# A Novel Indoor Adaptive Thermal Comfort System to Reduce the Energy Consumption for the Residential Dwellings

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# Abstract

The percentage of households in fuel poverty, who cannot afford adequate heating, has reached 25% in the United Kingdom (UK), resulting in a critical threat to life. Therefore, this issue is currently of interest to UK policymakers and stakeholders. Currently, the main areas of interest relating to thermal comfort are factors relating to indoor health, the energy crisis, and Global Climate Change.

There was a gap in the acknowledgements of adaptive thermal comfort (psychological and human behaviour aspects) due to the focus on human physiology (Predicted Mean Vote - Predicted Percentage Dissatisfied/ PMV-PPD). Furthermore, existing heating control systems need to be optimized for using an electric radiant heating panel to anticipate the future focus on renewable energy sources.

This work has developed a novel base system model that better reflects the user conditions for the future indoor thermal control system based on the existing ASHRAE RP-884 and Global Thermal Comfort Database II combined with new data collections and case studies. The system model has the compatibility to control the heating panels based on the network of sensors and flexible user control with a low-cost system approach to suit residential needs.

The artificial intelligence (AI) model with shallow supervised learning implemented in the system can enhance the existing model to produce a 98.49% comfort zone from all ASHRAE multiple databases. In contrast, the PMV-PPD only gives 69.91% comfort, while the Givoni approach gives 89.19%. With a 6.62% wider comfort area and the assumption of direct conversion to saving, the base system model can contribute to about 783.5 thousand tonnes of $CO_2$ equivalent per year with the 2030 emission factor. Widening the thermal comfort zone also acknowledges a particular group that needs a different set point. This work also recognized that acknowledging the human presence during the thermal comfort assessment can increase the comfort level more than 10% with the same heating arrangement.

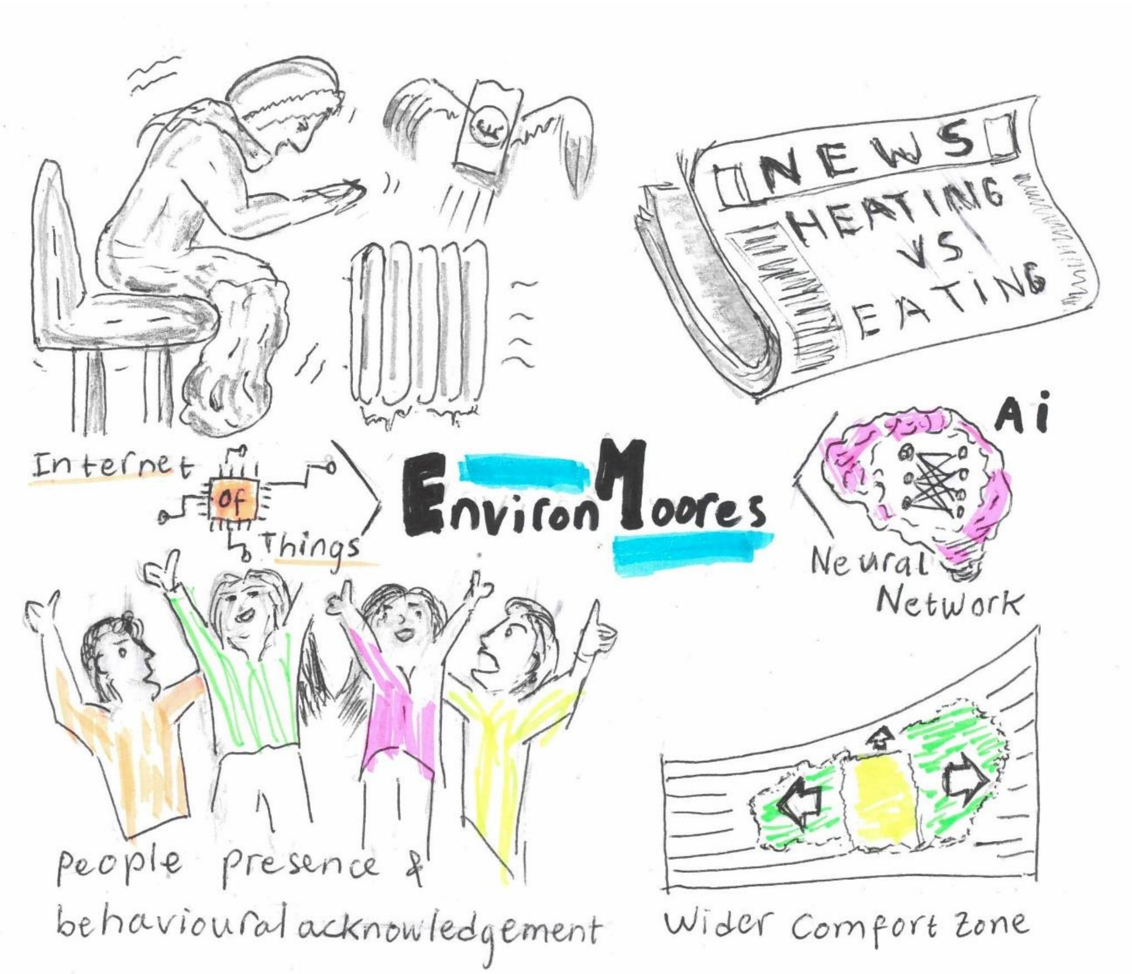
The initial model assessment was also developed using MATLAB to represent the UK's indoor conditions for typical residential properties built prior to the 1920s and after the 2010s and highlights the suitable parameters for indoor comfort with lower energy use. The simulation results recommend lowering the thermal set point for thermal comfort. The result is based on hourly thermal data across the UK on the different housing typologies.

This solution can bridge the physiology and psychology aspects and benefit the engineers and the researchers in the thermal comfort area.

Dedicated to

Lisa, Sasa, Mili and long lists of people who support this work

**EnvironMoores: Efficient NoVel Intelligent Reliable OccupatioN Monitoring for IndOor human-comfORt adaptivE System**



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Doing a PhD is complex, and the additional COVID pandemic made it more challenging. This thesis is dedicated to my family and the many people that supported me along this process.

I would like to express my deepest gratitude to my remarkable supervisory team for their invaluable advice, continuous support, and help during my PhD study even in the middle of the pandemic. Dr Badr M. Abdullah for becoming someone I can always rely on, Prof Alison J. Cotgrave, who has always encouraged me since the beginning of this program, Dr Ana Armada Bras for giving continuous challenges so that I can keep achieving better results and Dr Jeff Cullen for all the support and ideas as the hardware guru. I feel that you are all my perfect mentors, and no simple words can describe how I thank all of you for this long process.

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# List of acronyms/Abbreviations

| | |
|---|---|
| AB | Adaboost |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| ANSI | American National Standards Institute |
| ASHE | American Society for Health Care Engineering |
| ASHRAE | The American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| AT | Adaptive Thermogenesis |
| BAT | Brown Adipose Tissue |
| BES | building energy simulation |
| BMI | Body Mass Index |
| BN | Bayesian network |
| BP | Backpropagation |
| BRE | Building Research Establishment |
| BT | Boosted trees |
| CEDA | Centre for Environmental Data Analysis |
| CFD | computational fluid dynamics |
| CIBSE | Chartered Institution of Building Services Engineers |
| COMEAP | Committee on the Medical Effects of Air Pollutants |
| COTS | Commercial Off The Shelf |
| CT | Classification tree |
| DT | Decision tree |
| GBM | Gradient boosting machine |

| | |
|---|---|
| GCC | Global Climate Change |
| GPC | Gaussian process classifier |
| HAM | Heat, Air and Moisture |
| HMM | Hidden Markov model |
| HVAC | Heating Ventilation and Air Conditioning |
| I2C | The Inter-Integrated Circuit Protocol |
| IAQ | Indoor Air Quality |
| IBM | International Business Machines Corporation |
| ID | Identity |
| IESVE | Integrated Environment Solutions Virtual Environment |
| IoT | Internet of Things |
| ISO | International Organization for Standardization |
| KNN | K nearest neighbours |
| LDA | Linear discriminant analysis |
| LJMU | Liverpool John Moores University |
| LoR | Logistic regression |
| LR | Linear regression |
| MQTT | Message Queuing Telemetry Transport |
| NB | Naive Bayes |
| NST | Nonshivering Thermogenesis |
| PID | Proportional Integral Differential |
| PMV | Predicted Mean Vote |
| PPD | Predicted Percentage Dissatisfied |
| PTS | predict the Thermal Sensation |
| QoS | Quality of Service |

| | |
|---|---|
| RBC | Rule-based classifier |
| RF | Random forests |
| RH | Relative Humidity |
| SCL | Serial Clock |
| SDA | Serial Data |
| SDGs | Sustainable Development Goals |
| SET | Standard Effective Temperature |
| SSR | Solid State Relay |
| ST | Shivering Thermogenesis |
| SVM | Support vector machine |
| TR | Tree regression |
| TSO | The Stationery Office |
| TSV | Thermal Sensation Vote |
| UK | United Kingdom |
| VOCs | Volatile Organic Compounds |
| Wi-Fi | Wireless Fidelity (IEEE 802.11) |
| WSN | Wireless Sensor Networks |
| XAI | explainable Artificial Intelligence |

# List of Symbols/Notations

| | |
|---|---|
| A | ampere |
| A | Total surface area |
| Btu | British thermal unit |
| C | convective heat loss from the clothed body |
| clo | insulating value of clothing |
| Cout | Outdoor contaminants concentration |
| Cres | convective heat loss from respiration |
| Dim | Room dimensions |
| E | evaporative heat loss from the clothed body |
| Eres | evaporative heat loss from respiration |
| EX | Air exchange rate |
| ft | foot |
| G | Contaminants generation/deposition /removal concentrations/rates |
| g eq | gram equivalent |
| H | Ceiling height |
| H | hour |
| kge | kilogram equivalent |
| kWh | Kilo Watt Hour |
| m | meter |
| M | Metabolic rate |
| met | metabolic equivalent of task |
| N | Number of occupants |
| P | Penetration factor through envelope/door |

| | |
|---|---|
| ppm | parts per million |
| Q | Volume flow rate (Natural, Mechanical, Infiltration) |
| R | radiative heat loss from the clothed body |
| RHin | Indoor relative humidity |
| RHout | Outdoor relative humidity |
| S | the rate at which heat is stored in the body tissues |
| t | Exposure time |
| Ta | Indoor temperature |
| Ti | Temperature of surface |
| TMR | Radiant temperature |
| Tout | Outdoor temperature |
| V | voltage |
| va | Wind velocity |
| W | watt |
| W | mechanical work is done |
| $\rho$ | Air density |

# Declaration and List of Publications

No portion of the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Part of this thesis has been published in the following:

## *Journal articles*

- Karyono, K., Abdullah, B. M., Cotgrave, A. J., & Bras, A. (2020). The adaptive thermal comfort review from the 1920s, the present, and the future. Developments in the Built Environment, 4, 100032. doi:https://doi.org/10.1016/j.dibe.2020.100032
- Karyono, K.; Abdullah, B.; Cotgrave, A.; Bras, A. (2020). A Novel Adaptive Lighting System Which Considers Behavioral Adaptation Aspects for Visually Impaired People. Buildings 2020, 10, 168. https://doi.org/10.3390/buildings10090168
- Karyono, Kanisius, Abbie Romano, Badr M. Abdullah, Jeff Cullen, and Ana Bras (2022). The role of hygrothermal modelling for different housing typologies by estimating indoor relative humidity, energy usage and anticipation of fuel poverty. Building and Environment 207 (2022): 108468. (https://doi.org/10.1016/j.buildenv. 2021.108468) ©2022, Elsevier
- K. Karyono, B. M. A., Alison J. Cotgrave, Ana Bras, and Jeff Cullen. (2023). Developing a Reliable Shallow Supervised Learning for Thermal Comfort using Multiple ASHRAE Databases arXiv. doi:10.48550/ ARXIV.2303.03873

- Karyono, K., Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J. Field Studies of the Use of the Artificial Intelligence Model for Defining Indoor Thermal Comfort – under review

### *Book and Book Chapter*

- Patrick Reid and Kanisius Karyono (2020), The Smart yet Easy Way to Design Indoor Lighting Solutions, ISBN : 9786239245948, UMN Press.
- Karyono, Kanisius, Badr M. Abdullah, Alison J. Cotgrave, and Ana Bras. (2021). Experience and Memory Principle for Adaptive Indoor Thermal Comfort. Intelligent and Reliable Engineering Systems, pp. 14-19. CRC Press, 2021. https://doi.org/10.1201/9781003208365 ©9781003208365 | IEMERA 2020, Kumar et.al. | Edn. 1 – Chapter 3
- Karyono, K., Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J. (2022). Human-Centred Approach in Industry 4.0: Lighting Comfort in the Workplace. In: Batako, A., Burduk, A., Karyono, K., Chen, X., Wyczółkowski, R. (eds) Advances in Manufacturing Processes, Intelligent Methods, and Systems in Production Engineering. GCMM 2021. Lecture Notes in Networks and Systems, vol 335. Springer, Cham. https://doi.org/10.1007/978-3-030-90532-3_40

### *Conference Proceedings*

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- Karyono, K., Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J. (2022). Assessing the Human Presence in the Artificial Intelligence Based Adaptive Comfort System to Lower the Energy Use. LJMU Faculty Research Day 2022 Proceedings.

## *Awards*

- "JELAS, Jolly Efficient Lighting Adaptive System", PPI Aberdeen Online Student Poster Competition, August 2019, 2nd prize winner
- Best Presenters IEMERA 2020

# Chapter 1 Introduction

## 1.1 Human comfort

About eighty-seven per cent of the population spend their time in an artificial climate (indoor), according to the research of NHAPS (Klepeis et al., 2001). This fact justifies that over the past fifty years, there has been a dramatic increase in research on thermal comfort methods. Human comfort is a state of mind expressing satisfactory adaptation to the immediate environment. Human comfort can be divided into smaller aspects, such as lighting, acoustics, thermal comfort, and air quality. These aspects are not independent, but there are relations between these comforts, which are visualised in Building Bulletin 101 Guidelines on ventilation, thermal comfort and indoor air quality in schools (Daniels, 2018), as shown in Figure 1. The arrows represent the relations of each aspect of comfort.

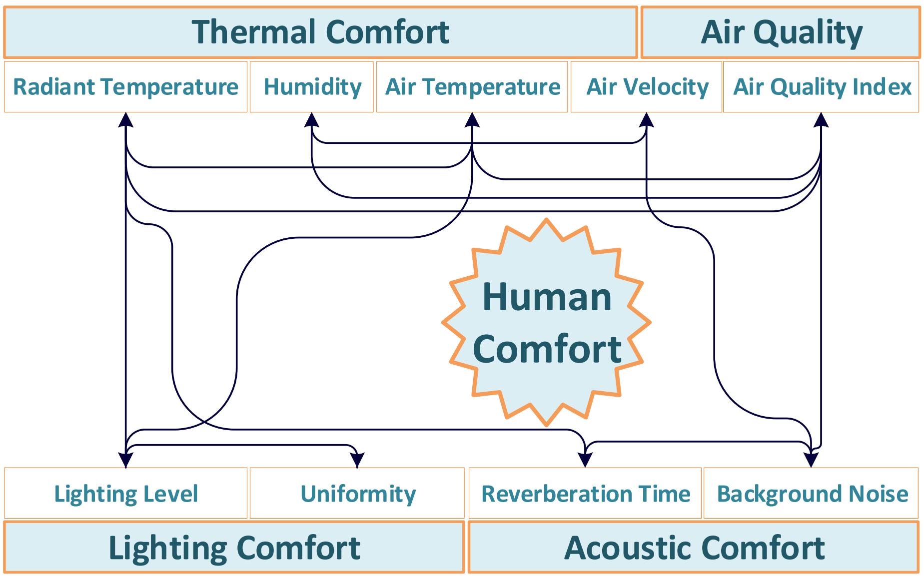



Figure 1 Human comfort aspects and their relations.

Although outdoor comfort is also studied in some of the papers (Höppe, 2002) (Coccolo, Kämpf, Scartezzini, & Pearlmutter, 2016) (Lai, Liu, Gan, Liu, & Chen, 2019), the majority of research is focused on indoor thermal comfort. Based on the Scopus search result, “indoor” “thermal comfort” returns 73.3% more dominant compared to “outdoor” “thermal comfort due to the nature of human living. Based on this fact, this work will focus on indoor thermal comfort.

Thermal comfort is one of the primary concerns in the design process of the artificial climate inside the building and significantly impacts health and safety. Some research found a strong relationship between ambient temperature and the cause of specific morbidities. The lag effect of hot temperature on morbidity was shorter than the cold and will also be affected by sociodemographic and pollution factors. There are enough studies to claim that mortality can be associated with cold and heat waves (X. Ye et al., 2012). Heat exposure was associated with increased cardiovascular, cerebrovascular, and respiratory mortality risk. Cold-induced cardiovascular morbidity increased in youth and the elderly (X. Song et al., 2017).

In the past 30 years, The World Health Organization estimates that yearly over 150,000 fatalities are caused by climate change (Patz, Campbell-Lendrum, Holloway, & Foley, 2005). Besides the human factors, the dwelling significantly influences the protection against heat and cold waves. Many existing dwelling stocks cannot provide enough protection against the heat and cold waves (Ormandy & Ezratty, 2016). Besides health and safety risks, thermal comfort will be beneficial also for productivity. If people work in an uncomfortable environment, they will behave unsafely due to the deterioration of their physical performance and thinking ability. The probability of committing an error will be higher due to the lower concentration. The indirect effect of thermal comfort is improving the working environment's morale (t. H. a. S. Executive, 2019).

## 1.2 Conditions Which Show the Need for This Research

### *1.2.1 Global Climate Change*

Thermal comfort has mainly focused on health and safety concerns. There is also a complementary shift for research focused on lowering energy consumption and climate change. The $CO_2$ emission has grown 1.7% to reach 33.1 Gt and become the highest growth since 2013. This growth is due to higher energy consumption (Eurostat, March 2018). The growth in the global economy and the increase in the energy demand for heating and cooling are the leading cause of this increase. Global climate change (GCC) can decrease heating needs by 2%.

On the contrary, the need for air conditioning has increased, especially in cooling during summer, due to the effects of increased humidity (Scott, Wrench, & Hadley, 1994). Increasing the global mean surface air temperature would benefit some countries but trigger higher losses for others. In the United States, the weather triggered about a 60% increase in $CO_2$ emissions (Tol, 2002a). The UK Climate Projections 2018 (UKCP18), which gives the UK climate projection tools, also predicts that the future will have warmer, more wet winters and hotter, drier summers (Jason A. Lowe, 2018). If the globally averaged values were used, the world impact would be excess spending of 3% to compensate the GCC (Tol, 2002b). The GCC impact will be worse in the later years and will have a worse impact on the more impoverished regions (Tol, 2002a). The development of energy-efficiency scenarios should differ from one location to another because the effectiveness of such designs will not be the same for each case (Scott et al., 1994).

HVAC (Heating Ventilation and Air Conditioning) systems are employed to maintain comfort. In Europe, the primary use of energy by households is for HVAC. It can reach more than 64% of the final energy consumption for the residential buildings (Eurostat, March 2018), which is very significant. The more power produced will always contribute to the carbon footprint and will have a consequence on climate change and temperature rise. The household sector represents 27.2 % of final energy consumption in Europe. Anticipating these trends, the UK will introduce a Future Homes Standard, mandating the end of fossil-fuel heating systems in all new houses from 2025 (HM Treasury, 2019), drive zero carbon emission and leverage the Paris Agreement. The target is to keep the global temperature rise this century below 2 degrees Celsius and even further to limit the temperature increase to 1.5 degrees Celsius (Change, 2018). More energy-efficient systems are proposed without ignoring the aspect of human comfort. There has been a tremendous increase in the papers published from the 1970s to the 2010s (Rupp, Vásquez, & Lamberts, 2015).

This work presents the comparative development timelines between the human thermal physiology approach and the human behaviour approach for thermal comfort. These will give an insight into the other researchers that want to focus on this area of work. This work aims to improve the adaptive approach using Artificial Intelligence (AI). This work uses the Artificial Neural Network (ANN) and combines the Predicted Mean Vote and Predicted Percentage Dissatisfied (PMV-PPD) approach taken from the ASHRAE database. The AI learning process acknowledges the behavioural aspects of thermal comfort. The aim is to produce a better intelligent system by coping with the limitation of AI. The approach is becoming the other alternative for Explainable AI, which is resource consuming.

### *1.2.2 New Regulations and Regulation Limitations*

Building regulations related to indoor comfort and fuel poverty are outlined in Part F: Ventilation (H. Government, 2010a) and Part L: Conservation of fuel and power (H.

Government, 2010b). These regulations cover both dwelling and other 'non-dwelling' building types. They consist of Approved Document L1A*: Conservation of fuel and power in new dwellings*, Approved Document L1B: *conservation of fuel and power in existing dwellings*, Approved Document L2A: *Conservation of fuel and power in new buildings other than dwellings* and Approved Document L2B: *conservation of fuel and power in existing buildings other than dwellings*.

In addition to building regulations, British Standards also give design parameters for indoor comforts, such as BS EN 15251:2007 *Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings* (Standard, 2007) and BS 5925:1991 *Code of practice for ventilation principles and designing for natural ventilation* (BSI, 2000). Besides the standard defined by the UK Government and Standardisation body, some guidance documents are published by professional bodies such as the Chartered Institution of Building Services Engineers (CIBSE). Although it covers residential buildings, many of the cases and annexes provided are targeted for buildings in general and non-residential buildings (Engineers, 2012).

#### 1.2.2.1 Residential Properties

Within the UK Building Regulations, Appendix A of Approved Document Part F of the Building Regulations (H.M.Government, 2013) outlines the maximum acceptable quantity of volatile organic compounds (VOCs), nitrogen dioxide, carbon monoxide and nitrogen dioxide within residential properties. These figures are based on the Committee on the Medical Effects of Air Pollutants (COMEAP) (H.M.Government, 2004). For newly built residential properties, standards for ventilation and Indoor Air Quality (IAQ) are demonstrated within H.M.Government (2019c). In terms of relative humidity, the recommended levels within domestic properties as outlined in H.M.Government (2013) and can be categorised as follows:

- The daily average is less than 85% RH
- The weekly average is less than 75% RH
- The monthly average is less than 65% RH

These regulations have been modified since the previous 2006 edition of the Building Regulations Part F. It was noted by H.M.Government (2013) that these regulations were reformed to comply with research conducted by Altamirano-Medina, Davies, Ridley, Mumovic, and Oreszczyn (2009).

#### 1.2.2.2 Workplaces

Apart from more generalised documents as per BS EN 15251: 2007 (Standard, 2007), the building regulations specific to building type are mentioned in Building Regulations Part L (H. Government, 2010b) Approved Document L2A and L2B, which are for buildings other than dwellings. CIBSE also published Guide F '*Energy efficiency in buildings'* (Engineers, 2012), further explaining and supporting Building Regulations Part L2. This CIBSE guide also provides more detailed information on how to comply with the Building Regulations Part L due to the complexity of compliance with this standard. Additional explanations and cases are given to support the building services engineers in complying with the standard.

Another CIBSE document that covers the issue of health aspects in the workplace is CIBSE TM40 '*Health Issues in Building Services'* (Engineers, 2020). This document outlines all aspects of health issues, including health and wellbeing, facilities management, thermal conditions, humidity, air quality, lighting, acoustic, electromagnetic field, and water quality. Supporting pre-existing legislation the TSO Workplace (Health, Safety and Welfare) Regulations 1992 No. 3004 (TSO, 1992), CIBSE TM40 further clarifies the implementation of the regulation in more practical resources.

Other relevant CIBSE documentation for workplaces include CIBSE Guide A: Environmental Design (Engineers, 2015), CIBSE Guide B2: Ventilation and ductwork (Engineers, 2016) and also CIBSE Guide F: Energy Efficiency in Buildings (Engineers, 2012).

In the US, the American Society of Heating, Refrigerating Air Conditioning Engineers (ANSI/ASHRAE) utilise ANSI/ASHRAE Standard 55-2017 Thermal Environmental Conditions for Human Occupancy (R. A. C. E. American Society of Heating, Incorporated, 2017). Another document created for a specific working environment is ANSI/ASHRAE/ASHE STANDARD 170-2017, '*Ventilation of health care facilities'* (Gary Hamilton P.E., 2018).

### *1.2.3 UK Housing Typology and Fuel Poverty*

The age range of residential dwelling typologies within the UK is vast, where only 17% of homes have been built in the last 30 years (Figure 2, (H.M.Government, 2019a)). With variation in age comes a variation in building standards, techniques and materials different from those used today to improve energy efficiency and, as a result, having different heating requirements. For example, within pre-1919 dwellings, energy costs are over 70% higher than their post-1990 equivalents (H.M.Government, 2019b). The comparison between the 1920s wall and the post-1990s can be seen in chapter 3.2.2, Figure 19. Considering Figure 2, over 20% of English residential dwellings are within this category (pre-1919 dwellings), producing around double the carbon emissions. Figure 2 also has a secondary y-axis representing the number of houses assigned to these dwelling ages.

The dwellings built using solid masonry bricks without air gaps (solid uninsulated walls) are referred to as '1920s' homes and were constructed from pre-1919 and 1919-44 in Figure 2. These homes are approximately 36.6% of the total dwellings, or about 8.76

million. The dwellings built using the latest well-insulated walls mentioned in Figure 2 as post-1990 are about 4.02 million or about 16.8% of the total dwellings. This study will focus on these two main groups, which are about 12.78 million houses covering about 53.4% of the total dwellings in the UK.

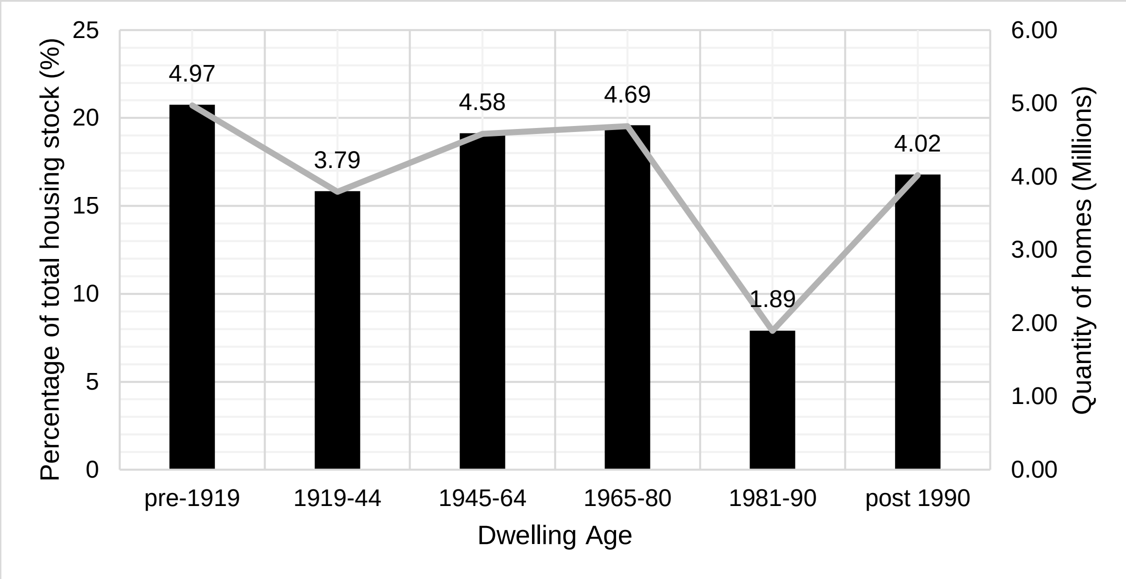



Figure 2 Dwelling age of properties of English homes (H.M.Government, 2019a).

Using heating contributes to approximately 61% of total energy consumption for UK homes ((NEF), 2014). As previously mentioned, there is also a requirement for more energy required to heat these older homes, which have a subsequently higher fuel cost. The inability to afford adequate, satisfactory heating energy in a home is defined as fuel poverty (Boardman, 1991), (Liddell, Morris, McKenzie, & Rae, 2012), (Moore, 2012). Particularly in pre-1919 homes, the likelihood of fuel poverty is double the national average, where all countries within the UK experience fuel poverty, as demonstrated in Figure 3.

Understanding how specific regions are affected by fuel poverty is imperative for developing a more profound knowledge and demonstrating locational requirements. Specifically, Figure 4 demonstrates two geographically opposite locations, Liverpool

(North West) and Kent (South East), which have been highlighted in purple and orange (respectively). In Liverpool, it is demonstrated to be one of only 14 local authorities in the whole of England to be at the highest end of fuel poverty with between 14.1-20.9% of homes experiencing it. By contrast, Kent has between 8.1-10% of homes in fuel poverty, one of 106 local authorities (H.M.Government, 2020b).

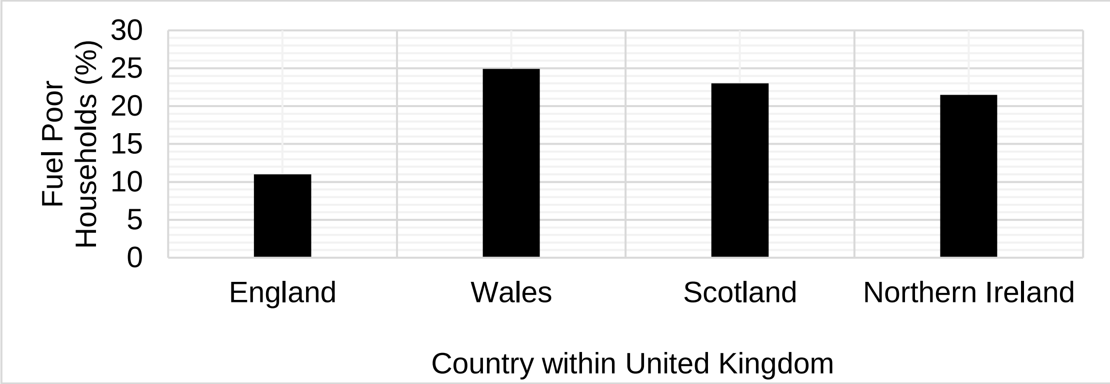



Figure 3 Percentage of fuel-poor households within the UK (Northern Ireland Housing N. I. H. Executive, 2019; Scottish S. Government, 2020; Welsh W. Government, 2019; H.M.Government, 2020a).

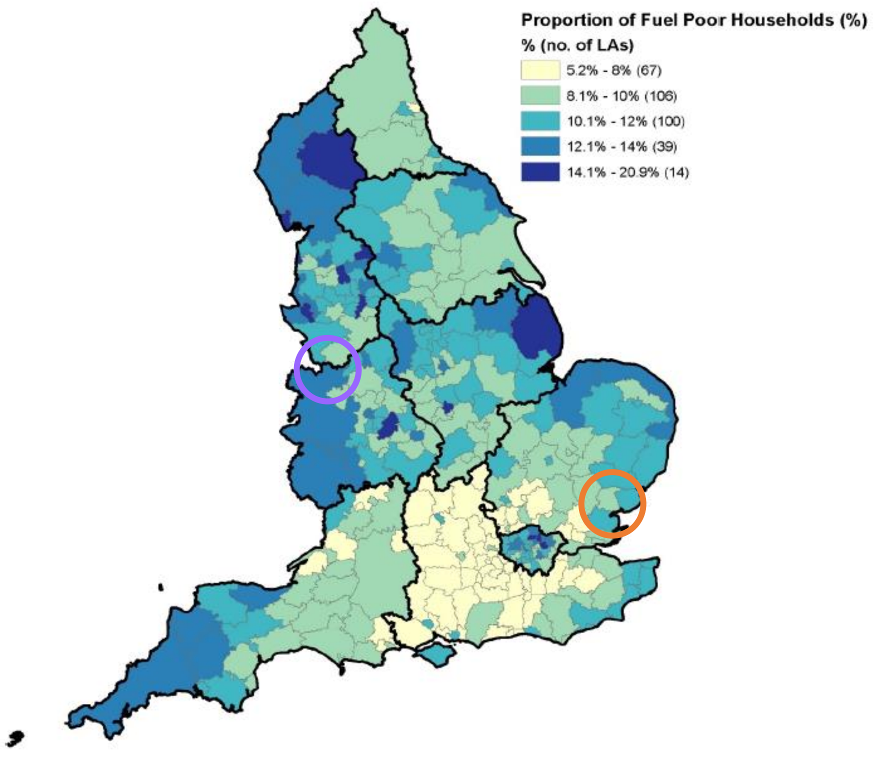



Figure 4. Sub-regional map of fuel poverty (by the proportion of local authority) within England (H.M.Government, 2020b).

By comparison, in Scotland, the national average for fuel poverty households from 2016-18 was 25% (S. Government, 2019); this is represented in Figure 5. An orange arrow highlights Aberdeen. The results demonstrated in Figure 5 are that within Aberdeen, fuel poverty is approximately slightly below the national average at 23% of all households in fuel poverty.

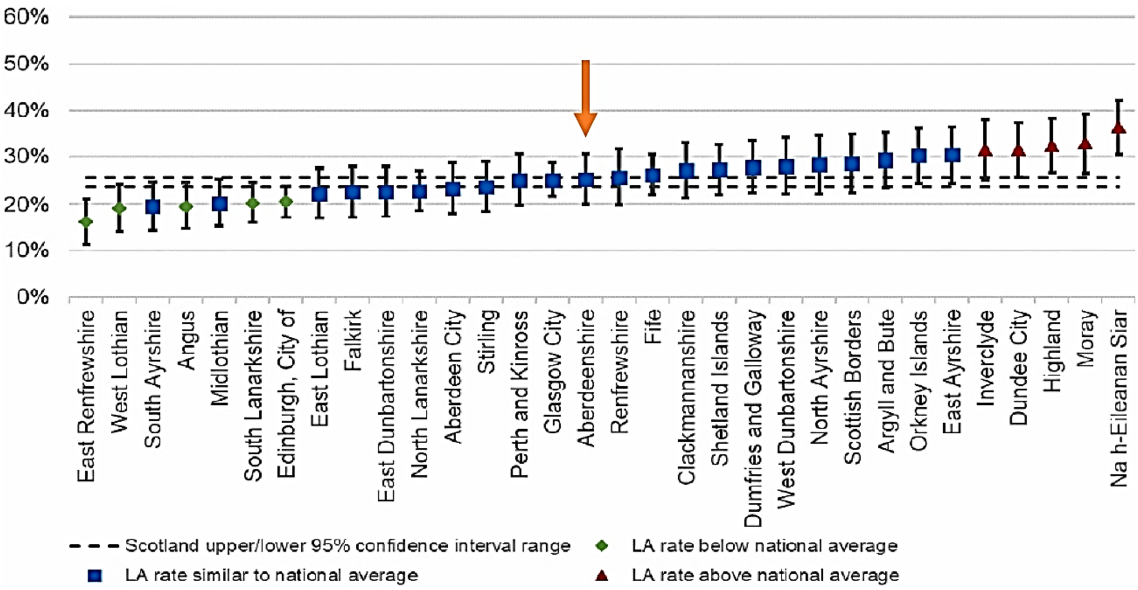



Figure 5. Percentage of fuel poverty homes in Scotland (by the local authority) (where an orange arrow highlights Aberdeen) (S. Government, 2019).

Further, Figure 6 (a) demonstrates a clear correlation between fuel poverty homes and the building envelope typology. Solid and un-insulated homes have the most significant proportion of homes that fall into the fuel poverty classification at approximately 16% of all homes. Figure 6 (a) shows that the average fuel poverty gap is the largest if residents live in solid uninsulated homes. The fuel poverty gap represents the value or quantity of money required to move the household out of fuel poverty; for solid, uninsulated homes, this is over £400 per year.

The fuel poverty problem gets worse due to the energy price increase and forces people in the UK to a choice between heating and eating, as shown in the headlines of some popular newspapers in the UK (Radnedge, 2022), (Partington, 2022), (Mirror, 2022), (Hiscott, 2022), (Alderson, 222), (Shaw, 2022). The energy price rise was steep, with the price more than doubling its value within the current year (E. I. S. Department for Business, 2022). The energy price chart showing the rise in gas and electricity prices can be seen in Figure 6 (b).

(a)

(b)

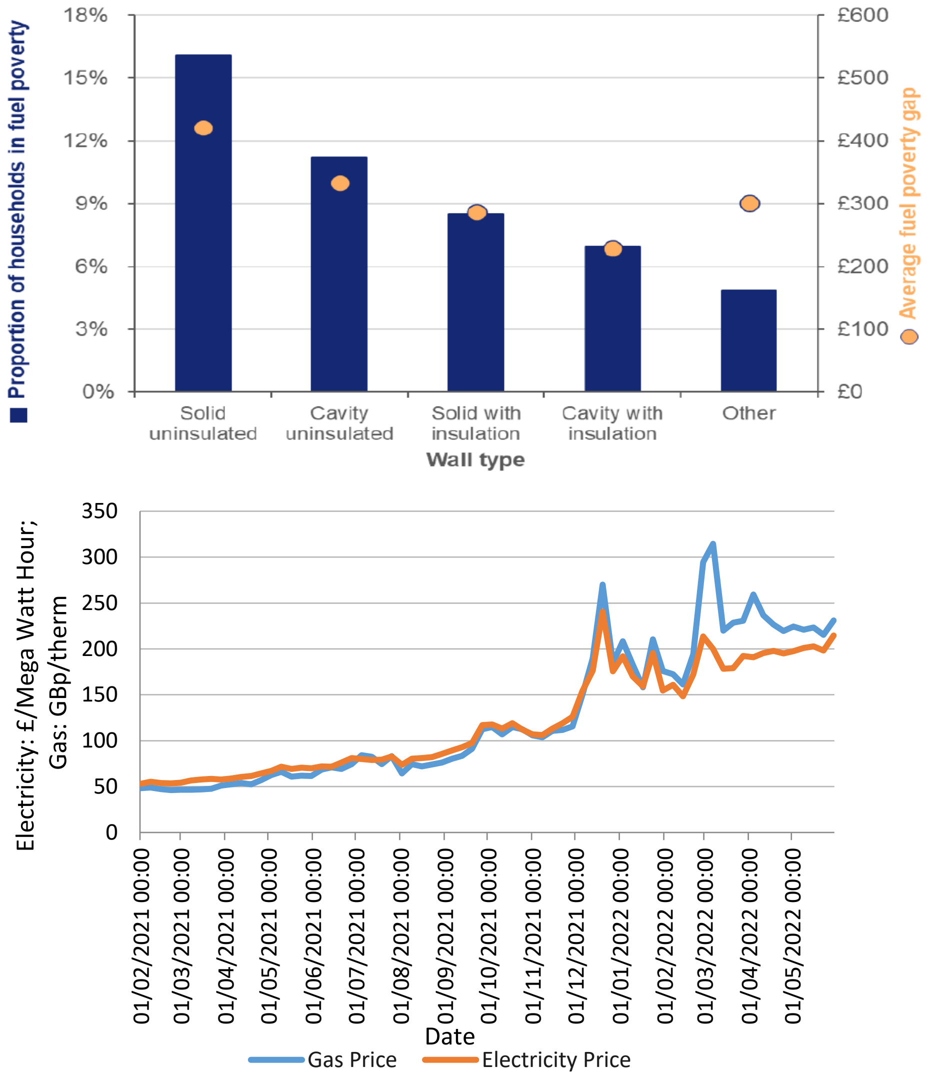



Figure 6. (a) Effect of wall type on the proportion of households in fuel poverty and average fuel poverty gap (H.M.Government, 2020a) (b) Weekly average prices forward delivery contracts of gas and electricity in the UK (Ofgem, 2022b) (Ofgem, 2022a) .

The poverty fight effort is also stated in the Sustainable Development Goals (SDGs) initiated by the United Nations, which are an urgent call for action by all countries in a global partnership (Development, 2016). The focus is on 17 goals which include fighting against poverty and other deprivations, tackling climate change and achieving sustainable cities and communities.

The UK Government commits to cutting greenhouse emissions to net zero by 2050. Since 1990, the UK has cut emissions by over 40%. The target by 2035 is cutting emissions by 78%. This target is also applied to energy use in buildings and residential dwellings, especially in heating and cooling. Decarbonising energy in buildings is also a key part of the Clean Growth Strategy. One of the ways to achieve it is to phase out the installation of natural gas boilers beyond 2035 (the Secretary of State for Business, 2021). There will be a move to a gradual transition to low-carbon heating. The new low-carbon heating will soon be the mainstream consumer option.

## 1.3 Aim and Objectives

### *1.3.1 Aim*

Aim: to develop a base system that predicts the current comfort state according to the adaptive thermal comfort to regulate buildings' thermal conditioning, resulting in enhanced comfort and efficiency through a novel solution based on the fusion of wireless sensors and artificial intelligence that sense the radiant temperature, relative humidity and monitor thermal comfort in real time with a reasonable price for residential dwellings.

### *1.3.2 Research Objectives*

In general, the outcome of the novel solution for achieving indoor thermal comfort for residential was reached by elaborating on four phases of research. Phase one activities are literature review, survey related to the smart system and identifying the novelty and planning review. The objective of this phase was mapping the gap and possible improvement in the thermal comfort field that not only focused on Fanger's approach but also acquired the Adaptive Thermal Comfort approach (this corresponds to phase 1 of Figure 7).

Phase two activity was the development of a model for heating to simulate the solution that can benefit the energy aspect of thermal comfort. The objective of this phase is to develop a thermal comfort model based on the housing typology and hourly outdoor data, representing the UK dwelling conditions (this corresponds to phase 2 of Figure 7). With the whole year's hourly weather data, this MATLAB model was able to give insight into the physical parameters that affect indoor thermal comfort, including the people's presence as a milestone for the development of the novel system.

Phase three has the activities of the development of the thermal comfort framework and using the multiple ASHRAE Database for AI training. The objective of this phase was to develop the real-time model using the adaptive approach for thermal comfort. The framework elaborates the wireless sensors and artificial intelligence to monitor thermal comfort in real time. The system was designed considering the price point of the residential use. The AI learning process were based on the multiple ASHRAE databases to give the ability for the framework to accommodate adaptive user processes for prominent energy saving and fitted in the local controller to increase the system's robustness and make it more cyber-safe (this corresponds to phase 3 of Figure 7).

Phase four's activities were testing the system in the laboratory, the BRE house to represent the 1970s housing typology and conducting five case studies to represent multiple dwellings’ conditions. This procedure had the objective to validate the system against the actual implementation of the framework and compare the system against the use of COTS sensors (this corresponds to phase 4 of Figure 7).

