words are sequenced in a dictionary (Yoon and Hwang, 1995). The method solves the decision-making problem in a sequential manner. In each sequence or iteration, the lexicographic method can be described as solving a single objective optimisation problem given by formula (6.2) (Marler and Arora, 2004).

$$\underset{x \in S}{\text{minimize}}\, f_i(\boldsymbol{x}) \tag{6.2}$$

Subject to $f_j(\boldsymbol{x}) \leq f_j(\boldsymbol{x}_j^*), j = 1,2, \dots, i-1, i > 1,$

$$i = 1,2, \dots, k.$$

In the upper function, $f_j(\boldsymbol{x}_j^*)$ is the optimal value of the jth objective function f_j . The optimal value of the jth objective function f_j becomes a constraint of the next objective function f_i. As illustrated in Function (6.1), k is the total number of objective functions. In every step, if there is only one set of solutions, the solution is the final solution.

6.3.2.2 ϵ-constraint method

The basic idea of the ϵ-constraint method is leaving one of the objective functions and converting the rest of the objectives into constraints (Hamalainen and Mantysaari, 2002). The boundaries of the constraints are defined by the user, then the method can be expressed as function (6.3) (Burke and Kendall, 2005):

$$\underset{x \in S}{\text{minimize}}\ f_a(\boldsymbol{x}) \tag{6.3}$$

Subject to $f_b(\boldsymbol{x}) \leq \epsilon_b$ b=1,2,…,k and k$\neq a$

$g_j(\boldsymbol{x}) \geq 0$ j=1,2,…m

$h_i(\boldsymbol{x}) = 0$ i=1,2,…,n

In function (7.3), it can be found that object function $f_b(\boldsymbol{x})$ is used as the constraint and f_a as the optimisation object.

6.3.2.3 The Grid Search Method

According to the multi-objective problem solutions proposed in sections 6.3.2.1 and 6.3.2.2, the solutions converted the original problem into one, or a series of, single-objective optimisation problems. In this research, the grid search method is applied to solve the single-objective problems.

In general, search algorithms can be regarded as problem-solving technologies (Weiss, 1999). The grid search method is applied to solve the problem here because of the property of the objective functions and their decision values. The grid search method is a type of exhaustive search and the optimisation process is as follows (Zabinsky, 2003):

1. First, the feasible decision space is equally discretised.
2. Then, the grid points are formed over the space.
3. Finally, the value of the objective function at the points is calculated and the optimal solution found.

In this research, the settings of the HVAC system as well as occupants' other behavioural adaptations form the decision vectors. From a practical point of view, it is reasonable to regard the real-life temperature settings of the HVAC system as discrete variables. Other adaptive reactions, such as putting on/taking off clothing, can also be represented by discrete variables. Then, a discrete, two-dimensional, feasible decision space can be created by the decision-making problem itself. Therefore, this problem can be solved by the grid search method. One dimension is set temperatures of the HVAC system within a certain range as defined by the facility manager. The other dimension represents occupants' activities other than changing the settings of the HVAC system. At each grid point, the values of the objective function can be calculated. All the points generate a search space. Then, an exhaustive grid search is performed to find the optimal solutions for the objectives.

One of the drawbacks of the exhaustive search method is that if the search space is too big, then a complete search is not possible (Burke and Kendall, 2005). However, in this research, the possible number of set points and people's actions are limited. So the grid search task can be accomplished by the PC as described in Chapter 2.

6.4 Multi-objective Decision-making Aided by the Lexicographic and Grid Search Methods

Based on the literature, the Lexicographic method has not yet been used to solve optimisation problems in the BEMS research. How to use the lexicographic method added to the grid search method to solve the optimisation problem in BEMS remains a question. A few researchers have suggested that the ϵ-constraint method can be applied to solve the multi-objective decision-making problem by converting the original problem into a single-objective decision-making problem. But no research solves the converted single-objective optimisation problem by using the grid search method. Whether using the lexicographic method to solve the original problem as a sequence of single-objective problems, or applying the ϵ-constraint method to transfer the original problem depends on the requirements of the particular optimisation tasks. Generally speaking, when the number of objectives is larger than two or some objectives are difficult to transfer into constraints, the lexicographic method is preferred. In this section, the decision-making process supported by the lexicographic method with the grid search method is discussed.

At the beginning of the optimal decision-making process, all the objective functions in function (6.1) are generated. The values of these objective functions are calculated by the relevant models or algorithms. If the lexicographic method is chosen, all of the functions are arranged in a sequence. Each single-objective optimisation problem is solved by a grid search in a single step. Then the optimisation result becomes the constraint of the next step until all the single decision-making problems are solved. During the process, if in a step, the optimisation problem only has one solution, then this solution is regarded as the optimal solution and the iteration stops. This process is illustrated in Fig. 6.1.

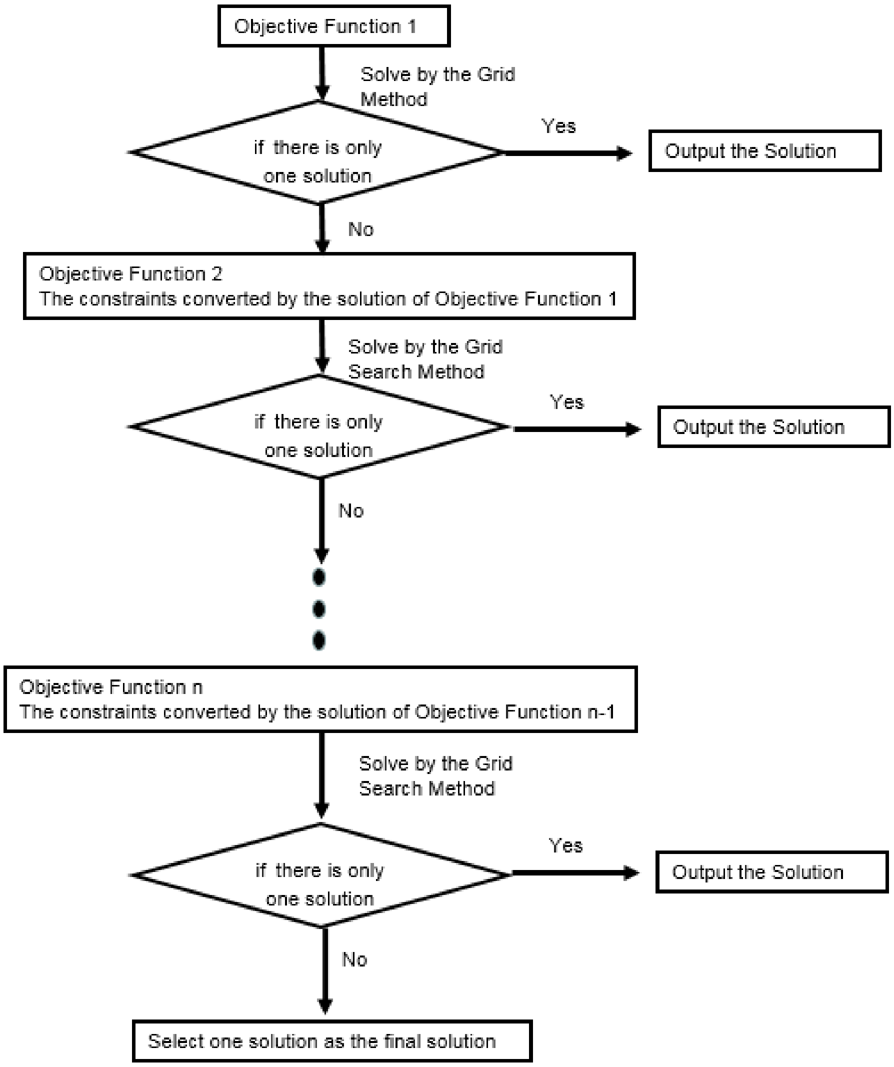


Figure 6.1 The Decision-making Process aided by the Lexicographic and Grid Search Methods

It can be seen from Fig. 6.1 that in each step, the optimisation outcomes are converted into the constraint of the next objective function. As it is aided by the grid search method, the transformation process is straightforward. Fig. 6.2 is an example diagram, which depicts the transformation process. In the figure, x_1 and x_2 represent the two decision variables in a decision vector. Together, these variables format a two-dimensional feasible decision space. The black dots represent all the possible decision variable combinations. The solution must be represented by one of the dots, which are scanned by the grid search method. Solutions for objective function one are labelled by the rectangular squares. The algorithm converts these solutions into constraints by limiting the feasible space to the area labelled by both black dots and rectangular squares for objective two. This means that when the grid search method searches for the solutions for objective function two, the search area is the smaller area labelled by both icons. There is only one point that fits the requirement of objective two, which is labelled by the red triangle. The values of x_1 and x_2 which are represented by that point represent the final outcome of the multi-objective optimisation process.

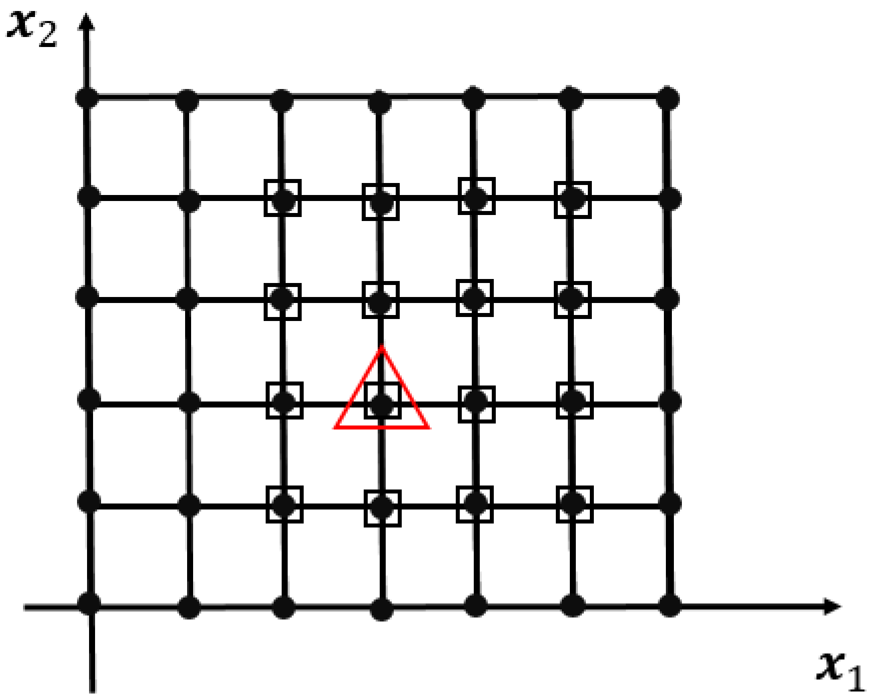


Figure 6.2 Example Diagram of Changes of Search Area when Applying the Lexicographic Method with Grid Search

6.5 Optimisation with the ϵ-constraint and Grid Search Methods

If the ϵ-constraint method is selected as the solution method, the grid search method will search for the solution of the transferred single-objective problem subject to the constraints. The process is depicted in Fig. 6.3. The process of making all other objectives into constraints is explained in Fig. 6.4. In the figure, it is assumed that the decision space is a one dimensional space defined by the decision variable $\boldsymbol{x}$. All the potential solutions are represented by the black dots. There are two objectives that need to be optimised. The objective two is converted into constraints and all the potential solutions within the range of constraints are represented by squares. In this case, the grid search performed to optimise the objective one only needs to search the dots labelled with squares. The final solution is represented by the red triangle.

The MATLAB software is used in this research to realise the lexicographic, ϵ-constraint and grid search methods in all the decision-making algorithms.

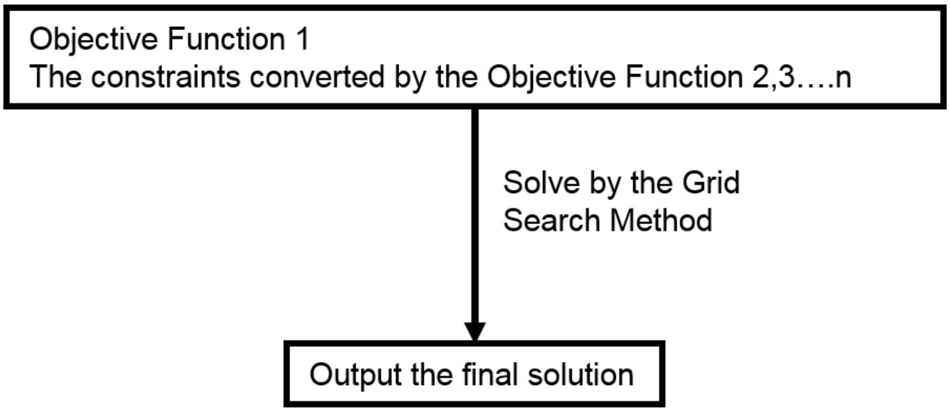


Figure 6.3 Decision-making Process with the ϵ-constraint Method

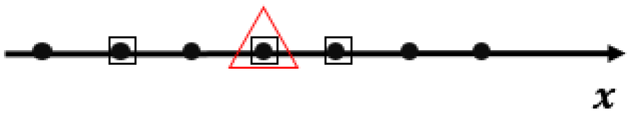


Figure 6.4 Converting the Objective Function into Constraints when Applying the ϵ-constraint Method with the Grid Search Method

6.6 The Combination of the Lexicographic and the ϵ-constraint Methods

Based on the definition of the lexicographic method, it can be seen that when converting an objective function into a constraint, the constraint should be defined by the optimal solutions of the objective function. This means that only those feature vectors that give the maximum or minimum values of the objective function should be used to define the feasible feature range for the next objective function. But for the ϵ-constraint method, it is not necessary to find the features giving the maximum or minimum values of an objective function to form the constraints of the next objective function. It only requires the selected features that give the values in a certain manually-defined range. The definitions of these methods reveal that the constraint converting condition of the ϵ-constraint method is not as strict as that of the lexicographic method. In a real-world application, it is not necessary to find optimal solutions for all objective functions. For example, when the PMV is used as the environment assessment model, sometimes it may be unrealistic to require the environment conditions to give an optimal PMV value which is zero. The required conditions may be between -0.5 and +0.5 instead. In this case, it is necessary to integrate the ϵ-constraint method into the lexicographic method to 'loosen' the requirement for constraint-converting in the lexicographic method. The new method containing both methods inside is illustrated in Fig. 6.5. From this figure, it can be seen that when converting objective function one into the constraints of objective function two, the algorithm applies the rule of the ϵ-constraint method. In the remainder of the process, the lexicographic method is used.

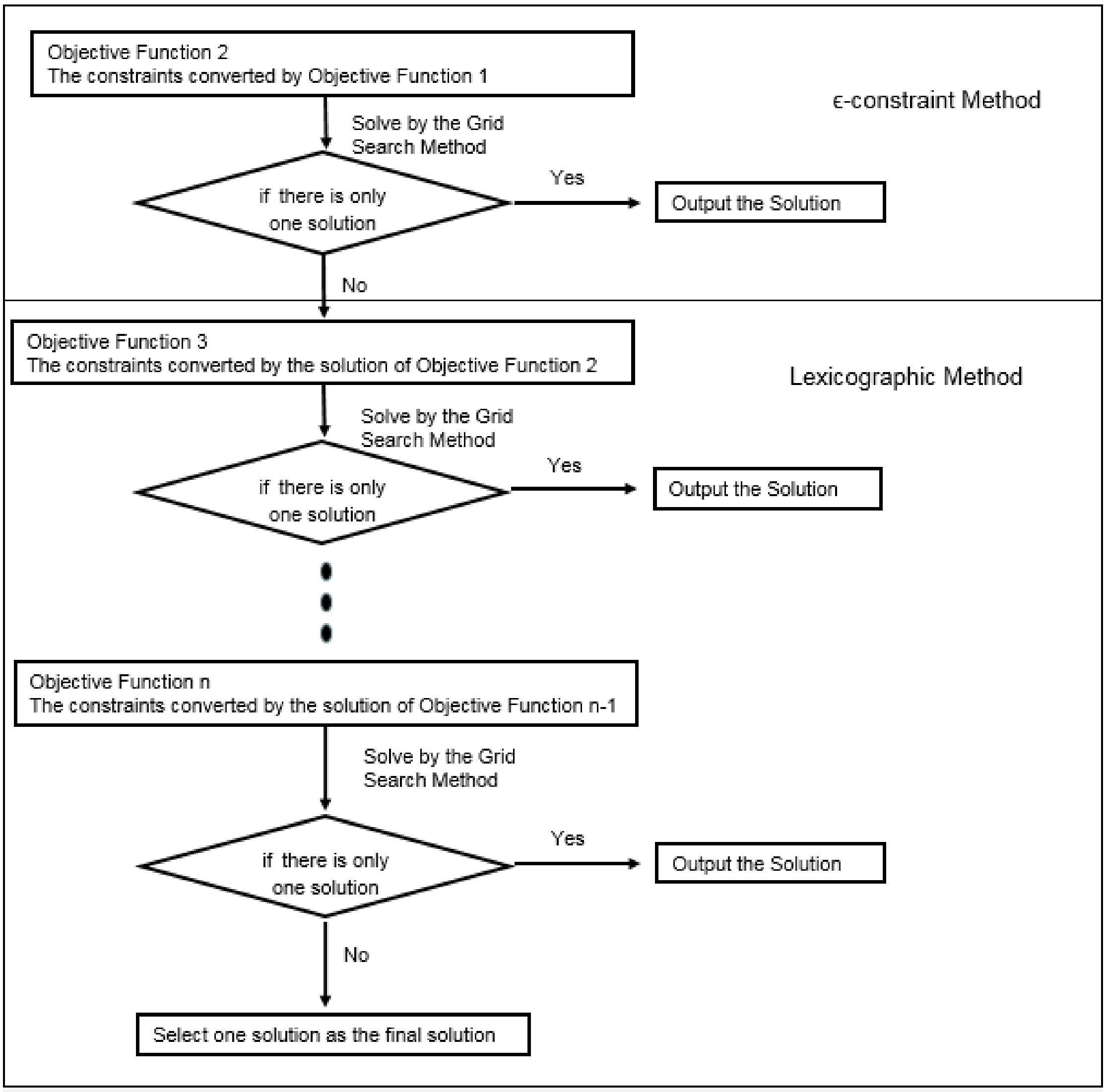


Figure 6.5 the Lexicographic Method with the ϵ-constraint Method

6.7 A Decision-making Algorithm with Condition-Action Rules

The decision-making algorithms discussed above are able to provide final decisions including the action plans from BEMS. However, when facing different end-users, ways of giving the action plan information to the users could differ because their individual differences. For example, the system may be aware that the action plan made does not correspond with user's usual behaviour. In this case, the information provided to the user is different from that given to users who commonly behave using the suggested actions. The generation of personalised information can be realised using Condition-Action Rules. Here, a set of Condition-Action Rules is developed to work with the optimisation method to realise the personal suggestion function. Rules are made according to objectives and occupants' personal characteristics such as their commonly-used actions/habits. Let DP represents the action plan decided by the system, CP represents the most common actions performed by the end-user, SPn represents the nth way of personal suggestion (n=1,2,3), and the SPf is the final suggestion shown to the end user via the human-machine interface. The pseudo code of the Condition-Action Rules is as follows:

```
If an action is needed:
  If DP=CP,
     DP= SPf,
  End if
  Elseif the energy consumption caused by DP is less than CP
     SP1=SPf
  End if
  Elseif the thermal comfort level provided by DP is higher than CP
     SP2=SPf
   End if
   Elseif the DP is easier for the user to perform than CP
     SP3=SPf
   End if
End if
```

In the above pseudo code, the suggestion SP1 could show the energy consumption difference between the DP and CP then let the user decide. SP2 could remind the occupant that if CP is selected, he/she may still feel uncomfortable. SP3 could tell the occupant that only by performing DP will he/she obtain a feeling of thermal comfort and CP may not be necessary. By using the Condition-Action Rules above, a reasonable suggestion based on the system decision is presented to occupants by considering their individual differences.

6.8 Summary

In this chapter, decision-making algorithms based on the lexicographic method, the

ϵ-constraint method, the grid search method and the condition-action rules are developed to decide the settings of the HVAC system, the behavioural adaptations for the occupants and the way of presenting the suggestions. Compared to existing algorithms, the newly-developed algorithms presented in this chapter do not need manually assigned weight coefficients for the objective functions during the decision-making process. The algorithms are able to deal with the situation when the number of objective functions is greater than two. It is also capable of dealing with the situation when it is difficult to decide the acceptable range for the value of an objective function when converting it into a constraint. By integrating the condition-action rules, personalised suggestions given to a particular occupant can be realised. How the multi-agent BEMS applies these algorithms and the performance of the BEMS are illustrated in the next chapter.

Chapter 7 : Multi-agent BEMS Operation Process and Energy Management Performances

7.1 Introduction

The multi-agent BEMS system structure with the local agent and personal agents based on the EDA agent model has been introduced in Chapter 3. The modelling algorithms for the thermal comfort models in the E-component and the decision-making algorithms in the A-component have already been discussed in Chapters 4 and 5. The developed models can be used as the objective functions representing the occupants' thermal preferences. They are needed by the decision-making algorithms in the A-components in both the personal and local agents. To fully realise agents in the BEMS system, methods need to be developed to generate the objective functions representing energy consumption and adaptive behaviours.