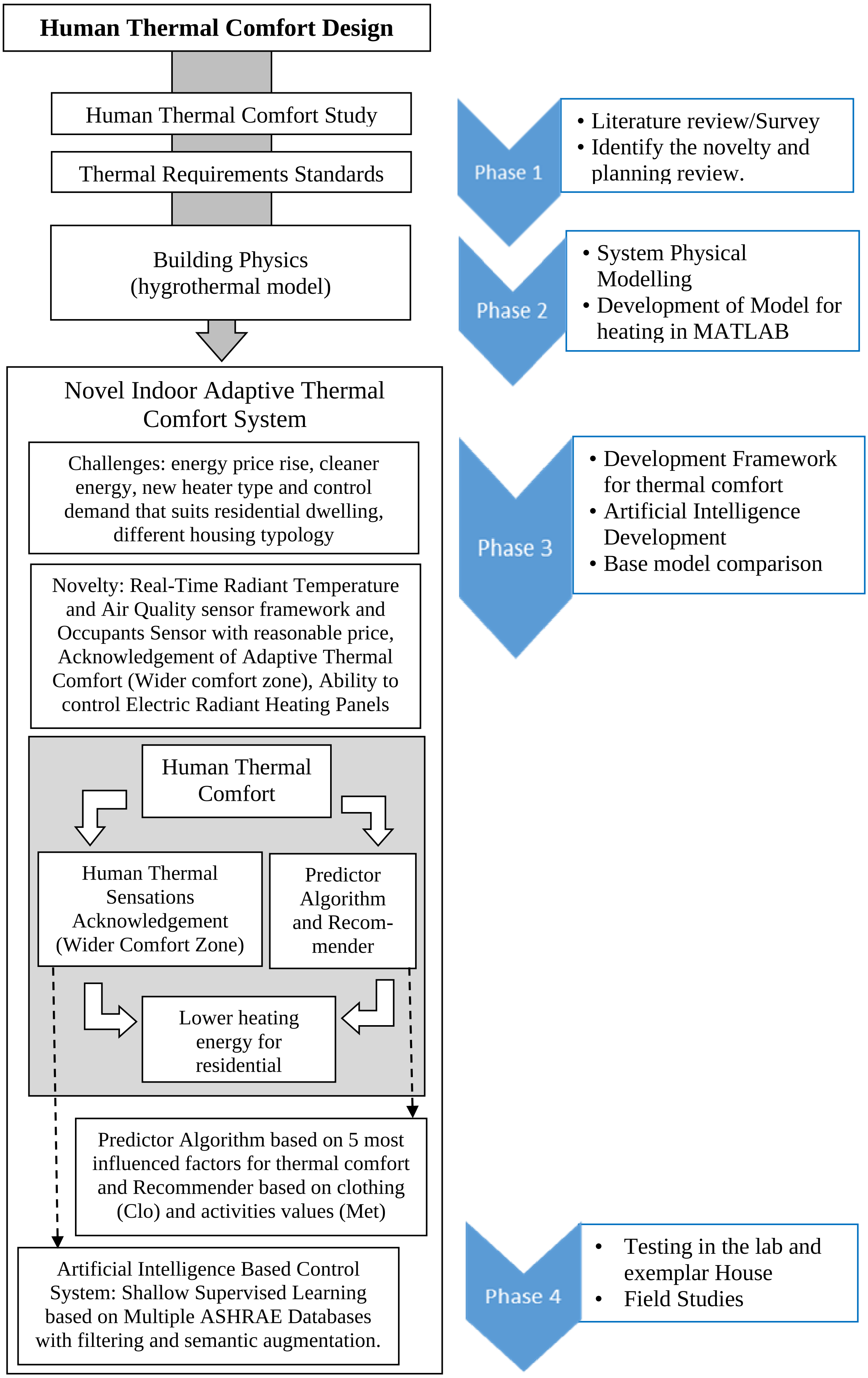



Figure 7 The developped entities and the research phases.

## 1.4 Novelty

This work focuses on the system to achieve indoor thermal comfort for residential use. The main novelty is the developed system model that can become the standard system for developing robust thermal comfort systems for residential with the ability to acknowledge the adaptive thermal comfort. The developed system predicts the comfort zone which can be integrated to control the electric residential heating. This base system can be said to have “intelligent at cost” because it uses affordable consumer-grade electronics to be implemented for residential use and work with real-time sensor data.

This system has the following properties:

- able to monitor multiple locations and control the heater in real time (based on IoT sensors)
- robust with the low cyber security concerns because the algorithm can be deployed in the local controller
- acknowledging the psychology approach of thermal comfort by the predictor algorithm
- able to acknowledge 6.06% wider comfort zone from ASHRAE data set compared to the PMV-PPD and the Givoni comfort zone

The initial phase of this work also assesses the possibility of lowering energy use without affecting health by using the digital twin model developed in MATLAB.

## 1.5 Chapter Overview

This thesis is divided into eight chapters that help the reader understand the background of this work, the approach taken, and the result and conclusion. The introduction gives the context and background of the importance of this research. Starting from the human comfort point of view, the global climate change and the current conditions drive the need for further work that needs to be done in this field. The first chapter also highlights the aims and research objectives and the novelty that this work can give to the society of knowledge. Part of this chapter has been published in the paper about the thermal comfort overview (Kanisius Karyono, Abdullah, Cotgrave, & Bras, 2020) and hygrothermal model (Kanisius Karyono, Romano, Abdullah, Cullen, & Bras, 2022).

The second chapter addresses the development of the field of thermal comfort that affects the currently defined standard. The highlighted previous works contributing to human physiology, human psychology and human behaviour developments are addressed along with their pros and cons. This chapter also includes the viewpoint of the health aspects and the special group of people like the young, elderly, and temporary ill who have different preferences in the thermal set point. The research progress based on the publication parameters are also assessed in this chapter, along with Daniel Kahneman's Principle related to the approach this work offered. The second chapter also discusses the latest development in simulation, WSN and AI technology that have become the enabler for the improvement in this field. Part of this chapter has been published in the paper about the thermal comfort overview (Kanisius Karyono et al., 2020) and experience and memory principle (Kanisius Karyono, Abdullah, Cotgrave, & Bras, 2021).

The third chapter focuses on the methodologies used in this work. This chapter addresses the phases conducted in the research, from the literature review, the simulation in MATLAB and prototype development. The last sub-chapter describes the test procedures for testing the prototype.

Chapter four discusses the simulations and the results obtained from the model which is one of the novelties and contributions of this thesis. This chapter describes the detail about the model, the parameters involved in the model, assumptions and model simplification then followed by the result from the simulation and the analysis of the simulation output. This chapter also address the validation for the simulation. The results of the simulations are validated against the ASHRAE Global Thermal Comfort Database II and the AI model that is explained in the chapter six of this work. The thermal comfort model recommends lowering the thermal set point to lower the energy use for thermal comfort. Part of this chapter has been published in the paper about the hygrothermal model (Kanisius Karyono, Romano, et al., 2022).

The fifth chapter discusses the system design for the proposed IoT system prototype. This chapter addresses the perception of the user about smart system and sensors use and addresses the needs of the adaptive system. The topology of the system and the system flow, the design of the hardware and software for the prototype are discussed in the next sub-chapter. The user interface and the database structure for the prototype are also addressed in this chapter. Part of this chapter has been published in the paper about the thermal comfort overview (Kanisius Karyono et al., 2020) and the adaptive system for industry 4.0 (Kanisius Karyono, Abdullah, Cotgrave, Bras, & Cullen, 2022).

Chapter six discusses the artificial intelligence part of the system, which is also becoming one of the novelties and contributions of this work. This approach proposes shallow supervised learning based on the multiple ASHRAE Databases with filtering and data Semantic Augmentation. The previous research only includes part of the database for learning or uses the more complex method for the artificial intelligence. This work offers the use of fundamental ANN shallow supervised learning methods for thermal comfort. This chapter discusses the need for filtering for the learning data set and the filtering algorithm. Increasing the accuracy of the learning process was done by implementing data semantic augmentation. The learning result was also compared with other existing methods. This chapter also proposes psychrometric-based verification and parameter visualisation. Part of this chapter has been published in the paper about the human presence (K. Karyono, Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J. , 2022) and the paper on reliable learning (K. Karyono, 2023).

The seventh chapter discusses the testing against the controlled conditions inside the lab and in actual conditions by using the BRE house to represent the condition of the 1970s house. This chapter discusses the result of these tests and compares sensors and validations. This step also shows that the people's presence can benefit heating energy conservation. Some case studies were also assessed to introduce the AI model's approach to assessing thermal comfort. The case studies include the case of a humid dwelling, the new dwellings, the refurbished flats, the use of the new materials for thermal improvement and the new modular house with advanced heating controls. Part of this chapter has been published in the paper about human presence (K. Karyono, Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J. , 2022) and the paper on AI field study (K. Karyono, Abdullah, B.M., Cotgrave, A.J., Bras, A., Cullen, J., 2022).

The conclusions and future works are provided in chapter eight, which is the last chapter. This chapter highlights all the contributions and novelty of this work for thermal comfort. The references and appendixes are also included in this thesis to provide more detailed materials for supporting the finding.

# Chapter 2 Literature Review

## 2.1 The Development of the Methods in Thermal Comfort

Thermal comfort began to gain attention in the early 1920s when it became possible to directly control the indoor environment's microclimate. In the traditional approach, using fireplaces to control the temperature was mandatory. In the second half of the nineteenth century, it was necessary to model the building as an open system and apply the laws of thermodynamics (Fabbri, 2015). Various electronic controllers were developed, which led to the evolution of comfort monitoring. Fanger's comfort model was introduced in the 1970s, focused on physically based determinism along with the introduction to the comfort equation. The quality of air movement and sophisticated models that map the human body's physics and physiology were also developed to build coherent, global thermal perception. These developments were also driven by energy efficiency (R. J. de Dear et al., 2013). In the twentieth century, the focus goes on humans as the centre point of the design to improve the health and comfort of people and their homes (Fabbri, 2015), (R. J. de Dear et al., 2013).

The equivalent temperature of an environment corresponds to the same temperature in an environment where the temperature is uniform, the air is stationary, and the moisture content corresponds to 100 %. Therefore, the human body cannot exchange energy with the environment. If the actual temperature of an environment is 22°C with a relative humidity of 50 % and airspeed of 0.2 m/s, it is equal to the temperature of 19.6 °C with a relative humidity of 100 % and no airspeed (Patz et al., 2005).

It is becoming essential to review the progress of thermal comfort due to the growth of low-cost sensing solutions. The provision of lighting and thermal comfort has been widely increased to existing and future intelligent buildings to aid productivity, health, and well-being. Thermal cameras, for example, have the potential to be used widely in the home comfort system nowadays. It used to be so costly that only the military, firefighters, and surveyors could use it due to its price (BBC, 10 January 1985; Tu, August 18, 1997; villo, 2002). Besides sensors, artificial intelligence also plays a vital role in creating more intelligent solutions for human comfort. The system can perform smartly to maintain comfort while lowering energy usage.

Figure 8 presents the evolution in the enhancement of the thermal comfort approach in houses from 1920 until the present. PMV-PPD is the typical method for comfort analysis. It focussed on thermal physiology. The other method, the adaptive method, is based on human behaviour. There are three thermal adaptation types (Brager & de Dear, 1998):

- Physiological which is related to the body's reaction due to the temperature change.
- Psychological which is derived from the state of mind of previous experiences.
- Behaviour related adaptation

The adaptive method can give the flexibility and personalisation needed to overcome the problem due to the variability of people's metabolism, historical exposure, and behavioural preferences.

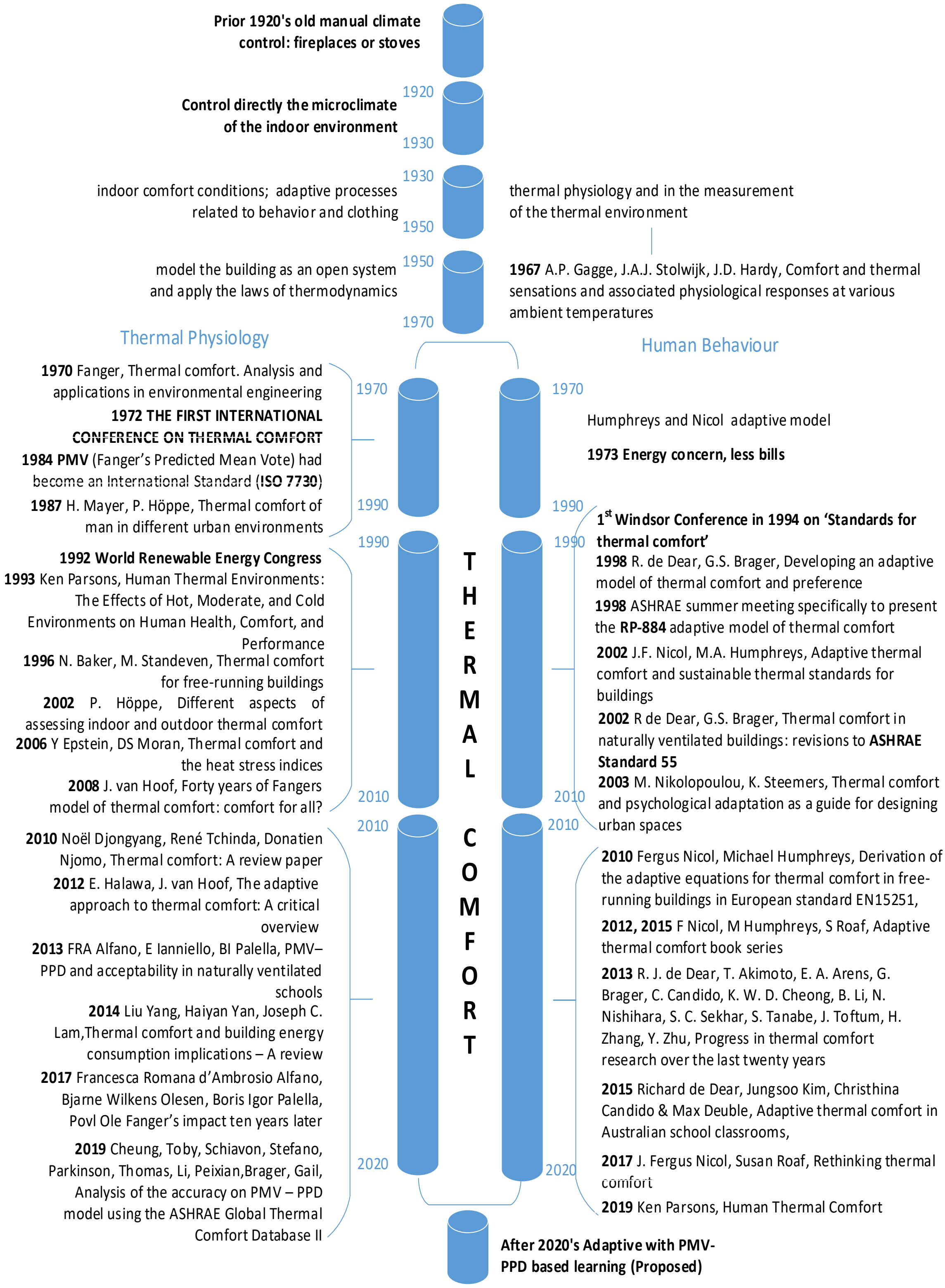



Figure 8 Timeline diagram for developing the methods in "Thermal Comfort" from 1920 until now.

### *2.1.1 Pre 1920s*

In pre 1920s times, people used fireplaces and stoves to control the indoor temperature. Another way to gain comfort was using adaptive human behaviour and clothing arrangement. Later, the study of thermodynamics was used to model the building to study the comfort parameter. The military also played their part in the history of comfort by the work to achieve comfort, for example, on ships. One of the pioneers in this era was John Bartlett Pierce, who founded a boiler factory, heating systems and radiators in 1892. The company was among the most important manufacturers of heating systems in the United States. His legacy is the foundation which became the institute to support the research in this field. The institute focuses on the population's health, which is achieved using space heating. The research was focused on two major topics, the thermodynamic study of the physiological processes and the relationship between the human body and the environment concerning well-being, physical and physiological behaviour (Fabbri, 2015).

The comfort also attracted interest because the thermal conditions affected the factory output. The notable works were from Vernon in 1919, assessing the workers in the steel industry, tinplate workers and the accident rate in the munitions industry related to the thermal condition. In 1927 Vernon also assessed the effect of temperature rise in coal mining. Weston conducted other research in 1922, Wyatt et al. in 1926 on the weaving linen industry, and Farmer et al. in 1923 on the glass industry. All had a similar result: a lower output or work rate in high-temperature exposure. Besides the lower output, the accident rate also increased (Parsons, 2020 ).

Houghten and Yagloglou began to research comfort based on empirical rules in the 1920s and published the paper “Determination of the comfort zone” in 1923. They proposed the lines of comfort on the psychrometric chart where the temperature is uniform, the air is stationary, and the moisture content corresponds to 100 %, where the human body cannot exchange energy with the environment. The air velocity later being included in the diagrams of wellness by Vernon H.M. and Warner and C.G (Fabbri, 2015).

### *2.1.2 Fanger PMV-PPD and Human Physiology*

The development of a thermal model by Fanger in 1970 (Fanger, 1970) was considered a milestone. This work has become a standard reference for thermal comfort due to the experiments and model it presented. The experiments were conducted in a controlled room condition. The formulated model makes it possible to calculate the effect of variables to gain comfort. This model stated that no significant difference was generated by sex, age, body build, menstrual cycle, ethnic differences, food, circadian rhythm, crowding, and colour. This model is known as the Predicted Mean Vote (PMV) /Predicted Percentage of Dissatisfied (PPD). This model has also become the basis of the ISO 7730-2005 (Höppe, 2002). The mean radiant temperature and radiation data can be calculated for human comfort.

Fanger's equation shows the relation of the parameters that can affect human comfort. This equation, also acknowledged by ASHRAE, comprises the PMV-PPD model in the ASHRAE-55 Standard (Enescu, 2017). This standard mentions the parameters which can have effects on human comfort. Six parameters are mandatory for thermal comfort.

Two parameters are related to the occupants, which are:

- metabolic rate
- clothing insulation

Four others are related to the surrounding environment, which are:

- air temperature

- radiant temperature
- airspeed
- humidity

The met unit represents the individual metabolic rate. One met is equal to 58.2 $W/m^2$ or 18.4 $Btu/h \cdot ft^2$, which is equal to the energy produced per unit surface area of an average person seated at rest. The surface area of an average person is 1.8 $m^2$. Writing for example, also equal to 1.0 met unit. The activities within 0.1 met units can be grouped into one entity. The limitation for this is for the occupants, whose time-averaged metabolic rate is more than 2.0 met. The basic equation for thermal balance can be calculated using the formula presented in equation 1 (Fanger, 1970).

$$M - W = C + R + E + (Cres + Eres) + S \quad (1)$$

Where:
M : the metabolic rate
W : mechanical work is done
C : convective heat loss from the clothed body
R : radiative heat loss from the clothed body
E : evaporative heat loss from the clothed body
Cres : convective heat loss from respiration
Eres : evaporative heat loss from respiration
S : the rate at which heat is stored in the body tissues

An empirical table lists everyday activities and their met units (ASHRAE, 2017). Clothing insulation is also presented as a table consisting of the clothing items and their clothing insulation values in clo units. One clo is equal to 0.155 $m^2 \cdot K/W$ or 0.88 $°F \cdot ft^2 \cdot h/Btu$. This corresponds to trousers, a long-sleeved shirt, and a jacket. The limit of occupants grouping is when the clothing difference is more than 0.15 clo. However, to use the table values, there are some limitations for the clothes with high impermeability to sweat, more than 1.5 clo, and if the occupants are in contact with bedding. The seven levels of people's thermal sensation can be seen in Figure 9.

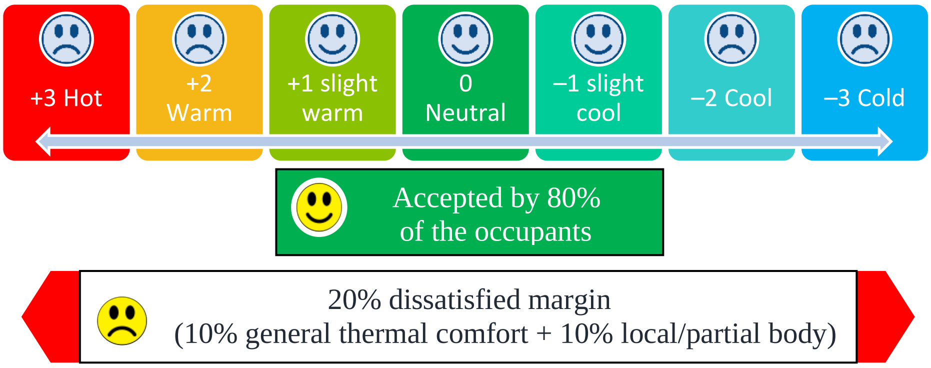



Figure 9 Thermal comfort definition from PMV-PPD acknowledged in ASHRAE standard.

The thermal indexes were added along with the equations in subchapter 2.1.2 Fanger PMV-PPD and Human Physiology, as follows:

Furthermore, one of the ways to predict thermal comfort and thermal sensation is by using the following equations (R. American Society of Heating, Air Conditioning Engineers, American Society of Heating, & Engineers, 2017):

$$t_{sk} = 35.7 - 0.0275(M - W) \quad (2)$$

$$E_{rsw} = 0.42\ (M - W - 58.15) \quad (3)$$

Where: M : the metabolic rate, in watts per square metre (W/m );

W : the effective mechanical power, in watts per square metre (W/m$^2$ );

$t_{sk}$ : mean skin temperature (°C);

$E_{rsw}$ : sweat rate (L/h)

The previous equations (1-3) were expanded to include a range of thermal sensations by using a Predicted Mean Vote (PMV) index. This was a way to cope with Fanger's equation when people were not satisfied. The PMV index predicts the mean response of a large group of people according to the ASHRAE thermal sensation scale. The PMV is calculated using the following equation:

$$PMV = [0.303 \exp(-0.036M) + 0.028]\, L \quad (4)$$

Where: M : the metabolic rate, in watts per square metre (W/m );

L : the thermal load on the body, in watts (W)

PMV gives good results for standard conditions of sedentary activity and light clothing but needs to be validated with the different range of clothing and different activities. The difference in clo values and met values can result in the increase or decrease of skin and body temperature and a change in thermal sensation. The predicted percent dissatisfied (PPD) can also be estimated from the PMV as follows:

$$PPD = 100 - 95 \exp[-(0.03353PMV^4 + 0.2179PMV^2)] \quad (5)$$

The ASHRAE thermal sensation was developed for use in quantifying people's thermal sensation vote (TSV). The acceptable comfort temperature range according to the ASHRAE thermal environment for general comfort is within the PMV range of -0.5 to +0.5 (R. A. C. E. American Society of Heating, Incorporated, 2017). Changes in temperature and water vapor pressure can change the thermal sensation vote. A person might experience a thermal sensation of -0.5 near the cooler zone's boundary and +0.5 near the warmer zone's boundary according to the ASHRAE thermal sensation scale (R. American Society of Heating et al., 2017). Thermal sense alone is not a good indicator of thermal comfort when there is excessive humidity. The discomfort was brought on by the sensation of moisture, which results in more friction between the skin and the clothing.

In the cold environment, the additional 0.1 clo or 0.1 met will impact saving energy because it can lower the operating temperature to approximately 0.8°C. On the contrary, a decrease of 0.1 clo or 0.1 met corresponds approximately to a 0.8°C increase in operative temperature (Enescu, 2017). Achieving comfort can be done by maintaining a humidity ratio below or the same as 0.012. The lower level is not specified, but if the humidity is very low, it can cause skin drying, irritation of mucous membranes, dryness of the eyes, and static electricity generation. The high airspeed can extend the thermal comfort range. This approach can be used if the occupants' condition is slightly warm. When the sunray falls on the occupant, the mean radiant temperature should be considered regarding the type of window glazing, the shade and the body exposed to sunray.

Regarding the procedure for measurement, the sample location should be selected where the occupants are spending their time, and the measurement must include the centre of the room and the 1 m inward from the centre of each room's walls. The measurement point shall be measured at the height of 0.1, 0.6, and 1.1 m above the floor for seated occupants and 0.1, 1.1, and 1.7 m for the standing occupants.

Since Fanger's trial was done in the chamber, it could not capture the difference between sex, age and special populations like people with disabilities, older people, babies and children, the sick, pregnant women, and people from different cultures. It is sometimes noted that males and females have different thermal comfort responses, which are also related to their clothes. Some work is being done to improve the PMV regarding these matters (K.C.Parsons, 2003) or focus on the particular aspects of the comfort factors like the inversely determined metabolic rate (S. Zhang, Cheng, Olaide Oladokun, Wu, &

Lin, 2020). Some of the work also led to the adaptive approach, which will be clarified in the following subsection.

### *2.1.3 Adaptive Approach, Psychology and Human Behaviour*

The other method, which is the adaptive method, was introduced by Nicol and Humphreys (Rupp et al., 2015) (Enescu, 2017) (Yao et al., 2022). The adaptive model is formulated on the nature of humans who can adapt. Besides acknowledging the PMV-PPD method, ASHRAE-55 Standard also acknowledges the adaptive method (ASHRAE, 2017). Unlike Fanger's model, this model defines the comfort zone, which is also related to thermal experiences, changes in clothing, activities, age, and gender. In this model, gender, age, and physical disabilities will affect thermal comfort. There are three thermal adaptation types. Physiological, related to the body's reaction due to the temperature change, while psychological, derived from the state of mind of previous experiences and behaviour-related adaptation (Brager & de Dear, 1998). This model can become the solution if the PMV cannot easily be obtained due to the properties that PMV is not individual, not adaptable and has no input modification.

This model is based on the work being done by Macpherson, which considers the heat balance of the body. This balance is affected by the personal parameters representing characteristics of the occupants and ambient parameters. The personal parameters can include the clothing insulation, metabolic heat rate or activity level. The temperature, air velocity, and relative humidity can become the ambient parameters considered for comfort (Enescu, 2017). This model allows the ambient parameters to be controlled by opening windows or fans (Rupp et al., 2015). Besides the fan, which can be used to influence the ambient condition, there is other equipment, for example, misting fan, heater (centralised or personal heating) and air conditioning. The personal parameter which affects the thermal experiences can be in the form of gender (W. F. Song, Zhang, Lai, Wang, & Kuklane, 2016) and age; for example, the elderly or disabled user group which needs a higher temperature setting (Salata et al., 2018). In this case, a particular group of people must be considered in the design of the human comfort system.

Many techniques are available for adaptive behaviours for assessing energy-efficient building indoor cooling toward buildings sustainability. However, these tools have not yet measured the energy efficiency index by involving user satisfaction from adaptive behaviours, which can determine the actual energy consumption versus the planned energy consumption of the building. Sensor technology development is crucial. A list of adaptive behaviours already identified regarding energy-efficient systems for an indoor environment is provided below (Keyvanfar et al., 2014):

a) Self-adaptation category: drinking cold beverages, less-sweating lifestyle, restraining physical activity level, changing, or adjusting clothes from warm to cool, decreasing the level of body skin moisture.
b) Adaptation to the environment category: taking a break and moving to a cooler location, changing position and direction, adjusting furniture/finishing material, opening, or closing doors using a feedback system, opening or closing operable windows (with/without a feedback system), using a portable fan, using a hand fan, adjusting room's thermostat, adjusting air-condition operative hours.

These are adaptive behaviours or actions to control the environment and combine it with physiological reactions. Time is essential for these behavioural interactions, and the periods can be grouped into four distinct period groups as follows:

1) Immediate, for example, the use of a coat in anticipation of a thermal change
2) Within-day, for example, the clothing changes to cope with changing environments within a particular day.

3) Day-to-day, for example, the learning process from one day to the next to cope with changing conditions such as the weather.
4) Longer-term, for example, the clothing adaptation with the seasonal changes and activities learned over a more extended period.

The value will dynamically and interactively change with climate, place and time (Fergus Nicol, 2012).

The following Figure 10 presents the parameters taking into consideration the Thermal Physiology methods (PMV-PPD) (left-hand side, horizontal stripes) and the Human Behaviour adaptive methods (right-hand side, vertical stripes area).

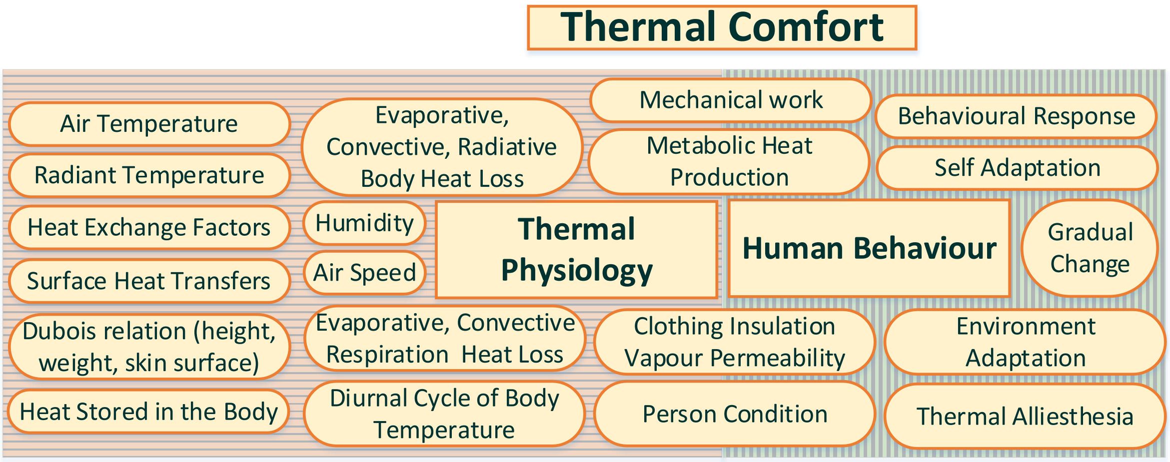



Figure 10. The Thermal Comfort Parameters

The adaptive approach considers the parameters listed on the left-hand side less critical since people will always behave to make themselves comfortable as far as possible (Fergus Nicol, 2015). This work also addresses the fact that those comfortable temperatures are changeable rather than fixed. Discomfort also can be caused by excessive constraints on these choices and adjustment processes, rather than merely the surrounding temperature. Comfort can be reached if there are sufficient opportunities for people to adapt. Only with the adaptive approach do all system parts become part of the comfort solution (Fergus Nicol, 2015).

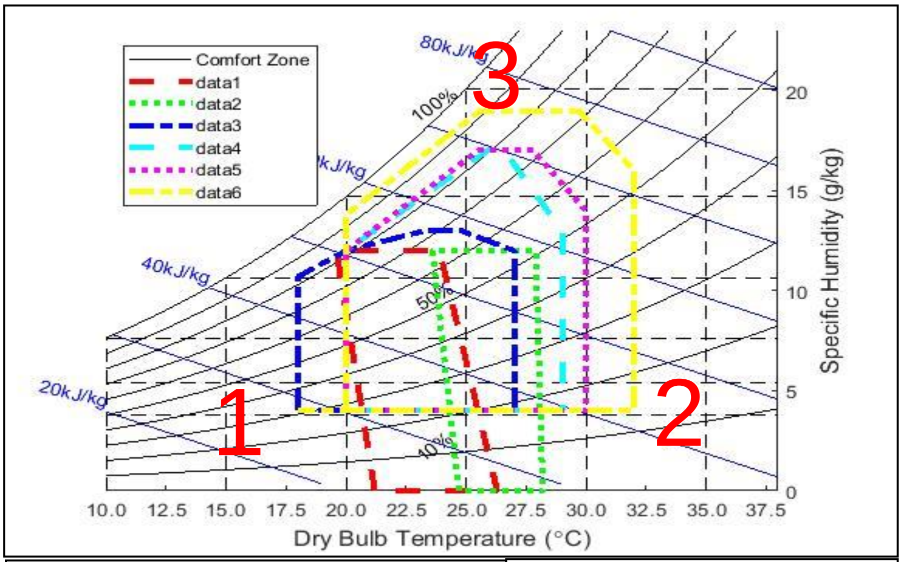
People can still be comfortable if the skin temperature changes happen gradually. The skin temperature will be non-uniform. The cold is comforting for overheated bodies but unpleasant for already cold bodies. The hot sensation is pleasant if the body is cold but gives discomfort if the body is already hot. The sensation effect will depend on time, clothing, and the temperature of the surroundings. The adaptive action is to drink water to maintain thermal balance in hot, dry weather. A sudden change in weather conditions will require people to act accordingly and avoid the danger of heatstroke (Fergus Nicol, 2012).

Figure 10 shows that the adaptive approach is goal-based, and the PMV-PPD is prescriptive. Therefore, the difference in the methods will affect comfort temperature values differently. The PMV-PPD approach will give more exact definitions of comfortable temperature (ASHRAE, 2017), while adaptive methods will not give exact boundaries on the comfortable temperature. The comfort zone (PMV-PPD) and potential adaptive comfort zone can be seen in Figure 11. This potential zone can be elaborated to minimise energy use.

### *2.1.4 Health Aspects*

#### 2.1.4.1 Elderly and Temporary Ill

The illustration in Figure 12 shows the difference between the temperature needs of disabled, temporarily ill, and elderly groups compared to the people without disability group mentioned in the previous research (Yung, Wang, & Chau, 2019), (Basu & Samet, 2002)




| | |
|---|---|
| Prescriptive:<br>data1: the PMV-PPD comfort zone for 1.0<met<1.3 and 1.0 Clo, ASHRAE Standard 55<br>data2: the PMV-PPD comfort zone for 1.0<met<1.3 and 0.5 Clo, ASHRAE Standard 55<br>data3: Givoni comfort zone for still air condition for winter<br>data4: Givoni comfort zone for still air condition for summer<br>data5: Givoni comfort zone for winter with an assumed air speed of about two m/s.<br>data6: Givoni comfort zone for summer | Goal-based method (red numbers):<br>1 The potential adaptive comfort zone by thicker clothing and main activity.<br>2 The potential adaptive comfort zone by light clothing, less sweating activity, and drinking cold beverages.<br>3 The potential adaptive comfort zone by moving to a less humid room and installing a dehumidifier. |

Figure 11 Psychometrics chart showing the comfort zone (PMV-PPD) and potential adaptive comfort zone (R. A. C. E. American Society of Heating, Incorporated, 2017), (Givoni, 1992)

Figure 12 (a) shows a gap between the behaviours of disabled people compared to those without disabilities. Besides this, the figure emphasises that the gap seems more significant for room temperatures below 23℃ and above 30℃, which are more frequent temperature domains due to climate change (cold and heat waves often happen). These temperature domains highlight the importance of this study. This figure also shows a gap between human temperature and the prediction from ASHRAE. This gap means that the PMV-PPD comfort zone is inadequate based on this research result. However, this figure may not have enough data to develop a more detailed analysis and generalise the result for all disabled people groups.

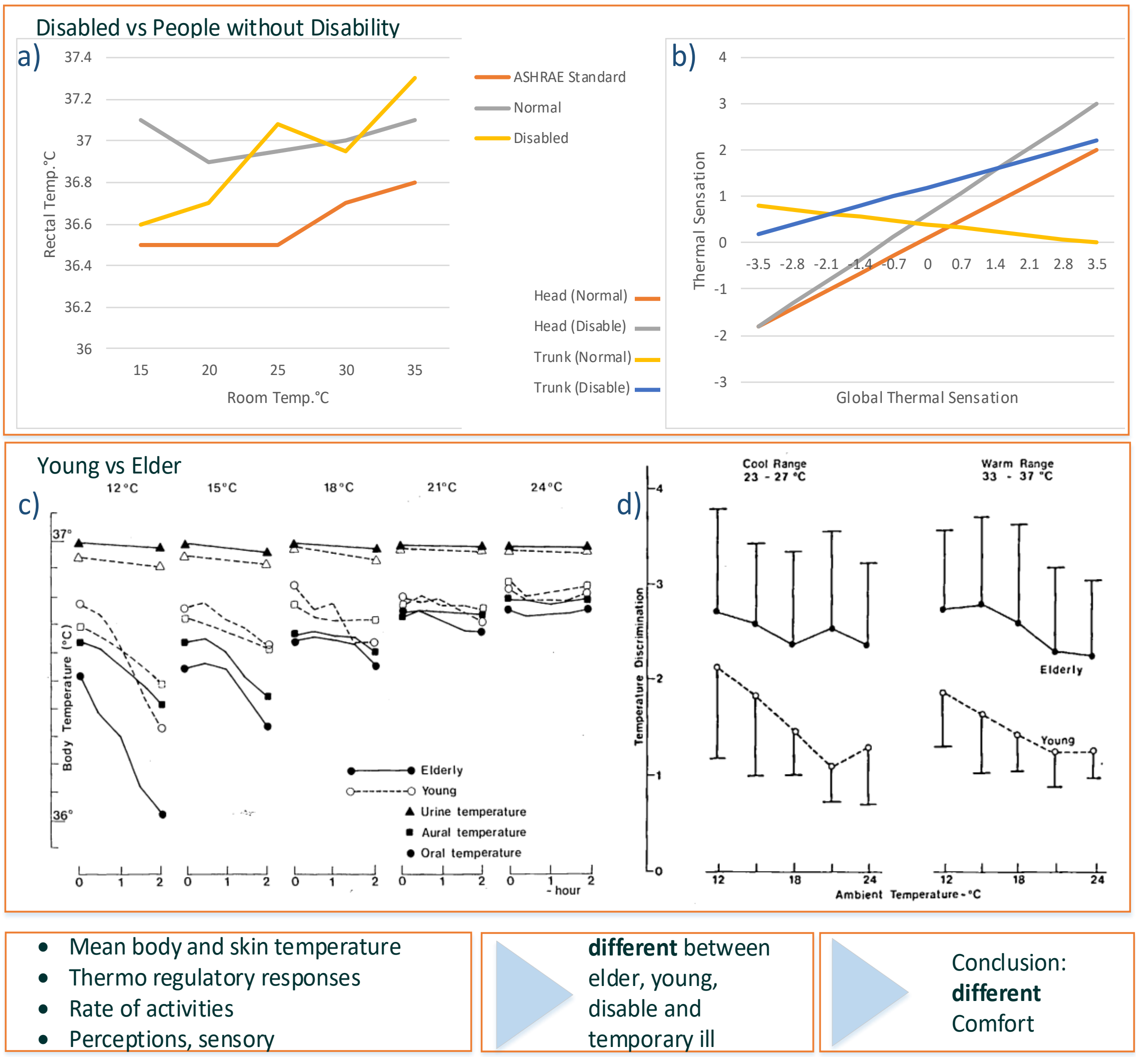



Figure 12. Illustration to show the difference in comfort temperature from previous research (Yung et al., 2019), (Basu & Samet, 2002) (a) and (b) for disabled (c) and (d) for older people.

Figure 12 (b) further compares the thermal sensation between the disabled and people without disabilities. For the head thermal sensation, the disabled feel that the thermal sensation is higher than people without disabilities. A very different result happened in the trunk thermal sensation. Not just the gap, the tendency of the disabled people is flipped compared to the people without disability. Again, this figure is based on limited data and cannot be generalised to all disabled people groups.

Aligned with the result in Figure 12 (a) and Figure 12 (b); Figure 12 (c) shows that the young people group also has a different average temperature compared to the elderly people group. This difference gap is not proportional, so the approach of thermal setting or regulation cannot be set based on the percentage of the correction based on the standard thermal settings. This difference again emphasises the importance of this study. The thermal setting cannot be generalised and become more personal. This thermal sensation also being validated by the trial shown in Figure 12 (d). The temperature discrimination between the young and elderly people groups is not proportional, and there are significant gaps between the two people groups.

The work which acknowledges similar results from the disabled people group is also stated in other studies (Brager & de Dear, 1998), (Parsons, 2020 ), and for older people (Maeda et al., 2005). In the case of the elderly people, thermoregulatory responses to both cold and hot temperatures were delayed. This delay is caused by the ageing degradation of vascular regulation ability and thermogenesis. The seasonal change and characteristics are also significant in the thermal sensation of the elderly people group (Salata et al., 2018), (Mishra & Ramgopal, 2013).

Defining the correct setting of thermal will be difficult because of individual variability in temperature (Collins & Hoinville, 1980). ASHRAE releases an Open Database of Global Thermal Comfort Database II (The Comfort Database) to simplify the implementation of the thermal comfort approach. The database maps the heating or cooling strategy, building type, meteorological context, indoor climatic physical parameter ranges, and various human factors. The human factors consider characteristics such as sex, age, clothing insulation, metabolic rate and the availability of indoor environmental controls, such as operable windows, doors, thermostats, blinds, heaters, and fans (t. H. a. S. Executive, 2019).

This complex and personalised parameterisation will be ideal to be solved with an adaptive approach. Intelligent technology can also support personalised parameter settings for minimising frequent user manipulation, generating uncomfortable activities and providing optimum thermal comfort for everyone without significantly increasing energy use (Hoof, 2006).

**2.1.4.2 Temperature and Obesity**

Increasing adaptive thermogenesis through activating brown adipose tissue (BAT) is a promising practical strategy for preventing obesity and related disorders. BAT is a thermogenic tissue in which heat is produced when the human body is exposed to a cold environment. BAT is inversely connected to BMI and body fat percentage. It gives the possibility to fight against obesity with cold weather exposure. When the unacclimatised human body is exposed to a cold environment, the body temperature is sustained by shivering thermogenesis (ST). If the cold exposures continue, the shivering (ST) will decrease, and the heat is sustained by the non-shivering thermogenesis (NST). The NST is entirely attributed to BAT in the preliminary research in rodents. This research is extended to humans, and the result shows that BAT is present in human adults. The metabolic adaptation is adaptive thermogenesis (AT) (A. A. J. J. van der Lans et al., 2013).

This work proposes ten days of cold acclimation to increase BAT in parallel with increasing the NST. There are no sex differences in the BAT presence. The acclimation also triggers the subjective changes in temperature sensation and makes the subjects feel comfortable in the cold with less shivering. The study recommends that the indoor environment introduce cold exposures to reduce the energy for heating and the possibility of obesity (A. A. J. J. van der Lans et al., 2013).

Like this trial, Hanssen et al. also propose that ten days of cold acclimation can increase BAT and improve the metabolic profile of skeletal muscle to benefit glucose uptake in patients with type 2 diabetes. BAT activity is inversely related to age and body fat percentage. At the end of the acclimation period, subjective responses to cold are slightly improved (M. J. W. Hanssen et al., 2016).

Another advancement has been done by Gordon et al. This trial was done with seven days of cold acclimation to reduce ST and increase NST with a significant decrease in core temperature. This work can achieve what has been achieved in four weeks acclimation procedure by Blondin in 2017. If exposed to a cold environment, people will rely on body heat production against the cold environment to anticipate the heat lost to the environment. The heat produced by the metabolic process will rely on activating the non-shivering thermogenesis (NST) and shivering thermogenesis (ST). ST is the primary heat production in the adult during cold environment exposure. One of the contributors to NST is known as the brown adipose tissue (BAT). The well-known cold acclimation protocol is the 31 days of cold air exposure by Davis in 1961 and two hours daily cold exposure for four weeks by Blondin in 2017. The acclimation protocol, which can increase the relative contribution of NST and decrease the part of ST, will be desirable (Gordon et al., 2019).