In this chapter, the method of developing energy consumption models and the method to build the behavioural adaptation evaluation algorithm in the E-component are developed. The developed model and algorithm are the objective functions representing energy consumption and adaptive behaviours. They are integrated into the decision-making algorithm in the A-component when making decisions. The action plans in the D-component are also discussed.

With all developed components, novel decision-making processes in newly-developed personal agents and local agents can be established. The decisions aim to save energy as well as to guarantee the occupants' thermal comfort by considering the effects of their behavioural adaptations. Occupants' individual differences and personal preferences are considered in the decision-making process.

In the end, the decision-making processes are examined and the energy-saving abilities of the multi-agent BEMS are tested.

7.2 Objective Functions for the Decision-making Algorithm

7.2.1 Objective Function Development for Thermal Comfort

The optimal decision-making needs an objective function to represent the occupants' thermal comfort level. In this research, the objective functions concerning thermal comfort are represented by the thermal comfort model. Both personal and group thermal sensation models have been developed in Chapters 4 and 5 and applied for different types of office.

The objective functions of energy consumption as well as behavioural adaptations are represented by the heating and cooling loads equations and behaviour evaluation methods. These models and methods will be discussed in the following sections.

7.2.2 The Heating and Cooling Load Models of the HVAC System

The previous research has already revealed that the domestic energy consumption is highly related to a building's heating and cooling loads (Wan *et al*., 2011). Both heating load and cooling load have been used to predict the energy demands of the HVAC system (Yao and Steemers, 2005) (Ben-Nakhi and Mahmoud, 2004, Zhao et al., 2014). In this research, beside the thermal comfort and adaptive behaviour aspects, the decision-making algorithm attempts find the set temperature of the HVAC system cost for minimum energy consumption. But the algorithm does not necessarily know the exact value of the energy consumption. It only needs to understand which action plan consumes the least amount of energy. The set-points of the HVAC together with outdoor climate conditions determine the required heating or cooling loads. Requiring higher heating or cooling loads means higher energy consumption. Therefore, without loss of generality, predictions of both the heating load and cooling load models are used as objective functions to represent the relevant energy consumption of the HVAC system in the built environment. The information on cooling and heating loads is enough for the decision-making algorithm to make rational decisions.

7.2.2.1 Cooling Load Model

The cooling load can be calculated by a load estimation form provided by the Air-Conditioning and Refrigeration Institute (ARI), and the calculation method is also called the ARI method (Brumbaugh, 1983). (Ansari et al., 2005) converted the unit in the form into the international system of units and the output cooling load is measured in Watts (W). As introduced in this literature, all of the loads caused by transmission, infiltration and ventilation are calculated by the indoor/outdoor dry bulb temperature difference multiplying factors. Based on the literature, the total cooling load of the air- conditioned built environment can be calculated by the following process (Ansari et al., 2005):

Let the length, width and height of the room be represented by the symbols L, Wr and H. The symbols Ww and Hw denote the width and height of the window respectively. The size of the wall exposed to the outside environment is $Wr * H$. The size of the window on the wall is $Ww * Hw$. Let DT present the indoor and outdoor air temperature difference, then:

$$DT = (t_o - t_i) \quad (7.1)$$

where t_o is the outdoor temperature and t_i is the indoor temperature. The symbols and the values of the factors used to calculate the sensible cooling loads are listed in Table 7.1. The factor selection is based on the physical properties of the built environment as specified in section 7.4.

Table 7.1 The Factors Used to Calculate the Cooling Load (sensible heat only)

Factor Name	Factor Symbol	Factor Value	Symbol of the Relevant Cooling Load
Direct Solar Radiation	Fds	158	Lds
Window Transmission	Fwt	0.46241+3.025756*DT	Lws
Walls	Fwa	8.3932+1.21465*DT	Lwa
Ceiling	Fce	2.82+1.144611*DT	Lce

Cooling load values calculated using the factors listed in Table 7.1 are expressed as equations (7.2) to (7.7):

$$Lds = \text{Fds} * (Ww * Hw) * 0.85 \quad (7.2)$$

$$Lws = \text{Fwt} * (Ww * Hw) \quad (7.3)$$

$$Lwa = \text{Fwa} * (Wr * H - Ww * Hw) \quad (7.4)$$

$$Lce = \text{Fce} * (L * Wr) \quad (7.5)$$

The total cooling load of the sensible heat Ls of the room is:

$$Ls = Lds + Lws + Lwa + Lce \quad (7.6)$$

The latent heat allowance Lls is given by:

$$Lls = Ls * 0.3 \quad (7.7)$$

The total heat for the four factors is:

$$Las = Ls + Lls \tag{7.8}$$

Please note that the table in Ansari et al. (2005) did not give the factor for people, lights and equipment. The factor values for these three items in Table 7.2 are from ((McQuiston et al., 2005) (Butcher and Craig, ASHRAE, 2001) (ASHRAE, 2013).

Table 7.2 The Factors Used to Calculate the Cooling Load Caused by People, Lights and Equipment

Factor Name	Factor Symbol	Factor value	Symbol of the Relevant Cooling Load
People	Fp	115w/ person	Lp
Light	Fl	10.5w/m^2	Ll
Equipment	Ff	10.8w/m^2	Lf

Let np represent the number of people in the room, then the heating is shown in:

$$Lp = \mathrm{Fp} * \mathrm{np} \tag{7.9}$$

$$Ll = \mathrm{Fl} * (L * Wr) \tag{7.10}$$

$$Lf = \mathrm{Ff} * (L * Wr) \tag{7.11}$$

The total heating load is calculated by:

$$L = Las + Lp + Ll + Lf \tag{7.12}$$

7.2.2.2 Heating Load Model

The energy consumption of the HVAC system is numerically represented by the heating load of the built environment when it is working under the heating mode. The heating load is equal to the sum of all heat losses (McQuiston *et al.*, 2005). The value of total heat losses of the built environment can be estimated by the 'Average Value Method' which is a simplified method introduced in Brumbaugh (1983). From the book, it can be found that the method utilises the indoor and outdoor temperature difference and the average value of the important basic factors of buildings to calculate the heat losses. The basic factors considered include the wall factor, contents factor and glass factor. Based on the introduction in the literature, the calculation process of the heat losses of the researched indoor environment can be expressed as follows (Brumbaugh, 1983):

The values of the three factors are defined in Table 7.3. It should be noted that the area and volume values related to these factors are in English units in this method. The output heat losses of the average value method are scaled by British thermal units (Btu) per hour where 1kW.h = 3,412Btu. The final result is the total heat loss from the environment per hour. However, in the rest of this research, the metric system units are applied to measure the length and the space. So, during the calculation, the Matlab program automatically transfers the units between the metric system units and the English unit. As with the cooling load, the output of the total heating load will be expressed in Watts (W).

1W=3,412Btu/hr. 1 (degree F)=9/5*(degree C)+32 (McQuiston *et al.*, 2005).

Table 7.3 The factors used to calculate the heat loss

Wall Factor (Wf)	0.32 Btu/(ft^2*hour* ºF)	1.82W/(m^2*K)
Glass Factor (Gf)	1 Btu/ (ft^2*hour* ºF)	5.68W/(m^2*K)
Contents Factor (Cf)	0.02 Btu/ (ft^3*hour* ºF)	0.37W/(m^3*K)

As the HVAC system is assumed to be working under the heating mode, the indoor and outdoor temperature difference is $t_i - t_o$. The heat loss through the glass HLG can be expressed as function (7.13):

$$HLG = Gf * (Ww * Hw) * (t_i - t_o) \quad (7.13)$$

where: $Ww * Hw$ = the total area of the glass.

The heat loss of the wall HLW is given by:

$$HLW = Wf * (Wr * H - Ww * Hw)) * (t_i - t_o) \quad (7.14)$$

where: $W * H$= the total area of the wall.

The heat loss caused by the contents of the spaces HLC is:

$$HLC = Cf * (L * Wr * H) * (t_i - t_o) \quad (7.15)$$

where: $L * Wr * H$ is the volume of the indoor space.

Then the total estimated heating load HL is:

$$HL = HLG + HLW + HLC \quad (7.16)$$

7.2.3 Objective Function for Behaviour

When the BEMS makes suggestions to occupants on behavioural adaptations, there are two aspects that need to be considered. The first one is that the system should select the easiest way for the occupants to act. The system considers that all of the behaviours only take one action to complete have the same complexity. For example, putting on some clothes, taking off some clothes and turning down the set point of the HVAC all require one action. In this case, the complexity value of performing one of these actions is set as one. If the system suggests that the occupants put on some clothes and turn up the set point, then this suggestion contains two of these actions and has a complexity value of two. In the decision-making algorithm, all the 'complexity values' of the actions are set up by the system. The complexity of the behaviour adaptations in a suggestion is defined as the sum of all the complexity values of the actions in the suggestion. The decision-making algorithm tends to choose suggestions with lower complexity values.

In addition, the system should choose those actions that the occupant is most accustomed to perform. Different people react differently when they feel uncomfortably cold or hot. Thus, when the energy management system notices that occupants will feel thermally uncomfortable, it is not appropriate to give identical advice to all the occupants without considering their individual differences. Furthermore, based on the field study result, even for one person, usually more than one type of behaviour will take place when he or she feels uncomfortable. Each occupant has their own habitual behaviour patterns to adjust their thermal conditions. Thus, when providing personalised behavioural advice, an occupant's customary behaviours should be considered.

However, in order to take occupants' personal habits into account, it is imperative to find a method to quantitatively represent the occupants' habitual behaviour based on the behaviour records in the database. It is not accurate to simply count the occurrences of a behaviour over a time period since some behaviours, such as the opening the windows, may occur for reasons other than seeking thermal comfort. In this research, the norm confidence inherited from the association rule mining method is utilised to represent the relatedness between a particular behaviour and a type of uncomfortable thermal comfort sensation. The association rule mining technology was developed to find the association rules between purchased items from transaction records in a database (Agrawal et al., 1993) and has been applied to create recommendation systems, such as the video recommendation system used by some commercial websites (Davidson et al., 2010). It is an algorithm for discovering interesting relations between variables in databases (Hahsler et al., 2007) by using 'measures of interestingness' (Han et al., 2012). The rule confidence is one of the measures of interestingness and it is used to numerically assess the strength of the association rules (Kotsiantis and Kanellopoulos, 2006). In this research, the uncomfortable sensations and occupants' reactions are regarded as two related variables in the database. During the field study and data processing, the rules and relationships between these variables have already been identified and recorded. Then the confidence is used to qualitatively analyse the associations between the thermal sensation and behaviour data and represent the possibility of performing the behaviour under certain circumstances. The scale of calculated confidence is a value in the range 0 to 1. 'Zero' means that the behaviour is never performed under an uncomfortable condition, and 'one' means that the behaviour always takes place when a situation occurred.

The calculation method of the rule confidence value is actually calculating the conditional probability, which process can be expressed as follows (Han et al., 2012): Let, t_i denote the uncomfortable thermal sensation feeling, where $i \in [1,2]$. t_1 represents uncomfortably cold and t_2 represent uncomfortably hot. b_j denotes a particular type of behaviour. $P(A)$ means the probability of A. The form of the association rule of these two variables is $t_i \Rightarrow b_j$, then the confidence of the association rule $c(t_i \Rightarrow b_j)$ can be expressed as a conditional probability:

$$c(t_i \Rightarrow b_j) = P(b_j \mid t_i) = \frac{P(t_i \cup b_j)}{P(t_i)} \tag{7.17}$$

Let n denote the total sample in the database, n_i be the number of the thermal sensation t_i occurrences and n_{ij} be the count of the behaviour b_j when thermal sensation t_i occurs. It can be found that:

$$P(t_i) = \frac{n_i}{n} \tag{7.18}$$

$$P(t_i \cup b_j) = \frac{n_{ij}}{n} \tag{7.19}$$

By substituting function (7.19) and (7.18) into function (7.17), and simplifying the expression of $c(t_i \Rightarrow b_j)$ into c_{ij}, the value of the association rule confidence will be calculated as:

$$C_{ij} = \frac{\frac{n_{ij}}{n}}{\frac{n_i}{n}} = \frac{n_{ij}}{n_i} \quad (7.20)$$

Because the purpose of using the confidence here is to find the numerical scale of a behaviour association with thermal comfort, no threshold is set for C_{ij}. From function (7.20), it can be found that if a type of behaviour was not recorded to be performed by an occupant at all, the value of the confidence is zero.

When carrying out the questionnaire survey, the subjects have already been asked to give the reason for one reaction, for example, putting on some clothes because of feeling cold. In this case, the value of n_{ij} and n_i can be retrieved from the collected data. With the confidence, the Condition-Action Rules introduced in section 6.7 understand whether the suggested action is the one the occupant is most accustomed to perform or not. In this case, personalised suggestions can be made by the Condition-Action Rules. The confidence value may also be used by the decision-making algorithm to select the most appropriate action plan. This is illustrated in sections 7.3 and 7.4.

7.3 Decision-making Process Development for the BEMS

7.3.1 Problem Analyses

It has been shown that to realise the aim of the BEMS, the system needs to fulfil three objectives: 1) is minimising the energy consumption; 2) is maximising the occupants' thermal comfort level and 3) is providing the personalised suggestion to the occupants with the simplest behavioural adaptation and considering the occupants' habits. It can be seen that objective one is a minimum optimisation problem as in the cooling load function (7.12) and the heating load function (7.16) which both need to be minimised to save energy. It also can be found that people's thermal comfort level should be maximised so objective two is a maximum optimisation problem. However, maximum optimisation problems can be transferred into equivalent minimum optimisation problems, so Function (6.1) can still use the symbol 'minimum' as the description of the multi-objective optimisation problem in this research.

Let f_e, f_c and f_b respectively represent the objective functions of the energy consumption, thermal comfort and personal behaviours in general. Every built environment has its own f_e, f_c and f_b functions. All of the objective functions have been discussed in the previous sections.

The relationship among objective functions and their related variables are depicted in Fig. 7.1. In the diagram, item(s) in the blocks at the beginning of the arrow will affect the items in those at the end of the arrow. The block with a 'P' in it means that items in that block are parameters. For a certain built environment, the physical parameters of the building are fixed. It can be found that some of objective functions are affected by common factors. The variables affecting its f_e value include the outdoor climate conditions, indoor thermal environment conditions and set temperatures of the installed HVAC system. The parameters affecting the f_c contain the indoor environment factors and the personal factors defined by the ASHRAE standard and ISO7730 (ANSI/ASHRAE55-2010, 2010, ISO7730, 2005). The value of f_b is determined by the suggested behaviours. It should be noted that occupants' behaviour will also change the personal factors such as cloth insulation value. If occupants are able to manually change the settings of the HVAC system, the personal behaviours also include changing set points of the HVAC system. In conclusion, behavioural adaptation may affect values in all three objective functions. Applying behaviour adaptations as one of the input variables of the objective functions is an effective way to take the adaptations into account when making decisions. This way is adopted by the decision-making algorithm in the A-component in the agent.

Among all the variables, the parameters that can be affected by the BEMS are the occupants' behaviours and the settings of the HVAC system. So they are the decision variables to build up the action plans in the D-component. The vectors of behaviours and the settings can be used to form the feasible decision space.

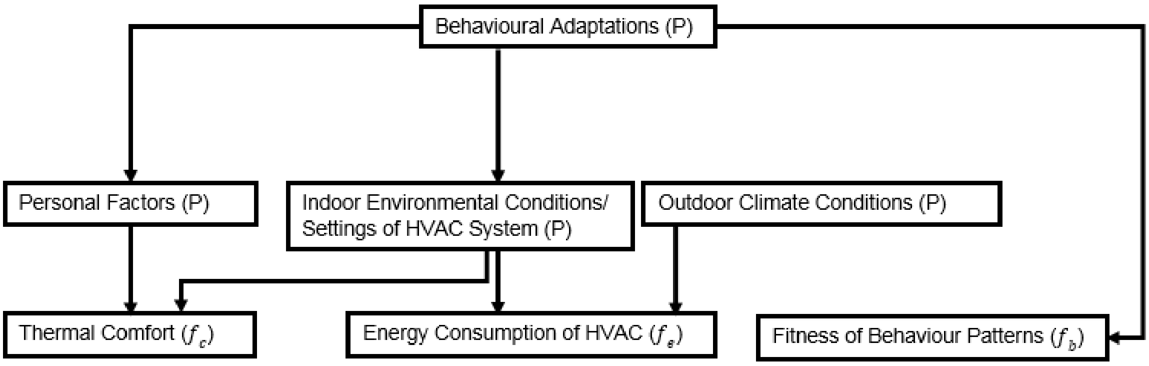


Figure 7.1 The Relationship between the Factors and Objective Functions

7.3.2 Operation Process of the Multi-agent BEMS in Single-occupancy Offices

The flowchart of the decision-making process of a multi-agent BEMS in a single occupancy office is illustrated in Fig. 7.2. The whole process can be divided into two phases. The first phase is the learning phase of the system. During the learning phase, the agent-based system utilises the data collected from the environment and the occupants to generate the objective functions for the decision-making algorithms in the local agents. The learning/modelling algorithms in the agents' E-components thermal are used to generate objective functions concerning comfort, energy consumption and behavioural adaptation.

Once the learning is completed, the agent is ready to make decisions to fulfil its design purposes. The decision-making process involves all three components in the agents. Firstly, the decision-making algorithm in the A-component downloads the generated models/algorithms from the E-component. Then, the action plans stored in the D-component are sent to the A-component for selection. Under the single occupancy office situation, action plans comprise changing the set temperature of the HVAC system and finding the best behavioural adaptation for the end user. The selection of the best plan is performed by the decision-making algorithm equipped with objective functions generated in the learning phase. The selection is an optimisation process based on the lexicographic method either alone or in combination with the ϵ-constraint method. The sequence of solving the optimisation problems is firstly to optimise the thermal comfort objectives, then minimise the energy consumption and, finally, to decide the best way to react if necessary. Once the optimised action plan is selected, the settings of the HVAC system are sent to the HVAC actuator directly or sent to personal agent for the occupant to perform. If behavioural adaptations are needed, this information will also be sent to the personal agent, which will then provide the suggestions from the system to the occupant based on suggestion plans and occupant's individual differences already stored in the D-component in the agent. The personalised suggestion is realised by the Condition-Action Rules in the A-component in the personal agent.

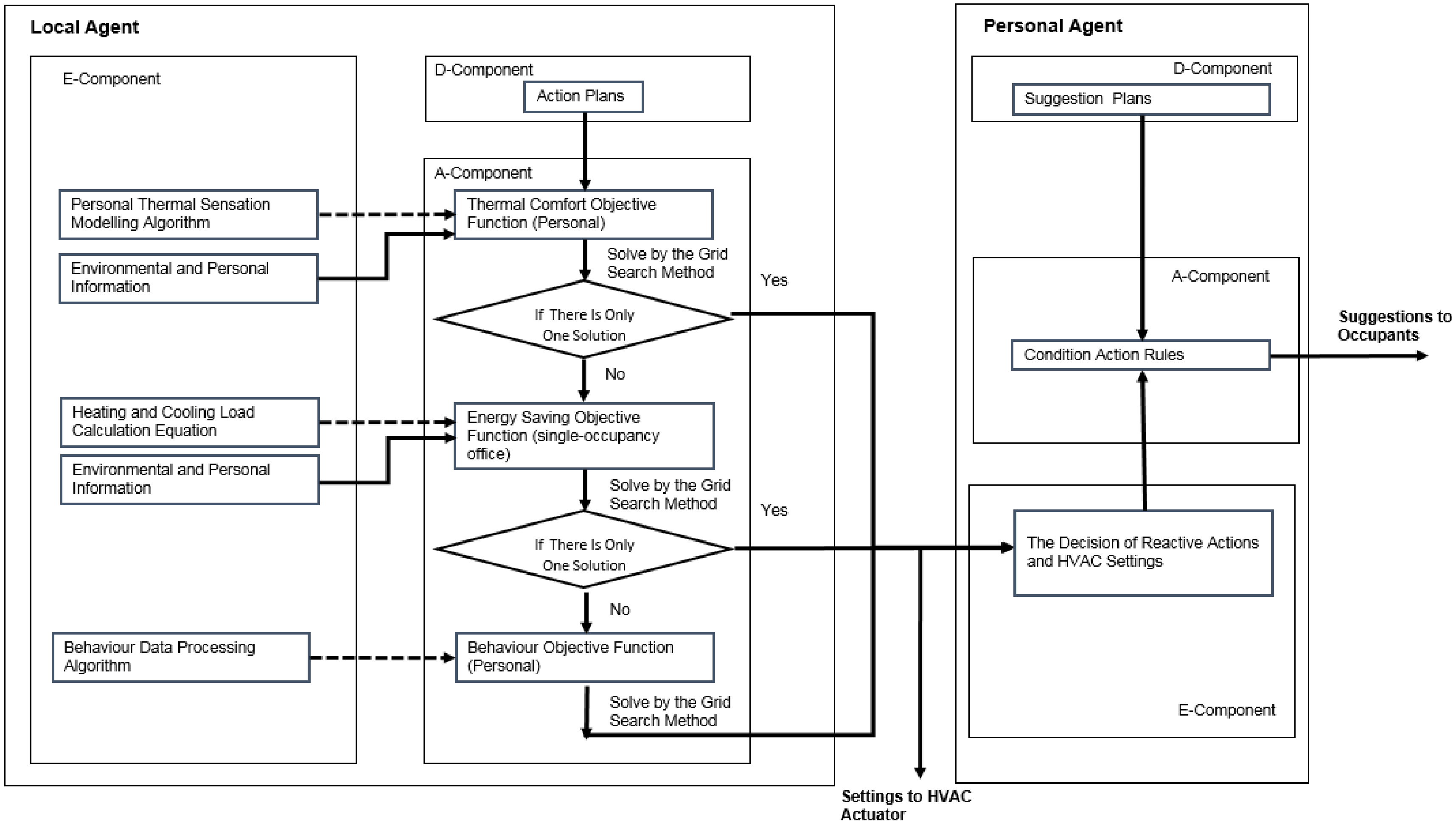


Figure 7.2 Operation Process in Single-occupancy Offices

7.3.3 Decision-making process in Open-Plan Offices

In an open plan office, the operation processes of the local agent and the personal agent are different from those in the single occupancy office. The operation flowchart of the multi-agent BEMS under the open-plan office condition is illustrated in Fig. 7.3. The first phase of operation is still the learning phase. However, in the decision-making phase, because multiple occupants are in in the environment, the local agent only makes decision on the set temperature of HVAC for the whole area. Once the settings are decided, the information is sent to the HVAC actuator as well as to the personal agents that serve their corresponding occupants. The personal agents examine if their occupants will be satisfied by the set conditions. If an occupant will feel uncomfortable, his/her personal agent will decide on a behavioural adaptation and then send out the message to the occupant. The message is also processed by the Condition-Action rules.

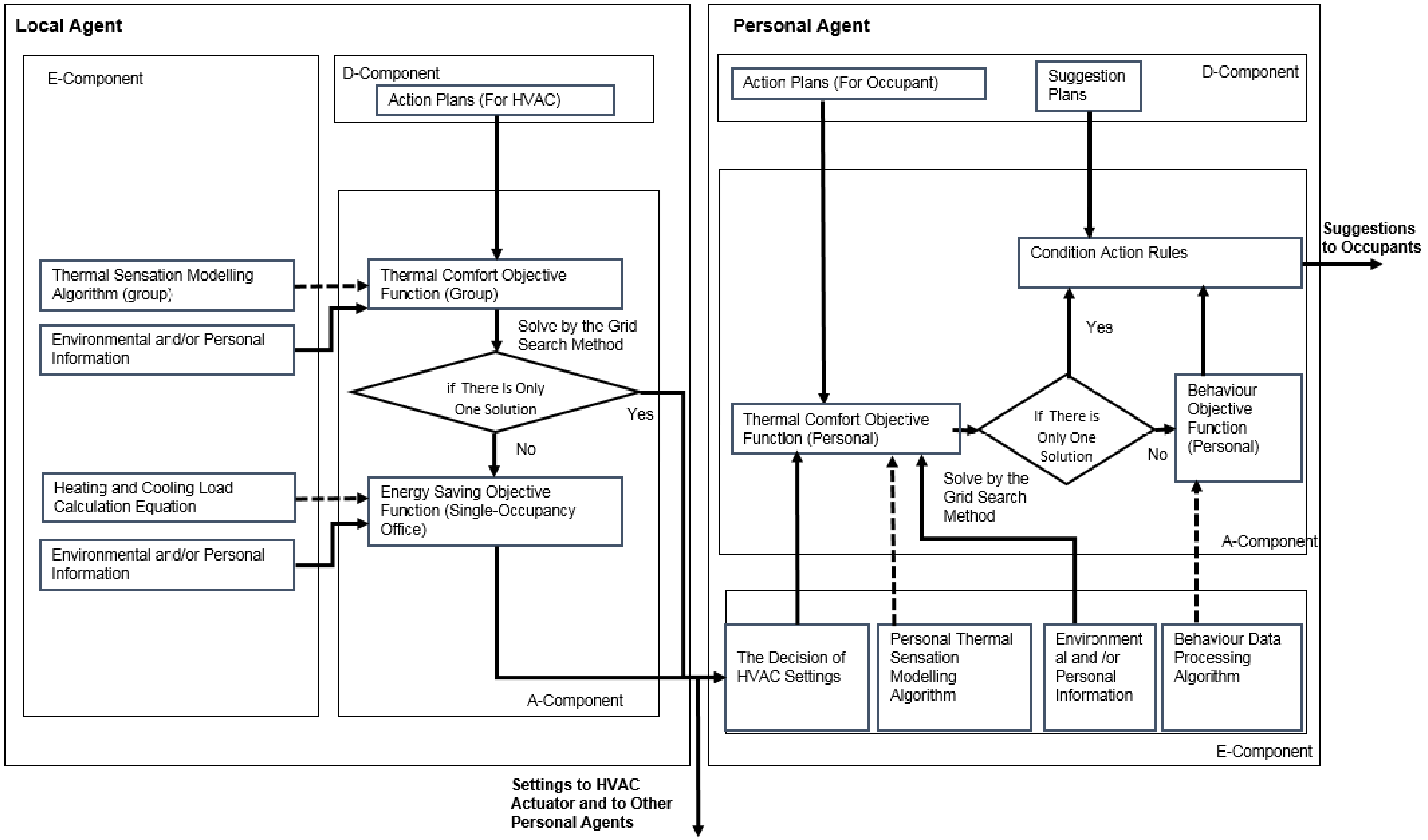


Figure 7.3 Decision-making Process in Open-plan Offices

7.4 Illustrating the Operations of the BEMS by Case Studies

7.4.1 The Building Model and Characteristics of the Occupants

In order to verify if the developed BEMS is functioning properly, the developed decision-making algorithm, thermal sensation models, adaptation evaluation algorithm and heating and cooling load calculation methods are integrated into the agent-based system then tested in a simulated air-conditioned office environment. The properties of the office environment, as well as the characteristics of the occupants inside, are based on the data collected from the experimental study carried out in the University of Reading. For more details of the data collection process and model generation, please refer to Chapter 2, Chapter 4 and Chapter 5.

In order to study the energy consumption of the office environment without losing generality, two typical office occupancy conditions are considered in this research. The first one is the single occupancy office, which is occupied by one person during office hours. The second one is an open-plan office, which is occupied by a group of people during the same office hours. The office hours are from 9:00a.m. until 5:00p.m. The occupants in both the open-plan office and the personal office have their fixed seats. Windows in both offices are facing the east and they are double-glazed. Only one wall with windows is exposed to the outside air. The rooms are under unconditioned built areas and over a basement crawl space. The rooms are next to air-conditioned zones and the doors of the rooms lead to another air conditioned zone. The dimensions of these two offices and the windows inside are illustrated in Table 7.4:

Table 7.4 Parameters of the Studied Rooms

Office Type	Room Length (L)	Room Width (Rw)	Room Height (H)	Window Width (Ww)	Window Height (Hw)
Single-occupancy Office	3m	5m	2.5m	2m	1.5m
Open-plan Office	5.5m	10m	2.5m	8m	1.85m

It is assumed that the HVAC system is able to adjust the indoor temperature, humidity and air velocity to achieve a stable level. The air in the controlled environment is evenly mixed and physical parameters of the air in the whole area are uniform. The ambient air temperature around each end-user is assumed to be the same as that set by the HVAC system. It is assumed that the temperatures and radiation fluxes of the surfaces in the indoor environment are uniform, so the mean radiant temperature is regarded as being equal to the air temperature (Walikewitz et al., 2015). Based on the data collected from the field study, the HVAC system's set points range from 18℃ to 27℃, with 0.5℃ steps. The relative humidity is 40%. When the outdoor temperature is higher than the indoor temperature, the air conditioning unit works in cooling mode and if the indoor temperature is higher, it works in heating mode. How the HVAC system stabilises the indoor environment at certain levels is beyond the scope of this research.

The personal factors and behavioural habits of the occupants come from subjects AC1, AC2, AC3, AC4, AC5 and AC6 who finished the experiment in the air-conditioned environment. In the single occupancy scenarios, it is assumed that subjects AC1 to AC5 had a single office as described above. For the open-plan office, all six subjects are sitting in the same area. Based on the collected data, the range of the clothing level for the simulation is set between 0.5 and 1.5CLO. The typical activity level is 1 or 1.1MET. The CLO and MET values will be specified in each simulated built environment.

Two types of behavioural adaptations frequently observed from these occupants during the field study are considered as the optimal decision-making process. The adaptations are: changing the clothing insulation level and changing the set-point of the HVAC system. The observation from the field study demonstrates that occupants sometimes do either of these two actions separately or do both of them at the same time.

Following the definition of Function (7.20), the rule confidence value C of the association rule of the thermal sensation and behaviour reaction of all the subjects in the air-conditioned are shown in Table 7.5:

Table 7.5 Confidences of Association Rules of the Sensations and the Adaptations

	AC1	AC2	AC3	AC4	AC5	AC6
Put on clothes when feeling cold.	100%	0%	0%	66.7%	80%	40%
Turn up the set point of the HVAC when feeling cold.	0%	50%	0%	0%	0%	0%
Put on clothes and turn up the set point of the HVAC at the same time when feeling cold.	0%	50%	0%	0%	0%	0%
Take off clothes when feeling hot.	66.7%	52.6%	100%	50%	66.7%	0%
Turn down the set point of the HVAC when feeling hot.	33.3%	21.1%	0%	0%	33.3%	100%
Take off clothes and turn down the set point of the HVAC at the same time when feeling hot.	0%	26.3%	0%	0%	0%	0%

If the decision-making algorithm attempted to suggest the actions the occupants' most usually carried out, the algorithm should select the behaviour having the highest confidence value. However, in the developed program, the function 'minimise' is used consistently in this part of program for ease of programming. This means that the program treats the optimisation problem as a minimisation problem. In this case, the program is developed to search for the minimum value of $C' = 1 - C$, which converts the maximum problem into a minimum problem.

7.4.2 Case Studies in Single-occupancy Offices

7.4.2.1 Basic Assumptions for Single-occupancy Offices

The simulated indoor environment is set up to test whether the multi-agent BEMS functions correctly with the desired output. It is assumed that the air-conditioning system is serving an office which is designed for only one occupant. Based on the generally defined information in the last section, the specifications of the built environment, the BEMS and the occupants are as follows. It is assumed that one of the occupants AC1, AC2, AC3, AC4 and AC5 is seated in an office and the outside temperature is 10℃ while the HVAC system is working under the heating mode. Or, alternatively, the outside temperature is 30℃ when the HVAC system is working under cooling mode. It is assumed that the indoor air velocity is 0.08m/s. When the HVAC system is working under heating mode, the initial indoor air temperature is

18℃. When the system is working under cooling mode, the initial indoor air temperature is 28℃.

It is also assumed that the BEMS is aware of the occupant’s activity levels and clothing insulation level. The occupant has the ability to control the set point of the air temperature within the given range. The occupant also has the opportunity to change his/her clothing insulation level. When the subject is inside the office, his or her activity level is one. The occupants can change the CLO into 1.25 or 0.75. The MET value of the occupant is one.

During the decision-making process, the control target of the thermal environment is the environment that lets the occupant feel ‘neutral’, which is the highest level of the thermal sensation values. For energy consumption, the system looks for the plans that consume minimum energy. If the system needs to decide the occupant’s reactions, the complexities of the behaviours or the accustomedness of the behaviours to the occupant can be used as a basis for the evaluation. The system either selects the simplest action or the most common action for the occupants. The lexicographic method is used to tackle the multi-objective problem.

7.4.2.2 Case Study One: Decision-making for AC1

When making decisions, the variables needing to be considered are the set temperature of the HVAC system and the CLO level of the occupants. From Fig.7.1, it can be seen that indoor environmental conditions affect the energy consumption and the occupant’s thermal comfort. Beside the indoor environment, the occupant’s behaviours, such as changing clothing level, affect his/her thermal sensation. Both of the actions affect the value of the behaviour objective function. So the feasible decision space can be a two-dimensional space with two factors: HVAC settings and CLO values. In addition to the value in an objective function, the grid search outcomes for every step in the lexicographic method can be displayed as a three-dimensional diagram.

Values of the objective functions of the thermal comfort and energy consumption based on different temperature settings and actions are illustrated in Fig. 7.4. Following the settled decision-making process of the local agent, the optimal solutions of the thermal comfort objectives are firstly found by the grid search method. Solutions to the thermal comfort objective are illustrated as black circles in Fig. 7.4.a.

As shown in the figure, these solutions guarantee the subject's thermal sensation at a 'neutral' level. It can be found that by co-operating with suitable CLO levels, the acceptable set point range is from 21 to 25.5℃. Once all possible solutions for the thermal comfort objective are selected, these solutions become constraints to the next optimal objective, which is energy saving. This means the optimal solution for the energy-saving objective should only be selected from the grid points which fit the requirement of thermal comfort. The values of energy consumption calculated at these grid points are also expressed as black circles in Figure 7.4.b. Then, the grid search method is applied again, and the selected optimal solution is expressed as a red star in the figure. In any step, if only one potential solution remains as the search result, this solution is claimed as the final solution. Here, the grid search gives only one solution as the optimal solution of the energy consumption problem. So the solution is the optimal solution to the whole multi-objective decision-making problem. The final decision can be interpreted as suggesting that the occupant increases the CLO level to 1.25 and configures the set point of the HVAC system to 21℃. The value of the required cooling load is 1,811.9W. According to Table 7.5, adjusting the CLO level is the most frequent way in which AC1 achieved his/her comfortable feeling, but changing the settings for the HVAC system is not. So the decision of the system needs to be processed by the condition-action rules in the personal agent to explain that only changing the CLO level may not enable the occupant to feel comfortable.

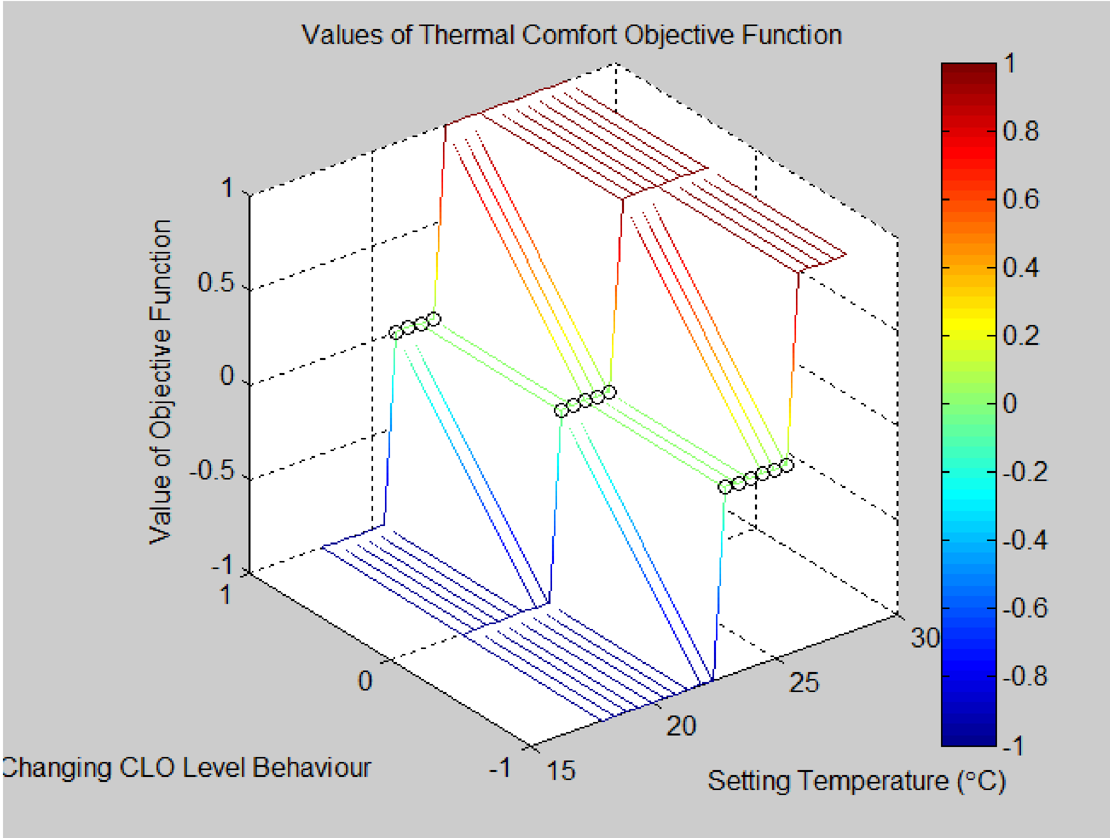


Fig. 7.4a

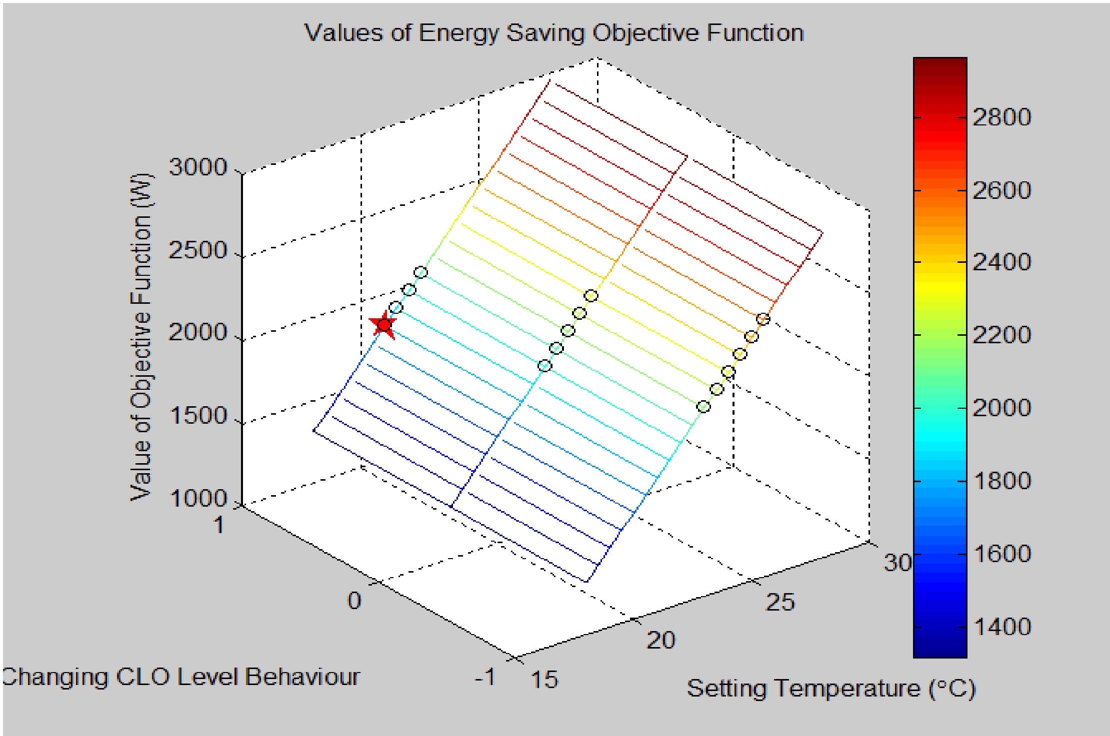


Fig. 7.4b

Figure 7.4 Values of objective functions of AC1 (Heating Mode)