The relation of cold acclimation with type 2 diabetes patients is shown in Remie et al. This cold acclimation can promote insulin sensitivity in humans, and in patients with type 2 diabetes can improve the patient condition compared with the effects of long-term exercise training. Insulin sensitivity is related to the increased translocation in the skeletal muscle. However, mild cold acclimation does not result in improved insulin sensitivity and only results in mild effects on overnight fasted fat oxidation. The lack of metabolic effects is due to the lack of shivering and muscle activation or contraction in skeletal muscle. This work also suggests muscle contraction is needed for mild cold acclimation to positively affect the human body (Remie et al., 2021).

## 2.2 The Research Progress on Thermal Comfort within the Last 2 and 7 Years

Indoor thermal comfort has increased exponentially within the last seven years. Human comfort is surprisingly not mentioned often in state-of-the-art publications, as it should be. The focus, based on the number of documents, is on air quality, thermal comfort, human comfort, acoustic comfort, and lighting comfort. Many researchers are still researching to produce a better solution for thermal comfort. It is now inseparable between the aim to achieve health and well-being, and the ability to minimise energy use.

The research progress parameter for this study is based on the comparison between the review conducted in November 2014 (Rupp et al., 2015) in November 2019 and the current condition (March 2022). The first comparison is based on the search that uses the term “thermal comfort” in Google Scholar, Web of Science, Scopus and Science Direct. The result is presented in Table 1. This comparison shows that there has been a significant increase in all the sources of publication within the last 2 and 7 years. Google Scholar shows an increase of about 40% of “thermal comfort” term usage. Similar conditions also applied to Web of Science, Scopus and Science Direct. The increase of the term usages is 21%, 33% and 29% increase from the last two years. Figure 13 shows the increasing trends for all the resources clearly. In order to have a more precise figure, the authors use the logarithmic scale on the y-axis, which represents the number of search results.

Table 1 Comparison results for general literature search on "thermal comfort" in different databases in 2 and 7 years.

| **Parameter/database** | **Google Scholar** | | | **Web of Science** | | |
|---|---|---|---|---|---|---|
| **Month-Year** | **Nov-2014** | **Nov-2019** | **Mar-2022** | **Nov-2014** | **Nov-2019** | **Mar-2022** |
| **Number of results** | 59,800 | 194,000 | 321,000 | 5,979 | 12,418 | 15,669 |
| **Search in** | All (not optional) | | | Title, abstract and keywords | | |
| **Sort Type** | Relevance (not optional) | | | Number of citations | | |
| **Meaning of classification** | Considers publisher, authors, number of citations, recent citations | | | The highest number of citations | | |
| **Parameter/database** | **Scopus** | | | **Science Direct** | | |
| **Month-Year** | **Nov-2014** | **Nov-2019** | **Mar-2022** | **Nov-2014** | **Nov-2019** | **Mar-2022** |
| **Number of results** | 8,302 | 15,978 | 23,917 | 2,285 | 5,243 | 7,380 |
| **Search in** | Title, abstract and keywords | | | Title, abstract and keywords | | |
| **Sort Type** | Number of citations | | | Relevance | | |
| **Meaning of classification** | The highest number of citations | | | The highest occurrence of search term | | |

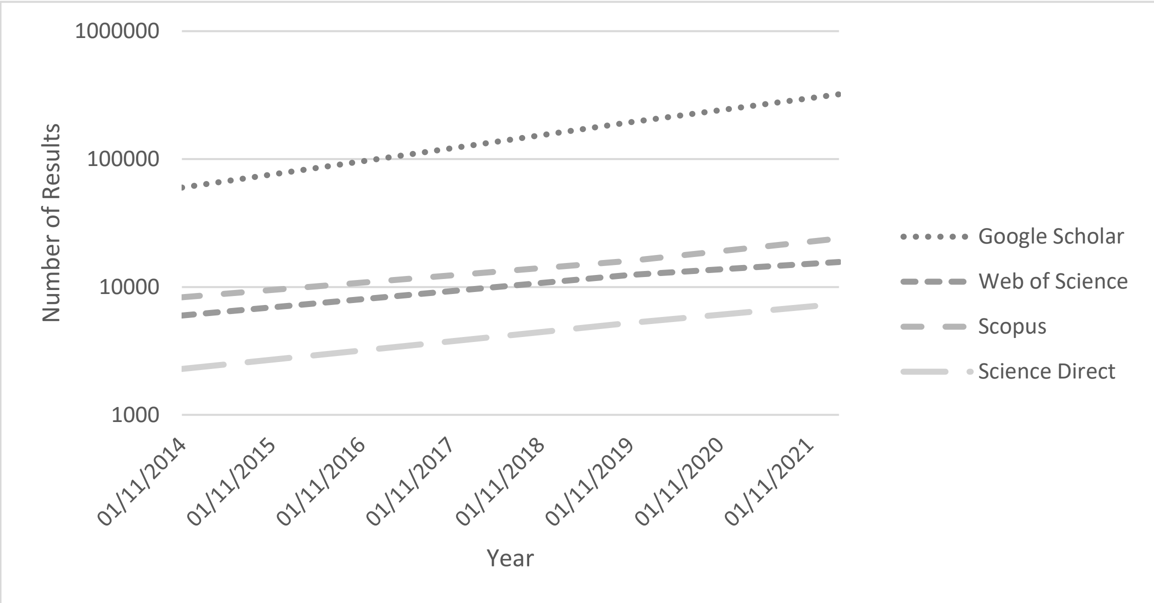



Figure 13 General Literature Search Result on Thermal Comfort for the Last 2 and 7 years (logarithmic scale).

The result in Google Scholar based on the relevance shows that: "Thermal comfort. Analysis and applications in environmental engineering" by P.O. Fanger (Fanger, 1970) became the top result. The adaptive methods publications are gaining popularity over these 2 and 7 years. The top results of the adaptive publications are "Adaptive thermal comfort and sustainable thermal standards for buildings" by J.F. Nicol and M.A. Humphreys (Nicol & Humphreys, 2002) and “Developing an adaptive model of thermal comfort and preference” by De Dear and Brager (R. J. De Dear, and G.S. Brager, 1998). Both groups of publications have increased significantly in 2 and 7 years. This result shows that the thermal comfort methods are dominated by this thermal physiology and human behaviour methods, and indoor thermal comfort is more dominating than outdoor. The reason is that people spend more of their time in artificial space. The detailed result can be seen in Table 2.

The result in Scopus based on relevance shows a similar trend to the result in Google Scholar. The physiology and the adaptive model dominate the thermal comfort methods. The adaptive methods publications are gaining popularity over these 2 and 7 years. The detailed result can be seen in Table 3. Table 2 and Table 3 also show that researchers are still trying to solve the problems that exist both in the human physiology and human psychology approaches. The fundamental papers citation value shown in Table 2 and Table 3 showed that the knowledge gap still needs to be solved in both approaches.

Based on the Scopus result on the search for thermal comfort, the authors have generated a similar chart generated seven years ago (Rupp et al., 2015) (upper inset Figure 14) and capture the trend of the thermal comfort topic within the last seven years (Figure 14). The trend is exponential, with the degree of increase becoming steeper than in previous years. This trend shows that this topic has gained much popularity over the years. In 7 years, the total number of publications in the thermal comfort field has increased almost three times.

Table 2 Top 10 Documents comparison in Google Scholar 2014 with the citation in 2019 and 2022

| Top 10 | Article title | Authors | Year | Published in | 2014 Cita-tion | 2019 Cita-tion | 2022 Cita-tion |
|---|---|---|---|---|---|---|---|
| 1 | Thermal comfort. Analysis and applications in environmental engineering | P.O. Fanger | 1970 | Danish Technical Press | 4690 | 8329 | 10900 |
| 2 | Comfort and thermal sensations and associated physiological responses at various ambient temperatures | A.P. Gagge, J.A.J. Stolwijk, J.D. Hardy | 1967 | Environ-mental research | 474 | 874 | 1168 |
| 3 | Developing an adaptive model of thermal comfort and preference | R. de Dear, G.S. Brager | 1998 | ASHRAE Transac-tions | 828 | 1815 | 2268 |
| 4 | Adaptive thermal comfort and sustainable thermal standards for buildings | J.F. Nicol, M.A. Humphreys | 2002 | Energy and Buildings | 541 | 1409 | 2028 |
| 5 | Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55 | R de Dear, G.S. Brager | 2002 | Energy and Buildings | 493 | 1138 | 1552 |
| 6 | Thermal comfort of man in different urban environments | H. Mayer, P. Höppe | 1987 | Theoretical and Applied Climato-logy | 309 | 731 | 1018 |
| 7 | Thermal comfort for free-running buildings | N. Baker, M. Standeven | 1996 | Energy and Buildings | 160 | 288 | 345 |
| 8 | Different aspects of assessing indoor and outdoor thermal comfort | P. Höppe | 2002 | Energy and Buildings | 233 | 529 | 757 |
| 9 | Thermal comfort in outdoor urban spaces: understanding the human parameter | M. Nikolo-poulou, N. Baker, K. Steemers | 2001 | Solar Energy | 245 | 574 | 826 |
| 10 | Thermal comfort and psychological adaptation as a guide for designing urban spaces | M. Nikolo-poulou, K. Steemers | 2003 | Energy and Buildings | 236 | 638 | 902 |

Table 3 Top 10 Documents comparison in Scopus 2014 with the citation in 2019 and 2022

| Top 10 | Article title | Authors | Year | Published in | 2014 Citati-on | 2019 Citati-on | 2022 Citati-on |
|---|---|---|---|---|---|---|---|
| 1 | Developing an adaptive model of thermal comfort and preference | R de Dear, G.S. Brager | 1998 | ASHRAE Transactions | 341 | 844 | 1250 |
| 2 | The physiological equivalent temperature—a universal index for the biometeoro-logical assessment of the thermal environment | P. Höppe | 1999 | International Journal of Biometeo-rology | 323 | 794 | 1208 |
| 3 | Adaptive thermal comfort and sustainable thermal standards for buildings | J.F. Nicol, M.A. Humphreys | 2002 | Energy and Buildings | 322 | 766 | 1139 |
| 4 | Thermal adaptation in the built environment: a literature review | G.S. Brager, R de Dear | 1998 | Energy and Buildings | 317 | 648 | 942 |
| 5 | Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55 | R de Dear, G.S. Brager | 2002 | Energy and Buildings | 301 | 623 | 887 |
| 6 | Comfort and thermal sensations and associated physiological responses at various ambient temperatures | A.P. Gagge, J.A.J. Stolwijk, J.D. Hardy | 1967 | Environment al research | 235 | 483 | 643 |
| 7 | The assessment of sultriness. Part I. A temperature-humidity index based on human physiology and clothing science | R.G. Steadman | 1979 | Journal of Applied Meteorology | 228 | 443 | 609 |
| 8 | Thermal comfort of man in different urban environments | H. Mayer, P. Höppe | 1987 | Theoretical and Applied Climatology | 176 | 442 | 624 |
| 9 | A field study of thermal comfort in outdoor and semi-outdoor environments in subtropical Sydney Australia | J. Spagnolo, R de Dear | 2003 | Building and Environment | 173 | 362 | 488 |
| 10 | A model of human physiology and comfort for assessing complex thermal environments | C. Huizenga, Z. Hu, E. Arens | 2001 | Building and Environment | 150 | 280 | 371 |

Further comparison of Scopus search results shows that the "Air Quality" topic has the highest number of papers, followed by "Thermal Comfort", "Human Comfort", "Acoustic Comfort", and the least popular is "Lighting Comfort". The result chart of these search results is presented in Figure 15. The previous figure shows that human comfort is surprisingly not mentioned often in state-of-the-art publications, as it should. The focus of the past and current research is on air quality and thermal comfort. This finding highlight that there is a gap in human comfort perception, and this emphasises the relevance of the current work. Human comfort publications represent only 1.6% of the total publications.

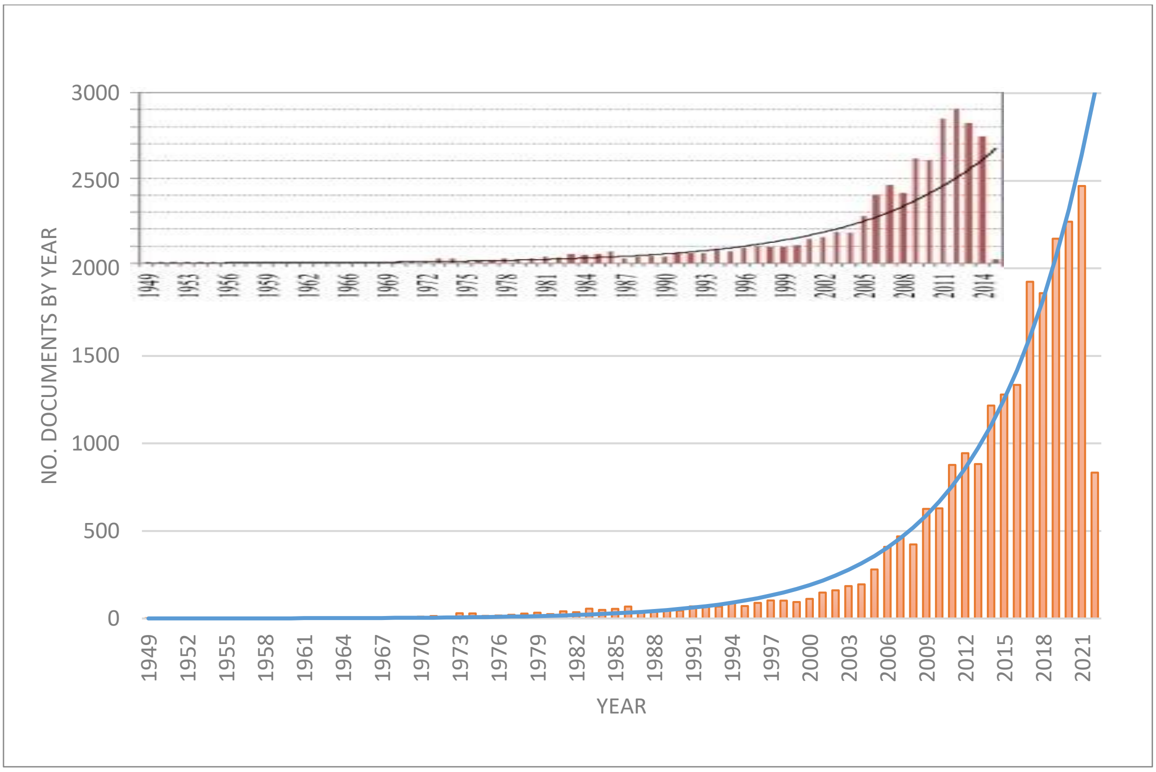



Figure 14 Scopus results in Thermal Comfort in 2014 (Rupp et al., 2015) and recent days.

From the Scopus resource, authors can also generate a list of journals with the highest number of papers in thermal comfort and compare the list with the same condition 2 and 7 years ago. The Elsevier journal Building and Environment and Energy and Buildings are dominating the number of documents point of view based on Scopus. The Energy Procedia is also among the highest number of documents, but it was discontinued in 2019, so no more documents will be accepted after 2019. Energies from MDPI has gained much focus in recent years due to the open access model of the journal. This list is presented in Table 4.

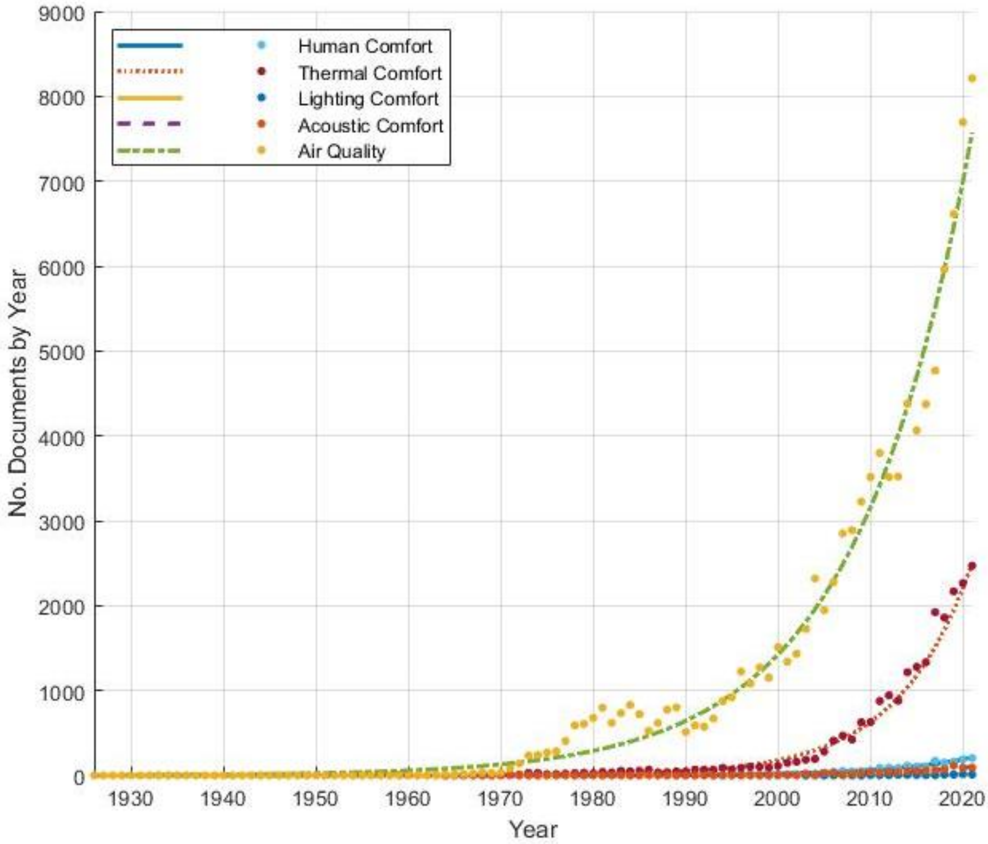



Figure 15. Scopus publication results in human, thermal, acoustic and lighting comforts and air quality.

## 2.3 Daniel Kahneman's Principle

### *2.3.1 Experience vs Memory*

One of the works of a Nobel prize winner, Daniel Kahneman, is about the eagerness for medical patients to undergo medical treatment based on their last memory of their previous medical treatment. Kahneman found an anomaly in the colonoscopy patients. The common perception, the experience approach, judges that the long process of colonoscopy, which triggers the pain, will be more memorable and avoided by the patients. The results of Kahneman's research are that the shorter process with higher pain for colonoscopy will trigger more threatening memory in the patients compared with the longer process but have less pain to be memorised (Redelmeier, Katz, & Kahneman, 2003). Patients who underwent the extended procedure also ranked the procedure as less aversive. The eagerness to face the same treatment rate will be higher than the other patients with shorter processes but more memorable pain (Redelmeier & Kahneman, 1996). Figure 16 shows the pain intensity and time chart in the Kahneman colonoscopy trial.

Table 4. International journals with the highest number of papers in Scopus with "thermal comfort" terms.

| 2014 | | | 2019 | | | 2022 | | |
|---|---|---|---|---|---|---|---|---|
| Rank | Journal | Docs | Rank | Journal | Docs | Rank | Journal | Docs |
| 1 | Energy And Buildings | 582 | 1 | Building And Environment | 1140 | 1 | Building And Environment | 1608 |
| 2 | Building And Environment | 560 | 2 | Energy And Buildings | 1117 | 2 | Energy And Buildings | 1496 |
| 3 | ASHRAE Transactions | 269 | 3 | Energy Procedia | 348 | 3 | Energy Procedia | 348 |
| 4 | SAE Technical Papers | 150 | 4 | ASHRAE Transactions | 271 | 4 | Energies | 319 |
| 5 | Advanced Materials Research | 118 | 5 | Procedia Engineering | 215 | 5 | Sustainability Switzerland | 318 |
| 6 | International Journal Of Biometeoro-logy | 109 | 6 | Applied Energy | 214 | 6 | Top Conference Series Earth And Environmental Science | 310 |
| 7 | Applied Mechanics And Materials | 102 | 7 | International Journal Of Biometeorology | 202 | 7 | ASHRAE Transactions | 307 |
| 8 | Renewable Energy | 88 | 8 | SAE Technical Papers | 195 | 8 | Applied Energy | 279 |
| 9 | Applied Energy | 83 | 9 | Indoor And Built Environment | 167 | 9 | Journal Of Building Engineering | 270 |
| 10 | HVAC and R Research | 75 | 10 | Applied Thermal Engineering | 148 | 10 | Sustainable Cities And Society | 253 |

In Figure 16, patient A experiences a shorter time of pain with a similar peak of pain intensity experienced by patient B. Patient B experience a long time of pain with the peak of pain intensity experienced by patient A, but patient B has less pain in the final medical treatment. This research shows that patient A memorises the pain higher than patient B. This experiment shows that the patients' memories of pain will reflect the experiences of pain at the worst part and the final part of the treatment.

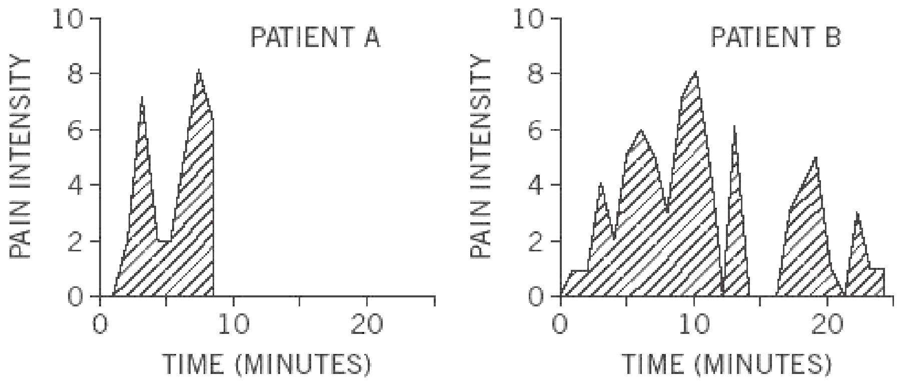



Figure 16. The pain intensity in Kahneman trials (Redelmeier & Kahneman, 1996)

The colonoscopy followed other Kahneman trials in 1993 with perception in dipping hands in the water (Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993). The respondents had to dip their hands in the 14 °C for 1 minute and the second trial with the same temperature and time, but then the water temperature was gradually raised to 15 °C for 30 s. By raising the water temperature, it will become less painful. The trial is repeated, and the respondents must select which trial they prefer to repeat. Most of the respondents select the second trial. These results also represent that the duration of the pain will not play a significant role in memory building. It will also show that memory will be formed more in the final moments of episodes.

### *2.3.2 Experience vs Perception*

The other trial from Kahneman involved the students' perceptions about living in California. The result says that students assumed that living in California should give them more satisfaction with the climate, but they failed to conclude that the weather does not affect all aspects of life. This perception represents that people cannot imagine the effect of adaptation that will impact their happiness. Similar findings also applied to the disabled people group. Their quality of life should be measured rather than having healthy people valuing if the disability condition occurred to them. This result will reflect the non-disabled people's reflection on their frightening feelings of being in the disabled condition (Chernoff, 2002).

Another trial also reveals that people are bad at predicting perception over time. This conclusion is taken after the trial of giving people their favourite ice cream flavour for seven days. Some participants are happy, but some are tired of it (Chernoff, 2002). This finding will also benefit the health and safety aspects where the consent is usually taken before the treatment, and the patient can be in profound decision change after experiencing the treatment.

### *2.3.3 Experience vs Adaptation*

One key factor that affects experience is also adaptation. This factor is identified by Kahneman's study on paraplegics and lottery winners. There will be some adaptation so that for a paraplegic person, it will be terrible one month after the accident and become lighter within a year. Similar happens to a lottery winner (Chernoff, 2002). This feeling happens because people imagine the transition to the condition without feeling or experiencing the actual condition. The evaluation of the condition should be done from time to time and not based on memory.

Regarding the experiences, there will be a stronger correlation between happiness and satisfaction. People can control the parameters that make them happy and allocate their time to this. So, giving more time to the activity which delivers happier activities can increase satisfaction in general.

## 2.4 Thermal Comfort Simulations

Modelling and simulations have a unique beneficial role where problems are characterised by uncertainty, complexity, repetition and flexibility in logic, especially when knowledge is needed to capture the system behaviour and an integrated and accurate solution is desired (AbouRizk, 2010). Simulations can model the probabilistic phenomena, for example, random resource availability and weather. Modelling also can introduce some level of abstraction. This abstraction allows the problems to be portrayed accurately according to the time and resources available. Repetitive tasks are subjects to be simulated and modelled. A similar process can be captured with modelling to optimise the process. Simulation languages can build the model's decision structures to accurately represent the problem. Integrating views and representations of all problems and processes involved in the system becomes a key advantage of using simulation and modelling. This feature can assist and facilitate effective scenarios and studies. Simulation is used because it allows the modeller the flexibility to define the details of resource interactions, activity relationships, and constraining logic with reasonable effort. The system can then be studied and analysed to excellent detail levels and within acceptable accuracy. Some approaches are also available to be used in modelling each fundamental aspect (Gwynne, Galea, Owen, Lawrence, & Filippidis, 1999).

A review of the algorithm used in the modelling process is listed in Xie, Li, Li, Zhang, and Luo (2020). The algorithms are Linear regression (LR), Tree regression (TR), Classification tree (CT), Linear discriminant analysis (LDA), Logistic regression (LoR), Decision tree (DT), Boosted trees (BT), Bayesian network (BN), Bayesian modelling, Naive Bayes (NB), Artificial neural networks (ANN), K nearest neighbours (KNN), Adaboost (AB), Gradient boosting machine (GBM), Support vector machine (SVM), Random forests (RF), Gaussian process classifier (GPC), Rule-based classifier (RBC), Fuzzy logic, Extra tree, and Hidden Markov model (HMM). Ma, Aviv, Guo, and Braham (2021) also assessed a similar review related to the use of machine learning Ma, Aviv, Guo, and Braham (2021). Ma et al. also list the variables related to comfort and health, such as Outdoor temperature (Tout), Wind velocity (va), Outdoor relative humidity (RHout), Outdoor contaminants concentration (Cout), Room dimensions (Dim), Ceiling height (H), Total surface area (A), Penetration factor through envelope/door (P), Radiant temperature (TMR), Temperature of surface (Ti), Indoor relative humidity (RHin), Volume flow rate (Natural, Mechanical, Infiltration) (Q), Indoor temperature (Ta), Air density (ρ), Contaminants generation/deposition/removal concentrations/rates (G), Number of occupants (N), Exposure time (t) and Air exchange rate (EX). Computational fluid dynamics (CFD) calculation and modelling are also common in analysing indoor thermal conditions (Buratti, Palladino, & Moretti, 2017).

Other research has also been conducted to consider the thermal comfort factors in dwellings by using mathematical models, laboratory testing, numerical calculations and further computer-based simulations to develop the desired performance of building materials (Reuge et al., 2020). Key examples of literature for developing new construction materials with a mathematical model are demonstrated in Lelievre, Colinart, and Glouannec (2014) and the further testing of the model (to ensure desired material performance) is highlighted in Richter et al. (2021).

Multiple simulation steps are also being done to increase the model's accuracy. In this work, Heat, Air and Moisture (HAM) models are being elaborated in three steps: the semi-infinite wall approach, adiabatic building envelope, and building envelope with heat and moisture internal gains. This basic model is followed by the complex model with an adiabatic building envelope with heat and moisture internal gains integrated with validated building energy simulation (BES) (Francesca, Elena, Cristina, & Maria, 2021). Besides using WUFI Plus, 3D hygrothermal modelling also uses other software such as COMSOL Multiphysics (Knarud & Geving, 2015) (Ferroukhi, Djedjig, Belarbi, Limam, & Abahri, 2015).

Some simulation software models such as TRNSYS and TAS only simulate thermal comfort based on the dry bulb temperatures and do not consider relative humidity. The hygrothermal simulation software such as WUFI Plus can consider the humidity and additional loads such as occupancy (Hall, Casey, Loveday, & Gillott, 2013) using the weather files for Nottingham. The thermal comfort parameter for relative humidity uses the ASHRAE thermal comfort envelope, which has the upper comfort limit of 70% RH using WUFI Plus. The calibration and validation process using the climatic chamber compared with the software model has been completed in Antretter, Sauer, Schöpfer, and Holm (2011). Compared with the simulation result, the validation using the accurate measurement in the real building has been explored in Coelho, Silva, and Henriques (2018) and Francesca et al. (2021). Coelho et al. (2018) address the importance of using detailed outdoor weather files and the soil temperature. The accurate data from the weather station, even if it is not located directly on the premises, will help obtain a more precise result. Using the weather files obtained from WUFI and EnergyPlus database resulted in a lower precision. The importance of using multiple geographical locations for simulation is also mentioned in work simulating moisture (Mukhopadhyaya, Kumaran, Tariku, & Reenen, 2006).

Further to the previous research, Yingchun Ji, Angela Lee, and Will Swan (2019) use a model to compare a 1920s house with a real house built inside the thermal chamber. The house model is developed in Integrated Environment Solutions Virtual Environment (IESVE) and implemented with a blocked chimney due to health and safety considerations. This model uses Manchester weather data for simulation. This work shows that the construction details will improve the model accuracy. The model is further extended by Yingchun Ji, Angela Lee, and William Swan (2019) to show the effects of a retrofit on a building. From this study, heating demands can be reduced by 27% in a retrofitted house, but the space heating demands can vary significantly depending on how the building is heated (as per the occupants' preference). This result addresses the importance of assessing the thermal settings concerning the indoor condition inside the house. Ventilation, including infiltration and leakages, also strongly impacts space heating energy demands.

This work utilises building typologies from typical residential properties utilising 1920s and 2010s building codes to model mean indoor relative humidity as a consequential effect of locational weather conditions with the simulation conducted for different thermal settings. The typology parameters can be seen in Table 6 in chapter 3.2.3 and the locational weather conditions presented in Figure 21, Figure 22 and Figure 23 in chapter 3.2.2. This work uses MATLAB and SIMSCAPE as the base environment for simulation. As previously demonstrated in Figure 2, in terms of the impact, this simulation has a potential influence on nearly 13 million homes. The locations analysed are Kent, Liverpool and Aberdeen, and due to their varied climates, to maintain thermal comfort, this model was also able to predict the percentage of time with the heater turned on.

The use of MATLAB and SIMSCAPE gave the benefit that the simulation of the humidity and temperature condition can be done concurrently, and the simulated electrical heater can be added to the model to predict the energy consumption for heating. The use of MATLAB simulation was then extended to process the dataset for shallow supervised learning. With the MATLAB library, different AI methods can be applied to select the best algorithm for the system. The neural network solution was also calculated using MATLAB support to calculate the weight of the layer and bias value. With all the features that MATLAB provides, the work can be done in a more integrated way.

## 2.5 Wireless Sensor Networks (WSN)

In recent years, due to the growing low-cost sensing solutions, the provision of thermal comfort has been widely increased in existing and future intelligent buildings to aid productivity, health, and well-being. Many sensors are widely used in the home comfort system with easier installation and control. The WSN will change the approach of the system solution. WSN is a network of sensors with unique characteristics. The nodes have limited power, limited processing power, and transmission. There might be a connection to more powerful servers (cloud). The circuit is relatively simple but has enough power to do its tasks. The use of these sensors is beginning to be very common and is sometimes called the internet of things devices. Their roles and tasks are unique and specific to overcome their challenges: low power, low price, limited range and scattered node position (Karyono, Martoyo, Uranus, Junita, & Kim, 2009).

Zigbee is one of the WSNs suitable for forming a real-time control system (Nguyen, Tran, Leger, & Vuong, 2010), (Uguz & Ipek, 2017). Zigbee can form a mesh network capable of giving fault-tolerant capability and sufficient data transmission distance for the distributed indoor controller (Samuel & Karyono, 2015).

## 2.6 Artificial Intelligence

The previous studies emphasise the need to improve thermal comfort methods for particular groups of people. Those methods focus on achieving comfort to maintain health and safety within the energy efficiency corridor. Besides the variety of human physiology, there is also the human behaviour factor, which can be different from one to another. In order to make the system able to cope with such variability and able to adapt to get optimal performances, some methods are used. These methods give the capability for the system to act like uninterrupted human control and are described as having artificial intelligence (AI) (Moon, Jung, Kim, & Han, 2011). Supported by AI features, the control system can gain a better solution and can cope with people's preferences. The setting adjustment can be made based on the setting for the specific use of the system as training data. The simplified system for thermal comfort can be seen in Figure 17. There are currently two most common methods in AI for thermal comfort. The first method is Fuzzy Logic, or fuzzy for short, and the second method is an Artificial Neural Network (ANN).

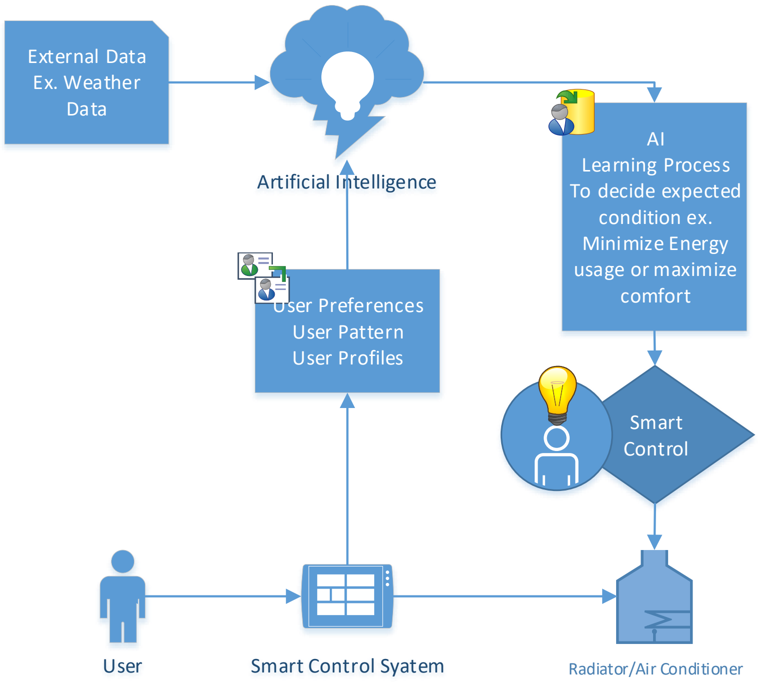



Figure 17. Simplified AI System for Thermal Comfort.

### *2.6.1 Fuzzy Logic*

This method can interpret the verbal human perception or preferences such as 'warm' or 'cool' which are not easily interpreted by the control system. The fuzzy methods are used in the control system to give more human comfort while minimising energy use. This approach is used to get a better result than the Proportional Integral Differential (PID) control. Some of the previous work results are implemented in the form of simulation, which is MATLAB-based (Lachiver, 1998), (Calvino, La Gennusa, Morale, Rizzo, & Scaccianoce, 2010), (Nowak & Urbaniak, 2011) (Rawi & Al-Anbuky, 2011), (Moon et al., 2011) and (R. Zhang, Chu, Zhang, Liu, & Hou, 2014). These methods have also been implemented in the form of the prototype for controlling air conditioning operations (Yonghong Huang, 2006), (Ciabattoni, Cimini, Ferracuti, & Ippoliti, 2015) or heaters (Walek, Žáček, Janošek, & Farana, 2014). The comfort parameter is based on the PMV model. The fuzzy method is also used in the research of material/fabric (Huang, Sun, Kong, & Wang, 2008) and comfort in the automotive industry (Farzaneh & Tootoonchi, 2008) (Beinarts, 2013). This system will also have the drawback if the data are widely varied, so the fuzzy membership function cannot be clearly defined. Some methods like a genetic algorithm (Shaikh, Nor, Nallagownden, & Elamvazuthi, 2014) or ANN are being used to compensate for the drawback of fuzzy methods (Duan & Li, 2010). This ANN and fuzzy hybrid method are becoming the most popular methods (Enescu, 2017).

### *2.6.2 Artificial Neural Network*

In ANN, deep learning and shallow learning, the system's intelligence is gained from the human sensory analogy. This method can work as a black box by giving a set of learning processes, mainly supervised, or directed learning. The learning process is essential for this method. The same system can have a different result when trained with a different training data set. This method is preferred by the system developer to build the thermal comfort system where not all of the connections between all of the thermal comfort factors are well known and well defined. The ANN research has been widely used and gives significant results in thermal comfort. Some of the previous work is implemented in the form of model and simulation (Liu, Zhou, Wang, Hu, & Liu, 2009), (Yalong, Qiansheng, Xiaolong, Zhenya, & Qinyan, 2011), (Moon et al., 2011), (Rodríguez-Alabarce, Ortega-Zamorano, Jerez, Ghoreishi, & Franco, 2016), (Moon & Jung, 2016), (W. Zhang, Hu, & Wen, 2018), and (Escandón et al., 2019). Some of these models are developed to be implemented in the tropical regions (Bingxin, Jiong, & Yanchao, 2011), (Zeng, Jin, Chen, & Meng, 2011), (Songuppakarn, Wongsuwan, & San-um, 2014), (Chaudhuri, Soh, Li, & Xie, 2017) or to overcome the extreme conditions (Liu et al., 2009), (Yalong et al., 2011). The result from the system prototype was also presented in other papers (Kojima, 2010), (Kojima, 2011), and (Zhai, Chaudhuri, & Soh, 2017), who implemented the ANN to overcome individual preferences. This method is also being used for research on fabric/materials (Baozhu & Shan, 2010), (Baozhu, 2011) and also in lighting comfort (Kandasamy, Karunagaran, Spanos, Tseng, & Soong, 2018).

The ANN method being used is a typical feedforward neural network architecture, and the learning use backpropagation methods (BP) to update the weight of the neuron (Liu et al., 2009), (Kojima, 2010), (Kojima, 2011), (Bingxin et al., 2011), (Zeng et al., 2011), (Moon et al., 2011), (Songuppakarn et al., 2014), (Moon & Jung, 2016), (Chaudhuri et al., 2017), (Zhai et al., 2017), and (Escandón et al., 2019). BP is the most common because of the simplicity of the model. There are other types of ANN architecture and methods of learning, such as Multilayer Feed Forward (Duan & Li, 2010), Radial Basis Function

(Yalong et al., 2011), Nonlinear Autoregressive Model (Songuppakarn et al., 2014), C-Mantec (Rodríguez-Alabarce et al., 2016) and Deep Neural Network (W. Zhang et al., 2018). The ANN has also come in hybrid with another model such as with Fuzzy (Nowak & Urbaniak, 2011), (Enescu, 2017) and with genetic algorithm (Bingxin et al., 2011). The ANN approach also performs better in thermal comfort applications than the Fuzzy approach (Moon et al., 2011).

Although this system is robust in processing unclearly defined relations, it negatively impacts the learning process. If the training process is not done with proper data or the data is not defined correctly with all the cases available, the system can perform falsely. In the system for recognising males or females, for example, if all data provided for women are always in the kitchen and men are always in the office, the system can interpret wrongly. If the new case appears that the man is inside the kitchen, it can be interpreted as a woman. That is why it can also be said that one pixel can make the wrong interpretation (Su, Vargas, & Sakurai, 2019). The classification can be easily altered by adding relatively small perturbations to the input vector and can become the source of an attack by only altering one pixel. This matter is one aspect that can be associated with producing natural stupidity in AI. The poisoning or perturbation introduced in the AI can cause misclassification, and even the deep learning approach has proved to be sensitive to spoofing (Hamon, Junklewitz, & Sanchez, 2020).

This thesis tried to address the gaps that were addressed in the previous works on using machine learning. The gaps that had been identified from the previous works are provided in Table 5. The underlined entries are the challenges outlined in previous research that were addressed by our solution as a means to provide a solution to overcome them and develop a better indoor thermal comfort system. The dataset that the authors use was having 65,256 entries while the 37 previous works assessed 6,851 entries

(Arakawa Martins, Soebarto, & Williamson, 2022). A larger dataset is needed to achieve higher performance (Luo et al., 2020), (Feng et al., 2022). The proposed system is also able to gain a wider comfort zone that has been identified as narrower over decades (R. de Dear, Xiong, Kim, & Cao, 2020) hence increasing the energy-saving potential (Qavidel Fard, Zomorodian, & Korsavi, 2022). This makes machine learning necessary (Čulić, Nižetić, Šolić, Perković, & Čongradac, 2021).