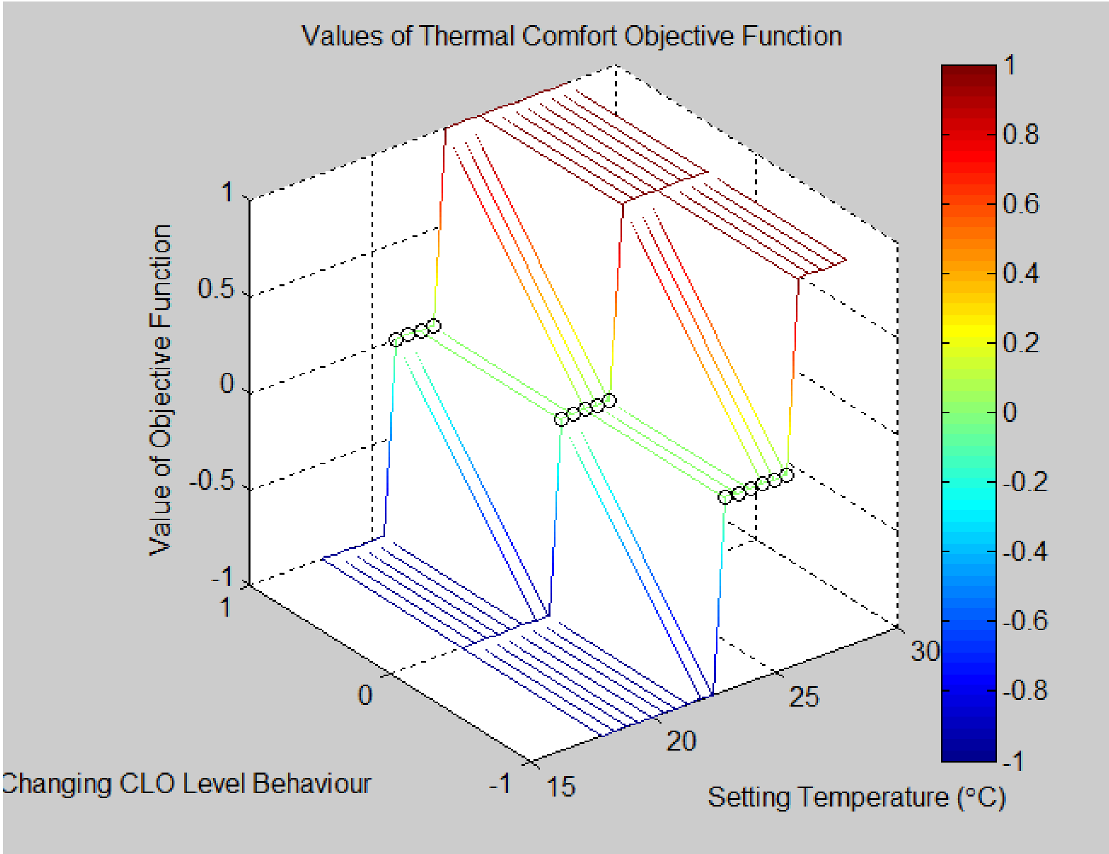


Fig. 7.5a

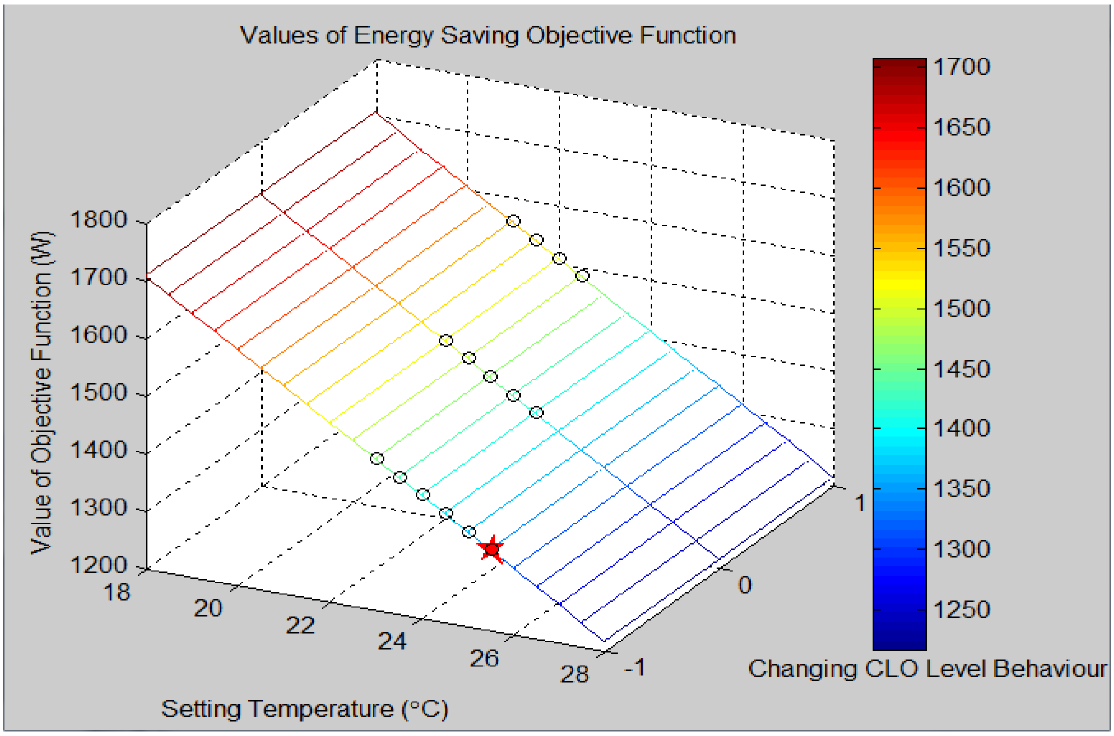


Fig. 7.5b

Figure 7.5 Values of objective functions of AC1 (Cooling Mode)

When the HVAC system is working under cooling mode, the decision-making process of the local agent is shown in Fig. 7.5. It can be found that the comfort zone for AC1 is the same as the one when the HVAC system is working under cooling mode, but the decision is different. The decision from the system suggests that **AC1** changes the clothing insulation level to 0.75; the recommended set point is 25.5℃ and the cooling load under these conditions is 1,339.8W. Again, the solution plan is not the one most commonly used by the occupant. So the information will be processed by the personal agent before being sent to the occupant.

7.4.2.3 Case Study Two: Decision-making for AC2

When the decision-making algorithm deals with AC2 in the same environmental and personal conditions, the decision-making process is different. Because of the limitations of the developed model, the case study only investigates the decision-making outcomes when the air conditioner is working under heating mode. The outcomes of the grid search whose thermal comfort value fits the requirements are illustrated in Fig. 7.6a. Compared to AC1, AC2 accepts a lower HVAC system set point. The final solution suggested to the occupant was to increase the CLO value to 1.25, with an HVAC set point of 18℃. The required heating load is 1,317.7W. However, from Table 7.5 it can be seen that the occupant is more used to changing the settings of the HVAC system than changing his/her clothing level. In this case, the personal agent will remind the occupant that changing the CLO level will guarantee his/her thermal comfort without overshooting the HVAC's settings.

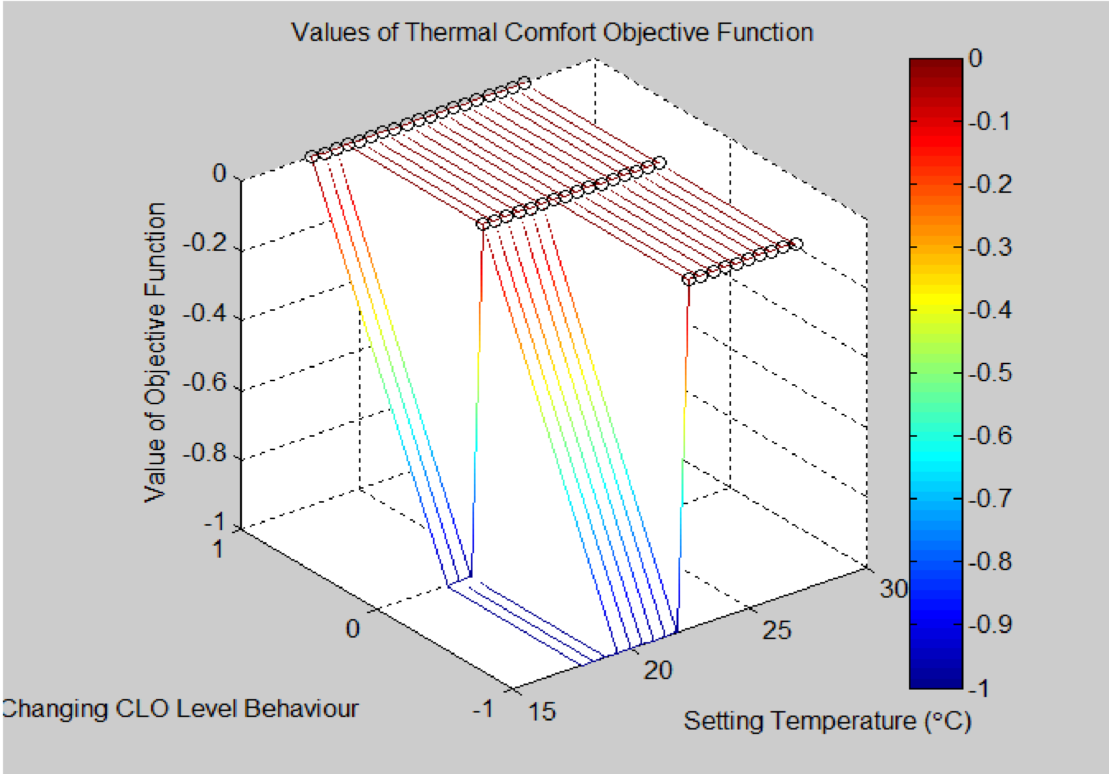


Fig. 7.6a

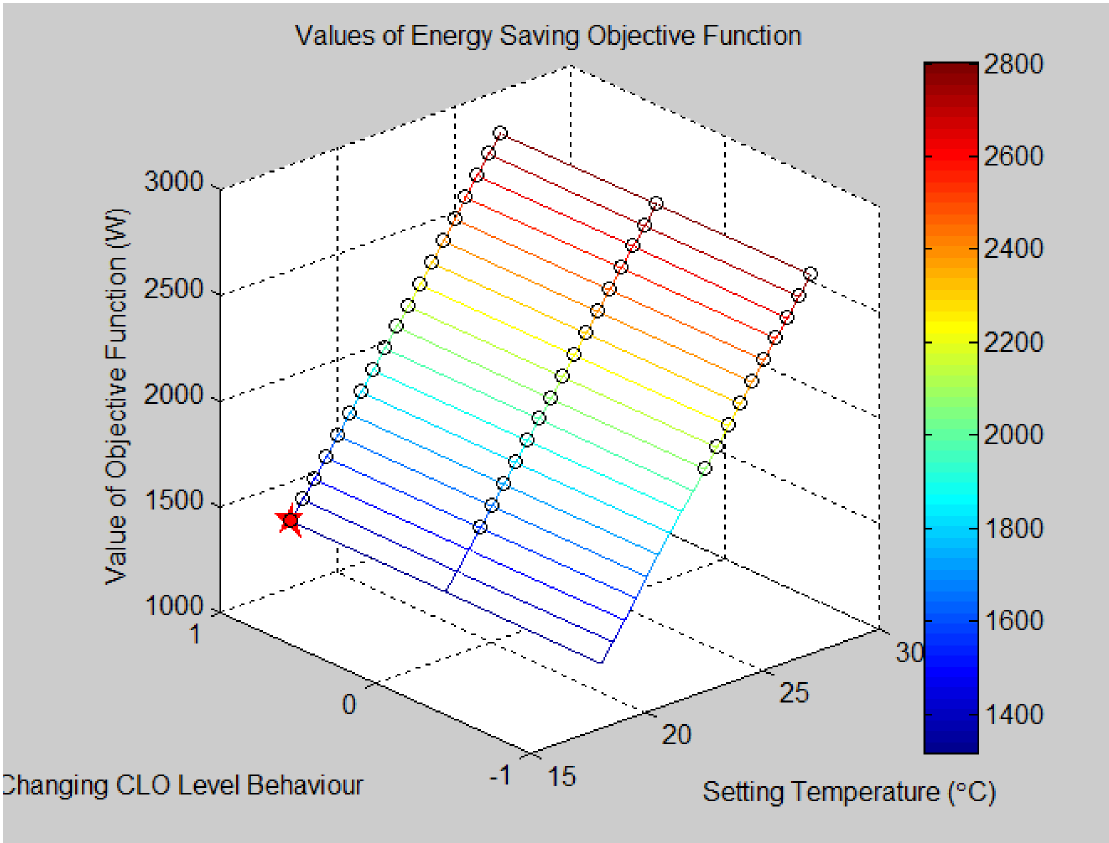


Fig. 7.6b

Figure 7.6 Values of objective functions of AC2 (Heating Mode)

7.4.2.4 Case Study Three: Decision-making for AC3

When the system is working under heating mode, the algorithm's decision-making process for AC3 is shown in Fig. 7.7. From Fig. 7.7a, it can be found that compared to subject AC1, subject AC3 is more sensitive to cold conditions. The suggestion from the system is to put on clothing with 1.25CLO level and change the temperature setting to 22.5℃. The energy consumption is 2,059W. According to Table 7.5, this decision will be directly forwarded to the occupant by the personal agent.

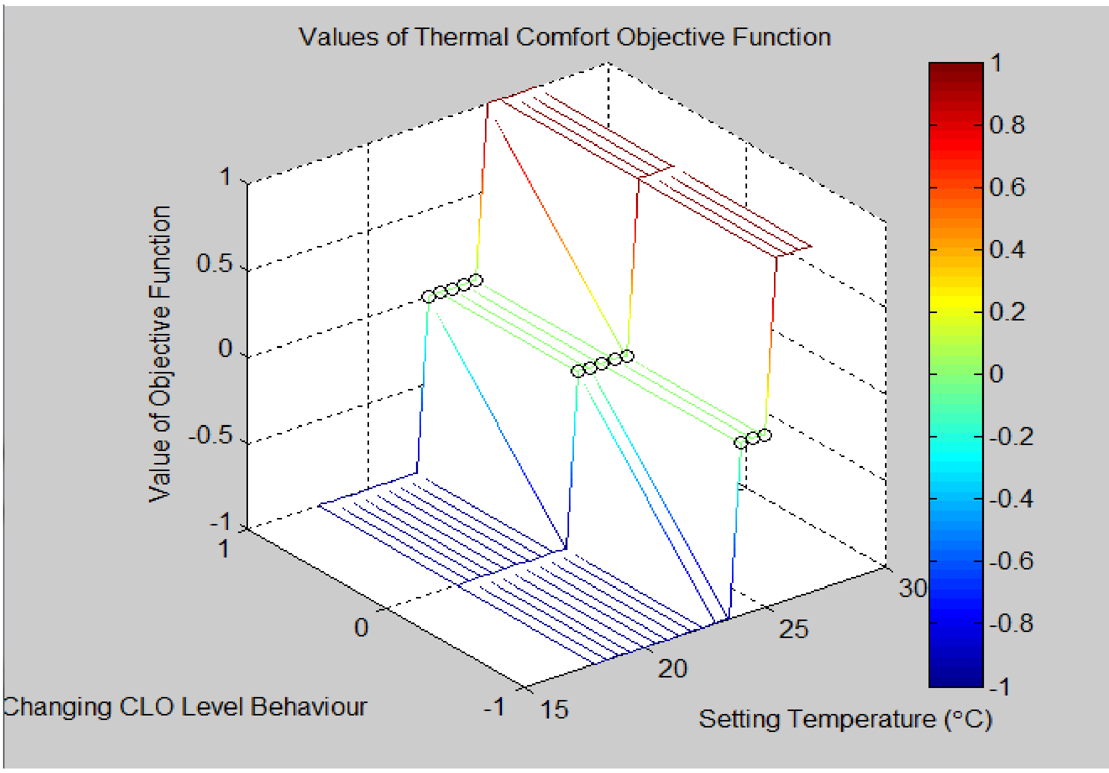


Fig. 7.7a

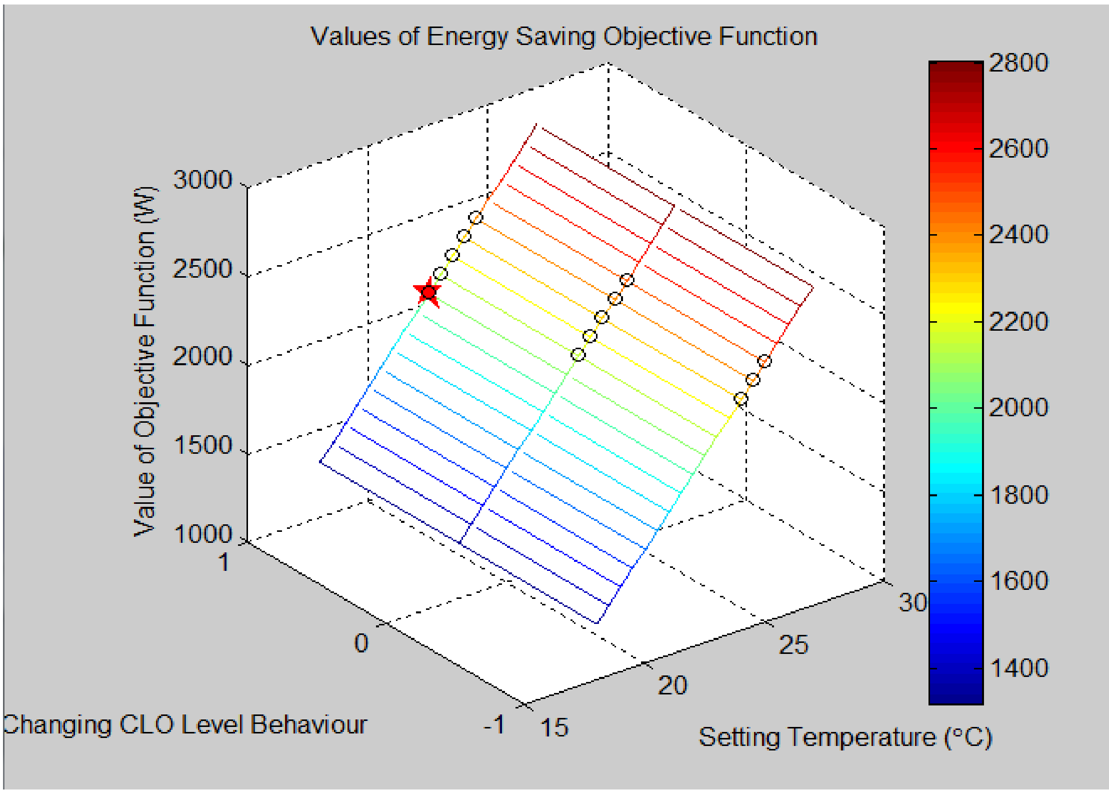


Fig. 7.7b

Figure 7.7 Values of objective functions of AC3 (Heating Mode)

When the system is working under cooling mode, the HVAC set point can be as high as 25℃. Unlike AC1, Fig. 7.8b shows that the final solution is not found by searching the values of the energy consumption objective function. Two action plan options exist in the figure. In this case, the behaviour objective function needs to be involved. By considering the complexity of the proposed action plans, the system's final suggestion is adjusting the temperature to 25℃ without changing the clothing level. The required cooling load is 1,963.9W. This decision outcome is shown in Fig. 7.8c. If the system wishes to use the accustomedness of the actions to evaluate the actions plans, the outcome is shown in Fig. 7.8d. Unfortunately, values of the rule confidence of both actions are the same. In this case, the system will randomly select a solution as both the solutions fit all the requirements set by the system.

If the system chooses the solution shown by Fig. 7.8c, again, it can be found that the action is not the commonly used one; in this case, the personal agent needs to give notice to the user regarding the energy consumption information to avoid overshooting the set point.

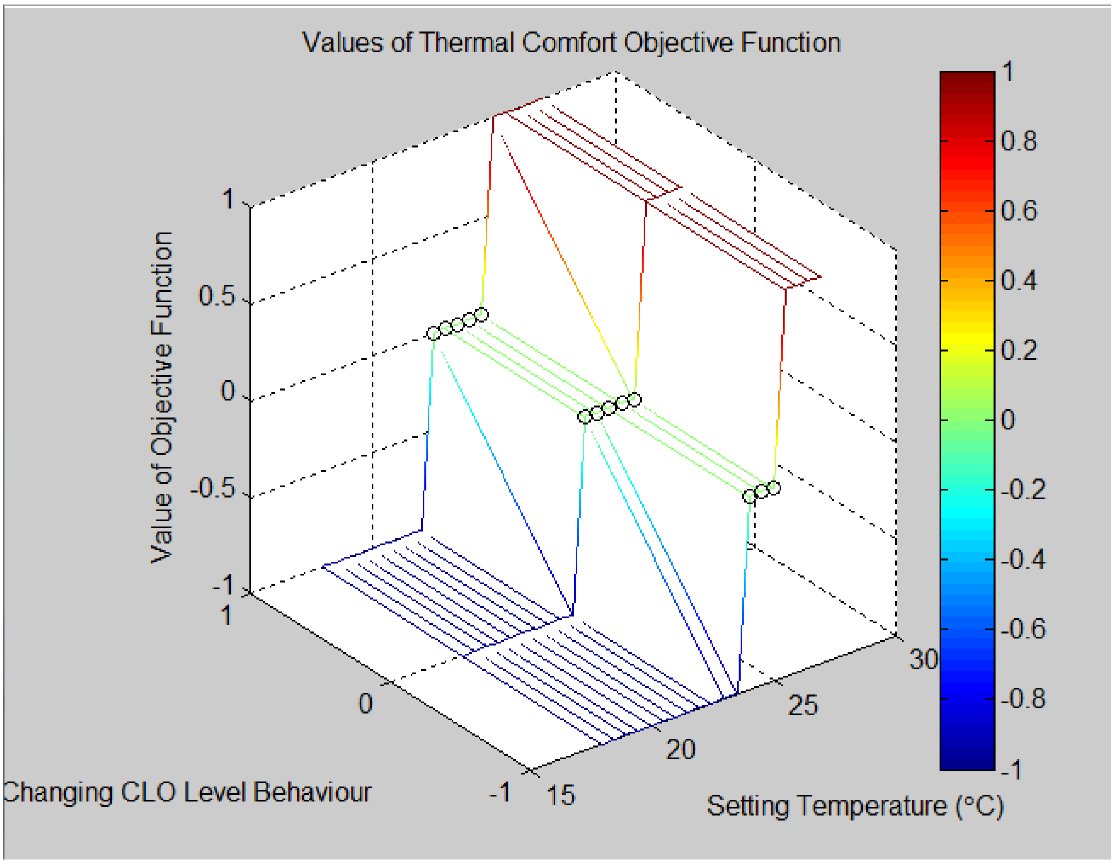

Values of Thermal Comfort Objective Function
Value of Objective Function
1
0.5
0
-0.5
-1
1
0
-1
Changing CLO Level Behaviour
15
20
25
30
Setting Temperature (°C)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

Fig. 7.8a

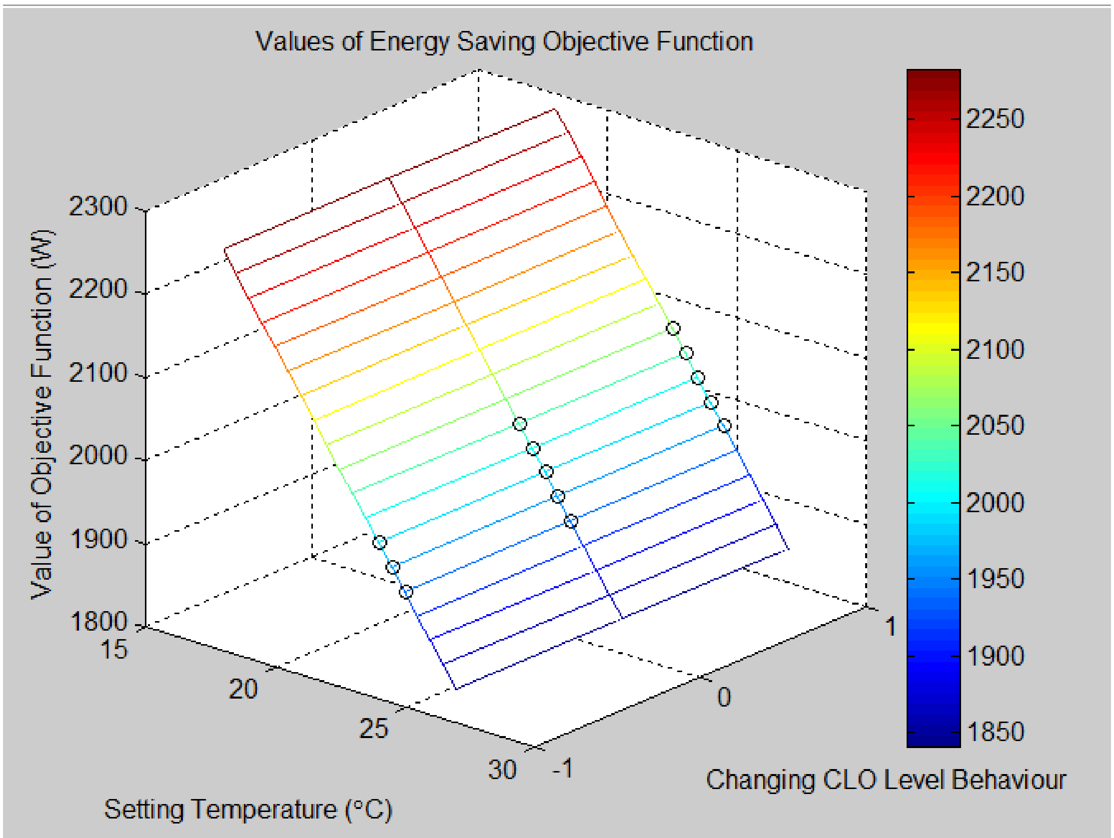


Fig. 7.8b

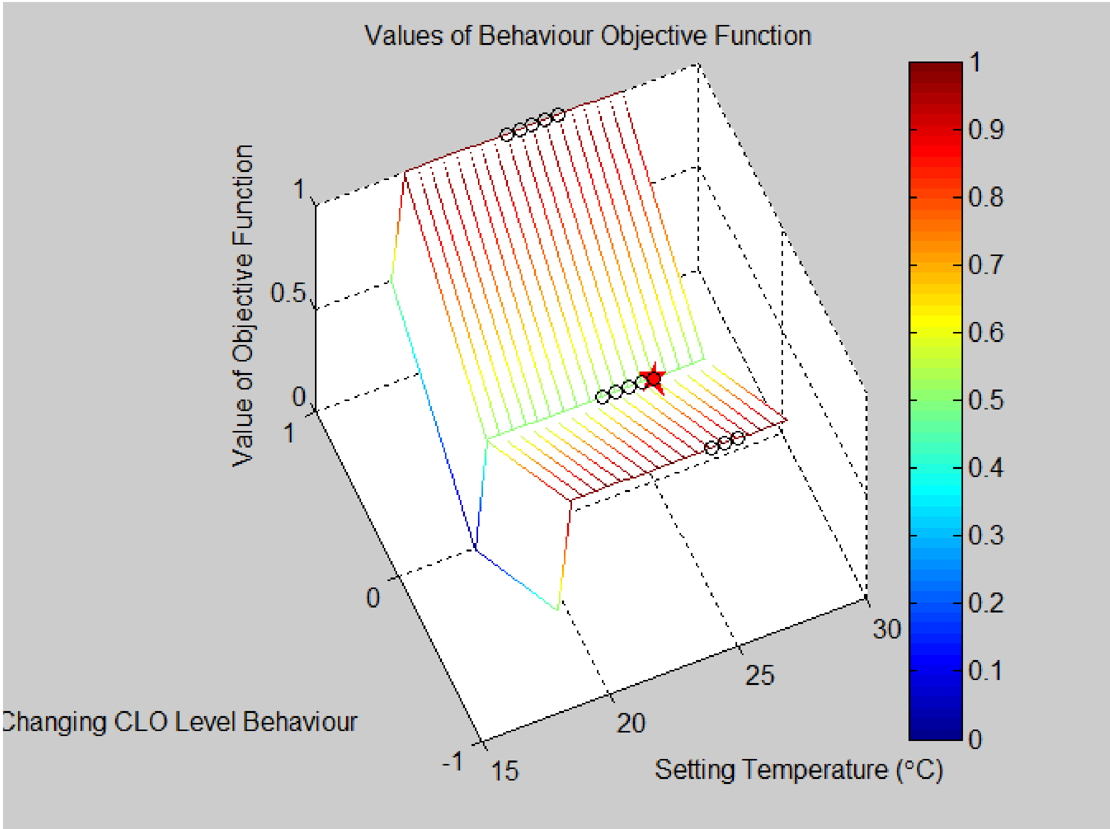


Fig. 7.8C

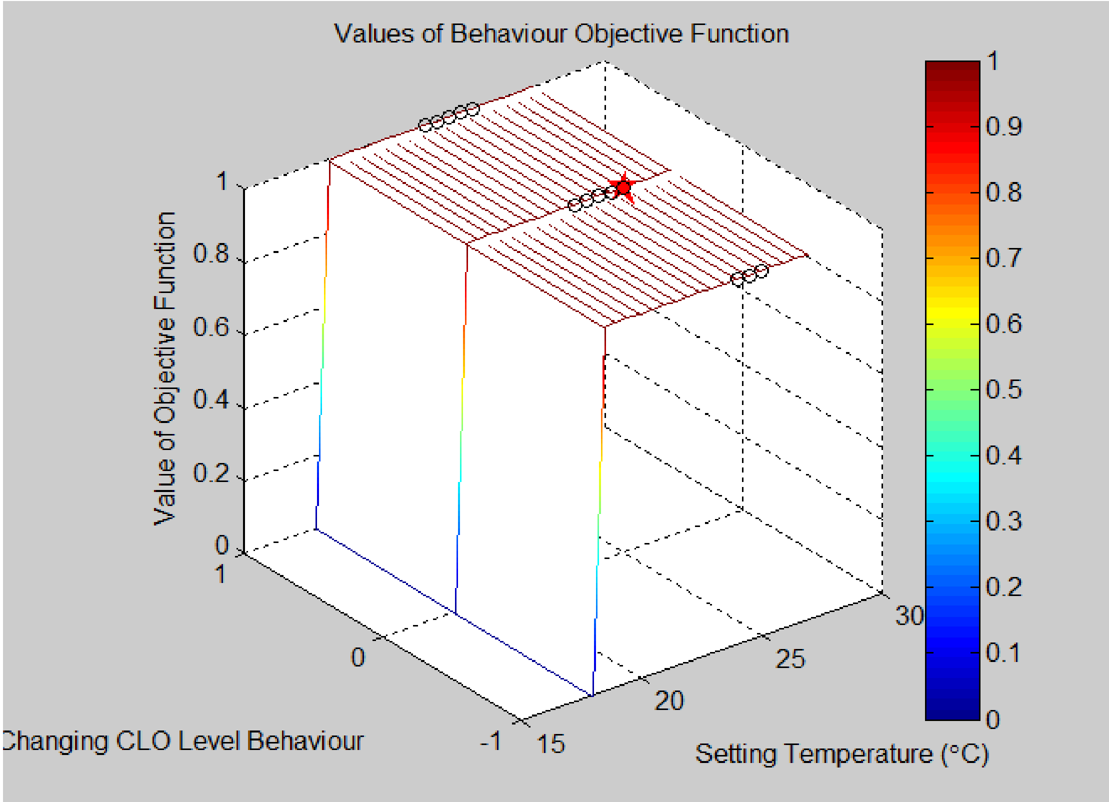


Fig. 7.8d

Figure 7.8 Values of objective functions of AC3 (Cooling Mode)

7.4.2.5 Case Study Four: Decision-making for AC4

For occupant AC4, the decision-making process shown in Fig.7.9 is similar to that for AC2. The final decision from the local agent is adjusting the HVAC set point to 21.5℃ while putting on clothing with a CLO level of 0.25. The heating load will be 1,894.3W. The decision information needs to be processed by the personal agent.

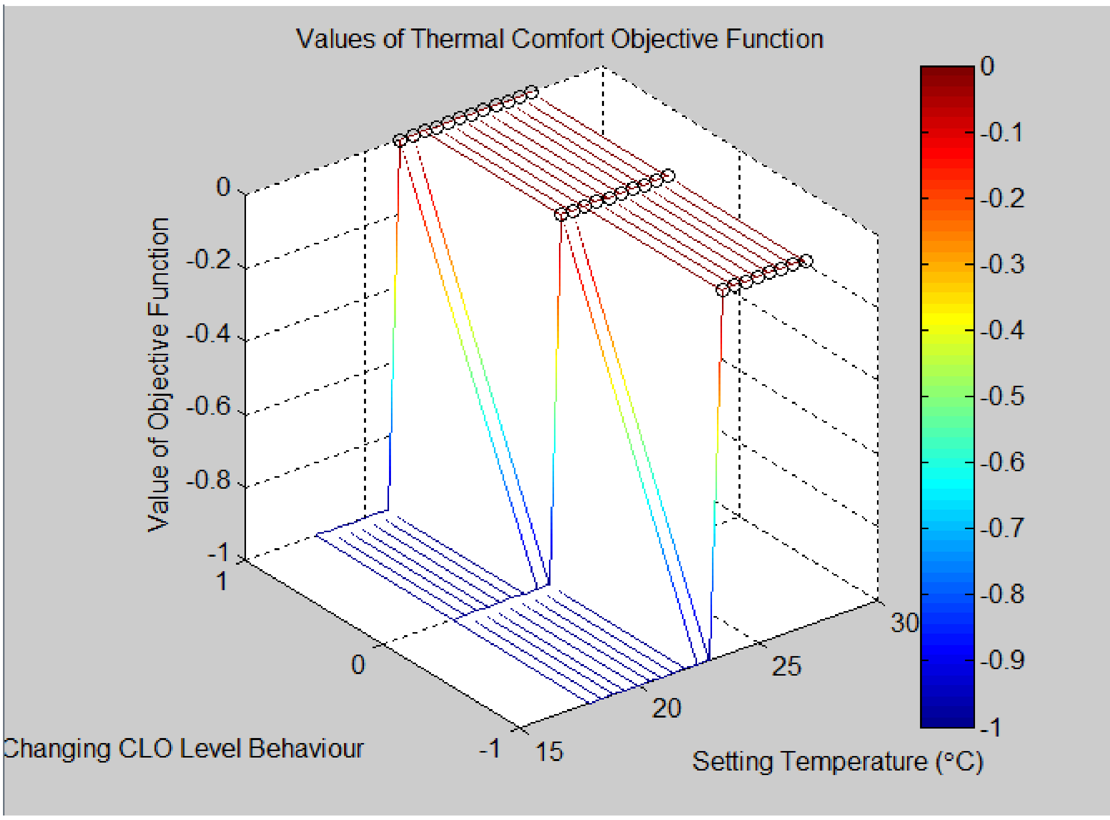

Values of Thermal Comfort Objective Function
Value of Objective Function
0
-0.2
-0.4
-0.6
-0.8
-1
1
0
-1
Changing CLO Level Behaviour
15
20
25
30
Setting Temperature (°C)
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
-1

Fig. 7.9a

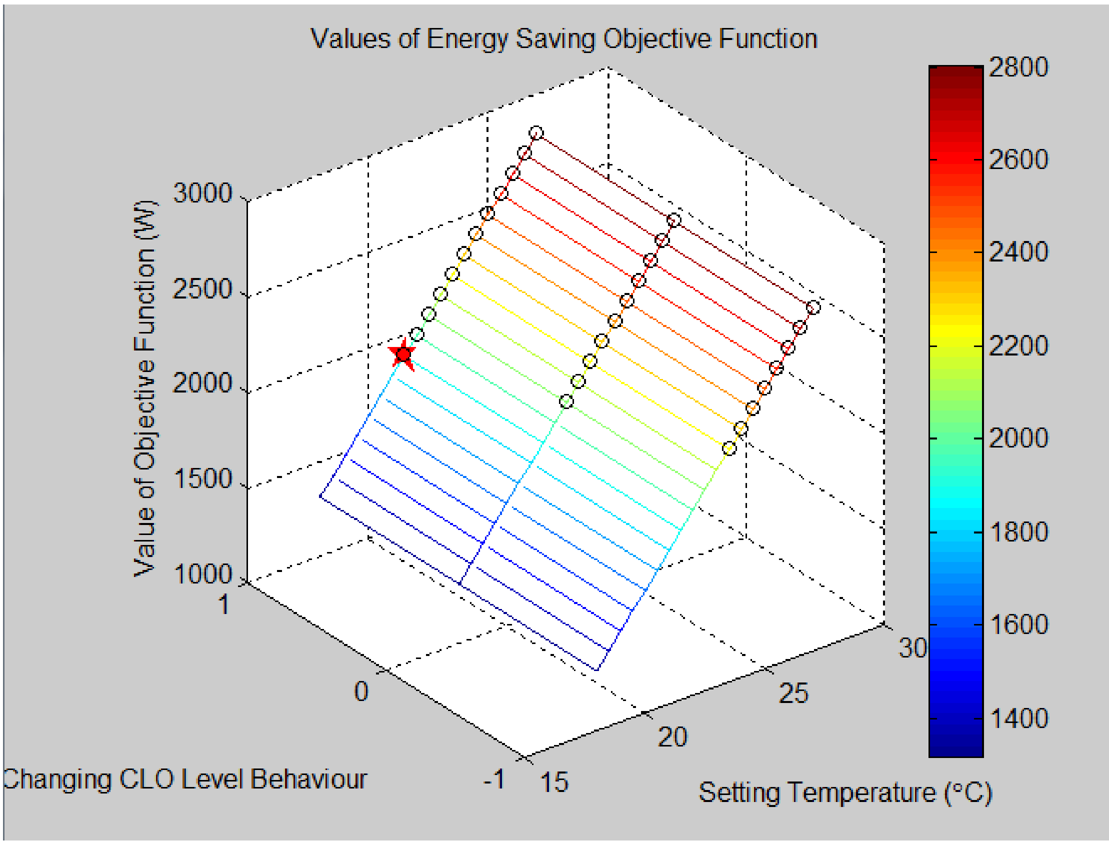
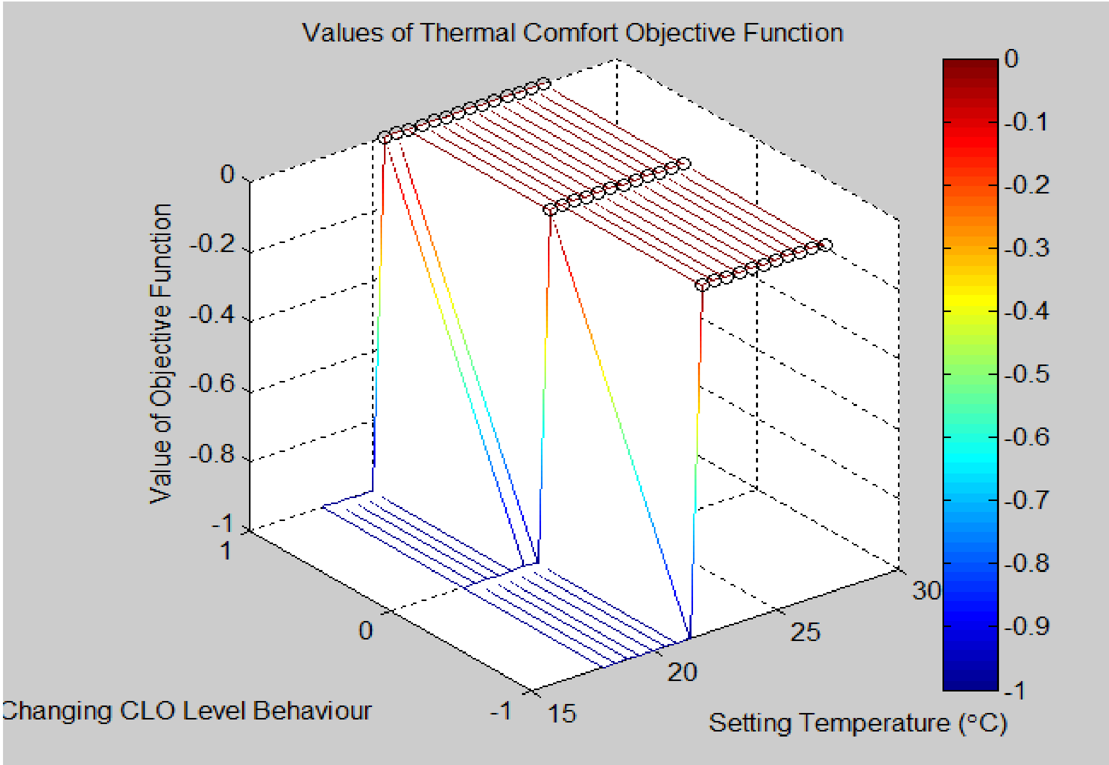


Fig. 7.9b

Figure 7.9 Values of objective functions of AC4 (Heating Mode)

7.4.2.6 Case Study Four: Decision-making for AC5

For occupant AC5, the decision-making process is illustrated in Fig. 7.10. In Fig. 7.10b, it can be seen that the final decision is: HVAC set point equals 20.5℃; the CLO level equals 1.25 and the heating load is 1,729.5W. This decision needs to be processed by the personal agent before being forwarded to the occupant.



Values of Thermal Comfort Objective Function
Value of Objective Function
0
-0.2
-0.4
-0.6
-0.8
-1
1
0
-1
Changing CLO Level Behaviour
15
20
25
30
Setting Temperature (°C)
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
-1

Fig. 7.10a

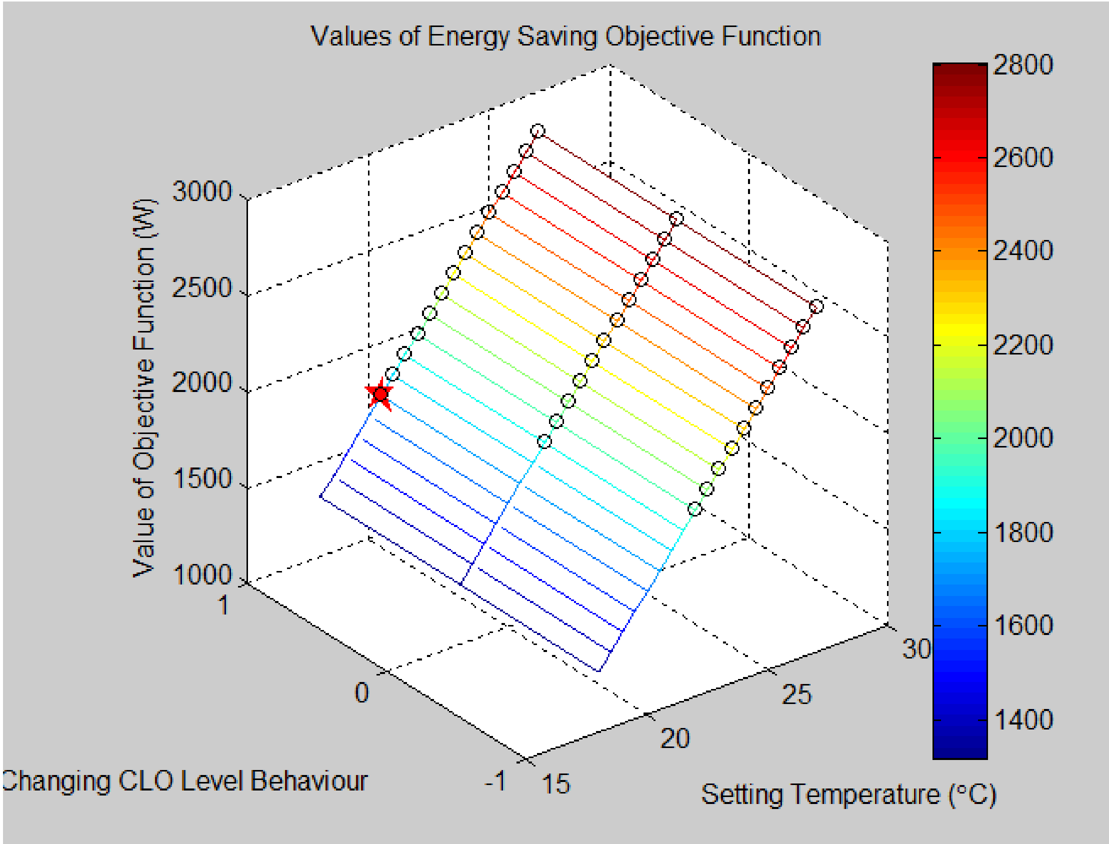


Fig. 7.10b

Figure 7.10 Values of objective functions of AC5 (heating Mode)

7.4.3 The Open Plan Office with Multi-occupant Scenario

7.4.3.1 Basic Assumptions of the Open-Plan Office

The physical dimensions of the open plan office are defined in Table 7.4. The indoor air velocity is 0.08m/s and the relative humidity is 40%. It is assumed that the six occupants, AC1, AC2, AC3, AC4, AC5 and AC6 are sitting in the area. Occupants inside cannot access the control panel of the HVAC system. The set point of the HVAC system is defined by the BEMS automatically. The occupants adjust their clothing level as necessary.