Table 5. Six recent review papers related to the use of AI and Adaptive Thermal Comfort and their gaps identification.

| No | Review Paper | Year | Work reviewed | Work Assessed |
|---|---|---|---|---|
| 1 | (Arakawa Martins et al., 2022) | 2022 | 2007 to 2021 | 37 |
| | Dataset comparison, with maximum data set size **6,851**. **Methods:** FC = Fuzzy Classification, RF = Random Forest, KNN = K-Nearest Neighbors, SVM = Support Vector Machine, DT = Decision Tree, LDA = Linear Discriminant Analysis, BI = Bayesian Inference/Classification, MLR = Multinomial Logistic Regression, GPM = Gaussian Process Model, LR = Logistic Regression, ANN =Artificial Neural Network, GB = Gradient Boosting, LVQ = Learning vector quantization, OP = Ordered Probit, LinR = Linear Regression, NB = Naive Bayes, RBC = Rule-Based Classifier, CART = Classification and Regression Trees, LLS = Least-squares linear estimation, J48 = J48 Decision Tree. | | | |
| | **Result and Gaps:** The field still lacks a more unified and systematic modelling framework. Model evaluation needs a clear comparison between studies and approaches. The generalization of the results is still debatable due to the small number of participants. Diversity needs to be introduced (more balanced datasets and expanding the application of the personalized models into other types of environments). Further assessment of inherently interpretable models and less transparent techniques. Although both environmental and personal characteristics have been used in most studies, personal features gathered through physiological sensing technologies could be further explored, especially in light of the rapid advances in wearable sensor technologies. | | | |
| 2 | (Qavidel Fard et al., 2022) | 2022 | 2016 to 2021 | 137 |
| | **Methods:** [ANN]: Artificial Neural Network; [SVM]: Support Vector Machine; [R]: Regression Method; [TBM]: Tree-Based Method; [BM]: Bayesian Method; [ENL]: Ensemble Learning; [GA]: Gaussian Method; [M]: Markov Model; [RNN]: Recurrent Neural Network; [ELM]: Extreme Learning Machine; [KNN]: K-Nearest Neighbors; [LDA]: Linear Discriminant Analysis; [RL]: Reinforcement Learning; [DL]: Deep Learning; [FOM]: Firefly Optimization Method; [FLS]: Fuzzy Logic System; [GP]: Genetic Programming; [CNN]: Convolutional Neural Networks; [LVQ]: Learning Vector Quantization; [BNN]: Bayesian Neural Network; [PSO]: Particle Swarm Optimization. | | | |
| | **Result and Gaps:** 62% focused on developing group-based comfort models, and 35% focused on personal comfort (recommended to be further studied). | | | |

| | | | | |
|---|---|---|---|---|
| | The most used tools for building ML were Matlab, Python and R.<br>The most frequently used algorithms among the reviewed papers were SVM, ANN and Ensemble Learning (mainly RF), followed by Tree-Based models and Regression methods (mainly LoR).<br>The metrics were accuracy, R2, RMSE, MSE, and r, (50%, 23%, 20%, 18%, and 15%). Future studies are recommended to consider both fitting and error metrics for model evaluation.<br>ML models could outperform PMV and adaptive models with up to 35.9% and 31% higher accuracy and the personal comfort model could outperform PMV models with up to 74% higher accuracy. Applying ML-based control schemas reduced thermal comfort-related energy consumption in buildings by up to 58.5% while improving indoor quality by up to 90% and reducing $CO_2$ levels by up to 24%. Moreover, using physiological parameters improved the prediction accuracy by up to 97%. | | | |
| 3 | (Feng et al., 2022) | 2022 | 2011 to 2021 | 25 |
| | **Methods:** Linear methods: LR and linear discriminant analysis (LDA) Non-linear methods: Quadratic discriminant analysis (QDA), support vector machine (SVM), support vector regression (SVR), K-nearest neighbours (KNN), K-neighbors regression (KNR), and naïve Bayes (NB), Decision trees: Classification and regression trees (CART), classification tree (CTree), DT, and tree regression (TR) Ensemble learning methods: Gradient boosting machine (GBM), adaptive boosting (AdaBoost), and random forest (RF) Gaussian processes: Gaussian process classification (GPC) and Gaussian process regression Neural networks: Neural network (NNET), artificial neural network (ANN), and multi-layer perceptron (MLP) | | | |
| | **Result and Gaps:** In-field studies give more realistic effects in terms of user behaviour. The measurement system's complexity was consistently reported in reviewed studies. A minimally invasive data collection system is needed for future studies and realistic applications. Contemporary machine learning techniques are already commonly used in the domain, and no obvious evidence indicates that one modelling technique outperforms another. More standardized individual/specific data with longitudinal information must be established and framed for personal thermal comfort modelling. Once sufficient data related to personal thermal comfort across different categories of individuals is attained, researchers will be able to move from intra-to inter-variability, and analyses of similarities among individuals performed via various online learning techniques and more beneficial for practical applications such as individual comfort monitoring, smart building control, and energy-efficient retrofits. | | | |
| 4 | (Čulić et al., 2021) | 2021 | 2018 to 2021 | 34 |
| | **Methods:** [ANN]: Artificial Neural Network; [SVM]: Support Vector Machine; Random Forest; Gradient Boosting; Decission Tree; [KNN]: K-Nearest Neighbors, Stochastic Gradient Boosting; C 5.0; Bagged Classification and regression trees; Rule based Classifier; Classification and regression trees; Logistic Regression; Proportional odds Logistic Regression Multinomial Logistic Regression; [DL]: Deep Learning; [LDA]: Linear Discriminant Analysis; Adaboost; Naive Bayes; [LVQ]: Learning Vector Quantization | | | |
| | **Result and Gaps:** Many proposed technological solutions are designed to be compatible with heating/cooling management systems in buildings becoming the potential path to greener BMS. Future work in this area should be focused | | | |

| | | | | |
|---|---|---|---|---|
| | on testing and integrating TC models with intelligent systems. Accomplished through the development of new personalized models tailored for individual TC and adjusting environmental parameters for purposes of both reducing consumption and increasing indoor quality. The applicability of the TC questionnaire should be investigated more thoroughly. It is indicated that a compatibility analysis of the classical questionnaire with new data-driven models is needed. Detailed analysis using machine learning and statistical modelling is necessary for future research work. Evaluation among models should be conducted and standardized for the basis of the accurate comparison of various modelling approaches. | | | |
| 5 | (R. de Dear et al., 2020) | 2020 | 1998 to 2019 | |
| | **Methods:** Calculation based on Dataset ASHRAE Standard 55 / RP-884; EN 15251 (and its revision prEN 16798)/SCATs, Field studies in India, Field studies in China | | | |
| | **Result and Gaps:** None of the published attempts at explaining the discrepancy between predictions of heat balance comfort models and actual observations inside adaptive comfort buildings. But there have been incremental contributions of new theoretical knowledge to the domain. The central challenge for the future: The absence of an evidence-based parameterisation of the concept of comfort expectation.<br>Broad consistency between the various regulatory documents and standards on adaptive comfort. A notable outlier seems to be the Chinese GB/T 50785 standard developed from a fundamentally different analytical approach.<br>Building typology exerts a discernible effect on occupant thermal responses and thermal sensitivity, varying adaptive opportunities. Residents in their own homes generally are more adaptable and tolerant of a wider range of indoor thermal exposures. School students tend to like cooler than adult thermal neutralities.<br>Boundaries of the comfort zone have become progressively narrower over the past several decades. Long-term thermal experiences can raise comfort expectations more readily than they can lower them. The adaptive comfort concept is central to addressing questions of how to enhance adaptive capacity in buildings and how to nudge occupant attitudes and behaviours relating to indoor climate.<br>The weight of empirical evidence supports an extended-U model of temperature-performance effects. We found no substantive, credible evidence to support the practice of overcooling to optimise the performance of their occupants. The cognitive performance plateau is bounded by regions of progressive performance deficits at the acceptability limits of the adaptive comfort range. | | | |
| 6 | (Luo et al., 2020) | 2020 | 2016 to 2019 | 20 |
| | **Methods:** Gaussian Processing classifier (GPC); K-neighbor classifier (KNC); Random Forest (RF) classifier; Support Vector Machine (SVM) classifier; Conventional Neural Network (CNN); K-nearest neighbours (KNN); Deep Neural networks; Bagging, artificial neural network (ANN), Logistic Regression (LoR); Gradient boosting machine (GBM); Decision Tree (DT); Polynomial; Naive Bayes (NB); ANOVA; t-Test; Extreme learning machine (ELM); Stepwise regression; Linear Discriminant Analysis (LDA); Gradient Boosting Machines (GBM); Gaussian Process Classification (GPC); Classification And | | | |

| | |
|---|---|
| | Regression Trees (CART); Gaussian Naive Bayes (GNB); Support vector regression; Adaboost; Gaussian process regression (GPR) |
| | **Result and Gaps:** Basic ML algorithms like NB and DT can get better TSV prediction than the conventional PMV; Tair, RH, CLO, Vair, Age, and MET are the top six important inputs; Large datasets like ASHRAE Comfort Database II and large data distribution may achieve higher performance than other balancing methods; Two different targets, higher TSV prediction accuracy aim or detailed occupants' thermal response; Compared machine learning (ML) algorithms in predicting thermal sensation (TSV); ML got 60–66% and 52–57% accuracy for 3-point and 7-point TSV prediction; ML algorithms got 10–20% higher prediction accuracy than PMV model; Random Forest got 62% prediction accuracy by using three input features; Tuning parameters and selecting input features are important for ML models. |

# Chapter 3 Methodologies

## 3.1 Research Phase

The research activities and the research phases can be seen in Figure 18. The left side of the figure shows the activities done on each phase on the right side.

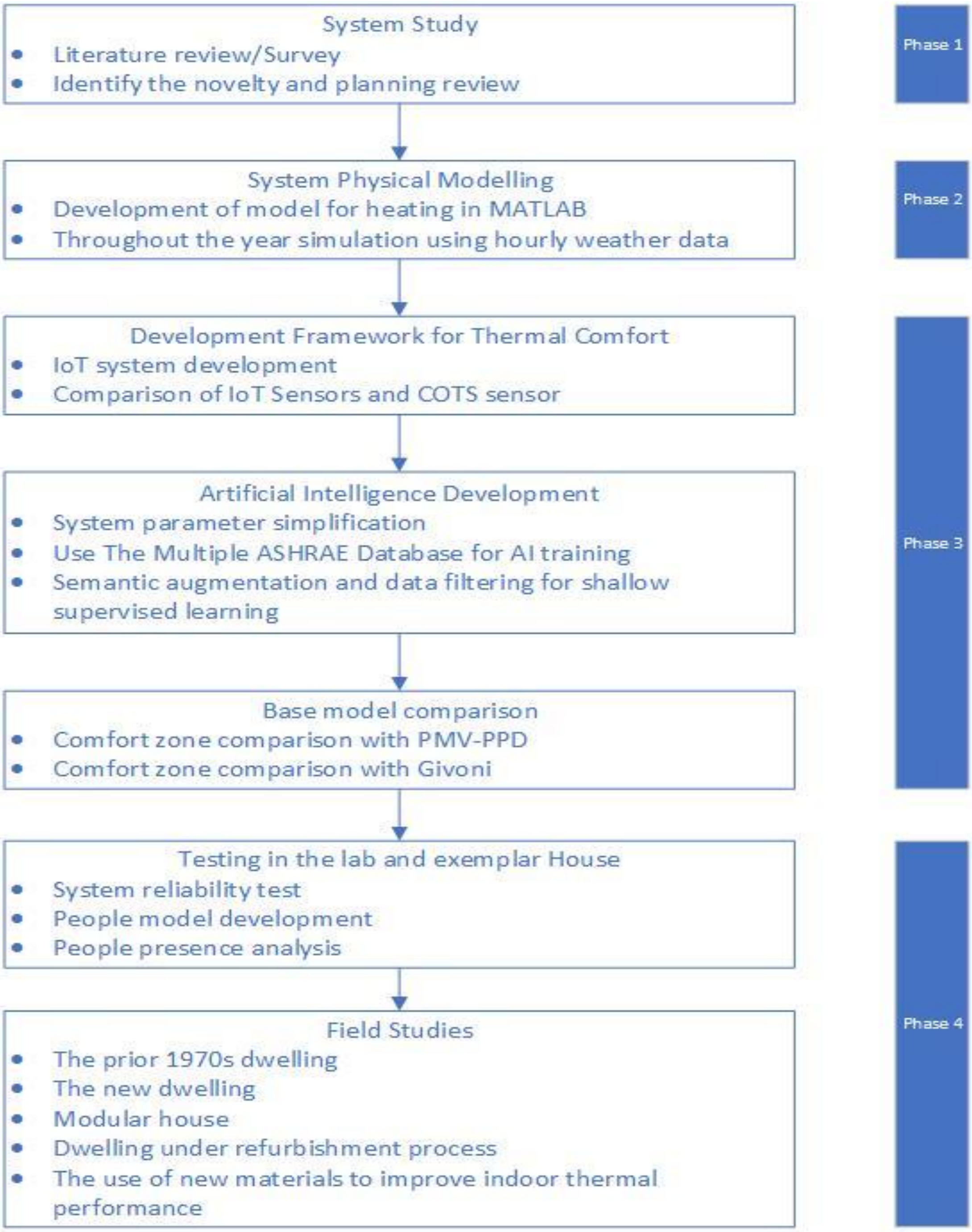



Figure 18. The research activities and the research phases.

## 3.2 System Study

The system design should be relevant to the advancement of the thermal comfort study with the support of the latest technology. The proposed system should also acknowledge the user aspects. In line with these acknowledgements, this work conducted the survey to be able to capture the occupants’ responses and comprehensive literature review in the field of thermal comfort.

There were two surveys in this work, firstly a survey was done during the tenant gathering of one of the Northeast of Liverpool dwelling agencies in 2019 in the initial phase of this work and the second survey was done by a third party and will be addressed in the field study subchapter.

The first survey had ninety-five respondents with females being dominant because the survey was done on weekdays. All respondents were given the option to select some features that they consider to be important for their homes in the future. Some respondents also gave comments regarding their knowledge of the smart house.

The concept of sensors is still not common for the respondents; therefore, additional questionnaires were conducted for 24 respondents. The questionnaire mentions the sensors and the data gathered by each sensor. Two aspects were assessed, the comfortability and the privacy issues of each type of sensor. The sensors involved in the questionnaires are the environmental sensor (temperature, humidity, and air quality sensors), wearable sensors, MOS/CCD Camera, and Infrared/Thermal Cameras.

The second survey was conducted during a field survey to get the behaviour of the occupants that impacted the indoor thermal condition. Example of the occupants' behaviour was the use of other heaters/fireplace, their habit to open the windows, external and internal doors, occupants' activities like showers and cooking and the most important data was the comfort that the occupants feel in their dwellings.

## 3.3 System Physical Modelling

This work utilises computer-based simulations to simulate the effect of outdoor temperature and humidity on the internal temperature and humidity in the presence of occupants within different dwelling typologies. This value was then used to predict the indoor condition in the houses with two different construction typologies: the first model is the houses built in the 1920s' where the wall and floor insulation was not standard. The second house model uses 2010s construction materials where the double-glazed windows and the wall insulation materials are implemented.

The model defined is a digital twin representation of the room where the parameters were derived from. Modelling and simulation nowadays have an important role in supporting design and validating system properties. In the manufacturing industry, the integration of sensor networks and the digitalization of production systems and machinery gave rise to the concept of the digital twin. A physical asset and a sensor network are needed for a digital twin, although neither is necessary for simulation during the design process. Digital twin is defined as “a comprehensive physical and functional description of a component, product or system together with all available operational data.”(Khajavi, Motlagh, Jaribion, Werner, & Holmström, 2019).

### *3.3.1 Construction Typology*

As demonstrated in Figure 2, approximately 16% of all homes were built within the 1920s, where the construction was a non-insulated solid brick (as per Figure 19 (a)). In this work, when the '1920s' home is mentioned, it does not simply refer to this period. It also refers to any dwelling built to the same building standard of a solid masonry wall. In comparison, the 2010s' construction represents the 'newer' and updated construction methodology (see Figure 19 (b)). Like that of the 1920s typology, for this work, any building with the same construction is included in this description. These construction typologies are based upon 'to scale' Building Research Establishment (BRE) exemplar houses built on-site at the Liverpool John Moores University (LJMU) Byrom Street (as pictured in Figure 20).

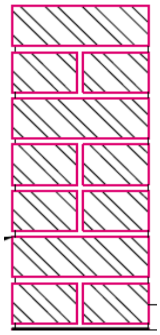
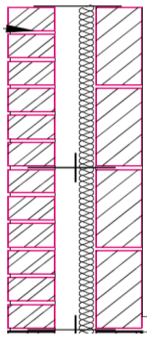
(a)  (b) 

Figure 19. (a) 1920s Solid masonry wall. (b) The 2010s Outer facing brick, 50mm clear cavity, 40mm insulation board, medium density inner.


Figure 20. Image of BRE Exemplar Houses on campus at LJMU (where building typologies from L to R represent the 1920s, 1970s and 2010s)

### *3.3.2 Location environmental conditions*

Using a computer simulation allows the indoor conditions to be simulated for different parts of the UK, based upon their differing weather conditions. The locations of the simulated dwellings are Liverpool (representing Northwest England), Kent (representing Southeast England) and Aberdeen (to represent Northeast Scotland). Besides the difference in the characteristics of energy poverty, Aberdeen was selected to represent the coldest place in the UK, Kent as the hottest and Liverpool as the location in the middle.

The data used for this simulation uses Centre for Environmental Data Analysis (CEDA) hourly weather data for 2017(Office, 2019) and is demonstrated for Liverpool, Aberdeen and Kent in Figure 21, Figure 22 and Figure 23 (respectively). The model is also able to simulate the indoor condition using the future weather forecast (for example, in 2030) (Herrera et al., 2017) in order to view the impact of climate change on indoor conditions. The future weather data prediction for the UK can be obtained from CEDA data sets ((MOHC), 2017; Buratti et al., 2017).

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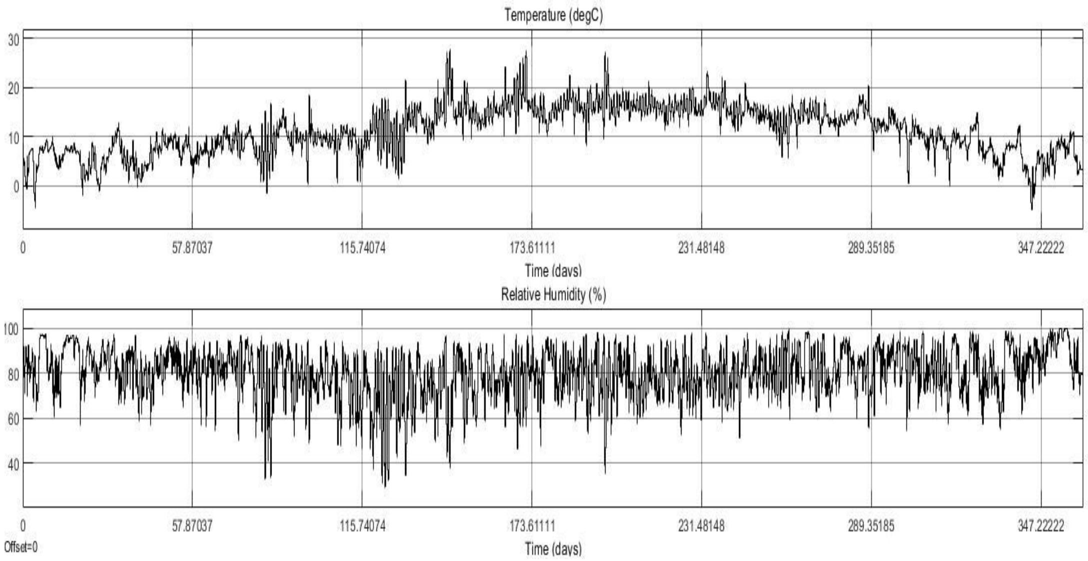
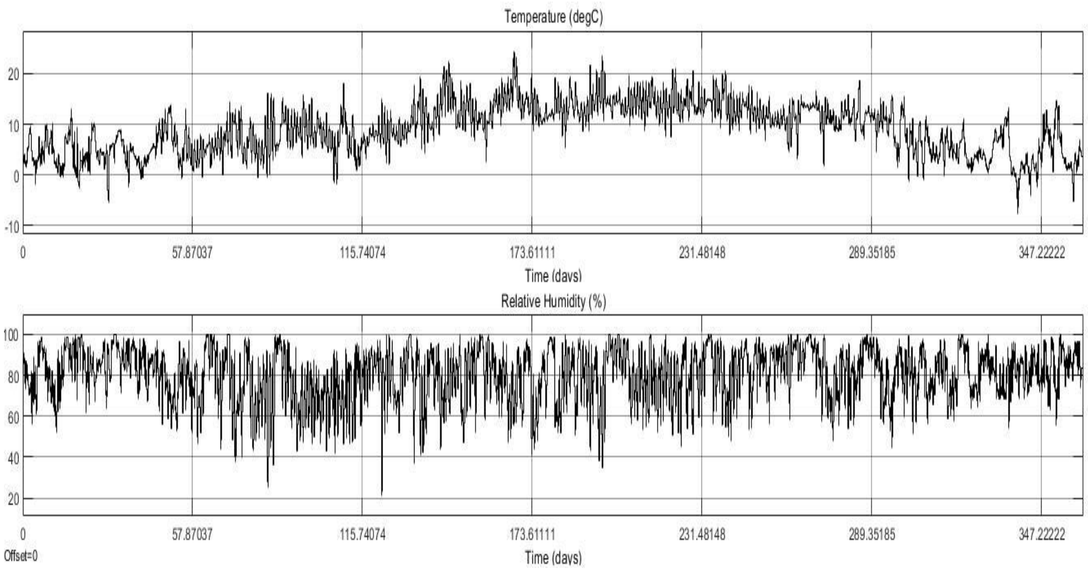
Figure 21, Figure 22 and Figure 23 demonstrate that out of the three locations; there is a greater temperature range in Kent compared to Aberdeen and Liverpool. Aberdeen had the coldest temperature reading among the three locations, but Kent had the lowest mean temperature (7.54°C) in 2017 compared with Aberdeen (8.56°C) and Liverpool (8.25°C). The mean temperature of all locations was still below 9 °C. When considering RH, Aberdeen had the lowest mean RH (80.57%RH), but all areas still had the mean relative humidity above 80% (Kent 82.99% RH and Liverpool 82.26% RH).




Liverpool

| Temperature | Value (°C) | Time (days) | Relative Humidity | Value (%) | Time (days) |
|---|---|---|---|---|---|
| Maximum | 27.800 | 146 | Maximum | 100.00 | 262 |
| Minimum | -4.900 | 345 | Minimum | 29.00 | 124 |
| Mean | 8.247 | | Mean | 82.26 | |
| Std. Dev. | 4.904 | | Std. Dev. | 11.15 | |

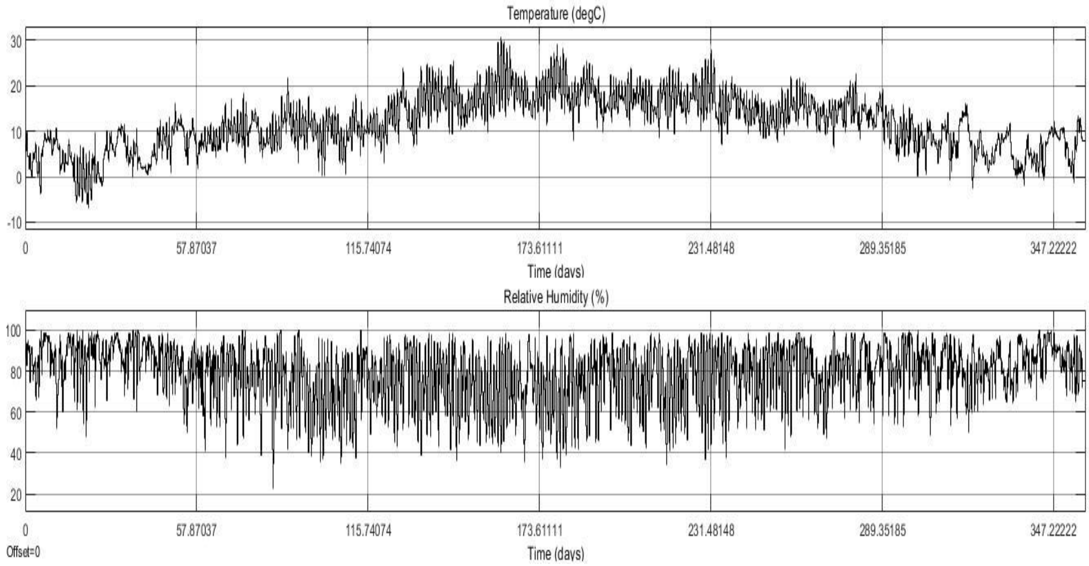
Figure 21. The chart of hourly annual temperature (upper chart) and relative humidity (lower chart) for Liverpool in 2017.




Aberdeen

| Temperature | Value (°C) | Time (days) | Relative Humidity | Value (%) | Time (days) |
|---|---|---|---|---|---|
| Maximum | 24.400 | 168 | Maximum | 100.00 | 18 |
| Minimum | -7.700 | 340 | Minimum | 21.00 | 123 |
| Mean | 8.559 | | Mean | 80.57 | |
| Std. Dev. | 4.908 | | Std. Dev. | 13.03 | |

Figure 22. The chart of hourly annual temperature (upper chart) and relative humidity (lower chart) for Aberdeen in 2017.




Kent

| Temperature | Value (°C) | Time (days) | Relative Humidity | Value (%) | Time (days) |
|---|---|---|---|---|---|
| Maximum | 30.800 | 161 | Maximum | 100.00 | 6 |
| Minimum | -6.800 | 22 | Minimum | 22.50 | 84 |
| Mean | 7.535 | | Mean | 82.99 | |
| Std. Dev. | 6.013 | | Std. Dev. | 14.15 | |

Figure 23. The chart of hourly annual temperature (upper chart) and relative humidity (lower chart) for Kent in 2017.

### *3.3.3 Model Input Parameters*

The model uses the approach of a single room (similar to PASSYS test cells (Strachan, 1993)) with two and four occupants constantly present inside the room. The two occupants model parameter was based on the data that the average household size in the UK was 2.4 (Statistics, 2021). The four occupants’ model parameter was selected for comparison if the occupants' numbers were doubled. This model is deployed using MATLAB-Simulink-SIMSCAPE software. Consisting of two related parts simulated simultaneously, the model contains both a thermal model and a moisture model, where the input parameters can be found in Table 6.

Table 6. Model Parameters.

| **General** | | | | |
|---|---|---|---|---|
| *Input Parameter* | *Value* | | | |
| Number of Occupants | 2 and 4 | | | |
| Sensible heat per occupant, (W) | 100 | | | |
| Ventilation area, ($m^2$) | 0.01 | | | |
| Flow (m/s) | 0.05 and 0.025 | | | |
| **Room Dimensions** | | | | |
| *Input Parameter* | *Value* | | | |
| Room Volume ($m^3$) | 31.84 (4.35 x 3.05 x 2.4) | | | |
| Window Area ($m^2$) | 2.8314 | | | |
| Door Area ($m^2$) | 3.4 | | | |
| **Housing Typology Characteristics** | | | | |
| *Typology Description* | *Specific Heat Capacity (J/(kg K)* | *Thermal Conductivity (W/mK)* | *Wall Thickness (m)* | *Density (kg/$m^3$)* |
| 1920s house solid brick wall | 800 | 0.98 | 0.215 | 1920 |
| 2010s house internal blockwork concrete block | 1000 | 0.51 | 0.1 | 1400 |
| 2010s house insulation | 1500 | 0.022 | 0.09 | 30 |
| 2010s house outer facing brick | 800 | 0.98 | 0.1025 | 1920 |

## 3.4 Framework Development and Test Preparation

People will need time to change their thermal state. The amount of metabolic heat released by the body in light activities is relatively small compared to the body mass. The heat input from metabolism and loss to the environment will be even smaller. A light person will respond quickly (feels cold quickly), and a heavy person will feel cold more slowly. Convection, radiation, and evaporation will happen to people, including the respiration process. People can still be comfortable if the skin temperature changes gradually. The skin temperature will be non-uniform. The cold is comforting for overheated bodies but unpleasant for already cold bodies. The sensation effect will depend on time, clothing and the temperature of the surroundings. A sudden change in weather conditions will require people to act accordingly and avoid the danger of heatstroke (Fergus Nicol, 2012).

The solution for thermal comfort is not simply due to the complex parameters in terms of:

- Physics; which is the regulation of thermal environment and clothing
- Physiology; which is the mechanisms of thermoregulation and acclimatisation
- Psychology; which is the perception of comfort and discomfort, relation to the health, age and behavioural aspect of people

Based on Kahneman's work on experience vs memory, it can be concluded that people will remember better, information which triggers their curiosity, and additional moments of episodes, especially the final moments. This was also acknowledged by the previous research that memory impacted thermal comfort. From the experience vs perception point of view, people are bad at predicting perception and the human body is not a good sensor. Based on these facts the intelligent system should have the ability to give recommendations based on the current indoor condition. With the experience vs adaptation principle, if given enough time, people can adapt gradually to indoor conditions. This can become the key to energy saving while still maintaining indoor comfort by adjusting the temperature gradually to lower the energy needed for comfort. Giving the chance for people to adapt can increase satisfaction in general.

Based on these principles and our surveys on an intelligent system, the design of the system should be:

i. Give memorable comfort experiences, especially before people leave the room.
ii. Giving people the ability to experience directly before they develop their assumed perception, and this experience requires continuous sensing and interaction.

iii. People are bad at predicting perception over time, and the system should be able to give a recommendation based on a certain standard.
iv. The system can give flexibility in access time, which delivers happier activities that can increase satisfaction in general.
v. People can have enough flexibility for the adaptation process which can lead to energy saving.
vi. The primary driver of the system is to lower the bills (the economic drive).
vii. The system is trustworthy, and the sensor should not become a privacy breach to the user.

The design criteria above give us the ideas to develop a system which can give thermal comfort to the occupants while still minimising the energy use by implementing:

i. The adaptive algorithm that can predict and acknowledge user needs.
ii. Ability to regulate the room based on real time readings from sensors that were installed as the integral component of the system and evaluated with the artificial intelligence.
iii. Avoid false prediction by giving the standard references according to the health regulation and the ability to alter the setting based on the occupant preferences.
iv. The system can provide a kind of gamification (K. Karyono, Andoko, & Ellianto, 2019) to give memorable comfort to the user. This system will give enough time for the perception to be experienced and challenge users to lower their energy usage profile.
v. The system can display the prioritisation selection to the user for maximal comfort, saving, or between the two. The algorithm will be adjusted according to user preference. The system can also use gamification to gain a more bill-friendly

system, reducing further over the years as the user has already adapted to the system and environment.

vi. The data output of the sensor should be securely stored and can be accessed by the customer based on the rights given.

vii. The ability of the settings to be manually overridden by the approved user.

### *3.4.1 Prototype*

The prototype represents three layers. Figure 24 shows the topology of the prototype with three layers. The upper tier is a services tier (cloud-based services). This entity consists of the database server and application server. The database server is used to store the sensor reading data and the preference data of the occupants. The sensor data will be used to calculate the recommendation settings, and the preference data will be used to calculate the setting that will be pushed to the local controller.

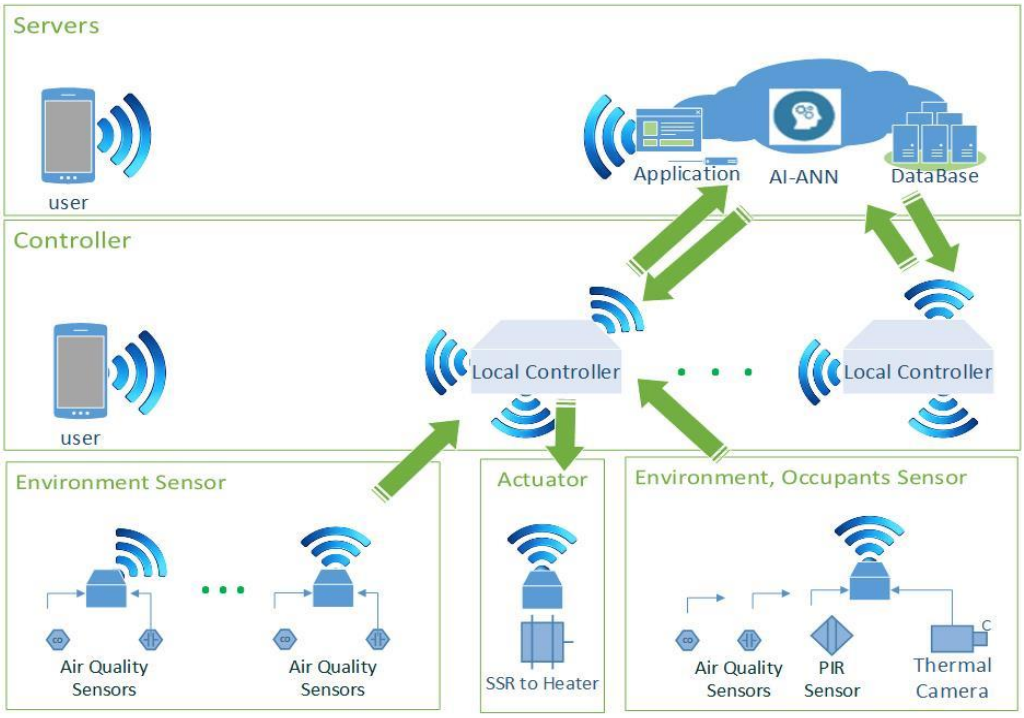
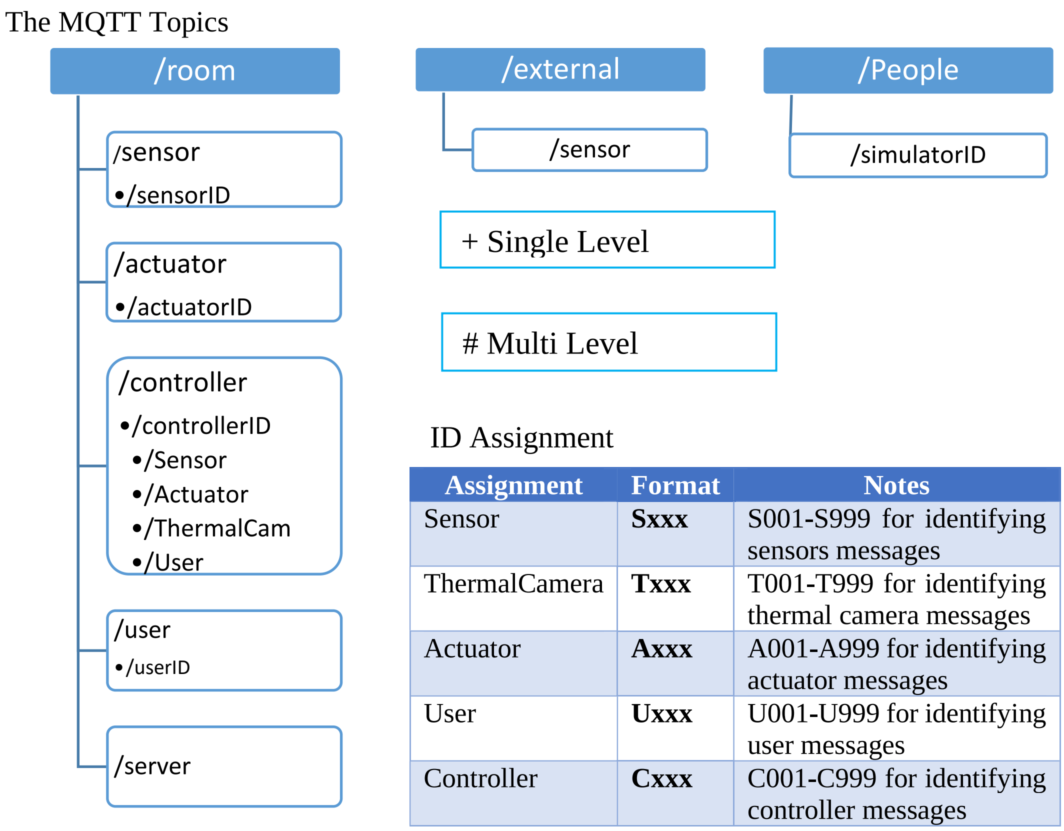



Figure 24 The topology of the prototype.

The middle tier is the controller located in the house or apartments. This controller has the ability to do the control locally if the server connection is faulty. The local controller also becomes the data concentrator for all sensors assigned to this local controller. The local controller also can relay the user requests. On the contrary, the local controller can also conduct action or command sent by the cloud to the actuator. The connection of the middle tier to the cloud can be made using Internet Protocol.

This prototype makes all connections using a Wi-Fi connection with Message Queuing Telemetry Transport (MQTT) protocol to simplify the connection demonstration. However, any modification to the communication layer can be easily deployed because all components support multiple communication protocols. The format of the MQTT messages is declared in Figure 25. The identity (ID) messages in this prototype were defined with four characters; the first character represents the originated sender types, followed by three characters as the ID number of the sender. The MQTT messages are structured like a tree which is differentiated using their topic. The designated topics can have multiple sub-topics to further differentiate the message. Using the tree structure of the MQTT topic, the message can be handled and translated correctly.

The lower tier is the sensors and actuators. The distributed controller (WSN) connects these sensors and actuators to the middle tier. The sensors can be a group of sensors to monitor indoor thermal conditions, a passive infra-red sensor to detect the presence of occupants and a thermal camera to detect occupant’s condition. The actuators for this system are the controller connected to a Solid-State Relay (SSR) to control the heater automatically based on the local controller or sensor command.




| Assignment | Format | Notes |
|---|---|---|
| Sensor | **Sxxx** | S001-S999 for identifying sensors messages |
| ThermalCamera | **Txxx** | T001-T999 for identifying thermal camera messages |
| Actuator | **Axxx** | A001-A999 for identifying actuator messages |
| User | **Uxxx** | U001-U999 for identifying user messages |
| Controller | **Cxxx** | C001-C999 for identifying controller messages |

Figure 25. The MQTT message format.

### *3.4.2 Test Preparation and Human model*

This work focused on the thermal effect of human presence, but the direct people presence was difficult in the case of health and safety risks, especially due to the COVID-19 restrictions. The thermal representation of humans can be simulated using the radial heater or light bulbs that emit heat like the human body heat. According to BS 5925:1991 (BSI, 2000) and ASHRAE standard 55 (R. A. C. E. American Society of Heating, Incorporated, 2017), the activity of people generates an 80W to 800W metabolic rate for an adult male. This human model focuses only on the body heat and does not compensate for the respiratory vapour or activities that generate vapour, such as cooking or showering.

For the indoor people simulation, the model will cover two people in sleeping conditions or one person in light or medium work, which is about 156 W using a radial heater (single 60W radial heater and double 40W heaters) and 20 W halogen lamp (which is assumed to have 80% energy converted into heat). For the two-person case, one person is simulated with two 40W radial heaters, and another is simulated using a 60W radial heater and 20W halogen lamp. Table 7 shows the example of the activity list along with its associated metabolic rate according to the BS 5925:1991.

Table 7 The relations between the activity and its associated metabolic rate (adult male).

| **BS 5925:1991** | Metabolic rate (M) | **ASHRAE standard 55** | Metabolic rate (M) | |
|---|---|---|---|---|
| Activity (adult male) | W | Activity | W/m^2 | Met units |
| Seated quietly | 100 | Seated, quiet | 60 | 1 |
| Light work | 160 to 320 | Office, Walking about | 100 | 1.7 |
| Moderate work | 320 to 480 | Light Machine work | 115 to 140 | 2.0 to 2.4 |
| Heavy work | 480 to 650 | Heavy Machine work | 235 | 4 |
| Very heavy work | 650 to 800 | Basketball | 290 to 440 | 5.0 to 7.6 |

| Note: | Surface | Adult male | 1.9 $m^2$ |
|---|---|---|---|
| | | Adult female | 1.6 $m^2$ |
| | | Children | 1.2 $m^2$ |

The human model was developed related to the case study that was discussed in subchapter 7.1.2 Testing in the BRE house (1970s house). This human model was the solution to comply with the case of health and safety risks, while still being able to introduce the impact of the people presence, in the dwellings. This method can be used and replicated in the new housing project or the refurbishment project to simulate the human presence to give a more realistic assessment where the occupants' presence is still restricted.

## 3.5 Field Study of the Proposed System

Previous research has identified that the field still lacks a more unified and systematic modelling framework(Arakawa Martins et al., 2022). Model evaluation needs a clear comparison between studies and approaches. The generalization of the results is still debatable due to the small number of participants. Diversity needs to be introduced (more balanced datasets and expanding the application of the personalized models into other types of environments). In-field studies give more realistic effects in terms of user behaviour (Feng et al., 2022). Future work in this area should be focused on testing and integrating TC models with intelligent systems. Detailed analysis using machine learning and statistical modelling is necessary for future research work (Čulić et al., 2021). Boundaries of the comfort zone have become progressively narrower over the past several decades. Long-term thermal experiences can raise comfort expectations more readily than they can lower them. The adaptive comfort concept is central to addressing questions of how to enhance adaptive capacity in buildings and how to nudge occupant attitudes and behaviours relating to indoor climate (R. de Dear et al., 2020). Large datasets like ASHRAE Comfort Database II and large data distribution may achieve higher performance than other balancing methods (Luo et al., 2020).

Based on these gaps, the case studies were done on five case studies that represent the problems most likely in the United Kingdom. The five cases were the case of humid dwelling (Dwelling Prior 1970s), the new dwellings, the refurbished flats, the Implementation of the new materials for thermal improvement, and the new modular house with advanced heating controls. With these extensive tests the model were expected to be mature enough and close the gaps identified by the previous research.

The field study began with sensors implementation in various installation locations according to the room type. Additional sensors were added to justify the parameters that need focus, such as the heater air temperature. The sensors collected the data within the predefined interval, for example, 15-minute intervals. The main parameters for this data collection were the black globe temperature and humidity. This interval was adequate to capture indoor temperature fluctuations and humidity changes.

The sensors involved in this research were the customer/end-user type of sensors that are very common on the Internet of Things (IoT) application. These types of sensors can also be associated with low-cost sensors, which have a measurement accuracy of 0.5°C for temperature and 2.25% for relative humidity. TC xx, TH xx and S0xx represent the sensor's ID used in the field studies. TC was used to measure temperature while TH and S0 were for temperature and relative humidity.

The data was then downloaded and combined with the data from the local weather station corresponding to the sensor data. This local weather station could deliver 15-minute interval data with the main focus on the outdoor temperature and humidity. The analysis phases mapped the data to form a chart for each room's temperature and relative humidity corresponding with the outdoor temperature, then focused on the minimum and maximum outside temperature for each period.

Based on this gathered data, the temperature and relative humidity data were fed to the Artificial Intelligence model to decide whether the occupants were in a thermal comfort situation. The psychrometric chart was used to map the data according to the temperature and humidity, along with the comfort condition of the occupants. These steps were done carefully to capture and simplify the parameters without ignoring the complex aspects of the indoor thermal condition. Additional parameters such as occupants' behaviour, for example, the habit of opening the window, the frequency of cooking and showering, the occupants’ humid and thermal sense, and other indoor conditions, such as the state of internal doors, were captured using the questionnaire where applicable. The overview of the methods can be seen in Figure 26.

The case of the prior 1970s dwelling was done in one of the flats in a three-story building in Liverpool (ASHRAE Climate Zone 4A). The data was collected from 17

February 2022, 22:00 to 02 March 2022, 16:30, at the end of winter. The room heaters in this house were turned off during the trial.

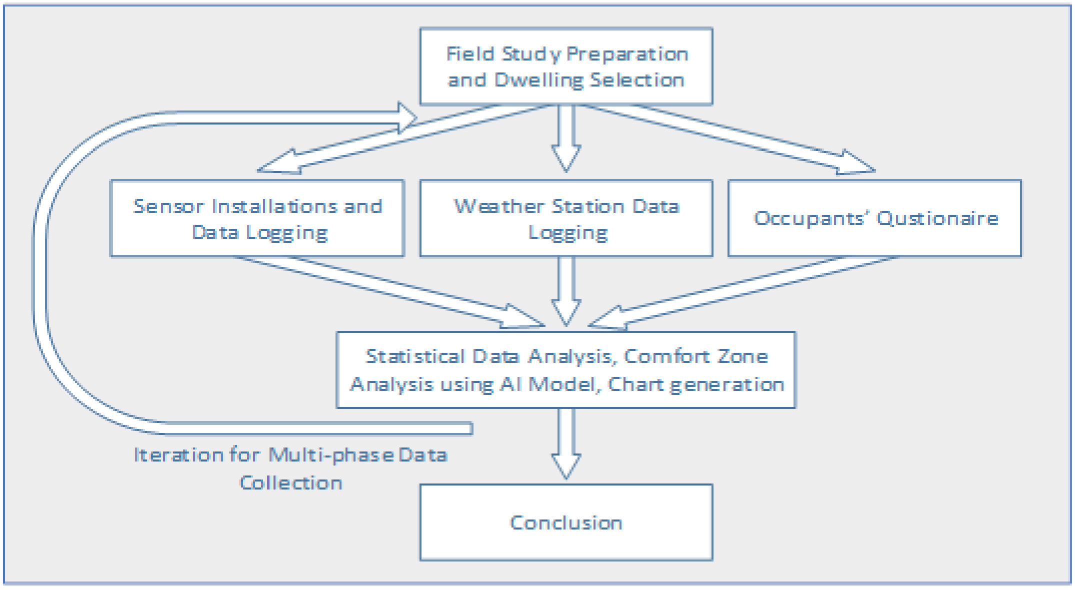



Figure 26. The overview of the methods used in this work.

The case of a new dwelling was done in two new semi-detached houses in Liverpool. The house was built with the proper insulation. The data was collected from 19 October 2020, 13:00 until 8 April 2021, 04:15, which was the autumn, winter, and spring. The room heaters in this house were turned off during the initial data gathering from 23 to 27 October 2020 and then turned on throughout the trial.

The case of the modular house with the advanced heating controller was done in the new modular house in Liverpool. The data was collected during the autumn season from 19 October 2021 to 29 November 2021.

The case of refurbished dwellings was done in five high-rise flats in Liverpool. The refurbished building is the high-rise flats, and the flat is on the 14th floor. The refurbishment processes were installing outdoor insulations, and the indoor refurbishment was done by upgrading the electric heaters into new electric heaters. The data readings were done four times from 20 December 2019 to 26 February 2021 during the pre-refurbishment phase, pre and during-refurbishment phase, during and post-refurbishment phase and post-refurbishment phase. The data logging was done in four periods to cope with the field condition.

The dwelling with additional material for thermal improvement was conducted in four bungalow houses in Liverpool and was done from February 2022 to May 2022 during the end of winter to spring. The trial was done by installing an additional layer in the glazing area to increase the thermal resistance and lower the leakage. The occupants also filled in the questionnaire regarding their behaviour, which might impact the trial result because the trial was done in a single dwelling with one room installed with the material and the other non-refurbished room for control.

The 1970s house typology assesses the people's presence impact on thermal comfort. The trial was based on the ten-week field study in the 1970s' BRE House, Liverpool John Moores University, Byrom Street Campus. The trials were divided into three groups: the trial with no people present, the trial with people model/simulator between 09:30 and 18:00 and the people simulator from 21:30 to 06:00, Monday to Friday, to represent the indoor conditions. The people simulator was introduced due to the health and safety reason of the trial location. The people simulator was based on ASHRAE Standard 55 (ASHRAE, 2017) value to represent two people in the sleeping or resting condition or a single person in the light work state. The people's presence time was set equally so it can be comparable. The field study was done during the transition periods from winter to summer.

Furthermore, the research on AI still has gaps in AI-based models for residential buildings area, limited amounts of data and biases in datasets, limited generalization, and limited deployment of comfort models (Qavidel Fard et al., 2022). This paper offers a solution to overcome these gaps by using the AI model that was previously developed based on the multiple ASHRAE Databases and deployed the model in the various field studies to show the benefit of using this model in the residential dwellings of various typologies. The AI implemented was of type artificial neural network (ANN) which has the capability of being deployed in the local controller node suitable for residential dwellings' control due to less memory and computation requirements. This AI method is capable to acknowledge adaptive thermal comfort, leading to lower energy use for comfort.

# Chapter 4 Thermal Comfort and Energy Simulation Results and Analysis

SIMSCAPE is a feature of SIMULINK in MATLAB, where the simulation of the physical model can be completed simultaneously to represent identical physical conditions. This hygrothermal modelling was implemented with two loops of physical properties. The first loop is for the water vapour property, and the second is the loop for the thermal property demonstrated in Figure 27.

Even when the model is divided into two loops, the simulation of the water vapour loop and the thermal property loop is completed simultaneously. The simultaneous simulation means that their parameters are integrated and strongly correlated between each loop. Splitting the model into two loops benefits the modularity aspects; the parameters defined in each loop can be adequately identified and modelled in different modules. Each loop can be isolated and executed to independently identify the effect of altering the simulation parameters. This approach can be made on each separated loop and in an integrated environment simulation. The intersection of the loop is in the constant volume chamber component. This block models the moist air behaviour inside a constant room volume. The mass and energy storage parameters are modelled with the possibility of changing the simulated input parameters. Pressure and temperature will change based on the thermal capacity and pressure of the moist air inside the chamber. The component overview of the model can be seen in Figure 28.

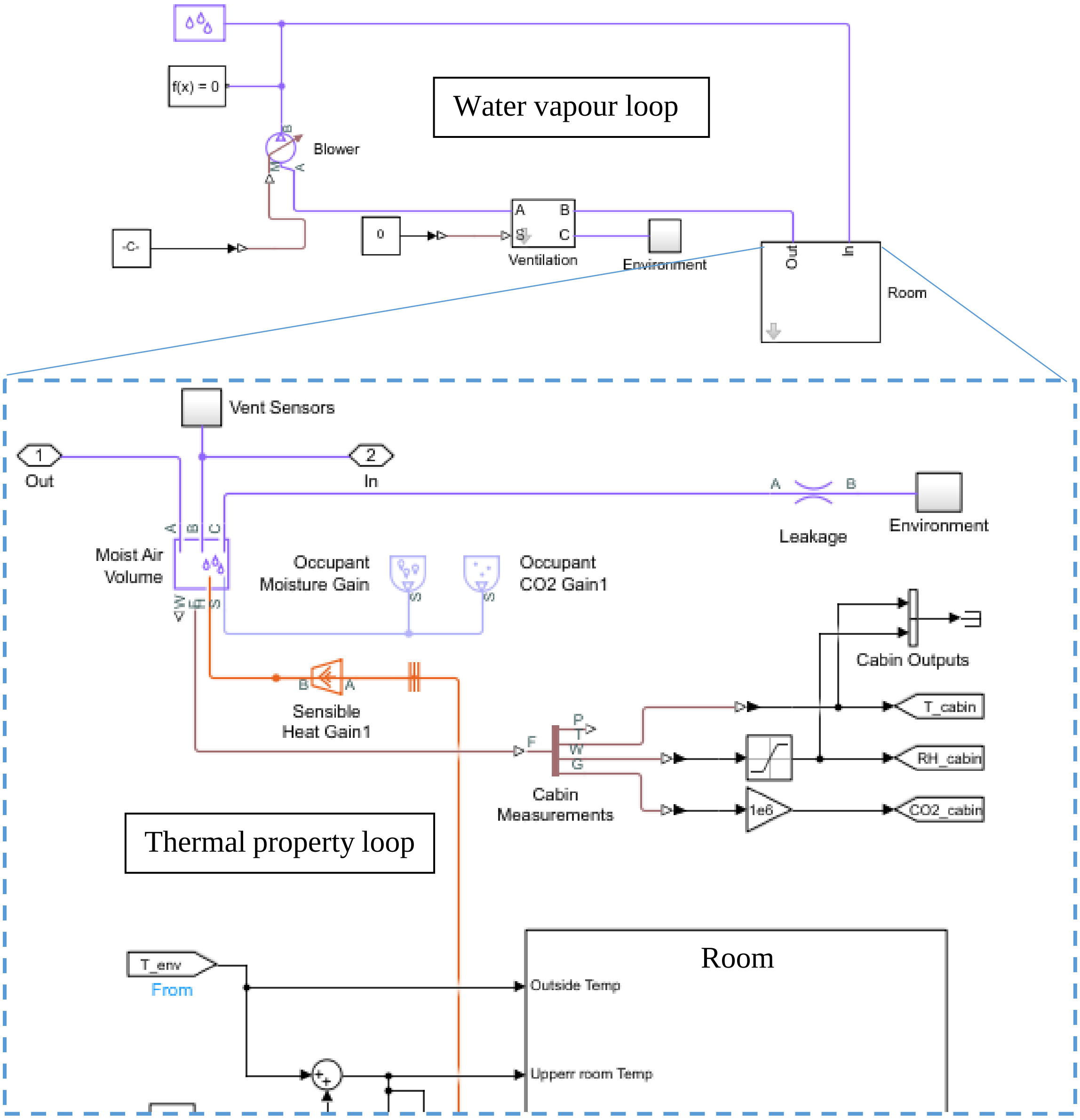



Figure 27. Thermal and vapour loop in the model.

## 4.1 Model Explanation

The moist air node is available for adding or removing moisture within the air. In this model, this feature is utilised to model the occupant's presence. The occupant's presence will give additional moisture due to the effect of human respiration. This component intersects the water vapour loop and the thermal loop. Besides affecting the water vapour loop in terms of increasing the humidity, the occupant's presence will also raise the temperature of the moist air volume due to the heat dissipated by the human body. Liquid water condenses out of the moist air volume when it reaches saturation. The convective and conductive heat transfer between the air, the surrounding wall, roof, floor and the occupants are simulated in the thermal loop.

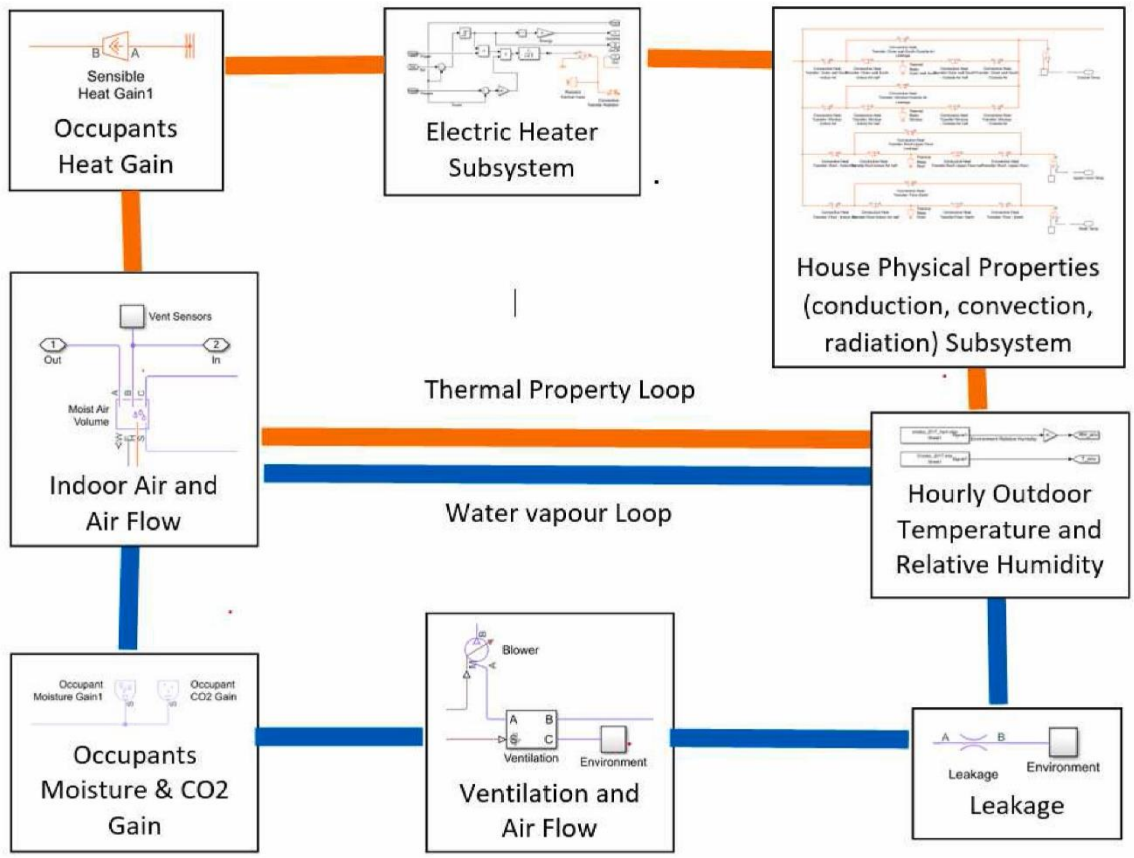



Figure 28. Overview of the SIMSCAPE MATLAB Model

The heater model in this simulation is the convective panel electric heater model with the closed-loop control. The heater will be turned on if the room temperature falls below the set point and turns off if the temperature rises above the temperature set point. Measuring the percentage of heater 'on' time between different housing typologies and locations will generate an annual quantification of energy usage for typology and locational comparisons. The heater part is connected to the thermal property loop in the constant volume chamber component; hence, a change in the heater state (heater is turned on or off) will impact the indoor air moisture. A simplified electric heater model is used within this research (see Figure 29); the model also utilised the capability of executing the Simulink model with batch processes.

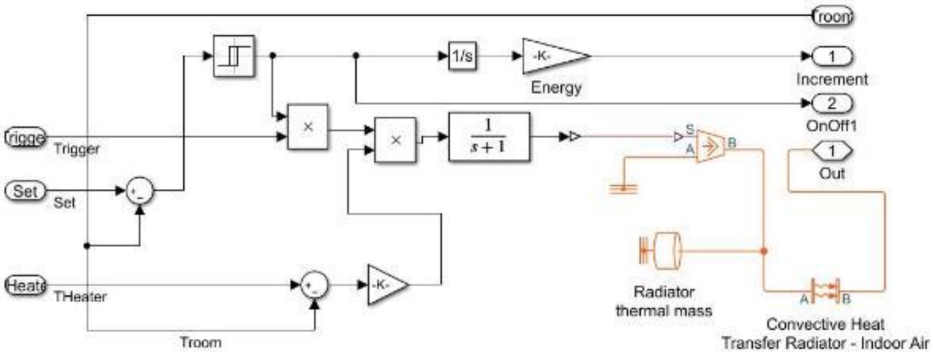



Figure 29. Simplified electric heater model in the SIMSCAPE simulation.

The simulation uses three UK locations, Kent, Aberdeen and Liverpool, to represent the conditions all over the UK and is also similar to the model validation, which uses the measurement data taken from ASHRAE Global Thermal Comfort Database II (Földváry Ličina, Cheung, Zhang, de Dear, Parkinson, Arens, Chun, Schiavon, Luo, Brager, Li, & Kaam, 2018) for all available UK data. The data selected is the data from all over the UK, with naturally ventilated buildings for offices, classrooms, and other types of buildings. The data set year is 1994, 1995, 1996, 1998, 1999, 2011 and 2012 throughout the year with the data entry of 14,187 measurements from the Midlands, London, Hampshire, Oxford, St. Helens, Chester, and Liverpool. The complete MATLAB model and the simulation parameters lists can be seen in the Appendix 1.

## 4.2 Model Assumptions

Within the model, the following assumptions have been made for this research:

- The heater is a model of the convective panel electric heater. The temperature of the panel when switched on is 40 ºC. Dimensionally, the panel heater is 0.9 x 0.4 $m^2$ with a mass of 46.7 kg, the radiator heat capacity is 447 %J/(kg K), and the heat transfer coefficient is assumed to be 100 %W/$m^2$K.
- Occupants are simulated to be present all the time (24 hours) and have the same activity level. The amount of moisture produced to use the approximation of occupants being at a low activity or resting and as per BS 5925:1991 RH is no greater than 70%. Each occupant is assumed to produce a 50 g/h moisture level as per BS 5925:1991standard (BSI, 2000) (as the value is 40 g/h for resting and 55 g/h for heavy activity)
- The solar heat gain is simplified in this model and not calculated using the weather files as temperature and humidity are.
- No air conditioning is used in this model, and the thermal set point is applied as a threshold for the heater to be turned on.
- Roof and floor constructions are identical to the 1920s and 2010s' house typology.

The ventilation state is also varied - ventilation with the air velocity rate of 0.025 m/s and 0.05 m/s. With this ventilation rate, the $CO_2$ level is below 1000 ppm for 2 and 4 occupants. This model uses the $CO_2$ gain per occupant value of 0.01 g/s, and the $CO_2$ level in the fresh air uses the assumption of 0.04 %, as stated in BS 5925:1991 (BSI, 2000).

## 4.3 Analysis of the Simulation Result

Simulations were completed to compare the performance of the housing location and construction typologies with 2 and 4 people inside a room over 24 hours, as demonstrated in Figure 30. The ventilation rate is 0.05 m/s for Figure 30 (a) and (c). For Figure 30 (b) and (d) the ventilation rate is 0.025 m/s. Regarding $CO_2$ levels, a ventilation rate of 0.05 for two occupants inside the room will reach about 650 - 700 ppm, whereas, for four occupants inside the room, $CO_2$ levels will reach about 900 to 950 ppm, both of which are still considered within the healthy region. By comparison, when the ventilation rate is halved to 0.025, the $CO_2$ level will rise to 900 - 950 ppm for two occupants, and with four occupants, these levels rise to an unhealthy level of 1400 - 1450 ppm. Besides simulating the $CO_2$ values, this work will also focus on relative humidity levels and if they can be considered healthy. What is demonstrated is that the annual mean indoor humidity is among the value range with no negative health effects, based on the simulation as outlined in H.M.Government (2013), except in the case of 4 occupants with a ventilation rate of 0.025.

There is only a slight difference in the humidity between 1920s dwellings and the 2010s' with a ventilation flow of 0.05 (shown in Figure 30 (a)). This result is observed particularly for both building typologies in Aberdeen after approximately 15$^{o}$C, where after there is no difference in mean indoor RH. The trend for all three locations is almost linear, proportionally with the temperature change. However, for Liverpool and Kent, at approximately 15$^{o}$C, the RH for 2010s homes remains negligibly larger than that of its 1920s counterpart. This difference is sustained until 21.5$^{o}$C for Liverpool and 23$^{o}$C for Kent homes. In terms of location, Liverpool and Kent-based homes have a similar RH with a difference in RH of 1% from 13-21$^{o}$C, whereas, above this temperature (21-25$^{o}$C), RH appears to be the same. However, initially, in Aberdeen, RH is only 2% lower than in Kent, but at approximately 16$^{o}$C, this difference increases to 3.5% RH and is sustained until the end of the simulation at 25$^{o}$C.

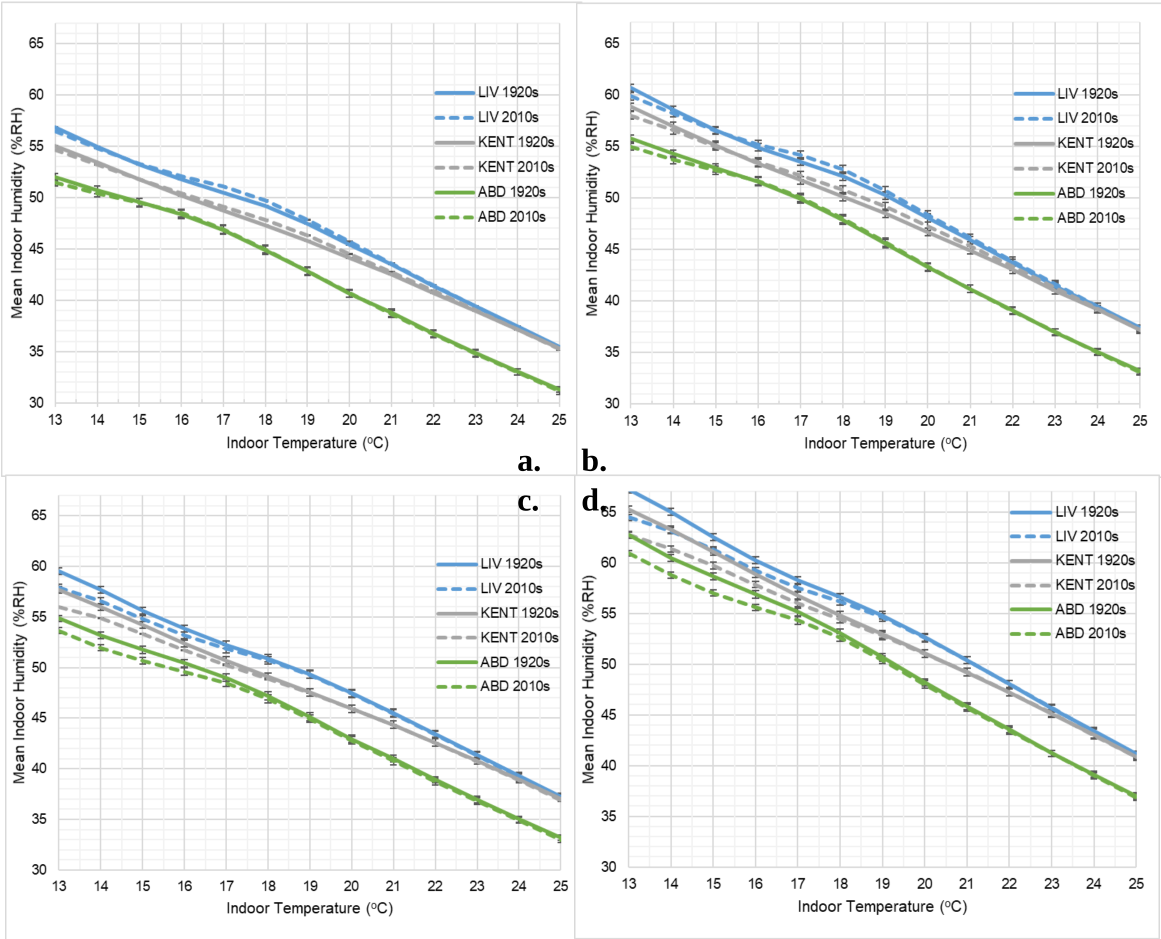



Figure 30. Comparison of mean indoor relative humidity (% RH) for the 1920s and 2010s housing typologies in Liverpool, Aberdeen, and Kent over the entire year of 2017 with a.) 2 occupants and flow 0.05m/s, b.) 2 occupants and flow 0.025, c.) 4 occupants and flow 0.05m/s and d.) 4 occupants and flow 0.025.

Similar to the case of 2 occupants (in Figure 30 (a)), the values of annual mean indoor humidity in Figure 30 (c) are among the healthy values based on the simulation. Figure 30 (a)-(d) demonstrate that due to the increase in people within the room, the starting RH values are approximately 3% high than those in Figure 30 (a). Figure 30 (c) demonstrated a gap (of approximately 1%) in RH between 1920s dwellings and the 2010s' in the temperature range 13-18°C. After this temperature, both housing typologies seem to have the same mean indoor RH; the only difference is the location of the dwelling, where the trends are almost linear, proportionally with the temperature change. With less ventilation flow, the mean humidity value difference between 1920s dwellings and 2010s' are distinguishable, especially with lower temperature settings. The efforts to reduce comfort temperature settings to conserve energy will be supported by the modern house typology, which has lower relative humidity than the old typology.

Figure 31 (a), (b) and (c) demonstrate the probability of the relative humidity exceeding 70%, and all the results show the value below 25%. Only in Figure 31 (d), for a dwelling with four occupants and ventilation flow of 0.025, has the relative humidity exceeded 70% value above 25%. Besides the $CO_2$ level, the value of the RH makes IAQ conditions unhealthy. The graph displayed in Figure 31 (a) – (d) is not linear because of the humidity change. The use of a heater will increase the temperature and decrease indoor relative humidity. The 2010s dwelling tends to have higher humidity than the 1920s dwelling. This condition happens due to the difference in the heater state. In the 1920s dwelling, the desired temperature must be achieved with the heater turned on, while in the 2010s dwelling, the temperature still can be reached with no heater as the 2010s dwelling has better insulation to maintain the indoor heat.

The chart of the percentage of the heater in the 'on' state cycle for the whole year (2017) is provided in the Appendix 2. This cycle of heater ON and OFF represents the additional heating needed and then switched OFF after the desired temperature setting was obtained. This cycle can represent a rough estimation of the heating energy comparison between house typologies. The more precise values were done in the simulation by using integrator component to also capture the transient heating energy values. The result of this process will be provided in Figure 32.

The probability of the relative humidity exceeding 70% shown in Figure 31 (a) and the percentage of the heater in the 'on' state shown in the Appendix 2 (a) is negatively correlated. In 1920s dwellings, for Liverpool, Kent, and Aberdeen, the values are -0.9579,

-0.9830, and -0.9345. For the 2010s' dwellings for Liverpool, Kent, and Aberdeen, the values are -0.9372, -0.9711, and -0.8817. This result shows that the decrease in the use of the heater will increase the probability of the relative humidity exceeding 70%, particularly in the dwellings in Kent that have the most significant inverse correlation values.

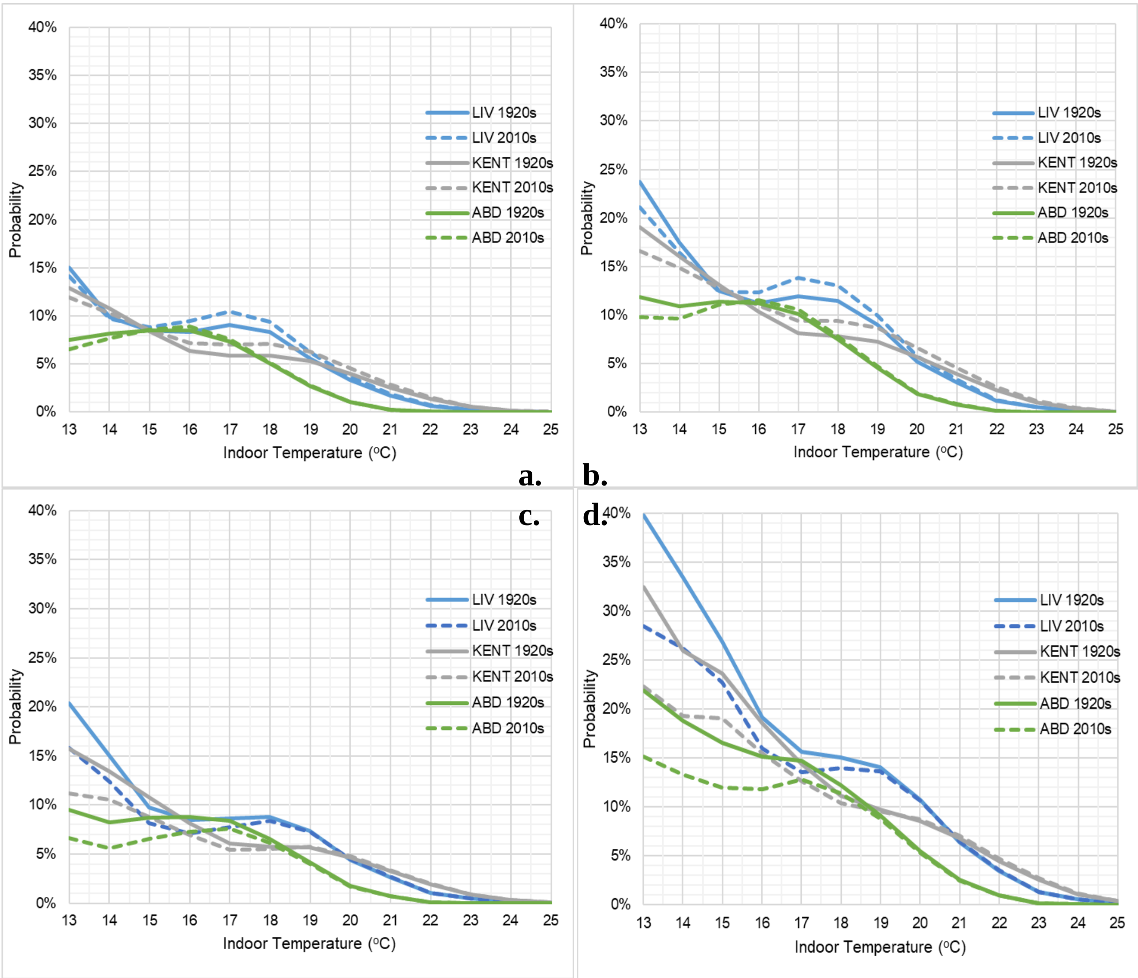



Figure 31. Comparison of the probability of indoor RH becoming >70% RH 1920s and 2010s housing typologies in Liverpool, Aberdeen, and Kent over the entire year of 2017 with a.) 2 occupants and flow 0.05m/s, b.) 2 occupants and flow 0.025, c.) 4 occupants and flow 0.05m/s and d.) 4 occupants and flow 0.025.

In order to minimise the probability of the indoor RH not exceeding 70%, the location will not give a significant value if the temperature inside the dwelling is maintained at at least 15 - 16ºC. With this temperature set point value, the number of people inside the room will have more of an effect more than the house location. Recommending this temperature set point to become the recommended standard temperature setting for comfort will consider giving a more uniform impact to the comfort.

Figure 31 (c) and Figure 31 (d) show that the 2010s' dwelling typology was beginning to demonstrate the superior result compared to the 1920s'. The probability of the RH exceeding 70% can be lowered while conserving indoor heating energy. Similar to the dwellings with two occupants, the dwelling with four occupants has the tendency that the location will not give a significant value to minimise the probability of the indoor relative humidity not exceeding 70%. This simplification can be used if the temperature inside the dwelling is maintained with the value of at least 16ºC in the house with four occupants. The housing typology will significantly impact thermal comfort when temperatures are below 16ºC. When the temperature set point is above 19ºC, the dwelling typology becomes no longer critical to the comfort, but only has an impact on the energy usage. Therefore, recommending a temperature set point around 16ºC - 19ºC to become the comfortable standard temperature would be desirable.

Figure 32 I. shows the relation between the heating energy needed and the house's location. The house that is located in the area with lower average temperature will need higher heating energy.

Figure 32 I. also highlights the impact of the number of occupants in the house although it was not as high as the ventilation impact. The higher number of occupants (c) and (d) needed a lower heating energy compared to the case (a) and (c). The lower the temperature set point, the higher the impact of the people's presence in lowering the heating energy.

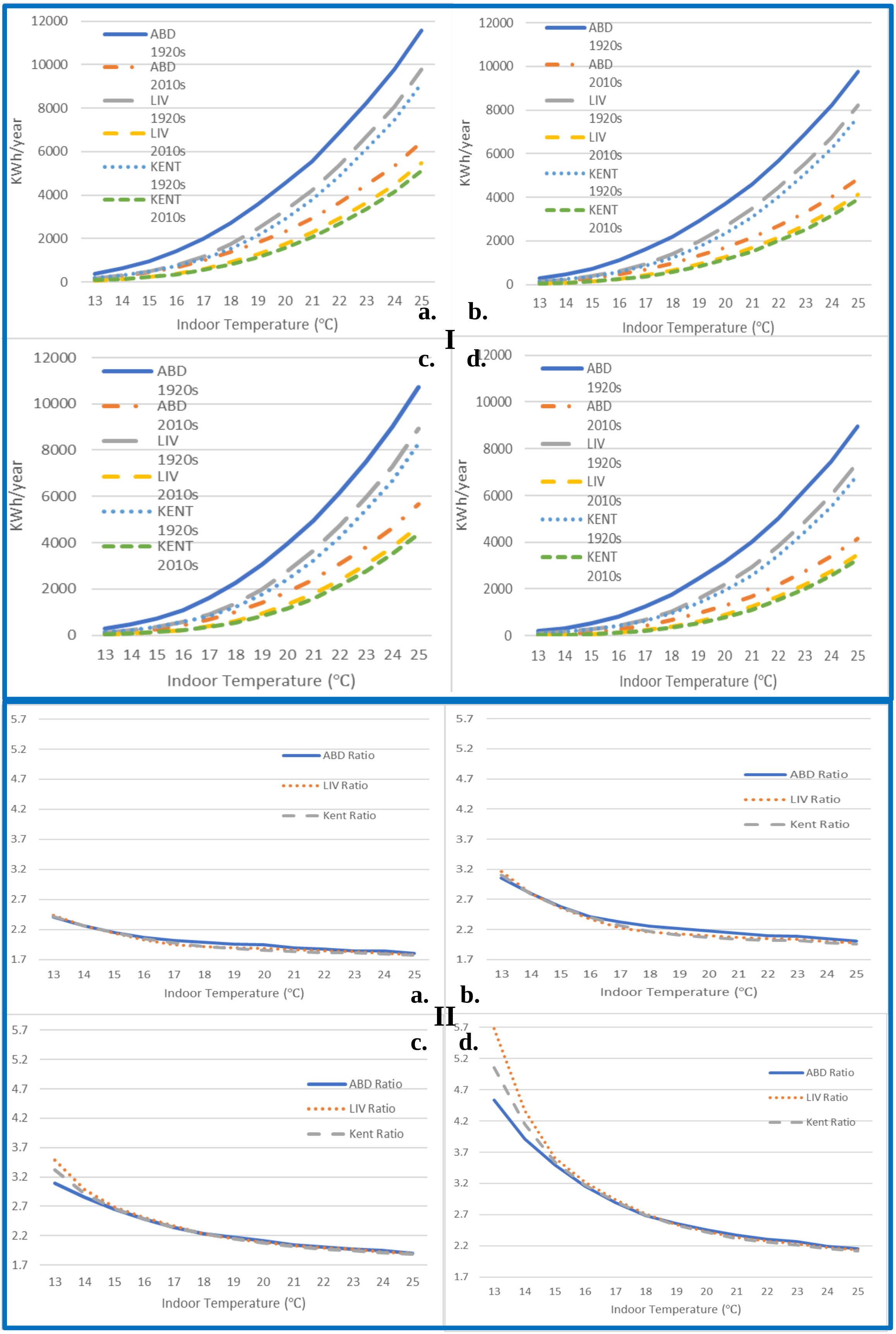



Figure 32. **I**. Heating energy comparison between the 1920s and 2010s housing typologies in Liverpool, Aberdeen, and Kent with a.) 2 occupants and flow 0.05m/s, b.) 2 occupants and flow 0.025, c.) 4 occupants and flow 0.05m/s and d.) 4 occupants and

flow 0.025. **II**. Heating energy ratio, Y axis represents the energy ratio 1920s against 2010s.

As outlined in

Figure 32 II (a) and (c), the energy used for the heating in the 1920s' house can be doubled compared with the 2010s' house throughout the year. The heating energy was decreased with better insulation material in the 2010s dwelling. The use of this material can have a higher impact compared to the impact of the different house locations across the UK. With lower ventilation value

Figure 32 II (b) and (d), the saving will be even higher. This value highlights the use of ventilation with heat recovery to conserve heating energy.

Figure 32 II also indicates that recommending a lower temperature set point for the modern houses will give even higher benefit in conserving heating energy compared to the 1920s’ house.

Appendix 2 also shows the heating energy curve for three hottest months and three coldest months. The results from three coldest months highlight the benefit of the modern house typology in the thermal energy saving. The gap between the heating energy usage in the 1920s house and the 2010s house was massive. Lowering the temperature set point for the 2010s house will give higher impact compared with the 1920s. The results from three hottest months gave an interesting result. The housing typology had less impact with the lower temperature set point. The people’s presence also had a greater impact beside the rate of ventilation. Like the results from the three coldest months, lowering the temperature set point for the 2010s house will give higher impact compared with the 1920s especially with more people present.

Based on the heating cycle simulation result where the 2010s dwelling typology can conserve 2% of heating energy and with the assumption of 16,500 kWh - 22,000 kWh on annual heating energy consumption per household per year, the energy-saving per house per year will be in the range of 330 - 440 kWh. If it was multiplied by the number of '1920s' homes which are approximately 36.6% of the total dwellings (approximately 8.76 million homes), the total energy conservation across the UK will reach about 2.89 - 3.85 billion kWh. The carbon reduction per year can reach approximately 635.8 - 847 thousand tonnes with 220 $gCO_2eq/kWh$. This result can be higher if the heating energy simulation is considered. More than half of the heating energy can be saved with the lower temperature set point, and the use of modern construction materials as used in the modern housing typology. The carbon reduction per year can reach 21 million tonnes.

## 4.4 Simulation Validation

### *4.4.1 Validation against ASHRAE Global Thermal Comfort Database II*

The simulation uses three cities within the UK: Kent, Aberdeen, and Liverpool, to represent conditions all over the UK. The measurement data taken from ASHRAE Global Thermal Comfort Database II (Földváry Ličina, Cheung, Zhang, de Dear, Parkinson, Arens, Chun, Schiavon, Luo, Brager, Li, Kaam, et al., 2018) for Liverpool and all available UK data were used to validate the model. The data from Liverpool were selected to represent one area of the UK with average weather conditions with 197 measurements data available in the database. All areas across the UK were selected from the database with the data entry of 14,187 measurements from the Midlands, London, Hampshire, Oxford, St. Helens, Chester, and Liverpool. These measurements were taken in naturally ventilated buildings such as offices and classrooms. The data set years are 1994, 1995, 1996, 1998, 1999, 2011 and 2012, with the data span throughout the years.

The measurement data in ASHRAE Global Thermal Comfort Database II are used as the comparison parameter to the air velocity values in m/s and the RH in percentage (%). For the Liverpool region, the measurement data shows that the average temperature is 21.18 ºC with a standard deviation of 1.60 and the RH value of 44.55 % with a standard deviation of 5.92. The average value of indoor air velocity is 0.06 m/s with a standard deviation of 0.05. Our simulation shows that for the Liverpool area, with an average temperature of 21 ºC and an indoor air velocity of 0.05 m/s, the RH is 44.52%. This result comparison can be seen in Table 8.

Table 8. Model Validation.

| | Simulation Result | | | ASHRAE Global Thermal Comfort Database II | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Area | Temperature (°C) | Relative Humidity (%) | Indoor Air Velocity (m/s) | Temperature (°C) | Std. Dev. | Relative Humidity (%) | Std. Dev. | Indoor Air Velocity (m/s) | Std. Dev. | Number of samples |
| Liverpool | 21 | 44.52 | 0.05 | 21.18 | 1.60 | 44.55 | 5.92 | 0.06 | 0.05 | 197 |
| United Kingdom | 22 | 40.63 | 0.05 | 22.67 | 1.93 | 41.87 | 13.14 | 0.07 | 0.06 | 14187 |
| | 23 | 38.70 | 0.05 | | | | | | | |

The global UK areas show that the mean of the RH is 41.87%, with a standard deviation of 13.14. This value is measured at the mean temperature of 22.67 ºC with a standard deviation of 1.93. The mean air velocity value is 0.07 m/s with a standard deviation of 0.06. Our simulation shows that for the average temperature between 22 ºC and 23 ºC with an indoor air velocity of 0.05 m/s, the RH is between 38.7% and 40.63%. The average RH value deviation is less than 2%, which justifies our simulation result.

### *4.4.2 Validation against the AI Model*

The other way to validate the model is by comparing it to the AI model using the ASHRAE database RP-884 and ASHRAE Global Thermal Comfort Database II. This model is fed with a temperature value of 22.67 ºC and humidity of 41.87%. Since, in the model, the air velocity parameter is omitted, the other parameters like the clothing insulation, activities and age are varied to capture the variability of the result. The value for the clothing insulation parameter is from 0 to 2.89, with an interval of 0.5. The value of activities ranges from 0.65 (sleeping) to 6 (very heavy work) with step 1. The age parameter is fed with 6, 36, 66 and 96 years. The combinations of parameters resulted in 144 combinations of data, with the data point in the psychrometric chart shown in Figure 33.

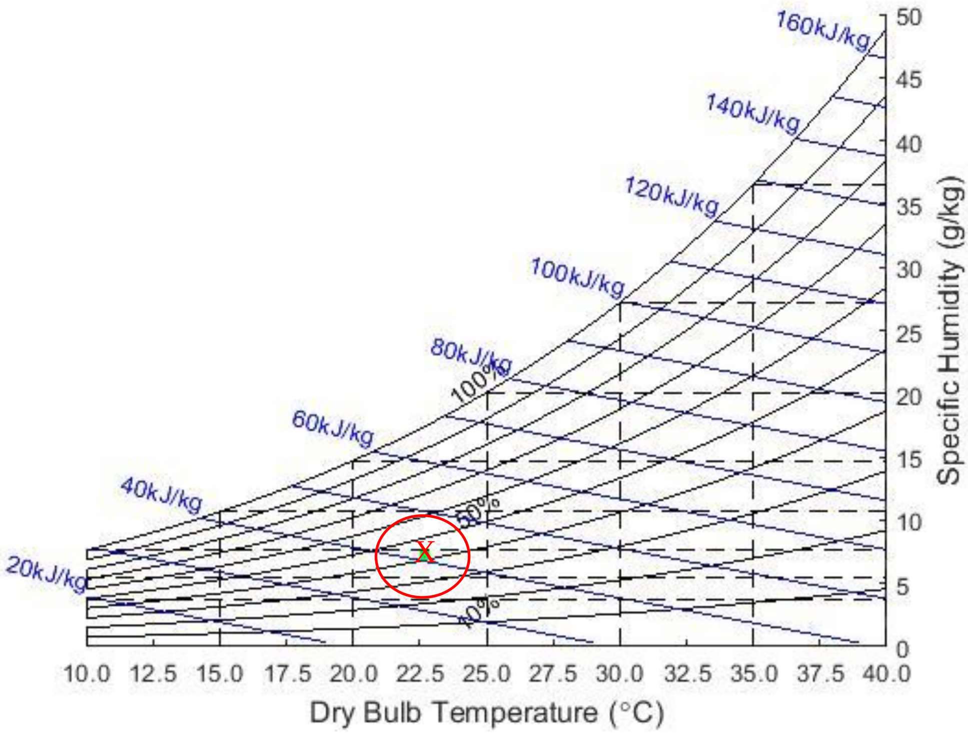



Figure 33. Mapping the validated value in the psychrometric chart.

The result of the AI model is analysed by observing the comfort percentage result from the AI model output. The validation used the assumption that the common clothing Insulation at home was 0.5 clo. The activities were assumed as sleeping and moderate work with a value of 0.65 to2.65 met. The occupants' ages assumptions were between 6 to 96 years. With these assumptions, the result of the comfort percentage was 100%. It means that all occupants were in a comfortable situation. This value justifies the result of the simulation. Other values are also interesting to be analysed. In this temperature and relative humidity value, the comfort percentage decreases if the clothing insulation value is higher than 0.5 or the occupants do heavy work (higher activity value). This highlights the recommendation for lowering the comfort temperature setting. The detailed result of the validation with the AI model can be seen in Table 9.

Table 9. Validation result with AI Model

| Conditions: | Percentage |
|---|---|
| All cases: Clothing Insulation: 0-2.5 clo; Activities: sleeping to heavy to very heavy work (0.65-5.65 met); age: 6-96 years | 65.97% |
| All seasons: Clothing Insulation: 0-1.5 clo; Activities: sleeping to heavy work (0.65-3.65 met); age: 6-96 years | 95.31% |
| Summer Clothing Insulation 0-1 clo; Activities: sleeping to moderate to heavy work (0.65-3.65 met); age: 6-96 years | 93.75% |
| Winter Clothing Insulation 1-2.5 clo; Activities: sleeping to heavy to very heavy work (0.65-5.65 met); age: 6-96 years | 61.45% |
| Common cases: Clothing Insulation: 0.5 clo; Activities: sleeping to moderate work (0.65-2.65 met); age: 6-96 years | 100.00% |

# Chapter 5 System Design

## 5.1 Perception of a Smart System

Based on the first survey, most participants that commented on the smart house, associated the smart house with a smart meter. Participants were interested in implementing sensors and were willing to invest more to lower their energy bills. Most of them who are aware of the concept of the smart house do not know the full capabilities of the smart house. When they know that the smart house will be able to do more, they say they want the solution. Based on this result, implementing an intelligent home system and spending more to lower the bills will be the driver of the system's acceptance. Only 6% of the people (5 respondents) reject the idea of using an intelligent system and paying more to lower their bills. If the majority want to pay more for the system, the acceptance of the system will be even higher if they do not have to purchase the system. A further question on their preferences about the system they wanted to have in their future home can be seen in Figure 34 (a).