7.4.3.2 Decision-making Outcomes of the BEMS in an Open Plan Office

The decision-making process of the multi-agent BEMS is depicted in Fig. 7.3. Here, both the PMV model and the group people-based thermal sensation model developed in Chapter 5 are used as the objective functions of thermal comfort. The system assumes that the outside temperature is 10℃ and the clothing insulation level is 1.0 CLO. The occupants' activity levels are one. Because for the local agent, the decision vectors have only one element, namely, the set temperature of the HVAC system, the feasible decision space can be regarded as a one-dimensional space. The decision variable, which is the set temperature and the values in the objective function form a two dimensional space. Following the guidelines provided by the ASHRAE standard, the optimisation target for the thermal environment is to maintain the average value of the thermal sensation votes at between –0.5 and +0.5. The target for the energy consumption is to minimise the energy consumption while achieving the thermal comfort goal. It is a typical bi-objective optimisation problem. The thermal comfort goal can be converted into the constraints of the energy consumption goal, so the ϵ-constraint method can applied to solve this problem. The grid search method firstly locates all the set points that fulfil the thermal comfort requirement. Then the range of the set points becomes a constraint of the energy consumption objective function. The grid search algorithm finds the most energy-efficient solution within the selected set point range.

Based on the simulated environmental conditions, the decision-making outcomes based on PMV model are illustrated in Fig. 7.11. In Fig. 7.11a, the area marked by the diamond mark is the range that fits the thermal comfort requirement. In this case, when the grid search method looking for the optimal solution gives the minimum energy consumption, the method only needs to search the region marked by diamonds. The method is integrated in the A-component of the local agent and the search outcomes are shown in Fig. 7.11b. The final decision made by the local agent is highlighted by the red star. It can be found that the lowest possible set point predicted by PMV is 22℃. The heating load required to reach this setting is 6,298.3W.

Fig. 7.12 illustrates the decision-making outcomes of the local agent equipped with the newly-developed group-of-people-based thermal sensation model. The decision-making process is the same as for the installed PMV model. The acceptable range of indoor temperature is marked with blue diamonds. The final decision of the local agent is 21.5℃, which is 0.5 degrees lower than the PMV prediction. In consequence, the required heating load is 6,035.9W. The decision based on the developed model has a heating load 256W smaller than its counterpart. If the HVAC system is working under a fixed schedule policy with a 23℃ set point, as observed in the field study, the system needs to produce a 6,823.2W heating load. In this case, the decision made by the group thermal sensation model requires a heating load more than 10% less than the fixed schedule method required in the field study.

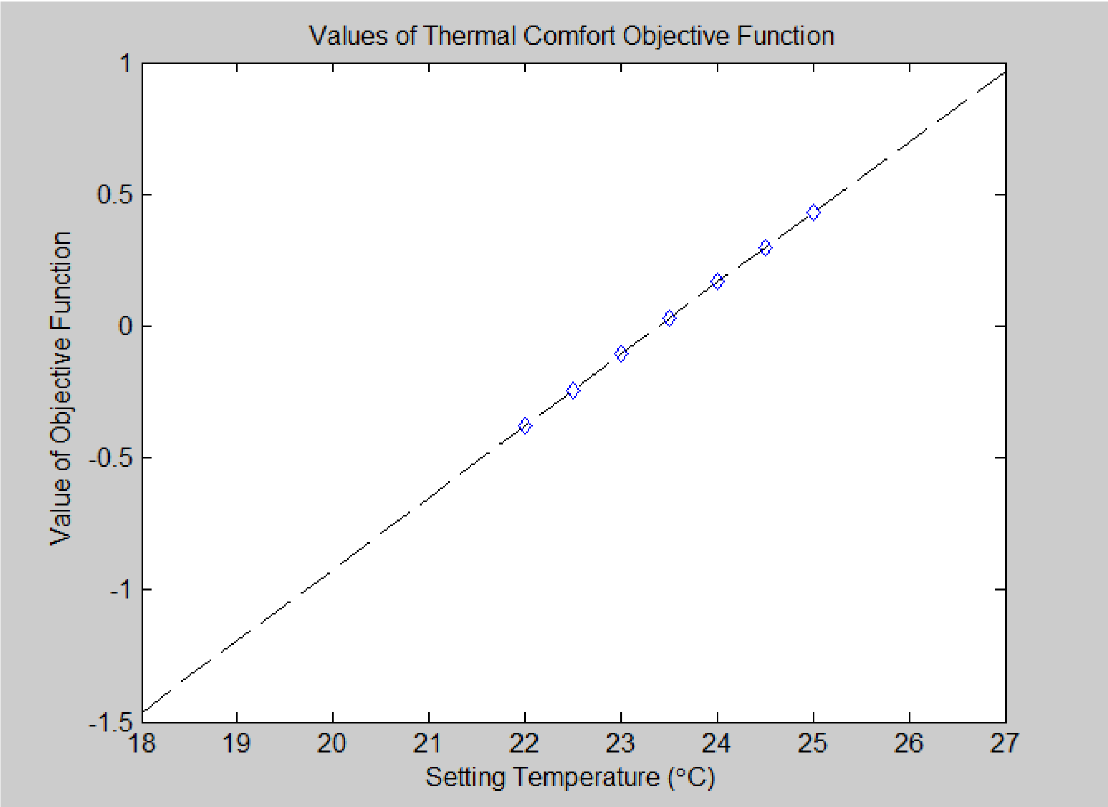


Fig. 7.11a

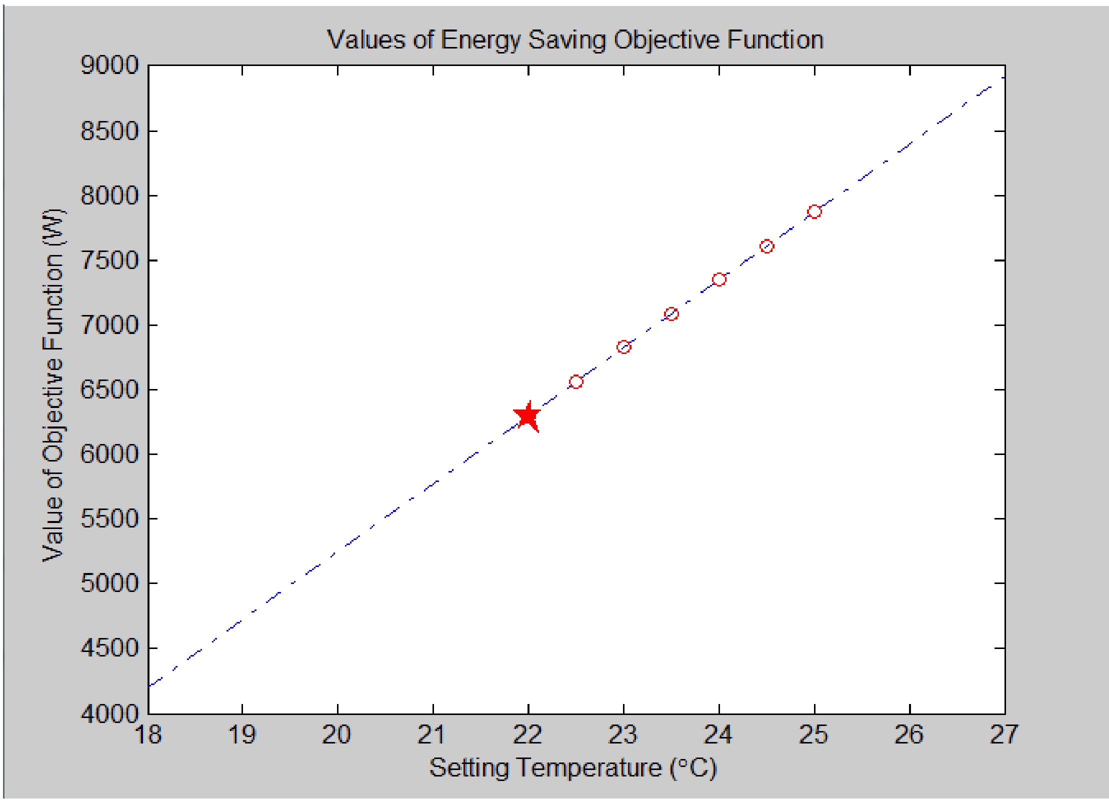


Fig. 7.11b

Figure 7.11 Decision-making Outcomes in an Open Plan Office (PMV Model-Based BEMS)

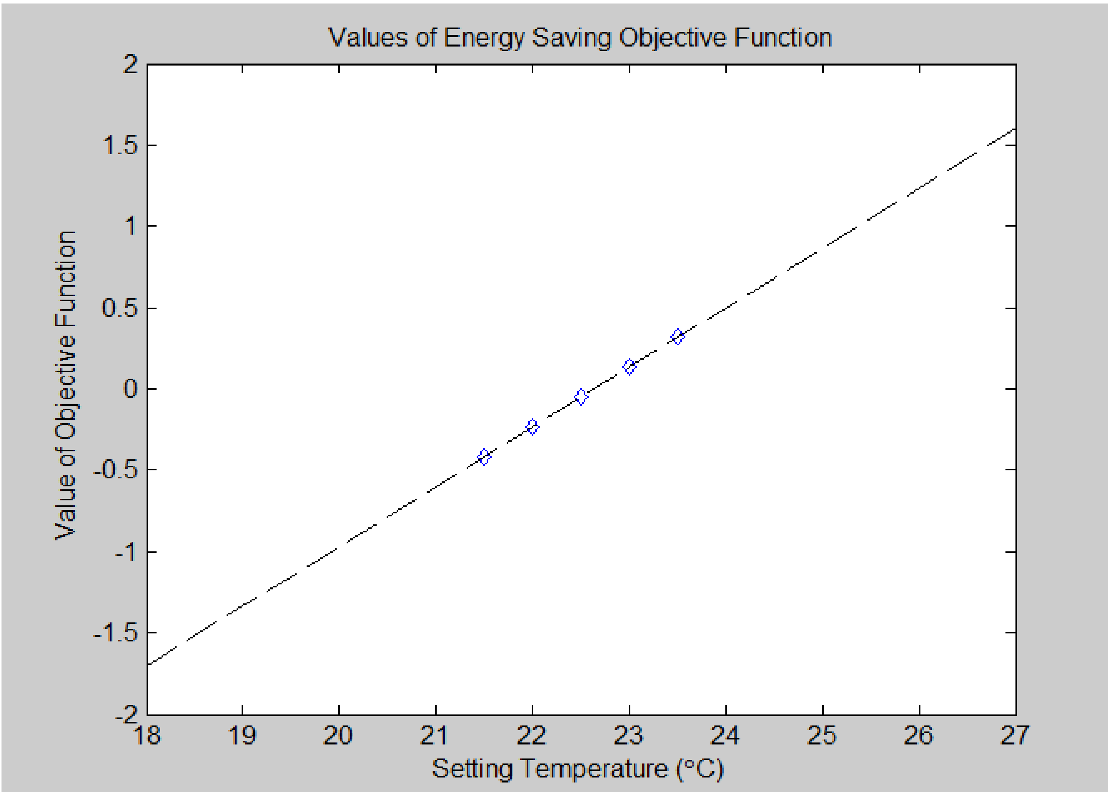


Fig. 7.12a

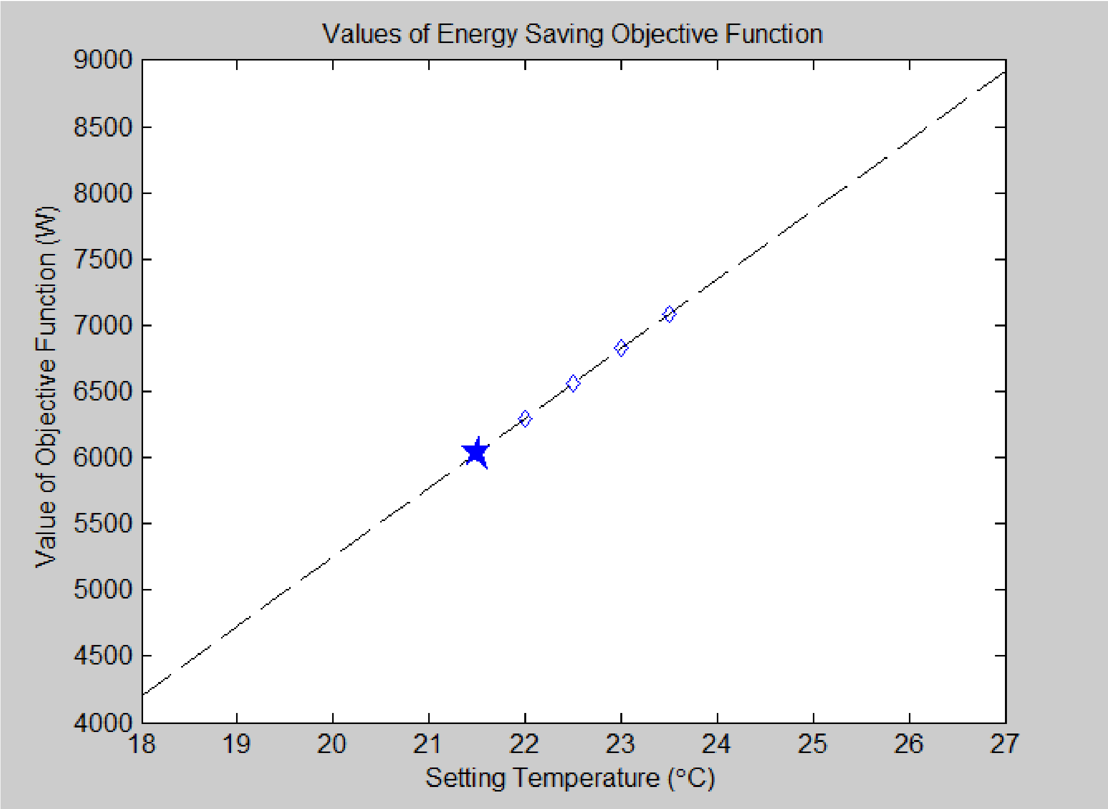


Fig. 7.12b

Figure 7.12 Decision-making Outcomes in an Open Plan Office (Group People's Model-based BEMS)

However, not all the occupants will feel 'neutral' under the decided condition. As illustrated in Table 7.6, the personal thermal sensation mode developed in Chapter 4 calculates that occupant AC3 will still feel 'slightly cold' when the set point is 21.5℃, and will not feel 'neutral' until the temperature rise is as high as 24℃. The thermal sensation vote from AC4 will be smaller than zero as well. If the system adjusts the set point to 24℃, a heating load of 7,348W is needed. Compared to the heating load needed for a set point of 21.5℃, more than 17.6% extra heating load is needed when the set point is 24℃.

In this case, the personal agent in the system will provide advice for the occupants to regain their comfortable feelings and try to avoid increasing the set points of the HVAC system. Here, the personal agent will only consider the action of changing the clothing level. The decision-making process for the personal agent is the same as the one shown in Fig. 7.3. The decision-making algorithm in the A-component of the personal agent considers thermal comfort and behaviour as optimisation criteria. The multi-objective decision-making problem is solved by the lexicographic method.

Once the system decides on the activities undertaken, it examines whether the recommended reactions are the occupant's most common ones. If it is, the system will directly provide the optimal decision to the end-user. If not, the system will utilise the Condition-action Rules to provide the personalised suggestion information to the occupant.

Based on the calculation of the personal thermal sensation model, if AC3 increases the CLO value to 1.5, he/she will feel neutral. It is also the most commonly used method of adaptation used by the occupant. So the system will suggest AC3 to increase his/her clothing level to 1.5CLO via a human machine interface. For occupant AC4, the decision-making process is the same and the decision from the system is to increase the CLO level to 1.25.

The requirement of the thermal comfort and the energy consumption can also be loosened if necessary. Then the values of the thermal comfort objective function and energy consumption objective functions are within a manually-defined range. Thus, the multi-objective optimisation problem can be solved by the ϵ-constraint method.

Table 7.6 Predicted Personal Thermal Sensations

Set Temperature	Predicted Personal Thermal Sensation Values for Five Occupants					
	AC1	AC2	AC3	AC4	AC5	AC6
20.5 ℃	-1	0	-1	-1	-1	0
21 ℃	-1	0	-1	-1	-1	0
21.5 ℃	-1	0	-1	-1	0	0
22℃	0	0	-1	-1	0	0
24℃	0	0	0	0	0	0

7.5 Energy Management Performance of BEMS

In this section, performances of the developed multi-agent energy management system are tested by using real outdoor climate data in both single occupancy offices and an open-plan office. The data is the hourly average outdoor temperature data from 9:00am until 17:00pm in March 2015. In total, 177 hours of data from the 1st of March 2015 until 31st of March 2015 are used. The data were collected by a meteorological station in the University of Reading. For more details of the data collection, please refer to Brugge (2015).

The assumption of the single occupancy office is as follows. The indoor air velocity is 0.08m/s. The relative humidity is 40%. Occupants AC1, AC2, AC3, AC4 and AC5 are regarded as research subjects. Each occupant sits in a single occupancy office with dimensions defined in Table 7.4. The default CLO level during the whole period is set as 0.75. The climate conditions in March are selected because in this month the occupants' CLO level is close to the assumed value. The average CLO level of occupants in March 2015 was 0.733. Occupants are able to adjust the set point of the HVAC system. They can also change their CLO level by ± 0.25, which is equal to putting on or taking off a sweater or a jacket.

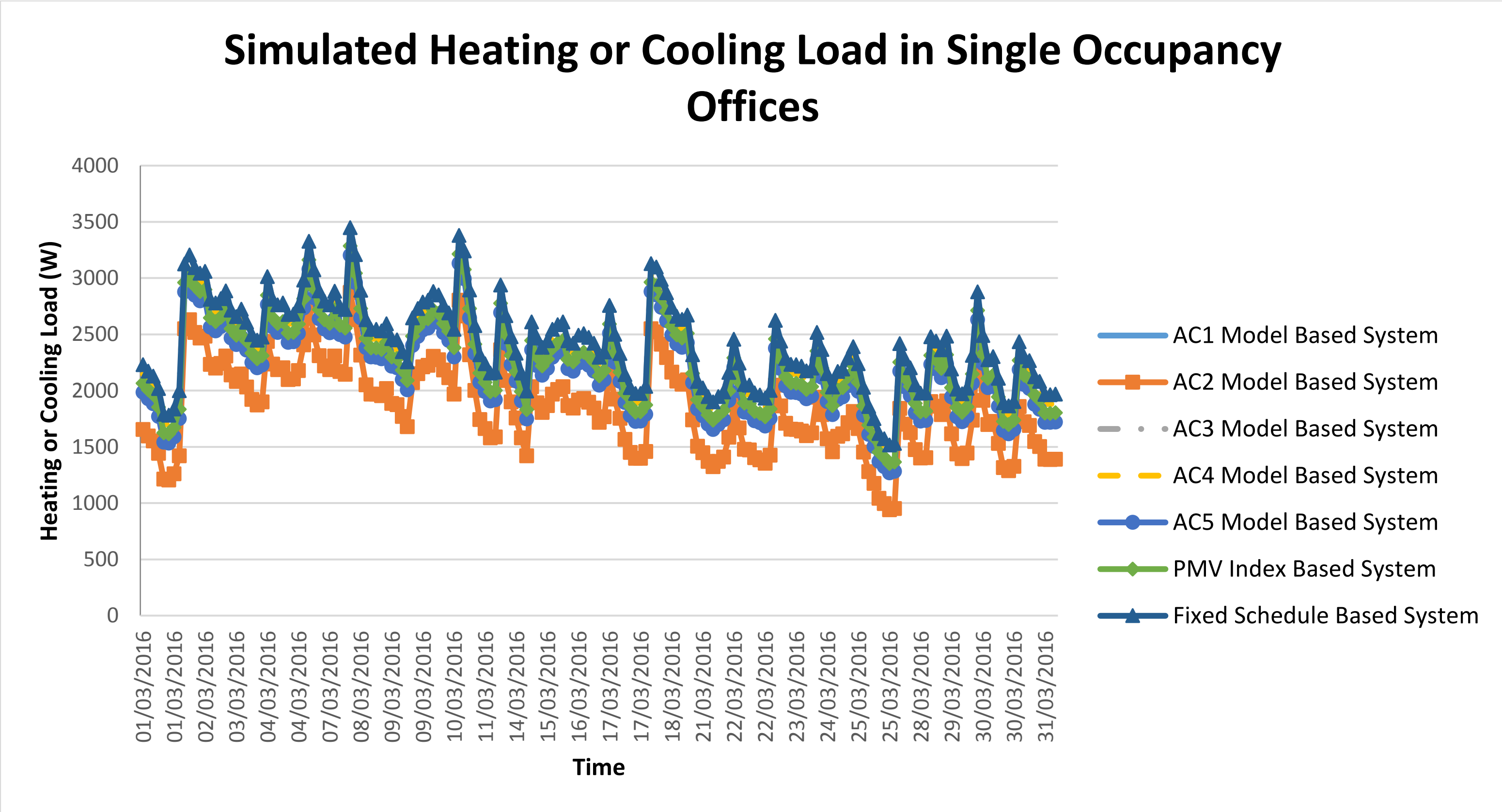


Figure 7.13 Hourly Heating or Cooling Load for Single Occupancy Offices

The hourly heating/cooling load values are illustrated in Fig. 7.13. The figure shows that, in general, offices managed by the BEMS need a smaller amount of energy to keep the occupants in a thermally comfortable environment compared to the offices managed by the fixed schedule management method.