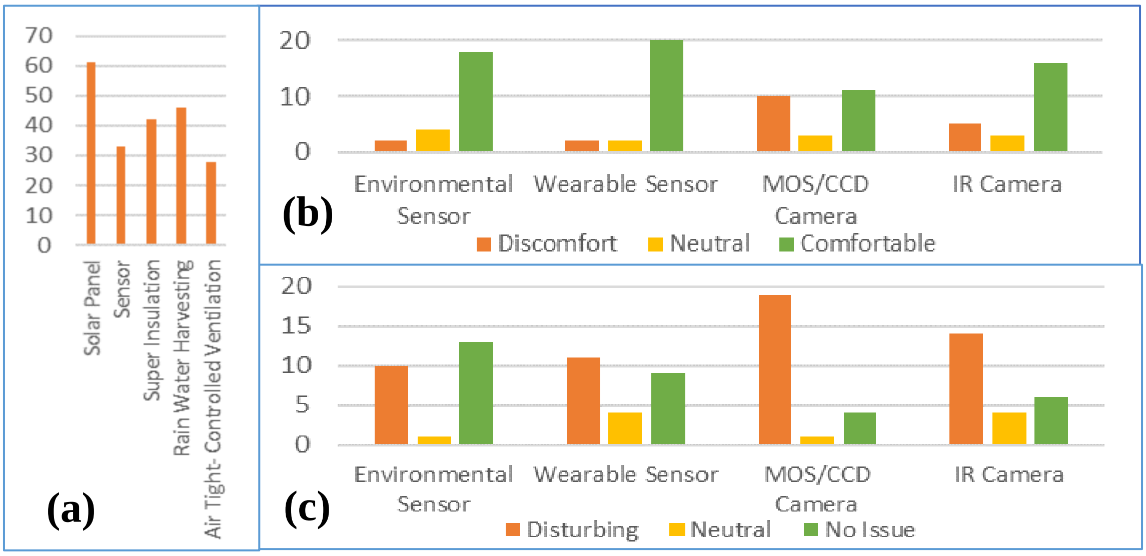



Figure 34. Survey on the perception of the intelligent system (a) future home features that occupants want (b) comfortability issue in sensor use (c) privacy issue in sensor use (Y axis represent number of respondents)

The solar panel is still the most commonly preferable solution for their future home. An additional sensor / smart system is still not popular, and people are still unclear about the sensor data, which will be related to their privacy. It is reflected in the result of the survey on the sensors employed by the smart home. The respondents who feel that there are no privacy issues are just about 2% higher than those who consider that the sensor will be intrusive.

Since the concept of sensors was not common for the respondents, the further questionnaire given to 24 respondents returned interesting results. The results of the comfortability aspect can be seen in Figure 34 (b). The questionnaire result shows that people are not very comfortable having the MOS/CCD Camera as their smart home sensors. The exciting finding is that people are still comfortable even when using the wearable sensor at home. This comfort might be due to the widespread use of smartwatches and fitness bands. The second aspect, the privacy issue, can be referred to in Figure 34 (c).

Based on the interview with eight participants from the group of 24, they feel that using sensors inside their homes will not breach their privacy as long as the data is well maintained. When they are introduced to the use of the IR thermal camera, most of them do not object. They feel their privacy will remain because the image cannot directly relate to them. They think the image results were funny and ask their children to be photographed using this camera. The questionnaire result says a bit different. The respondents still consider that privacy issues have become problems using some sensors. Even if the data are securely kept, they still do not want to use the CCD/MOS camera sensor type (the most untrusted on privacy) followed by the Thermal Camera and wearable sensor. There should be more elaboration for the smart home implementations regarding user education on the privacy aspects.

## 5.2 People with Special Needs and the Design

### *5.2.1 Adaptive Behaviour*

People naturally have adaptive behaviour to make a more comfortable environment condition. This action is known as self-adaptation. There are three types of adaptation. The first is a physiological adaptation, which represents the body’s reaction to the change in the surroundings. The second is psychological adaptation. This adaptation is derived from the state of mind of previous experiences. The third adaptation is related to human behaviour (Parsons, 2020 ).

### *5.2.2 Adaptive System*

Human comfort, particularly thermal comfort, is very personal. It can vary from person to person according to their condition and disability. Developing a personally customised system is very expensive. The framework review for personalised control is also presented to make the system perform the automatic task (O'Brien & Gunay, 2014). Automatic control, which aims to lower energy usage, has also been studied (Gunay, O'Brien, Beausoleil-Morrison, & Gilani, 2017; Nagy, Yong, & Schlueter, 2016). These systems focused on the implementation of the on-off system. The other parameter supporting energy saving, like blinds, can also be controlled automatically.

The adaptive system is the solution to develop a system that can cope with personal preferences. The system can be part of the Industry 4.0 development for supporting employees (Kanisius Karyono, Abdullah, et al., 2022). This system can adapt to personal preferences, increase human comfort, and increase productivity. Artificial Intelligence (AI) was used to acquire the system’s capability to be able to acknowledge adaptive thermal comfort. Neural Network is one of the preferred solutions for the core of the adaptive system. The various learning data from the ASHRAE multiple databases can lead to a unique response under specific circumstances. Using this system, the real user behaviour, which is unique, can be captured by the system.

## 5.3 Infrastructure Design

The infrastructure design approach uses the WSN to simplify the installation and allow system expansion and scaling. The infrastructure design can be seen in Figure 35. The lowest layer, or the edge, consists of the sensors and processor based on the ESP-32 WROOM modules programmed with the Arduino platform. This layer also contains the actuator that consists of the Solid-State Relay (SSR) to control the heater or air conditioner with the same processor based on the ESP-32 WROOM modules programmed with the Arduino platform. The sensors consist of two sensor types. The first type consists of a temperature and air quality sensor and a black globe sensor. The second type has the same temperature, air quality and black globe sensor component but has an additional PIR-based occupant's monitoring sensor and the thermal camera that can be used for future developments.

The second layer consists of the local control with the Raspberry Pi as the main local controller. The Raspberry Pi is running a local control program written in Node-Red. Moreover, the communication between these layers is being done using the MQTT protocol over a Wi-Fi connection.

The use of Raspberry Pi 3 Model B+ for the prototype was due to the product availability, but it is not mandatory. Any other brand or type of local controller with similar processor performance will be suitable because the algorithm used in the local controller is not heavy or require high computational performance. The AI algorithm of type Artificial Neural Network (ANN) is used based on this qualification. The local controller for residential has limited memory and computational power to form a low-cost system that was affordable for residential use.

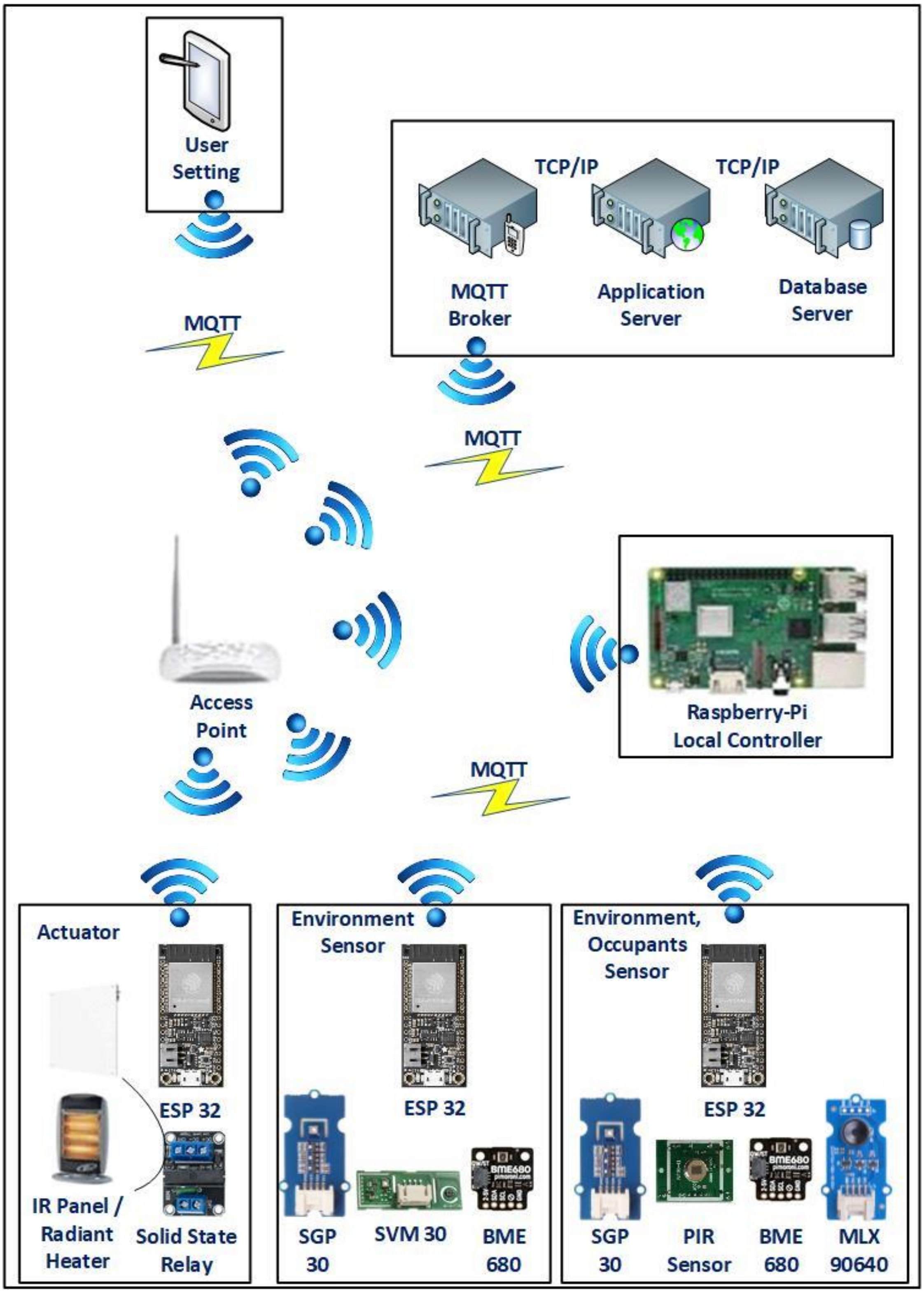



Figure 35. The Proposed System Diagram.

The highest layer is the server layer. In this prototype, the Application Server and the Database server are implemented using a single machine based on the Intel i5 processor. The database structure uses the MySQL-based database, and the data structure will be addressed in chapter 5.6. The application Server is also using a Node-Red-based program. For the user program, the application was developed using MIT App Inventor for cross-platform deployment possibility, which is the possibility to be deployed into user smartphones with different platforms such as Andriod-based smartphones and iOS-based smartphones.

The sensor hardware module diagram can be seen in Figure 36. The sensors are connected to the ESP-32 WROOM controller through the I2C communication protocol. I2C is a serial communication protocol whose primary connection includes the Serial Data (SDA) and Serial Clock (SCL). The other type of sensor module diagrams and actuator diagrams can be seen in Appendix 3. The flow chart of the sensor node can be seen in Figure 37, and the program of this sensor node can be seen in Appendix 4. The sensor node can enter the sleep mode to reduce the power usage. The sensor will automatically wake up according to the program and condition and perform its task. After completing the task, the sensor node will go to the sleep state again. This feature will be beneficial to conserving sensor node power, especially in this environment monitoring application where the data transmitted from the sensor is not very often. In this prototype, the period of each data transmission is once every15 minutes.

The local controller in the middle layer acts as an intermediary between the sensor/actuator layer and the server. The role is vital for the system to anticipate faulty communication to the server. In the case of faulty communication, the local controller can act as a temporary local server to handle the data and send the corresponding action to the actuator based on the algorithm stored in the local controller.

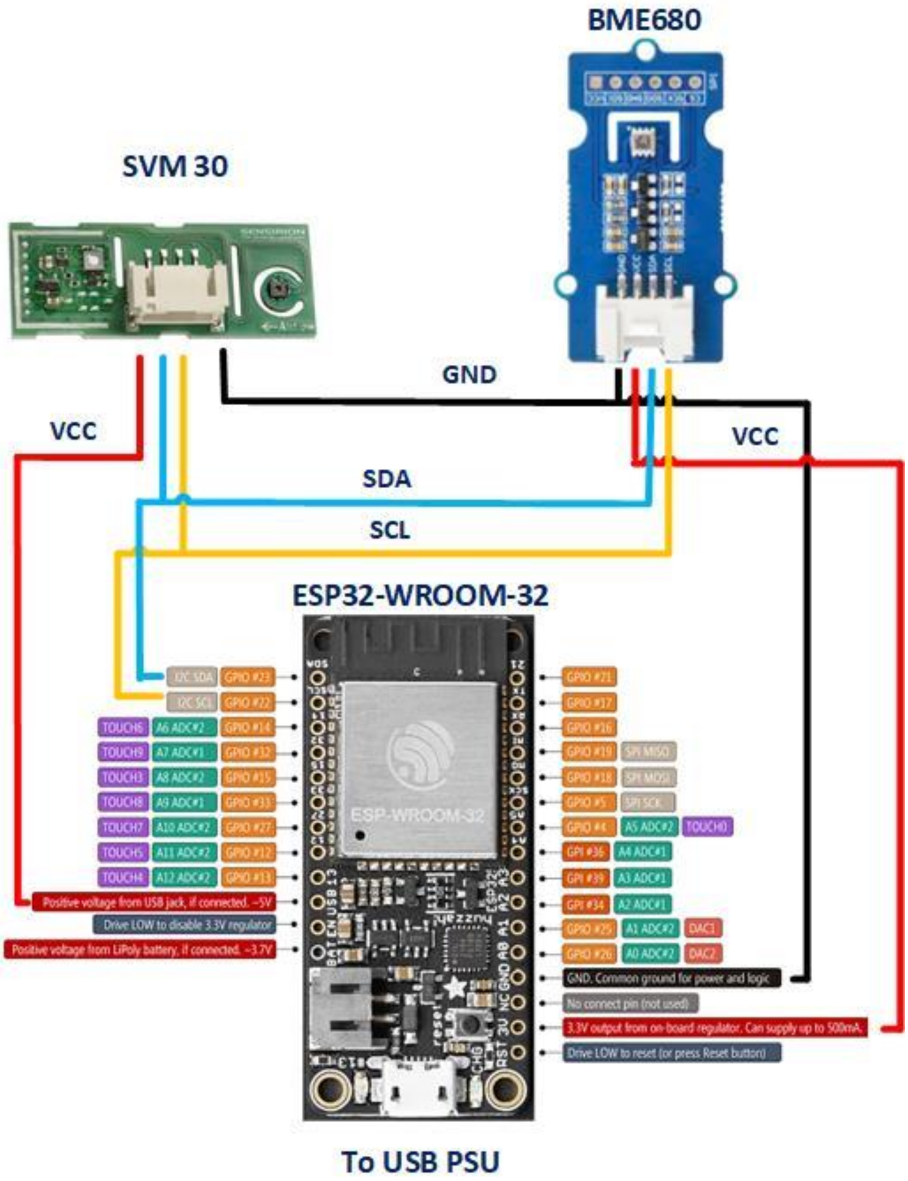



Figure 36 Standard sensor Module Diagram.

The flow chart of the local controller and the Node-RED program can be seen in Appendix 5. The web/application server program was also developed in Node-RED. Node-RED was originally developed by IBM for integrating hardware devices. This program is a flow-based development tool. This tool offers a visual programming development environment which provides modular libraries to be integrated into the program. The server receives the sensor data from the local controller through the MQTT protocol using Wi-Fi in this prototype. The server can also send the command to control the actuator via the same protocol. This protocol's implementation and connection methods can be altered according to the supporting infrastructure. The flow chart of the server and the Node-RED program can be seen in Appendix 5.

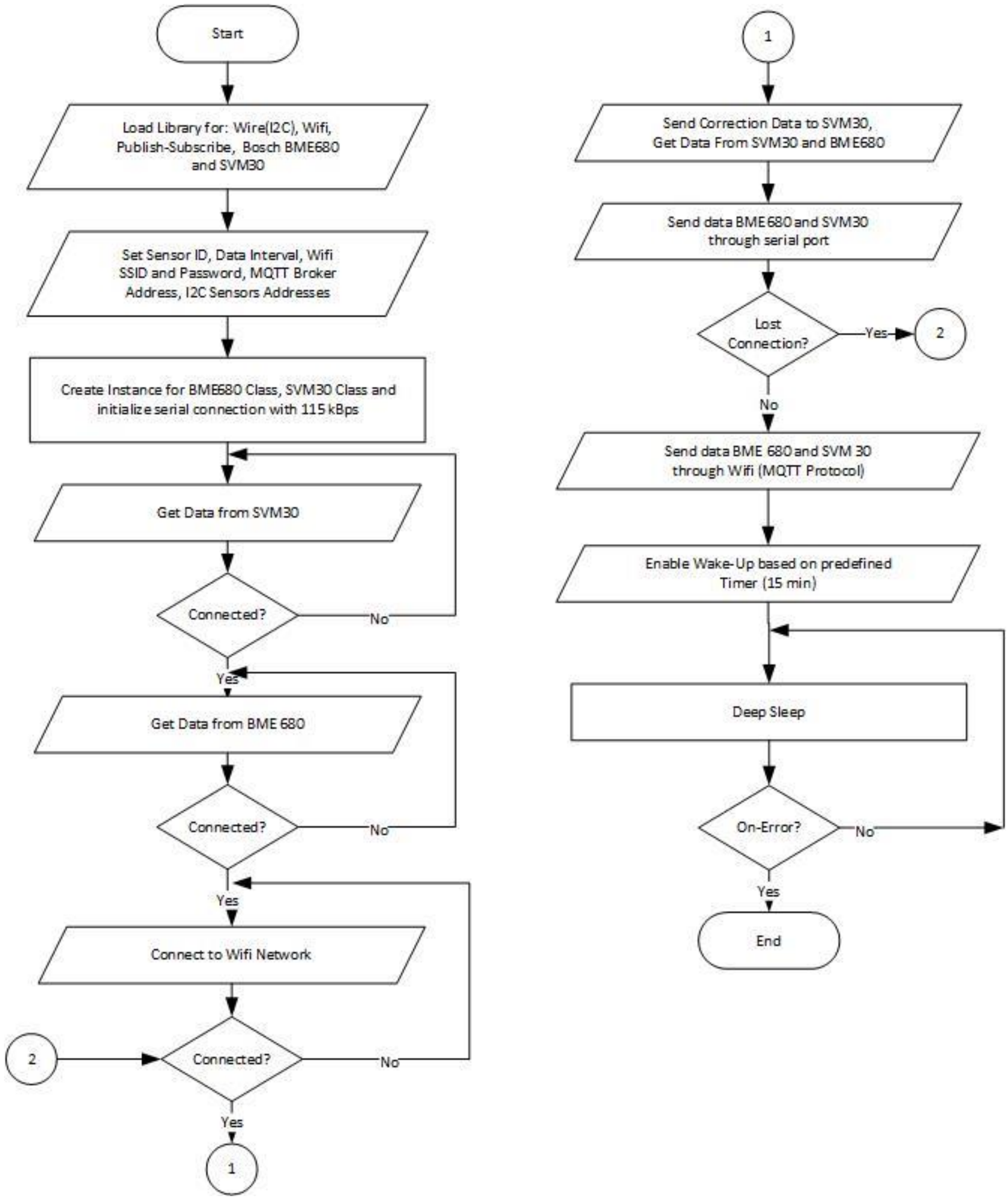



Figure 37 Standard Sensor Flow Chart

Cost was among the consideration of components selection and system design. The system was intended for residential implementation, so the low-cost approach was preferred. Based on Table 10, implementing 2 sensors of Humidity with Black Globe Temperature will cost £218.48, while the IoT-based sensors will cost £184.57. This shows that the cost of the IoT sensors is still comparable with the COTS offline sensors. This is to highlight that this fulfils the low-cost approach for residential dwellings. With mass production in the commercialization phase, the unit cost can be lower.

Table 10. The cost of the IoT system

| Component | Type | Price Each (£) | Link (last accessed at 20 July 2023) |
|---|---|---|---|
| Server | As a Service | | |
| Access Pont | TP-Link 1 Port Wireless AP 802.11 b/g/n | 30.00 | https://uk.rs-online.com/web/p/wireless-access-points/2558454 |
| Local Controller | Raspberry-Pi 3 B+ | 38.57 | https://uk.rs-online.com/web/p/raspberry-pi/1373331 |
| Sensor Nodes | ESP 32, SVM 30, BME 680 | 58.00 | https://uk.rs-online.com/web/p/sensor-development-tools/1845086,https://uk.rs-online.com/web/p/environmental-sensorics/1950685, https://uk.rs-online.com/web/p/communication-wireless-development-tools/1840479 |
| Actuator Nodes | ESP 32, i-Autoc Solid State Relay, 10 A | 36.30 | https://uk.rs-online.com/web/p/communication-wireless-development-tools/1840479, https://uk.rs-online.com/web/p/solid-state-relays/1025544 |
| PSU Plug-In AC/DC Adapter | XP Power 5W 5V dc Output, 1A | 5.27 | https://uk.rs-online.com/web/p/ac-dc-adapters/1217120 |
| **Offline** | **Type** | | |
| Offline Sensor 1 | Lascar EL-USB-2 Temp & RHumidity | 63.24 | https://uk.rs-online.com/web/p/data-loggers/4901064 |
| Offline Sensor 2 - BlackGlobe | Lascar EL-USB-1 Temperature Data Logger | 46.00 | https://uk.rs-online.com/web/p/data-loggers/4666115?gb=s |

## 5.4 User Interface Design

The user interface of this system is designed as to be as simple as possible and has only the essential components of the user interface for compatibility issues. The mobile application was developed using MIT app inventor, a web-based mobile application developer aiming to provide the native application through the web-based development environment. From their integrated development environment, the native code for the application, for example, Android, will be generated by the development tools. The web application aims to provide the native generated code for mobile, for example, Android and iOS. This developed application can be used to generate the essential parameters needed for thermal comfort analysis in a more precise value.

The user can set the clothing and calculate the clo value used in the AI system. The user also gets the suggestion from the application on what value is the best for winter and summer according to the ASHRAE standards 55. A similar feature is also applied to the activities. Users can enter their major indoor activities to be calculated, so the AI system can be adjusted to meet the user's major activities. This value is among the five most essential parameters in thermal comfort: age, clothing, activity/metabolism, temperature and humidity. The user interface design layout is shown in Figure 38.

## 5.5 System Flow

The system works by the user trigger. The trigger can be in the form of a user request from the application on their smartphone or their presence. These values will form rule-based and case-based reasoning to build core artificial intelligence (AI)(Aljaaf et al., 2018). The system will react based on the learning result of AI learning. Users can also give corrections directly to alter the system setting. This feature will make the system adaptive to user needs. The system flow of the adaptive thermal model can be seen in Figure 39.

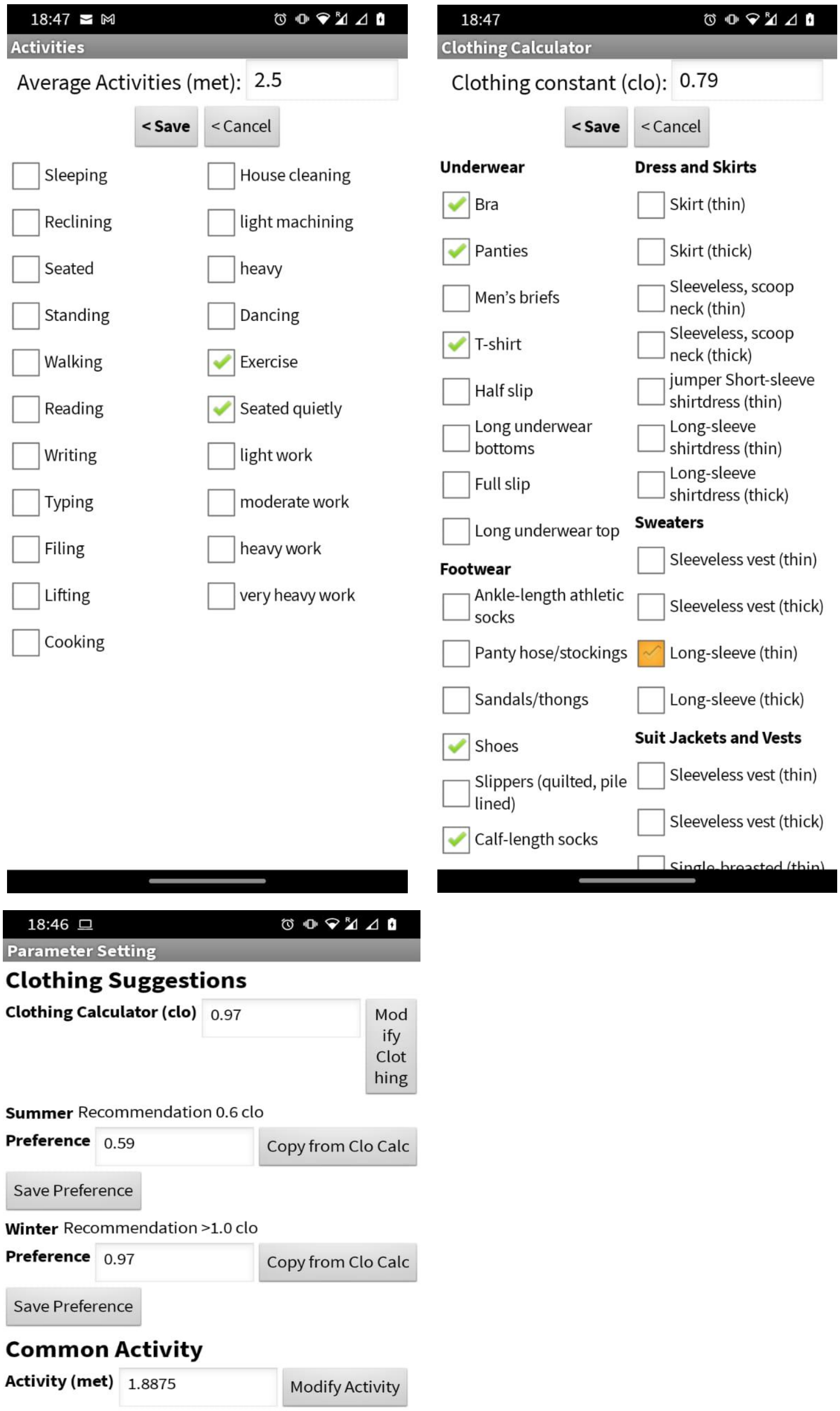
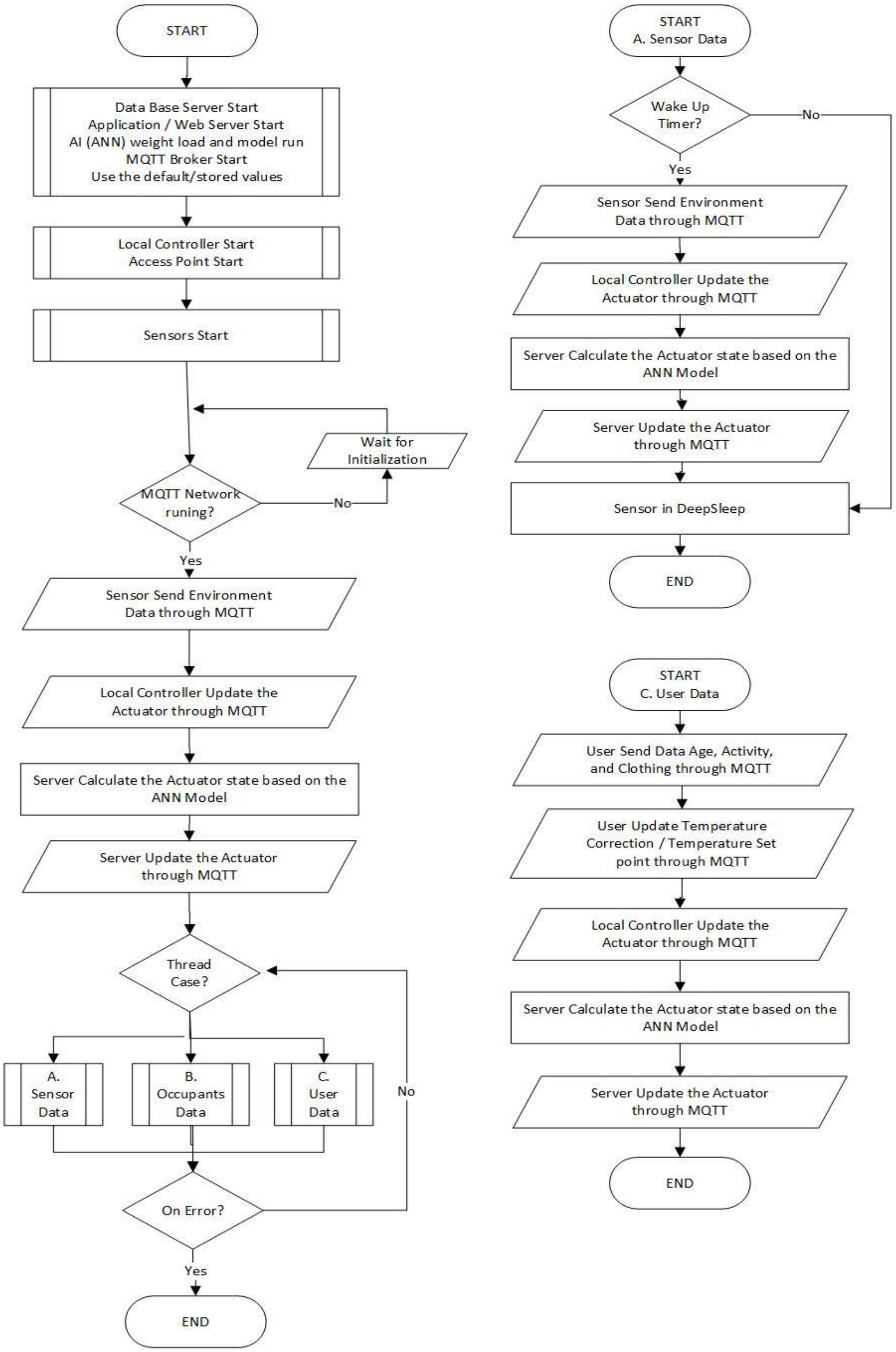



Figure 38. The User Interface for Clothing Suggestions and Activity Calculator.


START
Data Base Server Start
Application / Web Server Start
AI (ANN) weight load and model run
MQTT Broker Start
Use the default/stored values
Local Controller Start
Access Point Start
Sensors Start
Wait for Initialization
MQTT Network runing?
No
Yes
Sensor Send Environment Data through MQTT
Local Controller Update the Actuator through MQTT
Server Calculate the Actuator state based on the ANN Model
Server Update the Actuator through MQTT
Thread Case?
A. Sensor Data
B. Occupants Data
C. User Data
No
On Error?
Yes
END
START
A. Sensor Data
Wake Up Timer?
No
Yes
Sensor Send Environment Data through MQTT
Local Controller Update the Actuator through MQTT
Server Calculate the Actuator state based on the ANN Model
Server Update the Actuator through MQTT
Sensor in DeepSleep
END
START
C. User Data
User Send Data Age, Activity, and Clothing through MQTT
User Update Temperature Correction / Temperature Set point through MQTT
Local Controller Update the Actuator through MQTT
Server Calculate the Actuator state based on the ANN Model
Server Update the Actuator through MQTT
END

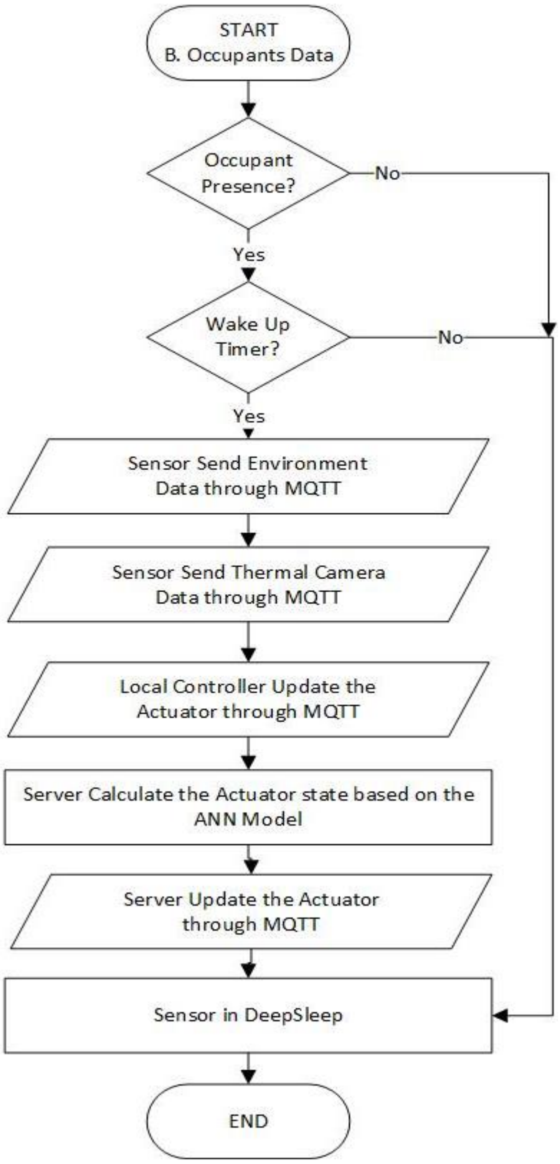



Figure 39. The Proposed Adaptive Thermal Model Flow Chart.

Thermal comfort is crucial to support the health and safety of all people groups. The young generation and mostly the elderly are susceptible to sickness because of heat- or cold-related causes (X. Ye et al., 2012). The wrong thermal arrangement can be fatal for some groups of people, especially in the GCC, when there can be sudden cold or hot waves. ANN can give the personalisation setting, but the result should be controlled and validated.

The system, targeted for precision and fault-tolerance and wanting to use ANN methods, now uses the novel approach called explainable artificial intelligence (XAI). The process can backtrack the learning process, to check whether it has the wrong interpretation (Samek W, 2018), (Joel Vaughan, October 2018). This process of tracking will require the use of excessive resources. Due to the limited processing power and memory, the devices used in the thermal comfort subsystems will have difficulties implementing this method. Strengthening the learning process for the neural network while still maintaining the processing power and memory usage will be challenging. This method is a work in progress for combining the human physiology and human behaviour methods (Fanger PMV-PPD model and the human behaviour AI system) to achieve a faster and more reliable solution for thermal comfort. Instead of backtracking the whole learning process, the PMV-PPD model can be used to check the training parameters and processes. If it deviates over certain levels from the standard or the comfort guidelines, the PMV-PPD equation can then be referred to validate the learning process involving the user or stored parameters. The learning process can be acknowledged by mapping to the PMV-PPD comfort map before the controlling result is sent to the controller for thermal correction actions. This method will enable the outliers to be validated and accommodated, increase security protection, lead to a more comfortable user, and gain more trust. This approach has the potential to perform better compared to the XAI approach. In the future, it will introduce a safer environment and a lower probability of error triggered by the limitations of AI and probably AI hacking. The diagram of the approach is presented in Figure 40.

The concern about the performance and the vulnerability of AI have been addressed, not only due to the poor performance and malfunction but also the intentional malicious attempt (Hamon et al., 2020). This work uses shallow supervised learning with the data source of learning from the ASHRAE multiple databases. With this prior system learning and the use of a large dataset, the possibility of poor performance of the result can be lowered, and the learning result has been validated using psychrometric chart mapping. The intentional malicious attempt can also be avoided because the model uses pre-trained ANN, and the base model has the weight and bias calculated using back propagation methods.

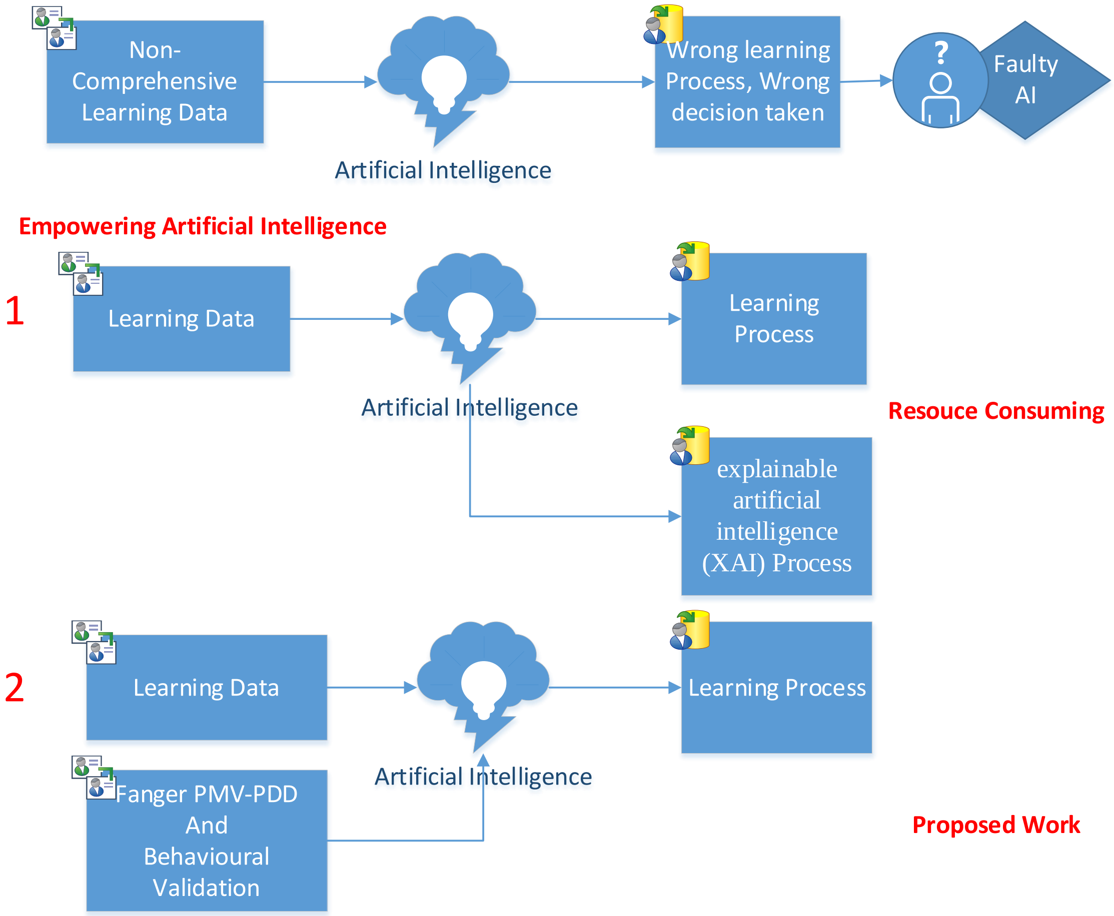



Figure 40. Proposed Solutions for Empowering AI using Fanger PMV-PPD and Behavioural Validation.

## 5.6 Database Design

The system uses the SQL-based database, which is deployed in MySQL. The prototype can also use the NoSQL type of the database, but in this stage of development, the SQL-based database was preferred. Data processing, searching, and analysis has often been done using general purpose software and the SQL-based database was preferred. The data The Entity Relationship Diagram of the database is shown in Figure 41. This diagram shows the relations between each item in the database that is grouped into fields of entities.

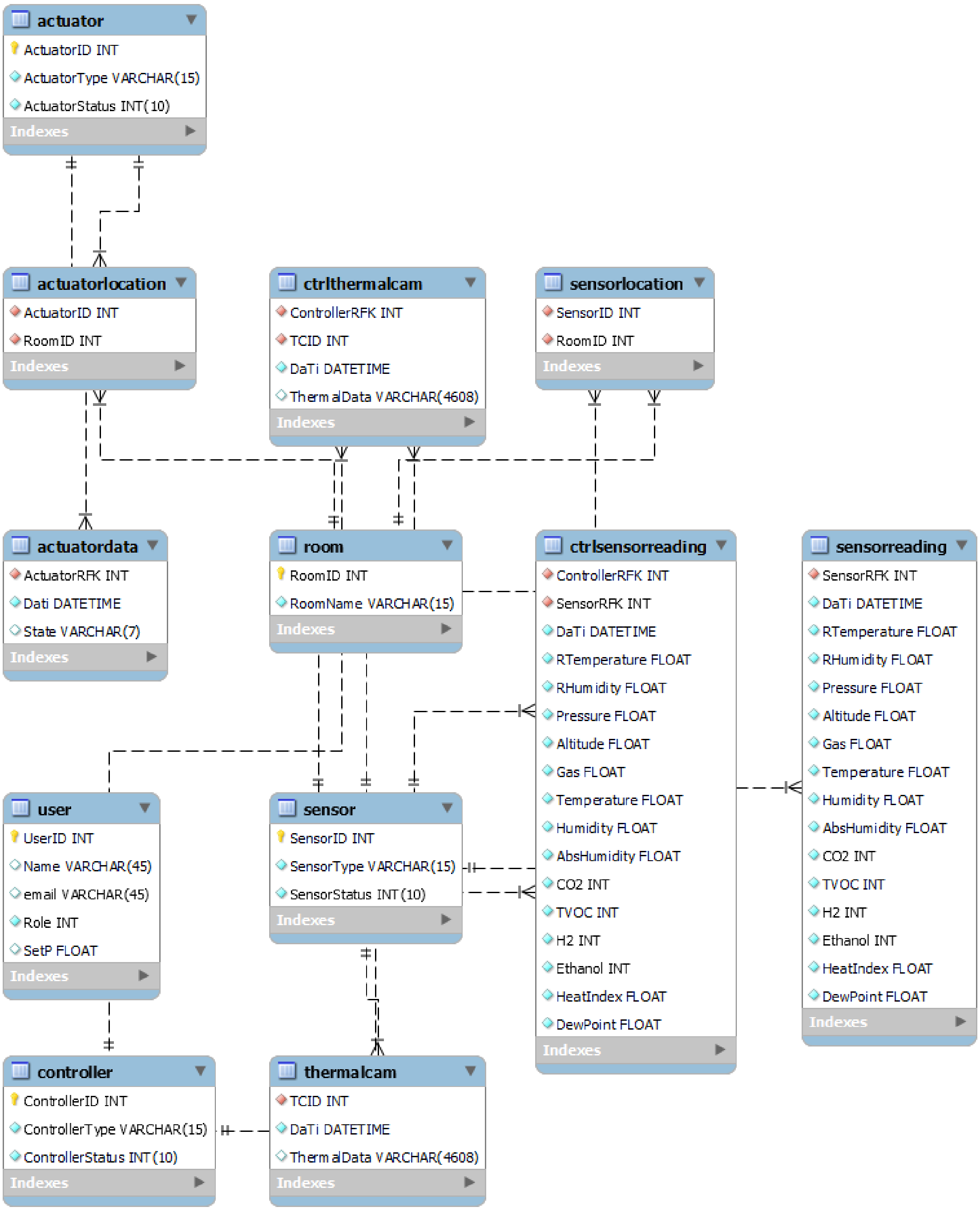



Figure 41. Database Entity Relationship Diagram.

# Chapter 6 Artificial Intelligence (AI)

## 6.1 The Development Gap

There has been much research to develop physiology and psychology (adaptive) approaches for thermal comfort until now but combining the two approaches is not an easy job. Due to the advancement in artificial intelligence (AI) technology, combining both approaches is now becoming possible. This work aims to elaborate on the human physiology and adaptive approaches to harvesting their benefit for better energy conservation whilst maintaining human comfort.

This work implements shallow supervised learning based on ASHRAE multiple thermal comfort databases as the training databases for the artificial neural network. The AI-based algorithm will calculate the thermal comfort state of the occupant in real time based on the network of sensors and do the thermal adjustment by turning the heater on or off.

This work also proposes new validation methods to check the learning process in the AI system for thermal comfort based on the psychrometric chart. This validation is crucial to avoid overfitting problems and minimise the need to use the explainable AI, which is not simple to be deployed on the Internet of Things (IoT) based system and still requires much research. Auburn's Nguyen even mentions that the field of explainability is getting somewhat stuck (C. Q. Choi, 2021).

## 6.2 The ASHRAE Databases and Supervised Learning

The AI part uses the most comprehensive thermal comfort data set, ASHRAE RP-884 and ASHRAE Global Thermal Comfort Database II. These databases are available online as open-source databases. The ASHRAE RP-884 consists of 25,616 entries, and ASHRAE Global Thermal Comfort Database II includes 81,967 entries (Földváry Ličina, Cheung, Zhang, de Dear, Parkinson, Arens, Chun, Schiavon, Luo, Brager, Li, & Kaam, 2018). This data set consists of objective indoor climatic observations and subjective questionnaire-based evaluations. The data were taken from the field experiments with the people doing their activities. The data even captured the PMV-PPD values; these values differed from the Fanger experiments done in the controlled indoor environment of a climate chamber (Földváry Ličina, Cheung, Zhang, de Dear, Parkinson, Arens, Chun, Schiavon, Luo, Brager, Li, Kaam, et al., 2018).

This data set will benefit the AI system developer rather than getting the value based on their own data gathering. Doing their own data collection will require the calibrated sensors equipment, the subject's consent and awareness of the thermal sensation and the subject questionnaire. The data collection also should be done in the different environmental conditions and building types to get a broad combination of training data. Controlling all these parameters is challenging in field studies. On the contrary, measuring these parameters in the climate chamber will be easier but not represent the building types and the actual occupants’ conditions. There is also the approach to using the simulated or generated data but validating the data can trigger another hurdle.

The ASHRAE database comprises different cities and countries, seasons, climate zones, building types, cooling, and heating strategy, and personal information about the subjects. This personal information includes sex, age, height, and weight. Other subjective essential factors are thermal sensation, acceptability, and preference. These subjective factors are taken with specific metabolic rate (met) and clothing insulation level (clo). The comfort indices such as PMV, PPD and Standard Effective Temperature (SET) were calculated uniformly and included in the database. The parameter measurements included in this data set are various temperatures, air velocity, relative humidity, and monthly average temperatures. Some indoor environmental controls include blinds, fans, operable windows, doors, and heaters (Földváry Ličina, Cheung, Zhang, de Dear, Parkinson, Arens, Chun, Schiavon, Luo, Brager, Li, Kaam, et al., 2018).

This data set has developed many approaches to predicting Thermal Sensation (PTS) (Ji, Zhu, & Cao, 2020) regarding the location. Another recent model based on this database is done to assess the PMV-PPD accuracy against the database (Cheung, Schiavon, Parkinson, Li, & Brager, 2019). This work concludes that accuracy varied enormously between ventilation, building types and climate. The authors have seen this gap to propose better models using the power of AI.

ASHRAE Global Thermal Comfort Database II consists of data from Europe (31,392 entries), Asia (29,064 entries), America (17,359 entries), Africa (2,163 entries), and Australia (1,868 entries). It includes field study data from 23 countries. This database covered 16 distinct Köppen climate classes. They are hot-summer Mediterranean (23,192 entries), humid subtropical (15,536 entries), hot semi-arid (8,471 entries), tropical wet savanna (6,633 entries), warm-summer Mediterranean (5,980 entries), temperate oceanic (4,968 entries), Monsoon-influenced hot-summer humid continental (3,809 entries), warm-summer humid continental (2,990 entries), hot desert (2,084 entries), tropical monsoon (2,075 entries), monsoon-influenced humid subtropical (1,588 entries), cool-summer Mediterranean (1,408 entries), subtropical highland (1,406 entries), tropical rainforest (963 entries), cold semi-arid (312 entries), and tropical dry savanna (152 entries) climate zones. Related to the season of the data collection, the observations were conducted in summer (30,545 entries), winter (30,440 entries), spring (9,455 entries) and autumn (9,177 entries).

In supervised learning, the role of the training data is crucial. Getting the field data during the system initialisation is not practical because the amount and variety of data will not be adequate. This approach will not give a comfortable experience for the user.

In order to accommodate this, a previous study has been done on developing the intelligent system using the previous ASHRAE database.

Previous studies have shown that the AI approach using the ASHRAE RP-884 has limited diversity and unbalanced distribution. This unbalanced distribution results in a model which is not reliable in extreme conditions (Zhou et al., 2020). This work uses 20,954 data entries from 25,616 entries after data cleansing. The other research uses ASHRAE Global Thermal Comfort Database II, which consists of a more significant amount of data (Luo et al., 2020). The other works use the combination of ASHRAE RP-884 and ASHRAE Global Thermal Comfort Database II (Z. Wang, Zhang, et al., 2020) (Z. Wang, Wang, et al., 2020). However, in the previous research, the data items are selected to represent each class or label. This selection is because the more extensive data does not guarantee higher accuracy and can cause overfitting issues (Luo et al., 2020).

Not all data from this data set can be directly elaborated in the training data. This limitation is due to the nature of the human psychological factor that the thermal comfort is personal or individual (Z. Wang, Zhang, et al., 2020). The ambiguity of the data inconsistency can be high. The previous work considers this data illogical and an anomaly (Z. Wang, Wang, et al., 2020). From the 107,583 entries, this work only uses 16,795 based on four thermal metrics. The work by Luo also populates only 10,618 entries out of 81,967 (Luo et al., 2020). This work uses the thermal sensation vote (TSV) to label the learning target. Eighty per cent of the data are allocated for training and 20% for testing. This work also mentions that allocating more data percentages for testing can decrease accuracy, indicating the lack of data available for training.

The work by Luo discovered that even with 66,3% maximum accuracy using the Random Forest, the approach already got 10–20% higher prediction accuracy than the PMV model. The model also got 60–66% for 3-point TSV accuracy and 52–57% for 7-

point TSV prediction (Luo et al., 2020). This work also introduced the six most influencing variables: temperature, relative humidity, clothing insulation, airflow speed, subject age, and activity/metabolism level. The work from Wang also has a similar result. The scalability and sample number are limitations, although the accuracy can be increased to 87% (Z. Wang, Wang, et al., 2020). The accuracy in predicting thermal acceptability is also higher than thermal preference.

Learning from the previous work based on the ASHRAE Database, this work proposes the uses of the database, which are:

- based on the TSV for the learning target, where three labels for the thermal conditions are used (no change, prefer warmer and prefer cooler)
- uses as much entries data as possible and does not pick pointing data to represent as many individual variations or preferences as possible
- compare the use of the four and five most significant variables, which are temperature, relative humidity, clothing insulation, activity/metabolism level, and subject age
- uses simple filtering to minimise the ambiguity of data by considering the psychological aspect of human

Although the ASHRAE data set is the most comprehensive, using the whole data set for training data is not popular due to the psychological factors present in the data, decreasing the accuracy of the result. This work fills the data conditioning gap to prepare the data to become the training data. This work also uses three-state TSV, simplifying the result to control the heating or cooling (no change, warmer and cooler).

## 6.3 Data Filtering

This work focused on the shallow learning AI for controlling, for example, the electric radiant panel to be deployed as part of the Internet of Things (IoT) system for the residential house. This work is focused on the three TSV values or the thermal preference (no change, warmer and cooler). The diagram that shows the methodology of this work is shown in Figure 42.

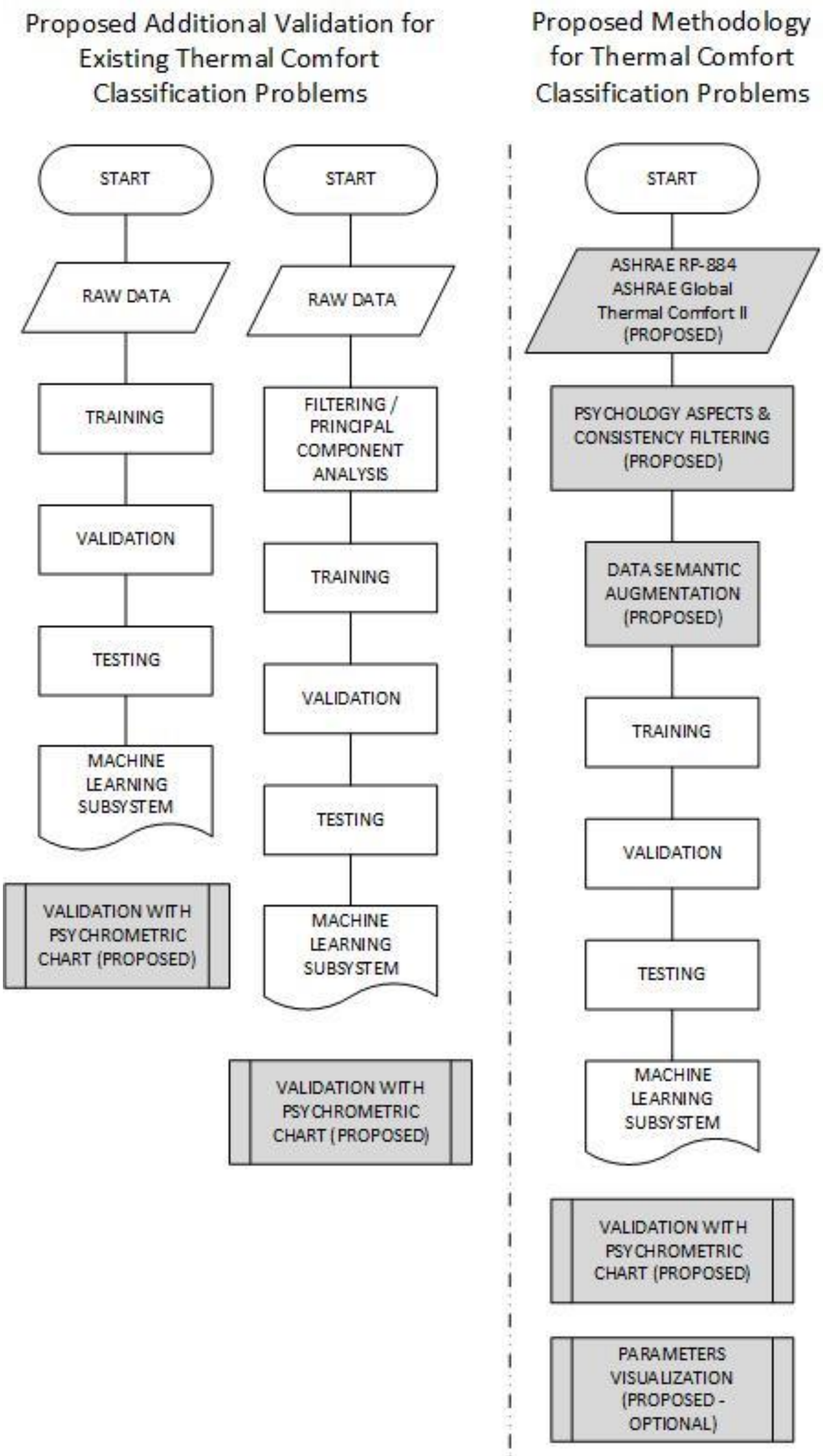



Figure 42. Proposed validation methods and proposed methodology for thermal comfort AI training

The ASHRAE database was used for the training data source, and the filtering process is applied to maintain the data consistency without eliminating the psychological aspect variations in the data. The semantic augmentation process is added to the data to balance the feature and enrich supervision learning. This work will implement four and five parameters from six dominant parameters due to the availability of IoT sensors.

This work proposes to check the AI learning result using a psychrometric chart. Testing the learning process using the testing data will not be sufficient to check the training result. Visual result validation with the psychrometric chart using a predefined input range to map the thermal comfort zone will result in a higher confidence level in the system. Further, with this visual validation, the parameters can be mapped to view the characteristic of each parameter regarding the impact on thermal comfort. The human psychological/behavioural aspects can be shown on this map.

Previous works that use the ASHRAE database did not use the complete entries, but selected entries based on each class to achieve balanced features. The data used for training was only less than 20% of the whole ASHRAE database. This selection makes the human psychological aspects not easily captured by the supervised training. On the other hand, the risk of overfitting is also implied in using this database. That is why this database is the most reliable for thermal comfort. Since it was published, few AI developers have been willing to use this data to develop their AI systems.

This work proposes simple yet powerful methods to filter the data based on human perception consistency. The need for filtering is because the data was based on precise measurement, but the human perception data was based on the questionnaire that was more prone to error and subjective judgment than the measured data. This filter worked based on the comparison of parameters and omitted the data that is considered to be inconsistent as follows:

1. The filtering is based on the consistency between the thermal acceptability (0 unaccepted 1 accepted) and thermal preference (warmer, no change and cooler). The warmer and cooler should have the thermal acceptability value of 0, no change should have the value of 1.
2. The filtering is based on the consistency between the thermal acceptability (0 unaccepted 1 accepted) and thermal sensation (-3 to +3). The value between -2 and 2 should have the thermal acceptability value of 1, and the other should have 0.
3. The filtering is based on the consistency between the thermal sensation (-3 to +3) and thermal preference (warmer, no change and cooler). The thermal sensation value of less than -2 should correspond with warmer, and more than 2 should associate with cooler. The state of no change should have a value between -2 and +2.
4. The filtering is based on the consistency between the thermal preference (warmer, no change and cooler) and thermal comfort (1-very uncomfortable, 6-very comfortable). The value 1-very uncomfortable should not have the value of no change. The value of 6-very comfortable should not have the value of warmer or cooler.
5. The filtering is based on the consistency between the thermal sensation (-3 to +3) and thermal comfort (1-very uncomfortable, 6-very comfortable). The 1- very uncomfortable value should not have the value of -2 to +2. The thermal comfort value of 6-very comfortable should not have the thermal sensation value below -2 or more than 2.

The target labels for the AI are based on the three states of TSV, -1 means that the occupants need a warmer indoor environment, 1 means that the occupants need a cooler temperature and 0 means that the occupants are satisfied with the indoor temperature.

This approach is the most straightforward arrangement for the subject because they are still comfortable in the current temperature, need a lower temperature, or need a warmer temperature.

Not many people can define their thermal preferences using seven scale levels. There is no crisp border between each scale, and even the same temperature can be mapped into the different seven-scale TSV. The border between these three scales is not crisp either. However, this map will better understand people’s thermal sensations due to its simplicity.

Previous research shows that there are six dominant parameters, and compared to the complete twelve parameters, it only increases by 2.6% in the performance compared to elaborating six dominant parameters (Luo et al., 2020). The IoT low-cost sensors can detect two of six dominant parameters: temperature and relative humidity. The occupant data entries can introduce the clothing insulation, metabolic rate or activities, and age. Low-cost sensors do not easily detect air velocity. This work also tried to narrow the parameters into five for easier deployment with a residential IoT system. The precise air velocity sensor and the sensor placement will not be feasible for the residential IoT system. This work will give the overview that even without the air velocity sensor, the result of the AI will still be acceptable.

Furthermore, the system which omits the parameter of age is also explored. This exploration is due to the high availability percentage for age unavailability in the ASHRAE database. The missing data for the five dominant parameters in the ASHRAE database can be seen in Table 11.

Data filtering aims to use the data entries from the ASHRAE database as much as possible by removing the inconsistent data while still capturing the psychological aspects of human comfort registered in the database. This filtered data can be used as a base training data so that the AI developer does not have to capture their data which needs much effort or will decrease the occupants' comfort. The user can then override the setting of the system with their personal preferences. Their personal preferences can be entered in the later stage of the system development.

Table 11. Missing data for the five dominant parameters in the ASHRAE database

| Dataset Name | Number of entries | Missing Data Entry | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Tempera-ture (items) | Tempera-ture in % | RH (items) | RH in % | Clothing (items) | Clothing in % | Age (items) | Age in % | Metabolic rate (items) | Metabolic Rate in % |
| ASHRAE RP-884 | 25616 | 3816 | 14.90 | 761 | 2.97 | 332 | 1.30 | 6899 | 26.93 | 2164 | 8.45 |
| ASHRAE Global Thermal Comfort Db II | 81967 | 3856 | 4.70 | 9060 | 11.05 | 7588 | 9.26 | 57105 | 69.67 | 15000 | 18.30 |
| TOTAL | 107583 | 7672 | 7.13 | 9821 | 9.13 | 7920 | 7.36 | 64004 | 59.49 | 17164 | 15.95 |

The number of data entries filtered in each filtering item in the ASHRAE database can be seen in Table 12. The ASHRAE RP-884 database has 25,616 entries, and the ASHRAE thermal comfort database II (1995 – 2015) has 81,967 entries. After the filtering process, the amount of data in ASHRAE RP-884 is 14,970, with filtered entries of 10,646 or 41.56%. The ASHRAE Thermal Comfort Database II entries are 50,286 after the filtering process, with the filtered value of 31,681 entries or 38.65%. In total the ASHRAE database after filtering is 65,256 entries or 60.66% (filtered value is 42,327 entries or 39.34%). This entry has at least three times as much data as the previous work. More elaborated data means the system can better capture the occupants' variations. The risk of overfitting can be eliminated with further processing of the data.

The filtering consists of five inconsistency checks. The simple algorithm for filtering is as follows:

**Algorithm 1**: Simple Data Filtering for the ASHRAE Database

```
//% simple filtering based on five inconsistency check
// entry will be marked as 0 to be filtered / excluded from the database
// the field with "NA" entries will be skipped
// TA=THERMAL_ACCEPTABILITY (0 unaccepted, 1 accepted)
// TP= THERMAL_PREFERENCE (warmer, no change, cooler)
// TS= THERMAL_SENSATION (-3 .. +3).
// TC= THERMAL_COMFORT (1-very uncomfortable .. 6-very comfortable)
Input: ASHRAE database
for ctr=1 to size (ASHRAE database) do
    //%ThermalAcceptability vs ThermalPreference
  IF (TA=1 and TP="no change") return 1
          ELSEIF (TA=0 and TP="cooler") return 1
                  ELSEIF (TA=0 and TP="warmer") return 1
                              ELSEIF (TA="NA" or TP="NA") return "NA"
                                        ELSE return 0
   //%ThermalSensation vs ThermalAcceptability
  IF (TA=1 and ABS(TS)>2) return 0
          ELSEIF (TA=0 and ABS(TS)<=1) return 0
                    ELSEIF (TA="NA" or TS="NA") return "NA"
                              ELSE return 1
   //%ThermalSensation vs ThermalPreference
  IF (TP="warmer" and TS<-2) return 1
          ELSEIF (TP="cooler" and TS>2) return 1
                  ELSEIF (TP="no change" and ABS(TS)<=1) return 1
                    ELSEIF (1<TS<2 and (TP="cooler" or TP="no change")) return 1
                              ELSEIF (-2<TS<-1 and (TP="warmer" or TP="no change")) return 1
                                        ELSEIF (TS="NA" or TP="NA") return "NA"
                                                  ELSE return 0
    //%ThermalComfort vs ThermalPreference
  IF (TC=1 and TP= "no change") return 0
          ELSEIF (TC=6 and (TP="cooler" or TP="warmer" )) return 0
                    ELSEIF (TP="NA" or TC="NA") return "NA"
                              ELSE return 1
   //%ThermalComfort vs ThermalSensation
  IF (TC=1 and ABS(TS)<=2)  return 0
          ELSEIF (TC=6 and ABS(TS)>2) return 0
                    ELSEIF (TC= "NA" or TS="NA") return "NA"
                              ELSE return 1
end for
Output: Marked ASHRAE database (the data marked with 0 will be filtered/excluded from the database)
```

Table 12. The number of data entries filtered in each filtering item in the ASHRAE database.

| Dataset Name | Number of entry | IC1 | % IC1 | IC2 | % IC2 | IC3 | % IC3 | IC4 | %IC4 | IC5 | %IC 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ASHRAE RP-884 | 25616 | 3051 | 11.91 | 1564 | 6.11 | 10192 | 39.79 | 192 | 0.75 | 129 | 0.50 |
| ASHRAE Global Thermal Comfort Db II | 81967 | 14236 | 17.37 | 10393 | 12.68 | 27341 | 33.36 | 1106 | 1.35 | 326 | 0.40 |
| TOTAL | 107583 | 17287 | 16.07 | 11957 | 11.11 | 37533 | 34.89 | 1298 | 1.21 | 455 | 0.42 |

Filtering items:
(IC1) Inconsistency 1: Thermal Acceptability vs Thermal Preference
(IC2) Inconsistency 2: Thermal Sensation vs Thermal Acceptability
(IC3) Inconsistency 3: Thermal Sensation vs Thermal Preference
(IC4) Inconsistency 4: Thermal Comfort vs Thermal Preference
(IC5) Inconsistency 5: Thermal Comfort vs Thermal Sensation

After filtering, the amount of data in ASHRAE RP-884: 14,970 (filtered value: 10,646 or 41.56%)
After filtering, the amount of data in ASHRAE Thermal Comfort Database II: was 50,286 (filtered value: 31,681 or 38.65%)
The Total data in both data set are 65,256 (filtered value: 42,327 or 39.34%)

The database that has been filtered is mapped and compared with the original ASHRAE database. Figure 43 shows the mapping with the temperature as the x-axis and relative humidity as the y-axis. The original database map is shown on the left, whereas the filtered database is on the right. This figure shows the data mapping based on the three TSV class groups, which are “no change”, “warmer”, and “cooler”. The ASHRAE database is shown to have major overlaps between classes. This significant overlap is the cause of the difficulties in training the AI using this database. It is challenging to have a proper classification process with the risk of overfitting.

The class overlap is reduced with the filtered data, as shown on the right side. This method gives the learning process a better chance to generate better training results for proper classification. The mapping position between the “warmer” and “cooler” classes looks physiologically better than the original database. The other parameters map can be seen in Appendix 6. The figure in Appendix 6 shows the database map for clothing insulation against the indoor temperature, the occupants’ activity/metabolism against the indoor temperature and the occupants' age against the indoor temperature. Like the relative humidity and temperature map, the classes in these parameters have a better condition to be classified after the database filtering process.

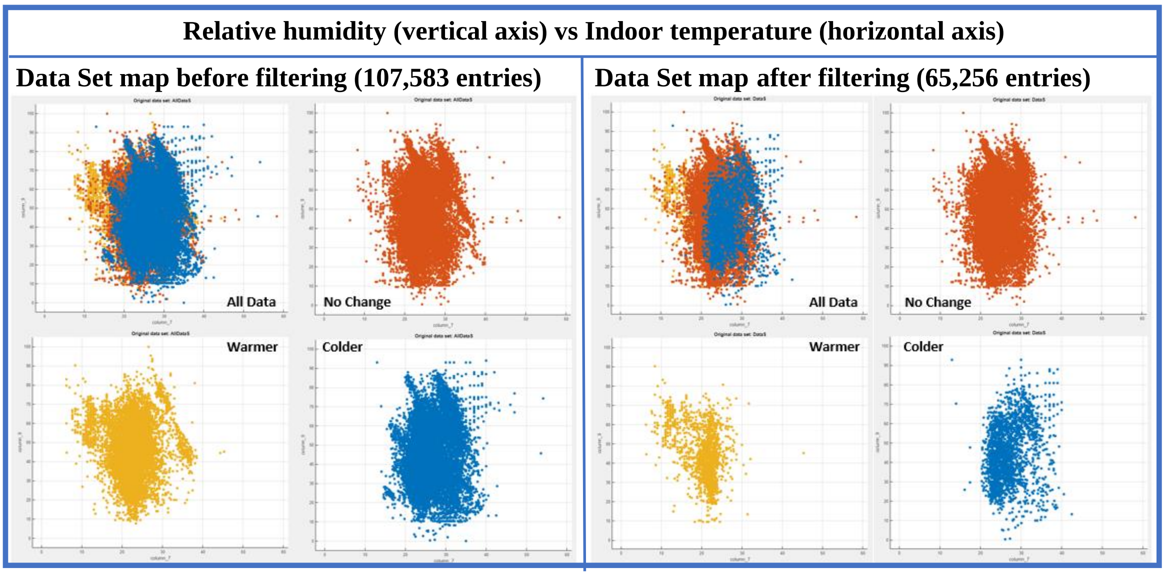



Figure 43. The ASHRAE Database Mapping for Relative Humidity vs Indoor Temperature Before Filtering and After Filtering

This map also shows a gap in the data availability for the "warmer" and "cooler" classes. Not only to make the feature space to be equal. Furthermore, the system needs a different range of data to be registered in the database for the "warmer" and "cooler" classes. It needs more data outside the comfort temperature zone for a better learning process. The answer to this problem is semantic augmentation.

## 6.4 Data Semantic Augmentation

Getting the data for thermal comfort training is not easy. It requires the proper instruments and consent from the occupants. Most of the entries in the ASHRAE database fall under the "no change" label (43,441 entries). Only about 14,966 entries need a warmer temperature, and about 27,093 need a cooler indoor temperature. This case is similar to the image processing and classification problem with highly imbalanced data. The training data for supervised methods are usually difficult to collect due to the costly human efforts and particular domain expertise.

A data augmentation strategy is introduced to balance the feature space and enrich supervision. The augmentation strategy can normalise the supervision process to improve the robustness by embedding such that the features of the same instance under different augmentations should be invariant and forcefully separated from the other instance features (M. Ye, Shen, Zhang, Yuen, & Chang, 2020).

The previous work shows that data augmentation can be more powerful in the image classification problem if the class identity is preserved, for example, with semantic transformations. Each class in the training set can be added with the samples from the generator. The procedure is computationally intensive and lengthens the training procedure. The training set data can be effectively augmented by searching the semantic directions. The random directions that may result in the meaningless transformation can be reduced (Y. Wang et al., 2021).

This work aims to develop data augmentation using the approach of semantic data augmentation. The class “no change” remains untouched while the “warmer” and “cooler” classes are added with the data in the semantic direction of the value that is not covered by the ASHRAE database. The “warmer” class is augmented with the lower temperature value under the value of mapped ASHRAE data. On the contrary, the “cooler” class is augmented with the data, which is higher than the mapped ASHRAE data. This method helps to balance the feature space to enrich the supervision. The benefit of this method is that the data obtained from the ASHRAE database is unaffected due to the non-overlapped semantic augmentation direction. In this case, the data related to the psychological aspects are still maintained, and the essence of using the ASHRAE database is sustained.

The base for semantic augmentation is the temperature data. This data is chosen because the class that needs the augmentations are “warmer” and “cooler”. The data map for "warmer", "no change", and "cooler" are shown in Figure 44.

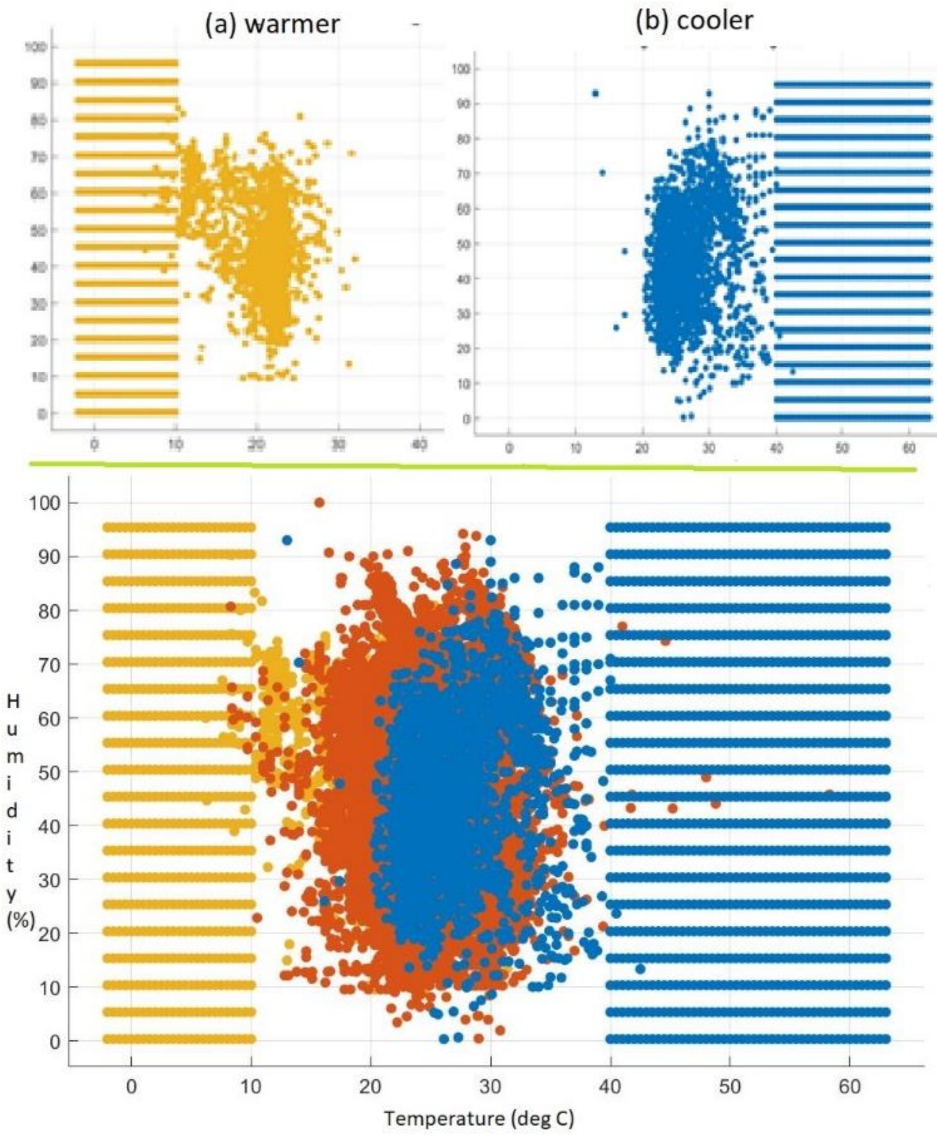



Figure 44. Database map after the filtering process and semantic augmentation: (a) warmer class (b) cooler class.

The class “no change” remains untouched due to the adequate data, and the augmentation process for this class might introduce errors to the existing measurement data. Figure 44 shows the map of both classes, the augmentation, and the data map. This method also retains the psychological aspects and the accurate measurements in the ASHRAE database.

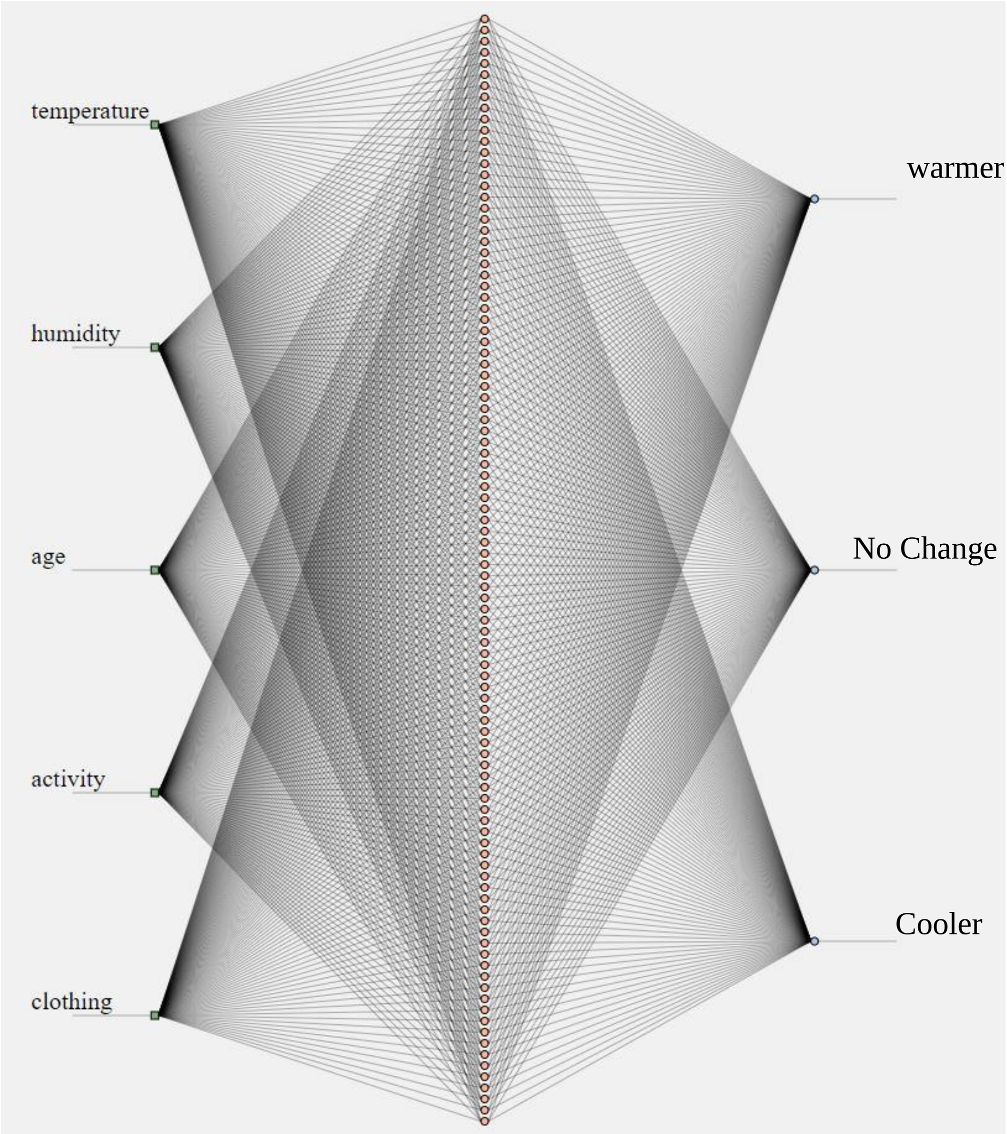
The augmentation data range was decided based on the notion that the augmentation data will not change the original data obtained from the ASHRAE database. The “warmer” class is augmented with the lower temperature value under the value of mapped ASHRAE data, which is 10 ℃. The "cooler" class is augmented with data above 40 ℃. It is shown that the semantic augmentation direction is non-overlapped. The essence of the ASHRAE database is sustained. It is shown in Figure 44 that this range of augmented data is also outside the comfort zone.

The algorithm for generating the semantic augmentation is as follows:

**Algorithm 2**: Semantic Augmentation Data

```
//%"for colder augmentation class"
Input: data intervals
row=0;
for clo=0 to 2.89 step clo_intervals do
   for met=0.65 to 6.83 step met_intervals do
      for tem=40 to 63.2 step tem_intervals do
         for RH=0.4 to 100 step RH_intervals do
           for age= 6 to 99 step age_intervals do
              row=row+1;
              AugMat(row,1)=clo;
              AugMat(row,2)=met;
              AugMat(row,3)=tem;
              AugMat(row,4)=RH;
              AugMat(row,5)=age;
              AugMat(row,6)="colder";
           end for
         end for
      end for
end for
Output: Augmentation Matrix: AugMat(row,[1:6])
//%"for warmer augmentation class"
// similar with warmer except this line:
//      for tem=0 to 10 step tem_intervals do
//
 //              AugMat(row,6)="warmer";
// temp can be expanded for more extreme temperature
```

The neural network model used in this work is shown in Figure 45. The artificial neural network model was implemented using MATLAB's artificial neural network generator function after the case was analysed using the classification learner function in MATLAB. This function supports the selection of classification methods to solve the problems. The result of the analysis is provided in Appendix 7.



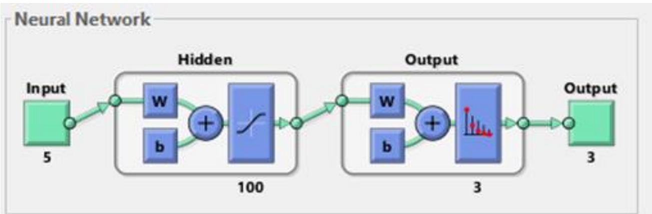




Figure 45. Simple Neural Network Structure for Psychrometric Chart Validation.

The artificial neural network was chosen because the shallow supervised learning process can be done in a more powerful machine with multiple ASHRAE databases. Once the training has been done in the artificial neural network, this huge amount of training data is no longer needed, and the trained network can be deployed in a less powerful machine such as a local server or controller.

The network was trained with the prebuilt function in MATLAB, which was the scaled conjugate gradient backpropagation. The training function could train any network as long as its weight, net input, and transfer functions have derivative functions. The process of updating weight was done with the backpropagation to calculate performance derivatives with respect to the weight and bias variables. The backpropagation allows the weight to be updated to reduce the error in prediction. The scaled conjugate gradient algorithm was based on conjugate directions, but this algorithm does not perform a line search at each iteration.

The AI impact on society has to be addressed so that the AI vulnerability will have less impact (Hamon et al., 2020). In terms of robustness, this work uses shallow supervised learning. The database source for training was based on multiple ASHRAE databases, which resulted from the precise measurement. These learning results update the weights and biases in the ANN. The scale of the database items and prior system learning will form a solid base for the ANN, minimize the AI's poor processing performance, and minimize the long-term impact of AI vulnerability. The result of the learning also has been validated using psychrometric chart mapping. This effort will minimize the possibility of error and false pattern mapping.

The AI model selection was based on the limitation of the solution deployment for the residential dwellings. The algorithm should be able to run in the local controller node with limited memory and computational power. The ANN which consists of the input layer, one hidden layer and an output layer was chosen although having slightly lower performances among K-Nearest Neighbors (KNN) and Ensemble Bagged Trees. The ANN has the benefit of being less computationally expensive and less memory usage with a better interpretability of the model. Table 13 shows the comparison accuracy between popular AI methods with the same training data without Principal component analysis (PCA).

Table 13. The accuracy comparison between popular AI methods

| Classification Methods | Accuracy (%) (without PCA) | | Classification Methods | Accuracy (%) (without PCA) | |
|---|---|---|---|---|---|
| | Case 1 | Case 2 | | Case 1 | Case 2 |
| Fine Tree | 93.90 | 93.80 | Coarse KNN | 77.70 | 89.30 |
| Medium Tree | 93.70 | 93.70 | Cosine KNN | 77.60 | 89.40 |
| Coarse Tree | 93.60 | 93.60 | Cubic KNN | 77.70 | 89.60 |
| Linear Discriminant | 77.40 | 89.20 | Weighted KNN | 78.80 | 92.50 |
| Quadratic Discriminant | 77.50 | 89.10 | Ensemble Boosted Trees | 96.10 | 96.10 |
| Gaussian Naïve Bayes | 95.50 | 95.50 | Ensemble Bagged Trees | 97.00 | **98.70** |
| Kernel Naïve Bayes | 95.60 | 95.60 | Ensemble Subspace Discriminant | 94.40 | 94.80 |
| Linear SVM | 78.30 | 89.60 | Ensemble Subspace KNN | **98.20** | 64.50 |
| Quadratic SVM | 78.40 | 72.10 | Ensemble RUS Boosted Trees | 93.70 | 93.70 |
| Cubic SVM | 78.20 | 81.70 | Narrow Neural Network | 96.00 | 89.70 |
| Fine Gaussian SVM | 78.50 | 89.70 | Medium Neural Network | 96.00 | 96.00 |
| Medium Gaussian SVM | 78.40 | 89.60 | Wide Neural Network | **96.10** | **96.10** |
| Coarse Gaussian SVM | 78.30 | 89.60 | Bilayered Neural Network | 96.00 | 89.70 |
| Fine KNN | 78.80 | 92.40 | Trilayered Neural Network | 78.50 | 89.70 |
| Medium KNN | 77.70 | 89.60 | | | |

Note:
Case 1: Training with Augmented & Filtered ASHRAE RP-884 database and ASHRAE Global Thermal Comfort Database II
Case 2: Training with the same dataset as Case1, but without Age parameter

## 6.5 Psychrometric Based Verification

Testing and validation for supervision learning are usually done using randomly populated data fractions. The typical value for testing and validation can be 10% to 20%. A higher percentage can decrease the accuracy (Luo et al., 2020). However, more extensive data does not guarantee higher accuracy and can cause overfitting issues.

Checking the learning against overfitting issues is not easy. This work proposes using psychrometric chart mapping to validate the supervised learning result. This method is based on the comfort zone map in the psychrometric chart. The overfitting results will lead to the map not showing the correct pattern if the system is fed with the data series. The example of the mapping result can be seen in Figure 46.

The pattern is generated using the validation data generated with the value range of relative humidity from 0% to 100% and temperature from 10 °C to 40°C. Other parameters like age, clothing insulation and activity can be predefined with median values. The result can be mapped with different colours or symbols to represent the output. The blue colour in the sample represents the class that needs warmer temperatures. The red represents the class that needs a cooler temperature, while the green represents the comfort zone (no change). In the case of overfitting, the generated pattern will be very different from the comfort zone shown in Figure 11.