The total required heating and cooling energy values are illustrated in Fig. 7.14 and the optimised set point for occupants is shown in Table 7.7. The table illustrates that even some of the set points consumed more energy than the set point recommended by the ASHRAE standard. In total, the energy consumption of the setting decide by the BEMS system with personal thermal sensation models is 2% less than the energy consumption of the settings decided by the BEMS system equipped with the ASHRAE-recommended PMV model. Compared to the offices managed by a fixed schedule, the BEMS system with personal thermal sensation models saved around 10% energy.

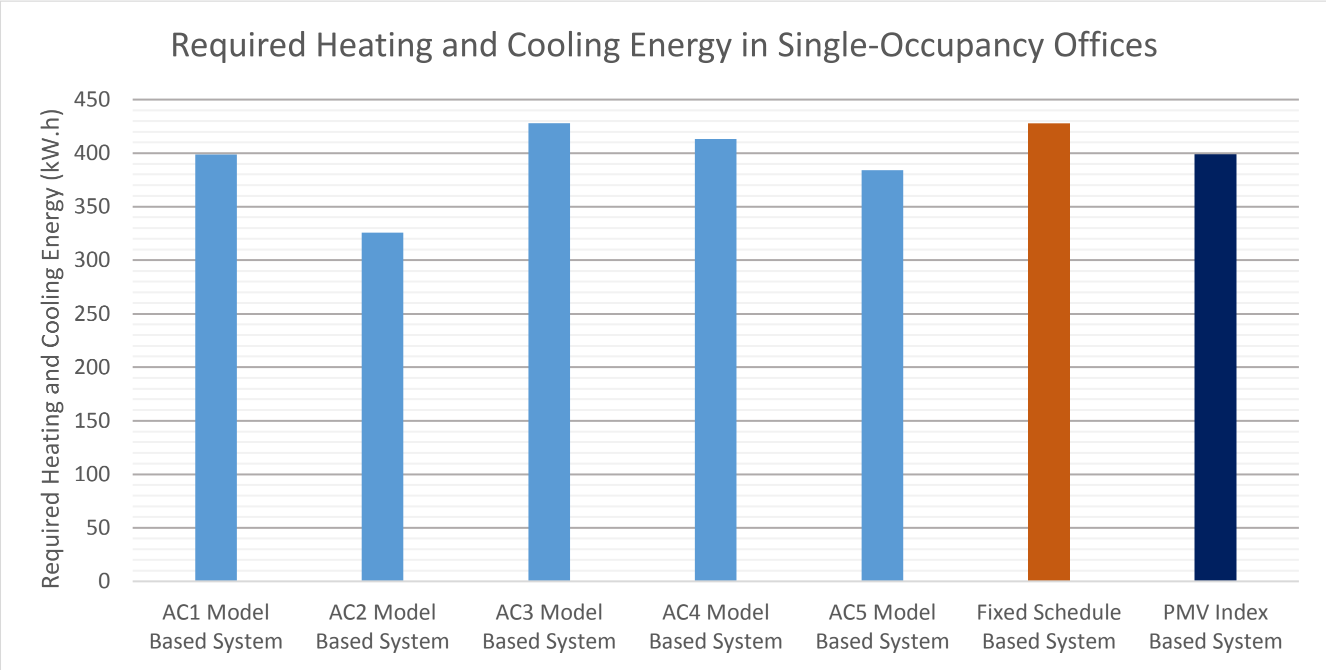


Figure 7.14 Required Heating and Cooling Energy in March (Single-Occupancy Office)

Table 7.7 Optimised Set Point and the Detailed Monthly Required Heating and Cooling Energy Values

	AC1 Model-based System	AC2 Model-based System	AC3 Model-based System	AC4 Model-based System	AC5 Model-based System	PMV Index-based System	Fixed Schedule-based System
Set Temperature (℃)	22	19.5	23	22.5	21.5	22	23
Required Heating/Cooling Energy (kW.h)	398.637	325.749	427.792	413.214	384.059	398.636	398.636

For the open-plan office, the outdoor data and the indoor environmental assumptions are the same as the ones in the single occupancy offices. The dimensions of the office is also defined in Table 7.4. Occupants AC1, AC2, AC3. AC4, AC5 and AC6 are seated in the office. For all the occupants, the default CLO level is 0.75 and the MET value is one. The assumption is that the occupants cannot change the settings of the HVAC but they can adjust their CLO level by ± 0.25. The settings of the HVAC system are calculated by the BEMS.

The hourly heating load and cooling load requirements are illustrated in Fig. 7.15. The monthly summary of the required heating and cooling energy is shown in Table 7.8. The recommended CLO levels from the personal agents are shown in Table 7.9. It can be found that compared to the BEMS based on the PMV model and the fixed schedule, the BEMS with the developed thermal sensation model saves 7% and 3.5% of energy respectively.

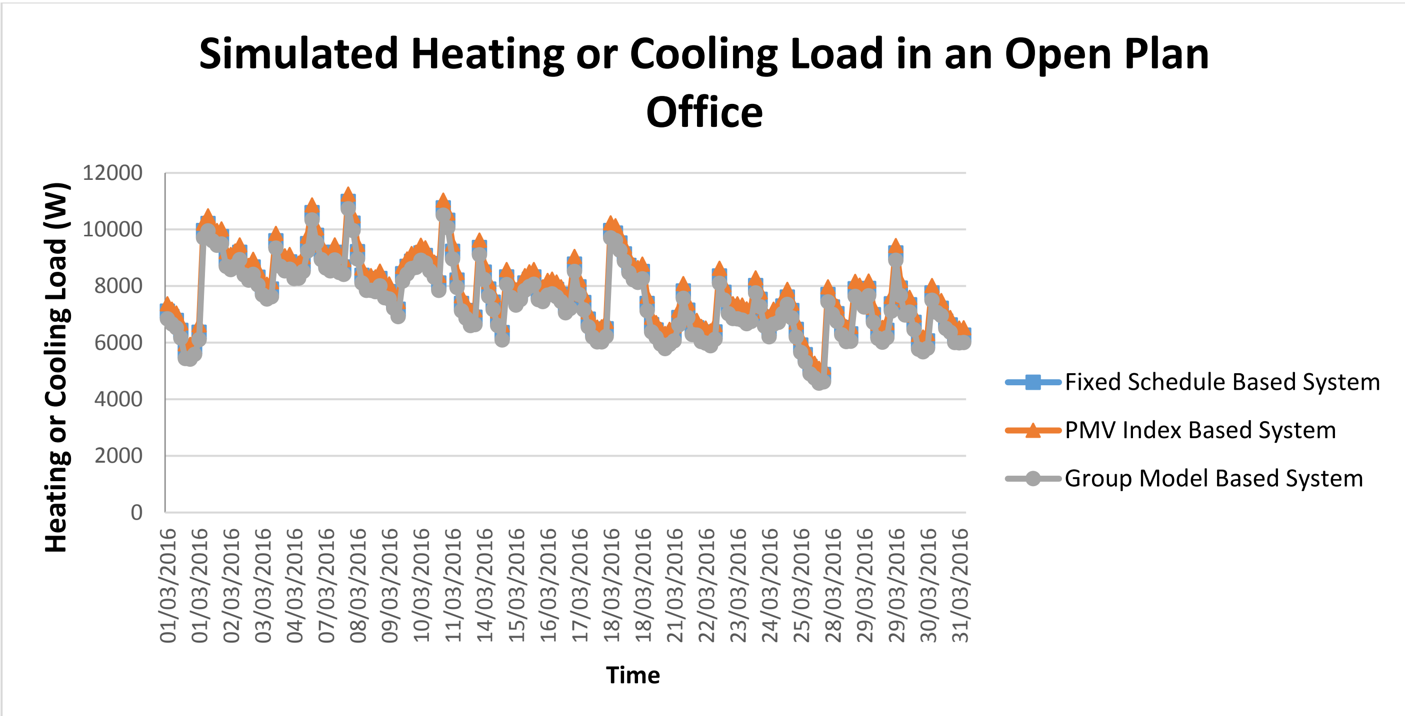


Figure 7.15 Hourly Heating or Cooling Loads for Single Occupancy Offices

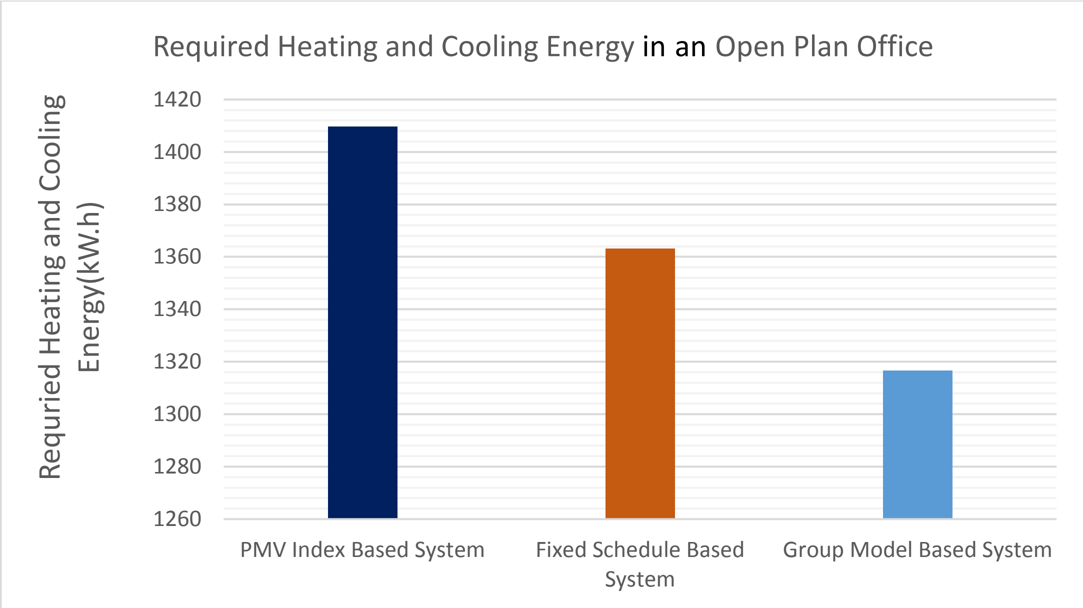


Figure 7.16 Required Heating and Cooling Energy in March (Open-plan Office)

Table 7.8 Optimised Set Point and the Detailed Monthly Heating and Cooling Load Values in an Open-Plan Office

Comfort Models	PMV Index-based System	Fixed Schedule-based System	Group Model-based System
Set Temperature (℃)	23.5	23	22.5
Heating and Cooling Load (kW.h)	1409.564	1363.115	1316.665

Table 7.9 Recommended CLO level for Occupants

AC1	AC2	AC3	AC4	AC5	AC6
1	0.75	1.25	1	0.75	1

7.6 Summary:

This chapter firstly applied the heating load and cooling load equations to represent the energy-saving objective functions of the BEMS and the method to evaluate adaptation behaviours for the occupants. The evaluation method forms the behavioural adaptation objective function. Then, these objective functions, together with the thermal comfort model (thermal comfort objective function) and optimal decision-making algorithms, are integrated into the E-component and A-component in the local agent and personal agents in the BEMS to complete these agents. The operation process including the learning process and the decision-making process for the local agent and personal agent in both single-occupancy offices and open-plan offices are developed. Case studies in the simulated single-occupancy offices and open-plan office prove the functionalities of the BEMS. By considering the behaviour adaptations, the multi-agent BEMS is able to make the desired optimal decisions to minimise the energy consumption while guaranteeing the thermal comfort feelings of the occupants. The performances of the BEMS are then further examined by using the climate data provided by a meteorological station. The outcomes indicate that the HVAC systems managed by the developed multi-agent BEMS equipped with thermal comfort models developed in Chapters 4 and 5 consumes 3% to 10% less energy than the ones guided by the fixed schedule management method in the simulated built environment. The personal thermal sensation model-based or group people's thermal sensation-based BEMS also consume 2% to 7% less energy than the PMV index-based BEMS does in the simulated environment.

Chapter 8 : Conclusions and Future Work

8.1 Introduction

This chapter presents the findings and conclusions drawn from this research, the aim of which is to develop a building energy management system that enables the energy consumption of an HVAC system to be reduced while meeting the occupants' thermal comfort requirements. The BEMS realises an optimised control of an HVAC system by determining a temperature set point which considers occupants' requirements and adaptive behaviours. It also contains an advisory function providing alternative behavioural adaptation suggestions to the occupants for the improvement of their thermal comfort. In order to hit its targets, the BEMS should have abilities to 1) Sense the existing environmental conditions in real-time; 2) Collect personal factors and occupants' responses to the current thermal conditions: 3) Learn occupants' thermal comfort preferences and identify their adaptive behaviour patterns; 4) Calculate the desired set points for the built environment and 5) Provide personalised suggestions to the occupants. To build a system with these abilities, the following research questions were set in Chapter 1.

- How can the energy management system understand occupants' real-time thermal comfort needs in a real building environment?
- How can the energy management system further eliminate the energy wastage of the HVAC system by using information from the occupants and the environment?
- How can the BEMS increase the thermal satisfaction level of occupants whilst avoiding energy wastage by improving the interaction between the buildings and the occupants?
- How can an energy management system be developed that takes care of the operation of the HVAC system whilst simultaneously addressing the thermal comfort issues of all the occupants?

In order to answer these questions, seven research objectives are set out in Chapter 1, and then being achieved in Chapter 2, Chapter 3, Chapter 4, Chapter 5, Chapter 6 and Chapter 7 respectively. By investigating these objectives, the achievements are illustrated in the next section. Then the chapter summarises scientific Contributions to the Knowledge of BEMS Development. Contributions to theories are also illustrated. This chapter ends by discussing the potential directions for future research.

8.2 Achievement of the Objectives

8.2.1 Achievement of Objective One

The first objective is to develop the architecture and identify the key components, especially the software components, of the BEMS. The objective is mainly realised in Chapter 3. The literature review section in Chapter 2 indicates that the agent-based technologies need to be applied to develop the BEMS. Then the system architecture is developed following the process of developing a multi-agent system. The problem faced by the BEMS is decomposed into smaller ones. They are used to define the types and functions of the agents needed in the BEMS.

By analysing the decomposed research problem, the BEMS is developed as a multi-agent system comprised of local and personal agents. The review of previous agent-based systems reveals that the BEMS system requires intelligent agents which are able to make their own decisions and act rationally. The Epistemic-Deontic-Axiologic (EDA) agent model is applied to guarantee the developed personal and local agents are rational agents. Structures of the personal agent and the local agent are defined by the EDA model. The functions of the E-component, D-component and A-component in personal and local agents are generated from the abilities needed by the personal agent and local agent to function in both the open-plan office scenario and single-occupancy offices. The procedure of generating output information for every agent based on input data is also defined.

Specifically, previous research did not provide the solution on how to build the A-component in agents for evaluating the different actions plans stored in the D-component in the BEMS. This research suggests that the evaluation abilities needed by the A-component in agents could be realised by a decision-making algorithm supported by the objective functions from control theory. The algorithm could also be supported by Condition-Action plans.

8.2.2 Achievement of Objective Two

The second objective is developing a modelling method for the system to dynamically predict the personal thermal comfort level for each occupant. The objective is realised by the C-SVC modelling algorithm in Chapter 4. This research finds that the personal thermal sensation modelling problem can be regarded as a classification problem, so C-SVC algorithm is employed as an effective tool to generate models to solve the classification problem. By using the data collected in China, the developed personal thermal sensation models reach 89% prediction accuracy. For UK subjects, the models' accuracy exceeds 85%. The performance of the models proves that the C-SVC modelling method could be an effective algorithm to generate personal thermal sensation models by using data collected from built environments similar to those used in the experimental field study here.

8.2.3 Achievement of Objective Three

The third objective is finding a method to estimate the thermal sensation level of a group of occupants in the same built environment in real time. This objective is achieved in Chapter 5. Group-of-people-based thermal sensation models are developed to estimate the mean thermal sensation values of the occupants. Both the personal-thermal-sensation-model-based modelling method and the SVR method are selected to generate the group-of-people-based thermal sensation model. The validation results indicate that both of the modelling methods are able to generate people-based thermal sensation models from the data collected in China. The SVR method is used to generate the people-based thermal sensation model by using the data collected in the UK. The prediction outcomes indicate that the generated model is able to estimate the occupants' average thermal sensation level. It could be used by an HVAC system to avoid unnecessary cooling and heating.

8.2.4 Achievement of Objective Four

The fourth objective is developing a method to numerically analyse and evaluate occupants' behavioural adaptations. The objective is investigated in Chapter 7. Two algorithms are proposed to evaluate the behaviours. The first one measures the complexity of the behaviours in the suggestions. In general, the suggested behavioural adaptations that require more actions to be performed have a higher complexity value than the ones with fewer actions. The second way to evaluate occupants' behavioural adaptations is by applying the confidence of association rules to measure how likely it is that an occupant performs a behaviour when he/she feels uncomfortably hot or cold. These two types of measurement can be applied to objective functions to help the decision-making algorithm choose the best action plan.

8.2.5 Achievement of Objective Five

The fifth objective is developing optimal decision-making algorithms for the system to decide the set point for the HVAC system. The objective is realised in Chapter 6 in which the settings of the HVAC system are found to be related to the occupants' thermal preferences, the occupants' adaptations and the energy consumption of the HVAC system. Choosing the action plan which includes the HVAC system's set-points and the occupants' behavioural adaptations is a multi-objective decision-making process. The process of making the decision can also be regarded as solving a multi-objective optimisation problem. Drawbacks of the previous solutions to the multi-objective optimisation problem are pointed out by a critical review. Based on the properties of the problem, the lexicographic, the ϵ-constraint and the grid search methods are selected to realise the multi-objective optimisation. It can be found that the decision-making algorithms developed by these methods overcome the drawbacks of the algorithms applied in the previous research.

8.2.6 Achievement of Objective Six

The sixth objective is developing an optimal decision-making algorithm for the system to provide personalised suggestions for the occupants. The decision-making algorithms to choose the appropriate suggestions are also proposed in Chapter 6. In detail, the decision-making process can be divided into two steps. In the first step, the lexicographic, the ϵ-constraint and the grid search methods can be applied to choose the most appropriate action plan for the occupants by considering the energy consumption, the occupants' personal thermal preferences and the properties of their behaviours, such as their complexity. In the second step, the Condition-Action Rules are applied for the BEMS to select the appropriate way to present the system's suggestions to the occupants.

8.2.7 Achievement of Objective Seven

The seventh objective is integrating the developed models and decision-making algorithm together into the energy management system structure and evaluating its performance. This objective is realised in Chapter 7. In the chapter, the developed personal thermal sensation models, group people-based thermal sensation models, the algorithm to evaluate behavioural adaptations, the heating and cooling load models and the decision-making algorithms are integrated together into the BEMS. The information and decision-making processes carried out by the local and personal agents are developed for both the open-plan and the single-occupancy office scenarios. Using the developed components and the planned operation process, the operations of the BEMS in both office scenarios are simulated. The BEMS targets making all occupants feel neutral in the built environment. Firstly, the detailed decision-making processes of the local and personal agents for the occupants in single-occupancy offices and an open-plan office are analysed. Then, the required heating and cooling loads of the BEMS in single-occupancy offices over one month are calculated. These loads are calculated based on the personal thermal sensation models of these occupants, the PMV index and the fixed schedule control method. The required heating and cooling loads of the BEMS in open-plan offices are also calculated. These calculations are based on the group-of-people-based thermal sensation model, the PMV index and the fixed schedule. The calculation results indicate that for simulated single-occupancy offices the BEMS supported by the developed personal thermal sensation models might save up to 10% of the energy compared to the system using the fixed schedule. In the simulated open-plan office, the BEMS with the group-of-people-based thermal sensation model might save up to 7% of the energy compared to the system using the PMV index. These data indicate that the proposed BEMS has the ability to save energy while maintaining a comfortable thermal environment for occupants under the under the environmental conditions defined in this research which means this research achieves its aim.

8.3 Scientific Contributions to the Knowledge of BEMS Development

In this research, a number of technologies are newly applied to solve problems faced by the developer. Applications of these technologies contribute to the knowledge of BEMS development. These contributions are summarised as follows:

- The personal thermal sensation modelling problem can be regarded as a classification problem.
- The C-SVC algorithm can be used to tackle the personal thermal sensation modelling problem.
- The SVR algorithm can be used to generate the group-of-people-based thermal sensation model.
- The ability of the A-component to evaluate action plans in the EDA model can be realised by the decision-making algorithms supported by objective functions and Condition-Action Rules.
- The lexicographic, the ϵ-constraint and grid search methods could work together to solve the multi-objective optimisation problem faced by the BEMS.
- Confidence of association rules and the complexity of the actions can be used to numerically analyse the behavioural adaptations in the action plans. The outcomes of the analyses can be used as objective functions during the multi-objective decision-making process.

8.4 Contributions to Theories

8.4.1 BEMS based on Adaptive Comfort Theory

This research indicates that adaptive comfort theory could provide guidelines for the design of the BEMS. Adaptive comfort theory points out that occupants will actively react to feelings of discomfort by making adaptations (Humphreys, 1997). The adaptive behaviours, such as changing the set point of the HVAC system, have effects on both energy consumption and thermal comfort. Therefore, by considering the occupants' behavioural adaptations, the BEMS is able to reach the goals of energy-saving and maintaining a comfortable environment.

This research further reveals that the adaptive comfort theory which defines occupants' adaptations could be involved in three stages of BEMS' operations. Correspondingly, relevant software components in the system should be orientated by adaptations to enable these operations. The three operation stages are the learning stage, the decision-making stage and the feedforward stage. In the learning stage, the agents in the BEMS are getting information from the environment and occupants and then processing it to generate the knowledge needed for the decision-making stage. For the EDA-model-based agent, the learning stage is mainly performed by the E-component. Key knowledge stored in this component to support decision-making can be objective functions. Therefore, in order to utilise the occupants' adaptations, in the learning stage, the BEMS should collect the information on occupants' behaviours. Generated objective functions should be able to reflect the effects of different adaptive behaviours. This can be realised by introducing the different adaptive behaviours as variables in objective functions.

In the decision-making stages, BEMS applies the knowledge learnt from the environment and occupants to make decisions on selecting appropriate adaptive behaviours and settings for the HVAC system. The behaviours are regarded as the direct ways to save energy and promote thermal comfort levels. In the BEMS here, the decision-making is realised by the A-component in agents.

The last stage of operation backed up by the adaptive comfort theory is the feedforward stage. In this stage, the BEMS forwards information to the occupants. The information not only contains the current environmental information but also contains the decisions made by the system on behavioural adaptations. The information should be organised, then presented to the occupants. The information could be sent out by the human-machine interfaces.

In general, the adaptive comfort theory not only helps the system find the optimum thermal conditions in a built environment, but also decides the best way to respond to the environment if necessary.

8.4.2 The Proof of Successful Functioning of EDA Agent Model

This research proves that following the EDA agent model from the social psychology theory is an effective way to build agents in a BEMS. Previous research only proposed that the EDA model was a potential way to develop the agents without fully realising the agents in the BEMS. The performance of the agents developed in this research provides solid evidence that the social psychology theory could provide guidance on the development of rational agents in a BEMS. All components in the BEMS agents proposed in the thesis are developed based on the EDA model and the performance of the system in different types of built environment is discussed. Results indicate that, guided by the agent framework provided by the EDA agent, researchers are able to generate the rational agents needed by the BEMS.

8.5 Limitations and Future Work

In this research, the simulated built environment has an HVAC system operating inside during working hours. This environment setting is from the air-conditioned environment where the field studies were carried out in the UK. The adaptive opportunities of the subjects in this research are limited by regulations from the building manager and the facilities in the building.

More studies can be carried out based on the results from this research. The potential future research directions are listed as follows:

- The future study could simulate other built environments such as the naturally-conditioned environment with central heating operating in winter but with no mechanical cooling in all other seasons. When the central heating is off, the BEMS system might still be able to provide suggestions to the occupants to guarantee their thermal comfort.
- The future research could collect occupants' behavioural adaptation data in other environments, which might allow the occupants to have more types of adaptive opportunities. Personalised conditioning systems could also be considered. In this case, the BEMS could provide more types of adaptation suggestions other than changing the set temperature of the HVAC system and/or changing clothing insulation levels.
- The energy consumption models of a certain type of HVAC system can be used to replace the heating and cooling load models in this research.

Supported by these models, the exact energy consumption values can be outputted by the system.

- Future studies could consider applying the BEMS proposed in this research in a building or block of buildings, which contain multiple offices. In these buildings, the renewable energy resources can be considered as a decision-making factor to further reduce carbon emissions.
- Future studies could also consider illumination comfort, acoustic comfort and air pollution as criteria when making decisions. This requires the researcher to find the appropriate objective functions to express the effects of these other forms of comfort.

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Appendix A: General Questionnaire

1. **Could you please fill in your initials and current time? Please use the 24 hour clock format for example (14:50).**
   initials___________;

   Fill in time____:___

2. **Activity Level (Please choose your current activity level. Please only choose one box.)**

Seated (quiet, writing or reading) ☐

Seated (typing) ☐

Seated (filing) ☐

Standing, relaxed ☐

3. **Clothes (Please choose all the clothes you are currently wearing. Please choose all that apply. Please choose all the appropriate items.)**

Upper:	**Lower:**
Long underwear top (like thermals) ☐	Long underwear bottoms ☐
T-shirt ☐	Thin trousers/leggings ☐
Short-sleeved shirt ☐	Normal trousers(like jeans) ☐
Long-sleeved shirt ☐	Thick trousers ☐
Long-sleeved sweatshirt ☐	Shorts ☐
Suit Jacket: thin ☐ thick ☐	Walking shorts ☐
Sleeveless sweater vest: thin ☐ thick ☐	Sweatpants ☐
Sweater: thin ☐ thick ☐	
Hat or Scarf ☐	
Other:_________	Other:_________
Dress and skirts:	**Footwear:**
Skirt: thick ☐ thin ☐	Short / ankle socks ☐
Light dress:	Long socks (knee socks or longer) ☐
no sleeves ☐ short sleeves ☐ long sleeves ☐	Stockings ☐
Thick (winter) dress:	Shoes ☐

no sleeves☐ short sleeves☐long sleeves☐ Other:_________	Boots ☐ Sandals/thongs ☐ Other:_________

4. **In general, do you satisfy with the indoor environment you are in at this moment?**
Yes☐ No ☐

If the answer is No, please tell us which aspect/aspects you are not satisfy with (you may choose more than one aspect).
Thermal Comfort☐ Illumination☐ Air Quality ☐

5. **Current Thermal Feeling (Please choose your thermal sensation at the moment. Please choose the one that is most appropriate.)**
Cold☐ Cool ☐ Slightly Cool ☐Neutral ☐Slightly Warm☐ Warm ☐Hot☐

6. **Previous thermal experience (Please tell us how many hours you have stayed in this environment).**
________hour(s) ________minute(s)

7. **Did you take any of these following actions in last 2 hours? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50). Please also brief a reason if the actions are not for improving thermal comfort. For example put the reason as 'feel thirsty' if drinking hot water is not for keeping warm.**

Clothing Level: Add☐; **Time_______; Reason_______;**

Remove☐; **Time_______; Reason_______;**

Drinking: Hot drinking☐; **Time_______; Reason_______;**

Cold Drinking☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ; ☐ **Time_______; Reason_______;**

Turn Down (cooler) ;☐ **Time_______; Reason_______;**

Portable Heaters: Start up☐; **Time_______; Reason_______;**

Turn off☐; **Time_______; Reason_______;**

Fans: Start up☐; **Time_______; Reason_______;**

Turn off☐; **Time_______; Reason_______;**

Windows: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

Blinds: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

Doors: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

Others______; **Time_______; Reason_______;**

8. **How would you rate the ventilation within your area i.e. the perceived feeling of draught across your body?**

Unacceptable - air speed is too high ☐

Acceptable - air speed seems high ☐

Acceptable – air speed seems just right ☐

Acceptable - air speed seems low ☐

Unacceptable – air speed is too low ☐

9. **At this point of time, would you prefer to be (Please only choose one box.)**
   Cooler ☐ The same as it is now ☐ Warmer ☐

10. **If you choose both 'acceptable- air speed seems just right' in question 8 and 'The same as it is now' in question 9, please skip this question. At this point, if you want to improve your thermal comfort, please select one action you want to take most. Please be aware that these actions/instruments should be available to you.**
    Put on some clothes☐ Take off some clothes ☐

    Drink hot water ☐ Drink cold water ☐

    Turn up the Air Conditioning/Central Heating Set Temperature (Warmer)☐

    Turn down the Air Conditioning /Central Heating Set Temperature (Cooler)☐

    Start up a portable heater or turn up the heater (warmer) ☐

    Start up a fan or turn up the fans (cooler)☐

Open the Window ☐ Close the Window ☐

Open the Blinds ☐ Close the Blinds ☐

Open the Door ☐ Close the Door ☐

Others______;

11. **If you choose both 'acceptable- air speed seems just right' in question 8 and 'The same as it is now' in question 9, please skip this question. At this point, if you want to improve your thermal comfort, but all action(s) you can perform currently are not sufficient, please select the actions you want to take but are not available to you**.

    Put on more clothes (more cloth is not available) ☐

    Take off more clothes (cannot take off any more cloth) ☐

    Turn up the Air Conditioning/central heating set Temperature (Warmer) ☐

    Turn down the Air Conditioning/central heating set Temperature (Cooler) ☐

    Turn on a portable heater to warm you up ☐

    Turn on a fan to cool you down ☐

    Open the window ☐

    Other:_________

End of the Survey

Appendix B: Activity Logger

On Arrival Time:_____________ Initials______________ Date___________	
Clothes (Please choose all the clothes you are currently wearing. Please choose all that apply. Please choose all the appropriate items.)	
Upper: Long underwear top (like thermals)☐ T-shirt ☐ Short-sleeved shirt ☐ Long-sleeved shirt ☐ Long-sleeved sweatshirt ☐ Suit Jacket: thin☐ thick ☐ Sleeveless sweater vest: thin☐ thick☐ Sweater: thin☐thick☐ Hat or Scarf ☐ Other:__________	**Lower:** Long underwear bottoms ☐ Thin trousers/leggings ☐ Normal trousers(like jeans) ☐ Thick trousers ☐ Shorts☐ Walking shorts☐ Sweatpants☐ Other:__________
Dress and skirts: Skirt: thick☐ thin☐ Light dress: no sleeves☐short sleeves☐ long sleeves☐ Thick (winter) dress: no sleeves ☐short sleeves☐long sleeves☐ Other:__________	**Footwear:** Short / ankle socks☐ Long socks (knee socks or longer)☐ Stockings ☐ Shoes ☐ Boots ☐ Sandals/thongs ☐ Other:__________

9:00 am-9:59am I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold ☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐
- **Current Facilities Status.**
  Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

  Portable Heater(warmer): on☐off☐Not Available☐ ;

  Fan(cooler): on☐off☐ Not Available☐ ;

  Air Conditioning Unit: on☐ off☐ Not Available☐;
- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler☐The same as it is now☐ Warmer ☐
- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**
  Clothing Level: Add ☐ ; **Time_______; Reason_______;**

  Remove☐; **Time_______; Reason_______;**

  Drinking: Hot drinking☐ ; **Time_______; Reason_______;**

  Cold Drinking☐; **Time_______; Reason_______;**

  Air Conditioning/central heating:

  Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

  Turn Down (cooler)☐ ; **Time_______; Reason_______;**

  Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

  Turn off☐ ; **Time_______; Reason_______;**

  Fans: Start up☐ ; **Time_______; Reason_______;**

  Turn off☐ ; **Time_______; Reason_______;**

  Windows: Open☐ ; **Time_______; Reason_______;**

  Close☐ ; **Time_______; Reason_______;**

  Blinds: Open☐ ; **Time_______; Reason_______;**

  Close☐ ; **Time_______; Reason_______;**

  Doors: Open☐; **Time_______; Reason_______;**

  Close☐; **Time_______; Reason_______;**

10:00 am-10:59am I am not in☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
Cold ☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐

- **Current Facilities Status.**
Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

Portable Heater(warmer): on☐off☐Not Available☐;

Fan(cooler): on☐ off☐Not Available☐ ;

Air Conditioning Unit: on☐ off☐ Not Available☐;

- **At this point of time, would you prefer to be (Please only choose one box)**
Cooler☐The same as it is now☐ Warmer ☐

- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**

Clothing Level: Add ☐ ; **Time_______; Reason_______;**

Remove☐; **Time_______; Reason_______;**

Drinking: Hot drinking☐ ; **Time_______; Reason_______;**

Cold Drinking☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

Turn Down (cooler)☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Fans: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Windows: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Blinds: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Doors: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

11:00 am-11:59am I am not in☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
Cold ☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐

- **Current Facilities Status.**

Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

Portable Heater(warmer): on☐off☐Not Available☐;

Fan(cooler): on☐off☐Not Available☐ ;

Air Conditioning Unit: on☐ off☐ Not Available☐;

- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler☐The same as it is now☐ Warmer ☐

- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**

Clothing Level: Add ☐ ; **Time_______; Reason_______;**

Remove☐; **Time_______; Reason_______;**

Drinking: Hot drinking☐ ; **Time_______; Reason_______;**

Cold Drinking☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

Turn Down (cooler)☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Fans: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Windows: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Blinds: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Doors: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

12:00 pm-12:59pm I am not in☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐

- **Current Facilities Status.**
  Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

Portable Heater(warmer): on☐off☐Not Available☐;

Fan(cooler): on☐ off☐ Not Available☐ ;

Air Conditioning Unit: on☐ off☐ Not Available☐ ;

- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler☐ The same as it is now☐ Warmer ☐

- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**

Clothing Level: Add ☐ ; **Time_______; Reason_______;**

Remove☐; **Time_______; Reason_______;**

Drinking: Hot drinking☐ ; **Time_______; Reason_______;**

Cold Drinking☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

Turn Down (cooler)☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Fans: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Windows: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Blinds: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Doors: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

1:00 pm-1:59pm I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold☐ Cool☐ Slightly Cool☐ Neutral☐ Slightly Warm☐ Warm☐ Hot☐

- **Current Facilities Status.**
  Windows: Open☐ Close☐ Not Available☐; **Door**: Open☐ Close☐ Not Available☐ ;

Portable Heater(warmer): on☐ off☐ Not Available☐;

Fan(cooler): on☐ off☐ Not Available☐ ;

Air Conditioning Unit: on☐ off☐ Not Available☐ ;

- **At this point of time, would you prefer to be (Please only choose one box)**

Cooler☐ The same as it is now☐ Warmer ☐

- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**

Clothing Level: Add ☐ ; **Time_______; Reason_______;**

Remove ☐; **Time_______; Reason_______;**

Drinking: Hot drinking ☐ ; **Time_______; Reason_______;**

Cold Drinking ☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

Turn Down (cooler) ☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up ☐ ; **Time_______; Reason_______;**

Turn off ☐ ; **Time_______; Reason_______;**

Fans: Start up ☐ ; **Time_______; Reason_______;**

Turn off ☐ ; **Time_______; Reason_______;**

Windows: Open ☐ ; **Time_______; Reason_______;**

Close ☐ ; **Time_______; Reason_______;**

Blinds: Open ☐ ; **Time_______; Reason_______;**

Close ☐ ; **Time_______; Reason_______;**

Doors: Open ☐; **Time_______; Reason_______;**

Close ☐; **Time_______; Reason_______;**

2:00 pm-2:59pm I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
Cold ☐ Cool ☐ Slightly Cool ☐ Neutral ☐ Slightly Warm ☐ Warm ☐ Hot ☐

- **Current Facilities Status.**
Windows: Open ☐ Close ☐ Not Available ☐; **Door**: Open ☐ Close ☐ Not Available ☐ ;

Portable Heater(warmer): on ☐ off ☐ Not Available ☐;

Fan(cooler): on ☐ off ☐ Not Available ☐ ;

Air Conditioning Unit: on ☐ off ☐ Not Available ☐ ;

- **At this point of time, would you prefer to be (Please only choose one box)**
Cooler☐ The same as it is now☐ Warmer ☐

- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**

Clothing Level: Add ☐ ; **Time_______; Reason_______;**

Remove ☐; **Time_______; Reason_______;**

Drinking: Hot drinking ☐ ; **Time_______; Reason_______;**

Cold Drinking ☐; **Time_______; Reason_______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

Turn Down (cooler) ☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up ☐ ; **Time_______; Reason_______;**

Turn off ☐ ; **Time_______; Reason_______;**

Fans: Start up ☐ ; **Time_______; Reason_______;**

Turn off ☐ ; **Time_______; Reason_______;**

Windows: Open ☐ ; **Time_______; Reason_______;**

Close ☐ ; **Time_______; Reason_______;**

Blinds: Open ☐ ; **Time_______; Reason_______;**

Close ☐ ; **Time_______; Reason_______;**

Doors: Open ☐; **Time_______; Reason_______;**

Close ☐; **Time_______; Reason_______;**

3:00 pm-3:59pm I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold ☐ Cool ☐ Slightly Cool ☐ Neutral ☐ Slightly Warm ☐ Warm ☐ Hot ☐
- **Current Facilities Status.**
  Windows: Open ☐ Close ☐ Not Available ☐; **Door**: Open ☐ Close ☐ Not Available ☐ ;

  Portable Heater(warmer): on ☐ off ☐ Not Available ☐;

  Fan(cooler): on ☐ off ☐ Not Available ☐ ;

  Air Conditioning Unit: on ☐ off ☐ Not Available ☐ ;
- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler ☐ The same as it is now ☐ Warmer ☐
- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**
  Clothing Level: Add ☐ ; **Time_______; Reason_______;**

  Remove ☐; **Time_______; Reason_______;**

  Drinking: Hot drinking ☐ ; **Time_______; Reason_______;**

Cold Drinking☐; **Time______; Reason______;**

Air Conditioning/central heating:

Turn Up (warmer) ☐ ; **Time______; Reason______;**

Turn Down (cooler) ☐ ; **Time______; Reason______;**

Portable Heaters: Start up☐ ; **Time______; Reason______;**

Turn off☐ ; **Time______; Reason______;**

Fans: Start up☐ ; **Time______; Reason______;**

Turn off☐ ; **Time______; Reason______;**

Windows: Open☐ ; **Time______; Reason______;**

Close☐ ; **Time______; Reason______;**

Blinds: Open☐ ; **Time______; Reason______;**

Close☐ ; **Time______; Reason______;**

Doors: Open☐; **Time______; Reason______;**

Close☐; **Time______; Reason______;**

4:00 pm-4:59pm I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold ☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐
- **Current Facilities Status.**
  Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

  Portable Heater(warmer): on☐off☐Not Available☐;

  Fan(cooler): on☐off☐Not Available☐ ;

  Air Conditioning Unit: on☐ off☐ Not Available☐ ;
- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler☐The same as it is now☐ Warmer ☐
- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**
  Clothing Level: Add ☐ ; **Time______; Reason______;**

  Remove☐; **Time______; Reason______;**

  Drinking: Hot drinking☐ ; **Time______; Reason______;**

  Cold Drinking☐; **Time______; Reason______;**

  Air Conditioning/central heating:

  Turn Up (warmer) ☐ ; **Time______; Reason______;**

Turn Down (cooler) ☐ ; **Time_______; Reason_______;**

Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Fans: Start up☐ ; **Time_______; Reason_______;**

Turn off☐ ; **Time_______; Reason_______;**

Windows: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Blinds: Open☐ ; **Time_______; Reason_______;**

Close☐ ; **Time_______; Reason_______;**

Doors: Open☐; **Time_______; Reason_______;**

Close☐; **Time_______; Reason_______;**

5:00 pm-5:59pm I am not in ☐ (Please skip this time slot if you take this box) **fill in time____**

- **Current Thermal Feeling**: (Please only choose the **one** that is most appropriate.)
  Cold ☐ Cool☐ Slightly Cool☐Neutral☐ Slightly Warm☐ Warm☐ Hot☐
- **Current Facilities Status.**
  Windows: Open☐ Close☐Not Available☐;**Door**: Open☐Close☐Not Available☐ ;

  Portable Heater(warmer): on☐off☐Not Available☐;

  Fan(cooler): on☐off☐Not Available☐ ;

  Air Conditioning Unit: on☐ off☐ Not Available☐ ;
- **At this point of time, would you prefer to be (Please only choose one box)**
  Cooler☐The same as it is now☐ Warmer ☐
- **Did you take any of these following actions in last 1 hour? If you did, please tell us the time of the action/actions in the 24 hour clock format for example (14:50) and please also brief a reason.**
  Clothing Level: Add ☐ ; **Time_______; Reason_______;**

  Remove☐; **Time_______; Reason_______;**

  Drinking: Hot drinking☐ ; **Time_______; Reason_______;**

  Cold Drinking☐; **Time_______; Reason_______;**

  Air Conditioning/central heating:

  Turn Up (warmer) ☐ ; **Time_______; Reason_______;**

  Turn Down (cooler) ☐ ; **Time_______; Reason_______;**

  Portable Heaters: Start up☐ ; **Time_______; Reason_______;**

  Turn off☐ ; **Time_______; Reason_______;**

Fans:	Start up☐ ;	**Time_______; Reason_______;**
	Turn off☐ ;	**Time_______; Reason_______;**
Windows:	Open☐ ;	**Time_______; Reason_______;**
	Close☐ ;	**Time_______; Reason_______;**
Blinds:	Open☐ ;	**Time_______; Reason_______;**
	Close☐ ;	**Time_______; Reason_______;**
Doors:	Open☐;	**Time_______; Reason_______;**
	Close☐;	**Time_______; Reason_______;**

Leave time____________ **End of the Survey**