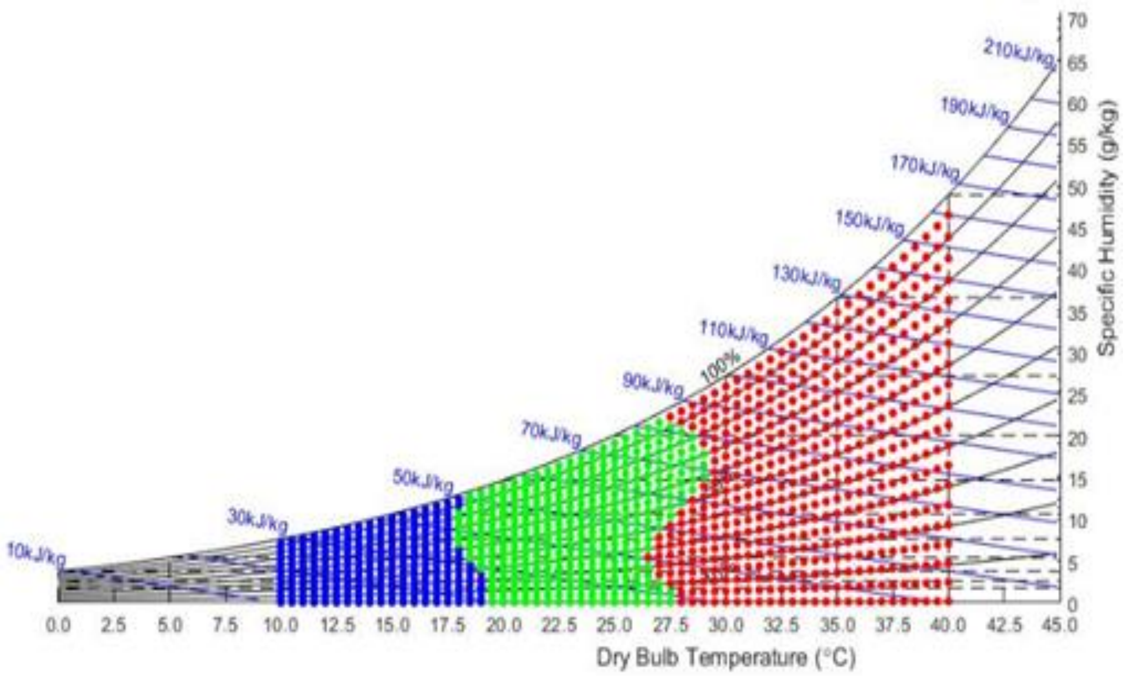



Figure 46. Mapping the comfort zone generated by the pre-trained system.

This verification process method can also be used to compare the effects of the parameter change. One parameter value can be altered while the other parameters are constant. The impact of each parameter on the comfort zone can be captured and simulated. This method can simplify the representation of the multidimensional parameters that impact thermal comfort.

Many previous AI works only limit the training validation with the available data. Usually, data is separated randomly into training, testing, and validation data, and the accuracy is purely based on this data. The problem raised is the edge of the comfort zone or the zone outside the predefined zone, which might still be comfortable to the occupants. This area should be explored to define the system's ability to conserve energy. The intelligent system can have the recommender function to lower energy costs by informing the occupants about clothing or activities that can keep them comfortable but with less energy. The occupants still have the probability of staying comfortable with higher clothing insulation during winter to conserve heating energy. On the contrary, the occupants will also have the probability to be comfortable in the hot summer by wearing lighter clothes, using the fan and consuming fresh beverages to conserve the cooling energy. This behaviour is the current gap in the previous work.

This work accommodates these needs by proposing the validation process using the psychrometric chart and test data generator. The test data generator works in a similar way to the **Algorithm 2** but with the parameter range to be more specific on the comfort zone map. The temperature can be between 10°C and 40°C, with a relative humidity value between 0% and 100%. The generated data then being fed to the intelligent system, and the result is drawn in the psychrometric chart. Each label can be drawn in the chart with a different colour to show the "no change" class, "warmer" class, and "cooler" class. The previous work also mapped the training result with the psychrometric chart without the test data generation. This method limits the validation to the available data, and the comfort zone cannot be adequately mapped. The comfort zone can be appropriately mapped using the generated data, with the edges of the thermal comfort zone visually presented.

In order to compare the learning result and the effect of filtering and semantic augmentation method, a similar neural network algorithm and model were used in this work. For this test, the parameters involved were the combination of indoor temperature, relative humidity, clothing insulation, and activity/metabolism. The age parameter is a single value, taken randomly to reduce the training data size. The learning data set composition for this Neural Network training was 70% training. 15% validation and 15% testing data. The data selection for these test groups is based on random selection. To be compared, the neural network structures were trained with the original ASHRAE data, the filtered data, and the filtered semantic augmented data.

The first comparison parameter was done using the learning from the plain ASHRAE database. The result of training returned an accuracy of 45.6%, and the AI system is then fed with the generated test data. The class result is drawn in the psychrometric chart, as shown in Figure 47 (a). This result shows an incomplete comfort zone. Only class "no change" and "cooler" classes dominate, and the comfort zone is not drawn correctly. The class “no change” is represented with green colour, “cooler” with red colour and “warmer” with blue colour. The comfort zone range is from 10°C up to 30 °C, which is not valid compared with the PMV-PPD results.

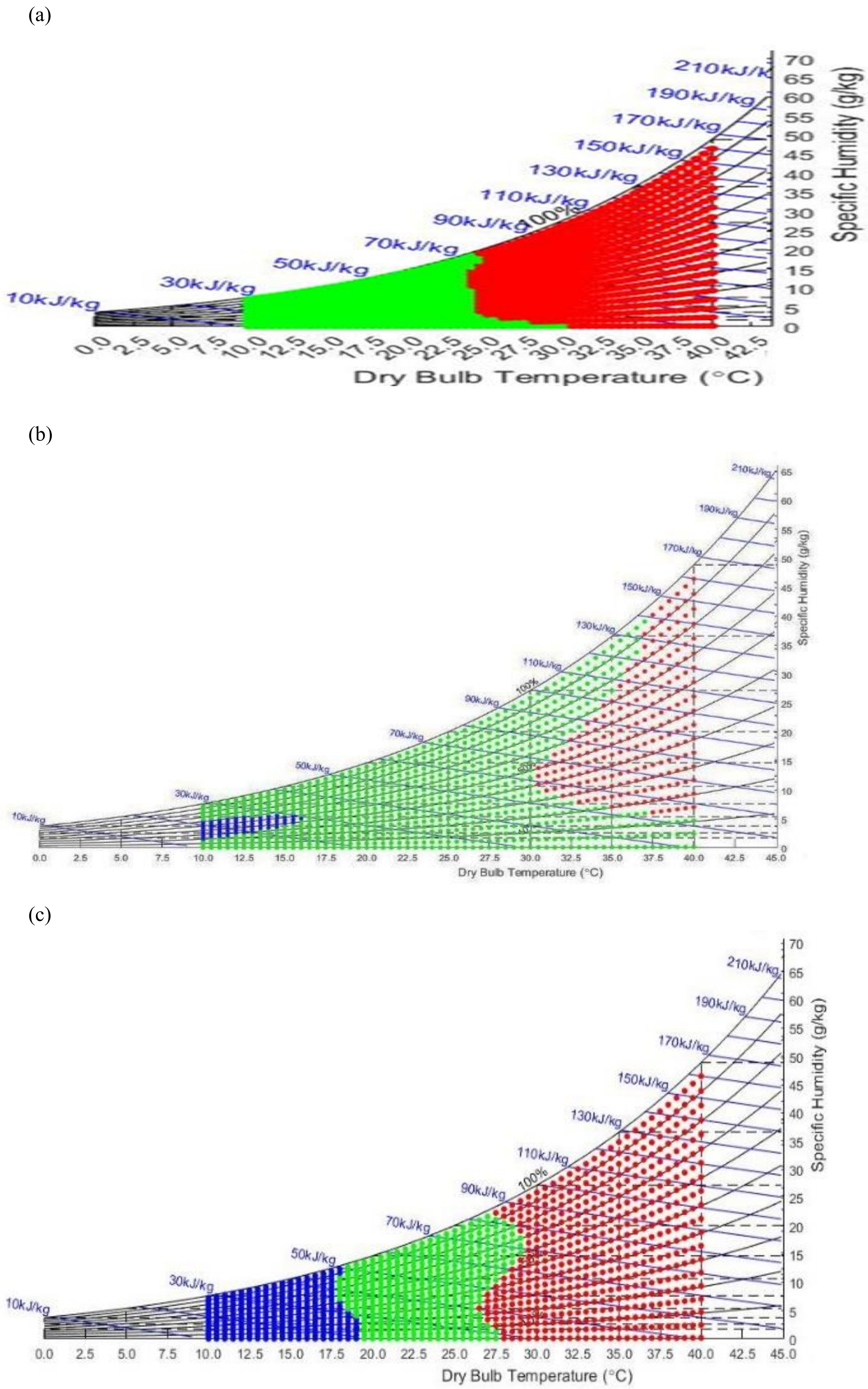



Figure 47. Psychrometric Mapping for the Comfort Zone Trained with (a) the Original ASHRAE Database (b) the Filtered ASHRAE Database (c) the Filtered ASHRAE Database with the Data Semantic Augmentation

The second comparison parameter used the filtered ASHRAE database for the supervised training database. Figure 47 (b) shows the psychrometric map of the generated test data for the system, which was trained using this database. The parameters and data set grouping method are like the trial shown in Figure 47 (a). The accuracy of the training for this dataset was 55.5%. All three classes are visible, but the comfort zone is still not drawn correctly. The class "warmer" only covers a small portion of the chart, and the comfort zone range spans 10°C up to more than 40 °C, which is not valid compared with the PMV-PPD results. This problem shows that the system needs semantic augmentation to generate the correct result.

The third comparison parameter used the semantic augmentation filtered ASHRAE database and was deployed with the accuracy of this training data about 98%. The parameters and data groupings are similar to the trials for Figure 47 (a) and Figure 47 (b). The psychrometric map generated for the semantic augmentation filtered ASHRAE data is shown in Figure 47 (c). The comfort zone is better represented in this result. The comfort zone ranges from 17.5°C to about 29 °C. The result is better than the previous mapping, shown in Figure 47 (a) and Figure 47 (b). This result represents the comfort zone presented in Figure 11.

Learning from the accuracy of data training, which can be high, as shown in Appendix 7, the system training result still needs further validation. The validation method can be the psychrometric mapping of the comfort zone. Figure 47 highlights the importance of validation using a psychrometric chart.

## 6.6 Parameter Visualisation

One of the six crucial parameters in thermal comfort is air movement. However, this parameter cannot be easily obtained from the IoT sensor system. This work deploys the system with five and four parameters without the age data of the occupant. This case study is for simulating in case the occupants' age information is unavailable. The result of both systems is compared to show their characteristics. This combination of the original and filtered ASHRAE database was then used for the training data for 29 well-known AI algorithms for classification. The accuracy of each database and method can be seen in Appendix 7. The parameters for each classification method used in the result were defined in the table in Appendix 7. The average of the accuracy results is given in Table 14.

Table 14. The Average Accuracy from 29 Classification Methods

| Database | Average (%) |
|---|---|
| DB1 | 51.87 |
| Filtered DB1 | 76.09 |
| Filtered DB1 Tested with All Data | 49.05 |
| DB1 without age | 55.05 |
| Filtered DB1 without age | 80.40 |
| Filtered DB1 without age Tested with All Data | 50.70 |
| DB2 | 42.00 |
| Filtered DB2 | 70.23 |
| Filtered DB2 Tested with All Data | 47.23 |
| DB2 without age | 50.51 |
| Filtered DB2 without age | 81.57 |
| Filtered DB2 without age Tested with All Data | 49.44 |
| DB1 and DB2 | 43.69 |
| Filtered DB1 and DB2 | 74.90 |
| Filtered DB1 and DB2 Tested with All Data | 48.75 |
| ASHRAE DB1 and DB2 without age | 50.53 |
| Filtered DB1 and DB2 without age | 81.52 |
| Filtered DB1 and DB2 without age Tested with All Data | 50.87 |
| Augmented & Filtered DB1 and DB2 | 86.43 |
| Augmented & Filtered DB1 and DB2 Tested with All Data | 44.28 |
| Augmented & Filtered DB1 and DB2 without age | 90.12 |
| Augmented & Filtered DB1 and DB2 without age Tested with All Data | 48.51 |

Note: DB1 = ASHRAE RP-884 database
DB2 = ASHRAE Global Thermal Comfort Database II

The result shows that the data filtering increases the accuracy of the training results. The proposed filtering methods can improve the ASHRAE database for each RP-884 database, Thermal Comfort Database II and the combination between databases. The accuracy increases for all methods of training. The result is still better for the filtered data when tested against the original database than the original data. Besides this data filtering, data normalisation is already included in the AI process to gain better results. The result also shows that reducing the parameter (age parameter) can maintain accuracy. This result can be caused by the overfitting or the unbalance of the feature space. The semantic data augmentation will give better accuracy results for this problem.

The parameters are shown before can show the differences between classes “warmer", "no change", and "cooler" for the particular value of a parameter such as age to show the potential comfort zone for each parameter value. If the parameter is changed accordingly, the impact of this parameter change on the thermal comfort zones can be mapped and studied. The impact of the parameter change in the thermal comfort zone can be seen in Figure 48.

This work assesses the age parameter impact on the thermal comfort zone. This assessment becomes an example of the parameter assessment with this method. The age parameter is one parameter that can show the human condition aspect of thermal comfort. The thermal comfort is not standard and is based on personal factors. It has been studied that the young, elder, disabled or temporary ill people group will have a different comfort zone.

Figure 48 (a) displays the adult's comfort zone representation based on the filtered ASHRAE database with the data semantic augmentation. Figure 48 (b) shows the same comfort zone for the elderly group. They were based on the filtered ASHRAE database with the data semantic augmentation. Based on this chart, the system designer will have insight into designing and testing the AI system since the borders between the comfort zone are not crisp but more personal.

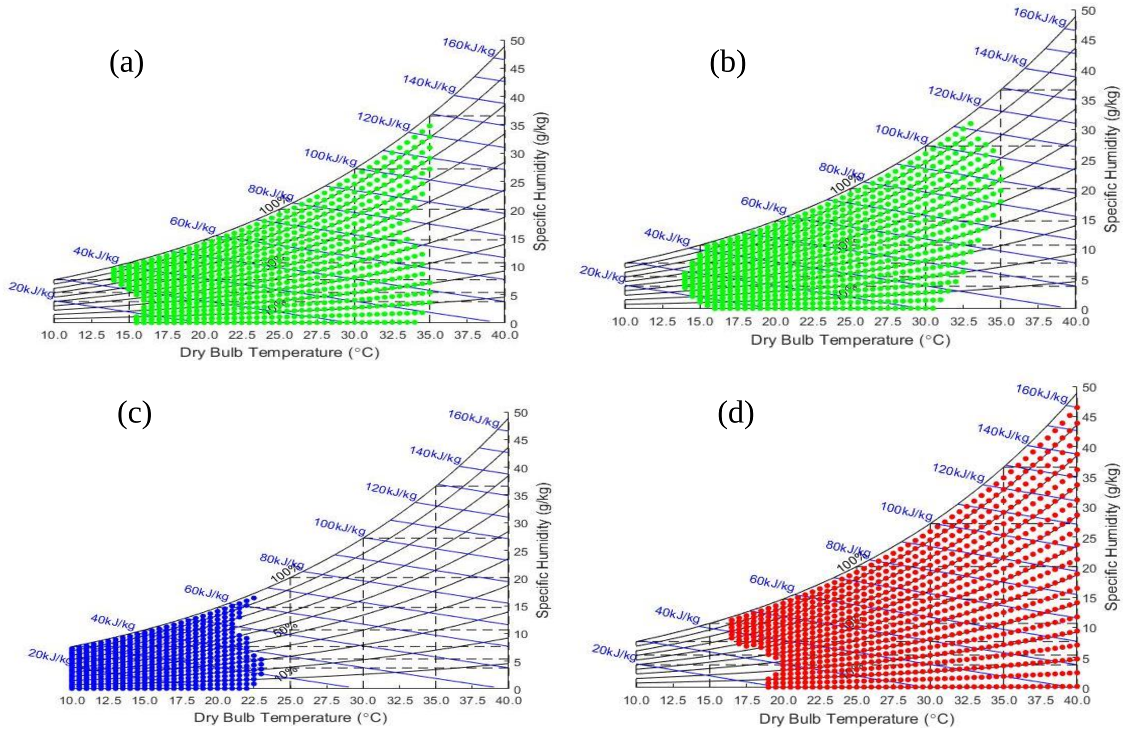


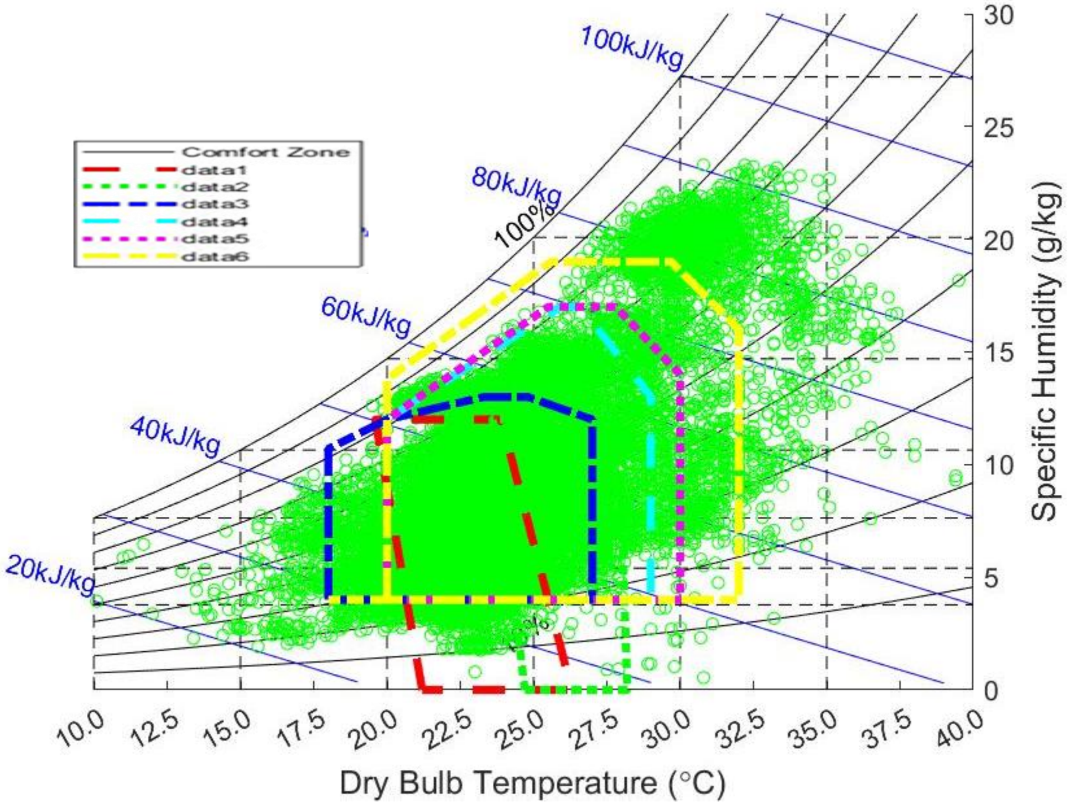

Figure 48. Psychrometric Mapping for (a) the Comfort Zone Trained with the Filtered ASHRAE Database with the Data Semantic Augmentation for adults, (b) for an elderly people group, (c) the "warmer" class of the elder people group, (d) the "cooler" class of the elderly people group.

A similar result also happened in the same age group. The differences in clothing insulation and activity/metabolism can have different thermal conditions. This condition is shown in Figure 48 (b), Figure 48 (c) and Figure 48 (d). Figure 48 (b) represents class “no change”, Figure 48 (c) represents class “warmer” and Figure 48 (d) represents class "cooler". This map shows that the class "no change" intersects with the class "warmer" and "cooler". This case means that if one person feels cold and needs a warmer environment, another can feel comfortable. When one person feels hot and needs a cooler indoor environment, the other can feel comfortable. The more extreme condition is the overlapping chart between Figure 48 (c) and Figure 48 (d). It means that one person wanted the temperature to be warmer at the same temperature, but the other person wanted a cooler temperature. This condition highlights the need for the system to have a manual override so that the occupants can alter the system setting.

The psychrometric chart mapping for ASHRAE multiple database comfort region based on the parameter comfortable or uncomfortable data field can be seen in Figure 49. Figure 49 shows that the comfort data from the ASHRAE database covers much more area outside the PMV-PPD Comfort Zone. The map generated from ASHRAE RP-884 Database and ASHRAE Global Thermal Comfort II database is wider than Givoni Comfort Zone. Since the ASHRAE Database comes from the precise sensor reading and extensive data collection, including the personal interview process from the thermal sensation, this will become legitimate proof to mention that the possibility of expanding the thermal comfort zone is valid.

The individual mapping of the PMV-PPD and Givoni Comfort Zone against the ASHRAE multiple thermal comfort databases is shown in Figure 50. Figure 50 (a) shows that from the ASHRAE multiple thermal comfort databases, which consider being in comfortable situations, only about 69.91% is acknowledged by the PMV-PPD Comfort Zone. Similar to this result, about 89.19% of the comfortable occupants' data from ASHRAE multiple thermal comfort databases are acknowledged in the combination of all Givoni Comfort Zone (Figure 50 (b)).

The conclusion from these figures is the possibility of obtaining comfort for the occupants at higher temperatures in summer or tropical areas and lower temperatures in winter. Even with both PMV-PPD and Givoni comfort zone combination (Figure 50 (c)), more than 7 per cent of the ASHRAE comfort data have not been covered. This result shows that thermal comfort is personal. A group of people have different preferences for the thermal comfort set point, and the thermal comfort zone is not prescriptive but is subject to differences due to human adaptive behaviour.




data1: the PMV-PPD comfort zone for 1.0<met<1.3 and 1.0 Clo, ASHRAE Standard 55
data2: the PMV-PPD comfort zone for 1.0<met<1.3 and 0.5 Clo, ASHRAE Standard 55
data3: Givoni comfort zone for still air condition for winter
data4: Givoni comfort zone for still air condition for summer
data5: Givoni comfort zone for winter with an assumed air speed of about 2 m/s.
data6: Givoni comfort zone for summer with an assumed air speed of about 2 m/s.
Green Dots: the Data items from Multiple ASHRAE Thermal Comfort databases that represent occupants' comfort

Figure 49. The Comfort Area from ASHRAE Database is mapped with the PMV-PPD comfort zone and Givoni Comfort Zone (R. A. C. E. American Society of Heating, Incorporated, 2017), (Givoni, 1992).

Figure 51 presents the similar comfort zone bit mapped with the result of the AI model with a specific age group. The main temperature values are similar between the AI model and the ASHRAE database map. The difference lies in the humidity value predicted to be in the comfort region. This value is due to the shallow learning process, which does not have enough training data in extreme humidity conditions. Introducing semantic augmentation for extreme relative humidity data will be possible, but since there is only a tight area open for semantic augmentation, the validation process for this augmentation will be complex. If the uncomforting condition is introduced in augmentation without proper judgement, it will affect the overall learning process.

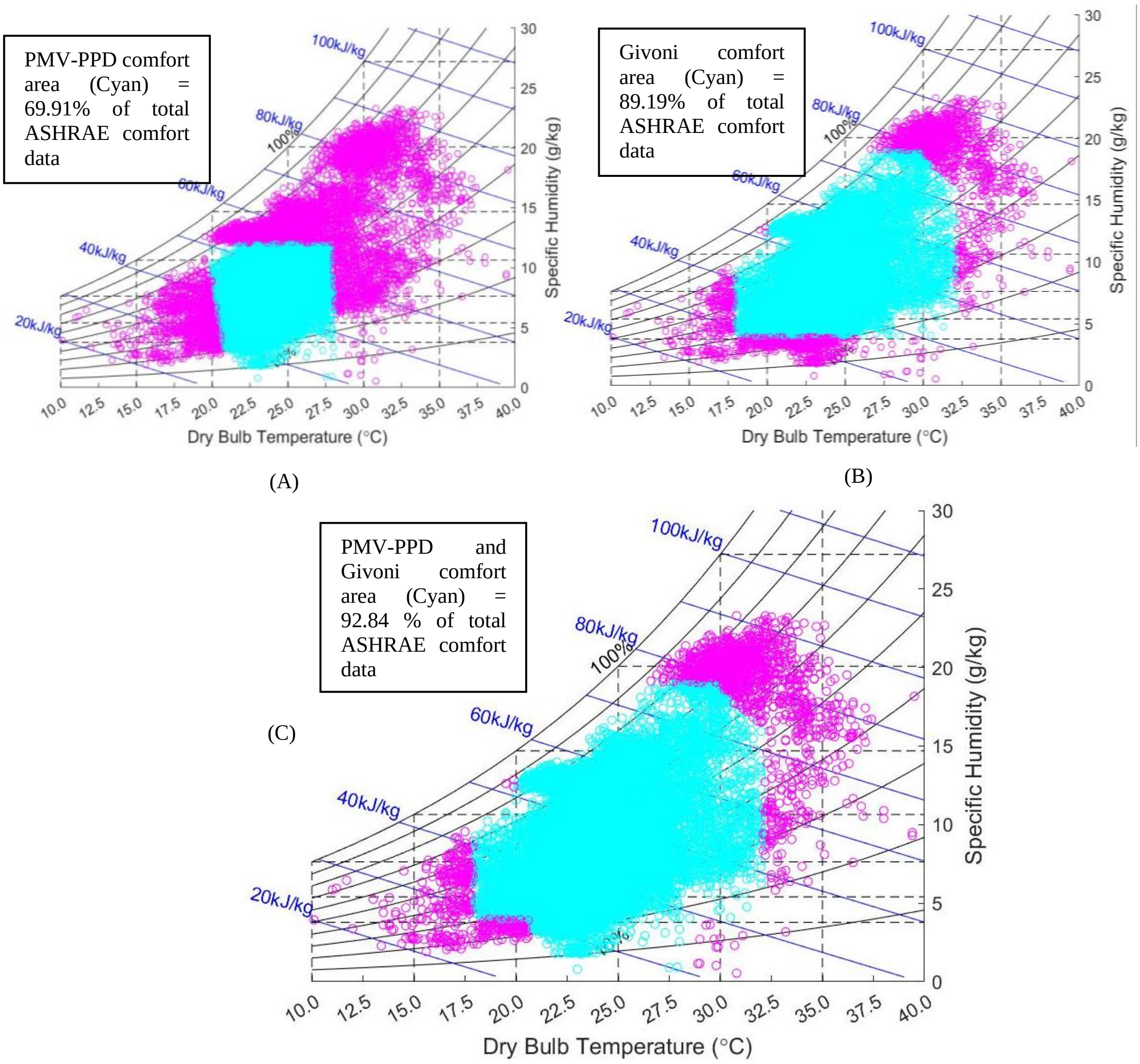



Figure 50. Individual map of the comfort area from ASHRAE Database against (a) PMV-PPD comfort zone, (b) Givoni Comfort Zone and (c) both comfort zone.

In Figure 51, the AI model uses the parameters of clothing value as 1 clo as recommended in ASHRAE for winter, shown in Figure 51 (a) and 0.5 clo as recommended in ASHRAE for summer, shown in Figure 51 (b). The other parameters are the activity with the value of 1.5 met, which represents the light works, and the people's age which uses the value of 40.5 years as the median value of the people living in the UK. With the winter parameters, the acquired comfort percentage is 98.03% from all the ASHRAE multiple databases, compared to the PMV-PPD value of 69.91%, the Givoni comfort zone value of 89.19% and the combination of both with the value of 92.84 %. There is an increase of 5.19% in the acknowledgements of the comfort zone. With the summer parameters (clothing value of 0.5 clo), the acquired comfort percentage is 98.49% from the ASHRAE multiple databases. There is an increase of 5.65% in the acknowledgements of the comfort zone compared to the combination between the PMV-PPD and Givoni.

(a) (b) (c) (d)

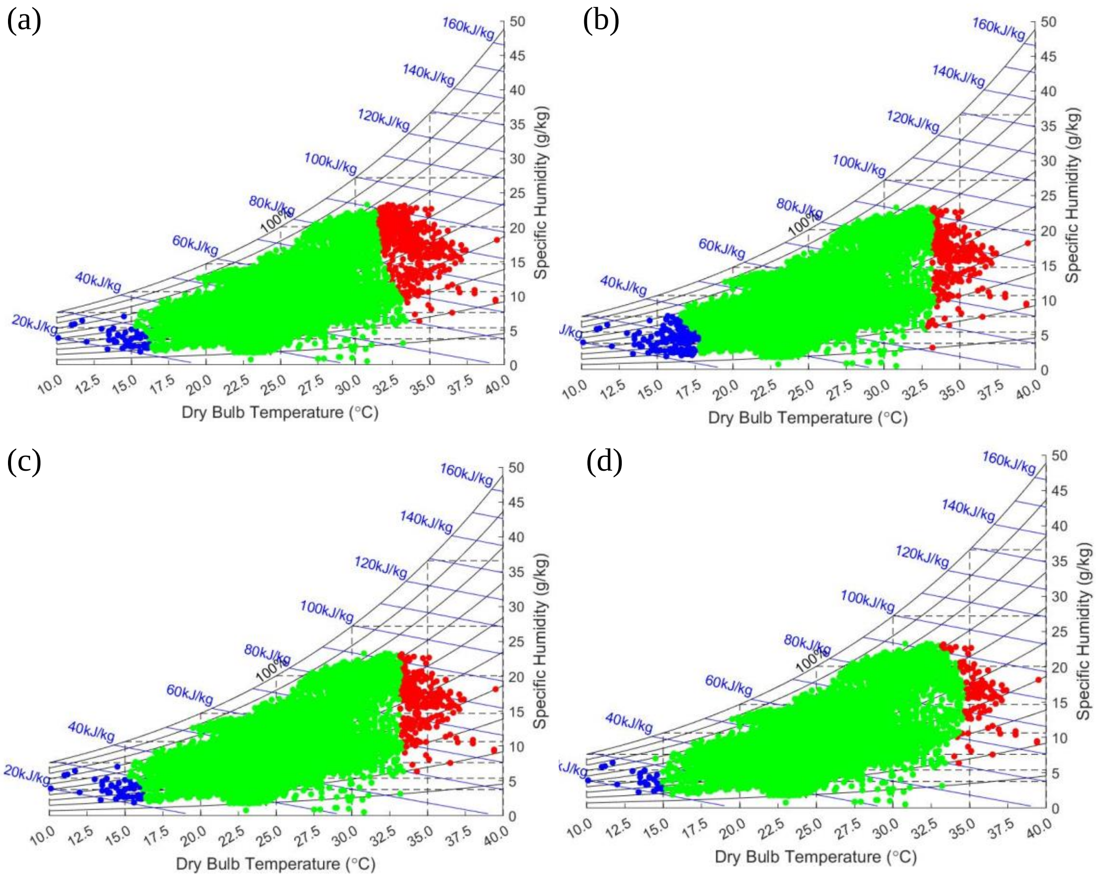



Figure 51. Maps the Comfort Area (in green colour) from the AI model with parameters (a) 1 clo (winter); (b) 0.5 clo (summer); (c) winter and summer; and (d) model with multiple ages parameter

If the clothing parameters are combined (summer and winter), the value of comfort percentage rises to 98.90%, an increase of 6.06% of the acknowledgement. The comfort zone is displayed in Figure 51 (c). The value can still increase, but the other parameters, such as age and activity values, will need to be altered. Figure 51 (d) shows the age variations effect in comfort map results according to the ASHRAE multiple databases, from 6 to 96 years old. The value of comfort percentage rises to 99.46% compared to the whole ASHRAE multiple databases, which is an increase of 6.62% of the PMV-PPD and Givoni acknowledgement.

Based on the assumption that there are 27.8 million households in the UK (Statistics, 2021) and the annual median energy consumption for the UK household is 15,400 kWh/year (E. I. S. B. Department for Business, 2021) and the assumption that 61% of energy is used for space heating ((NEF), 2014), the total energy spent for the annual domestic heating energy across the UK is 261.1532 billion kWh/year. With this massive amount of value, if the 6.62% wider comfort area acknowledgement is directly associated with the same amount of energy saving, it will equal 15.67 billion kWh/year. If the $CO_2$ emission factor is 0.309 kge / kWh ((BEIS), 2018), this work will contribute to 4,842 thousand tonnes of $CO_2$ equivalent. If the emission factor used is 50 g $CO_2$ eq/kWh, which is the target for 2030 (Technology, 2011), the contribution of this work will be about 783.5 thousand tonnes of $CO_2$ equivalent per year. With the UK reaching emissions of around 6 t CO2e per person in 2020 (E. I. S. Department for Business, 2023), the work is equivalent to saving the carbon spending of 131 person's annual CO2 emissions per year. This value shows that using an AI model to acknowledge thermal comfort can significantly conserve energy and help reduce carbon emissions.

## 6.7 Potential Refinement of the Model

Obtaining the data set for thermal comfort is not an easy task. This work develops the filtering and semantic augmentation for the ASHRAE database, one of the most reliable databases for thermal comfort. This work also proves that the database can perform well in the thermal comfort zone prediction. This work shows that even though the training for the AI process has been done with an excellent training validation percentage, it does not guarantee that the system will perform well for the data with extreme value or within the comfort zone borders. In line with that finding, this work also proposes validation methods based on the test data generation and validation through psychrometric comfort zone mapping. This method will help analyse each impact of the parameters for thermal comfort based on the psychrometric mapping of the thermal comfort zone.

Semantic augmentation has proven to be robust in the processing of thermal data. There is the possibility that the semantic augmentation can be implemented in other parameters without changing the notion of comfort that is stored in the ASHRAE database. The humidity parameter can be one of the candidates for future work. There is no comfort recommendation for the humidity value for comfort, but the healthy range for the relative humidity is not more than 80% and not less than 15%. This gap can lead to registering the semantic augmentation for the relative humidity comfort value. This system can be developed to control the indoor humidifier or the dehumidifier.

Another potential development of the system is implementing the recommendation and gamification system to lower energy use but maintain comfort. Since thermal comfort is the state of mind related to memory and not just physiology, the gamification feature and the intelligent system pre-set can help achieve the goal of lower energy use either for heating or cooling. The system can influence the user to feel comfortable with the gamification and recommendation, but it will need a long adaptation process (Kanisius

Karyono et al., 2020). For low temperature, for example, exposure to cold acclimation can improve the subjective responses to cold (M. J. Hanssen et al., 2016). Due to this gap, the research for the use of the ASHRAE database is essential to give the fundamental ability to the intelligent system to deliver comfort. A healthier target can also be set in the system, like exposing the user to lower temperatures to decrease body fat (A. A. van der Lans et al., 2013).

# Chapter 7 Testing and Case Studies

## 7.1 Testing Steps

The purpose of these testing steps was to introduce the data analysis using the AI model and analyse the comforting result against the parameters gathered by the sensors. The outcomes of the tests are whether the AI model results conformed with the readings from the sensors in terms of the thermal comfort region. The tests were done in the artificial indoor condition and model house, which can represent an actual dwelling. Both the IoT Sensors and commercial off-the-shelf (COTS) sensors were deployed so that both can be analysed.

Implementing the Artificial Intelligence model will give an overview of the benefit of implementing this model in real life. Previous implementations were always done using the PMV-PPD model, which is proven not to give enough flexibility due to the prescriptive nature of this model. Since this model was derived from the test done in the thermal chamber, this model does not acknowledge enough flexibility for the individual thermal differences such as sex, age group, and the memory of the person's thermal experiences. This AI implementation model can look at the potential energy saving due to thermal flexibility.

### *7.1.1 Testing in the laboratory*

Some sensor spots are introduced in the laboratory area. The first spot is the workbench in the laboratory; the second spot is the computer desk area in the simulation and modelling area in the laboratory; and the third spot is the spot that was exposed to sunlight and became the lowest temperature spot in the laboratory. These sensors are also compared with offline sensors installed in the exact location as the online sensors and the heater temperature inside the laboratory. This work also includes the outside temperature and humidity data obtained from the weather station.

### *7.1.2 Testing in the BRE house (1970s house)*

Tests are being done in a similar way to the test in the laboratory but with a temperature range lower than the laboratory to capture the house's performance during winter in the 1970s house. The tests were divided into two parts, the empty house condition and with occupants' condition. Due to the COVID restrictions, two thermal models of the human bodies were developed using radial heaters and halogen bulbs to represent a single person with moderate activities or two people with resting (sleeping) conditions. The radial heaters employed in model 1 are two 40Watt radial heaters. Model 2 consists of one 60W radial heater and a 20W halogen lamp. Figure 52 shows the people models.


Figure 52. The human thermal model for testing in the BRE house

The people model power supplies are connected with the programmed timer to simulate the human presence at the desired time. The first arrangement was using office hours during which the people were present at 09:30 AM and left at 18:00. In total, the presence of the people was 8 hours and 30 minutes. This arrangement was necessary to ensure that the model was safe enough to be left unattended. The second arrangement had the same duration but started at 21:30 to 06:00 AM. These tests were conducted to determine human presence's impact on indoor thermal conditions. The insight about this is because the current measurement of the comforts was usually done without the presence of the occupants. This process can lead to overheating or a slightly higher thermal set point. This trial might save a little heating energy, but it can be a considerable amount of energy in the long run. The people model represented the heat dissipated from the people's presence but didn’t consider the $CO_2$ produced and the water vapour generated from people's activities.

The sensor network was deployed with the local network, with the sensors located inside the room, inside the room close to the window and outside the room (stairs) to capture and measure the comfort inside the room and its affecting parameters. For this trial, the local controller and the server are also located on the same premises. The data from the LJMU Byrom Street Campus weather station was used to capture the outdoor condition of the BRE house. With these sensors, the combination of main parameters to predict thermal comfort can be obtained. There are many affecting parameters for thermal comfort, and it will not be easy to gather all the parameters. In this trial, five major parameters were the main focus: humidity, temperature, clothing value, metabolism value and age. The sensor set-up inside the room in the 1970s BRE house is provided in Figure 53.

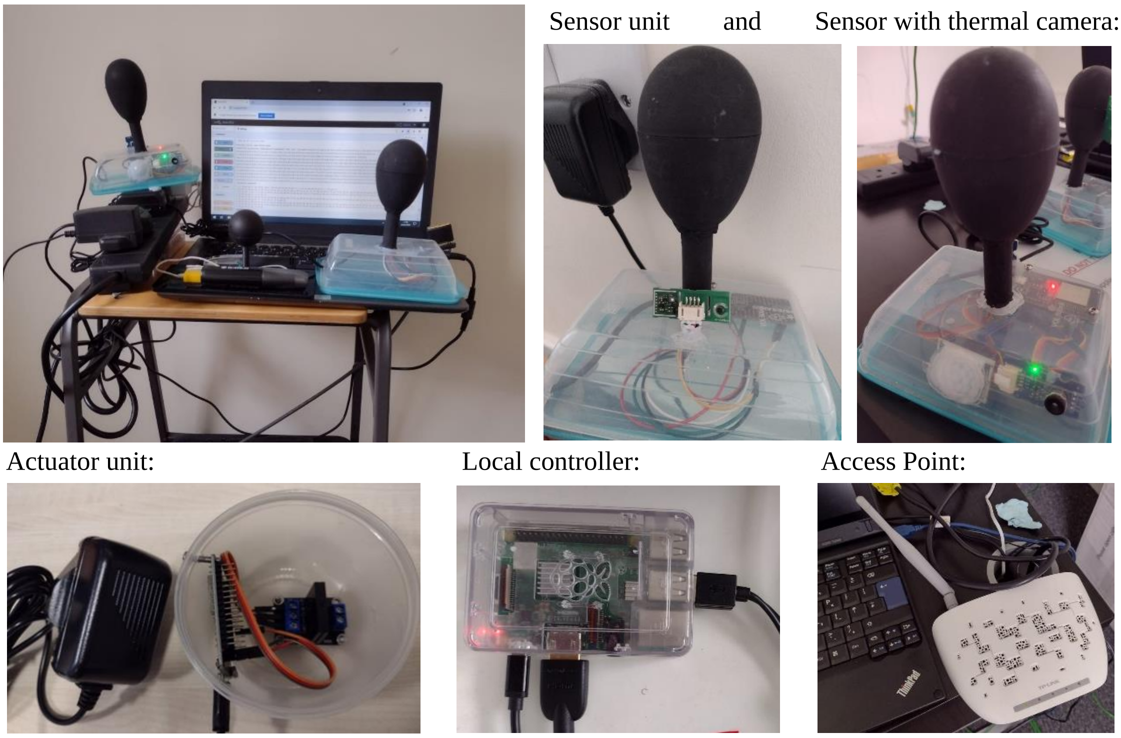



Figure 53. The sensors arrangement in the 1970s BRE House room.

## 7.2 Data Acquired

### *7.2.1 Testing in the laboratory*

The sensors are located on the computer desk and the workbench. The outdoor data were obtained from the weather station installed at the Byrom Street campus. The data was taken at 15 minutes intervals. The chart from the data obtained during laboratory trials is provided in Figure 54, Figure 55, Figure 56, and Figure 57, respectively. The X-axis shows the date, the primary Y axis represents temperature (in °C) and the secondary Y axis represents RH value (in %). The other charts from the other sensor inside the laboratory are provided in Appendix 8.

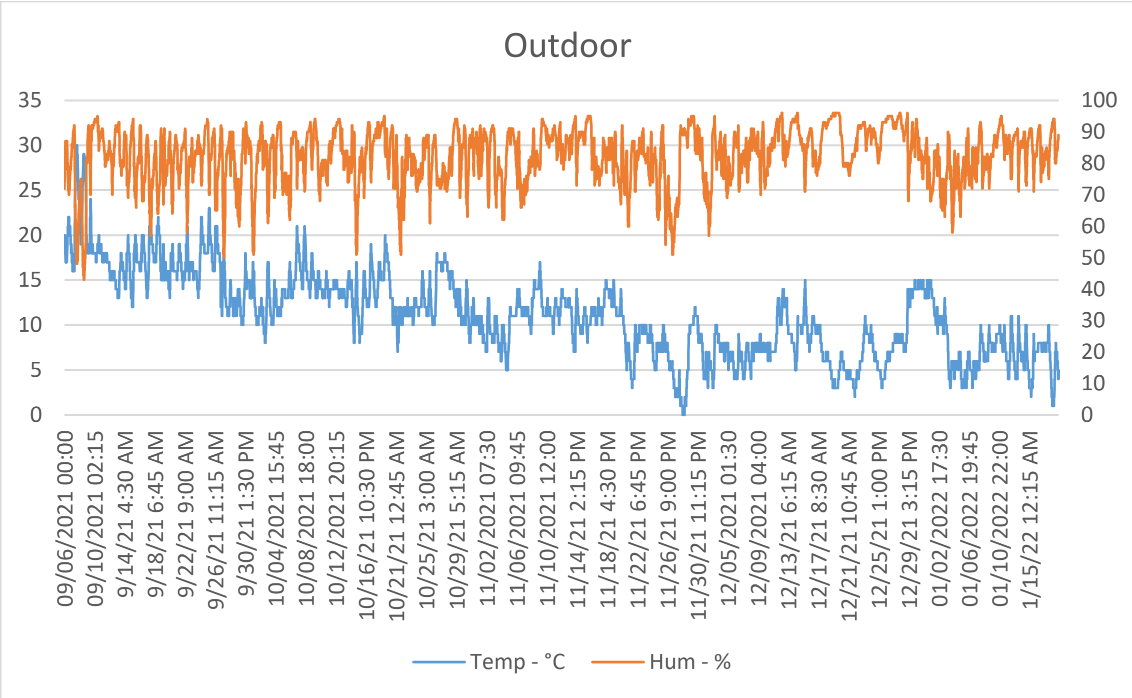



Figure 54. Outdoor temperature and humidity from the weather station.

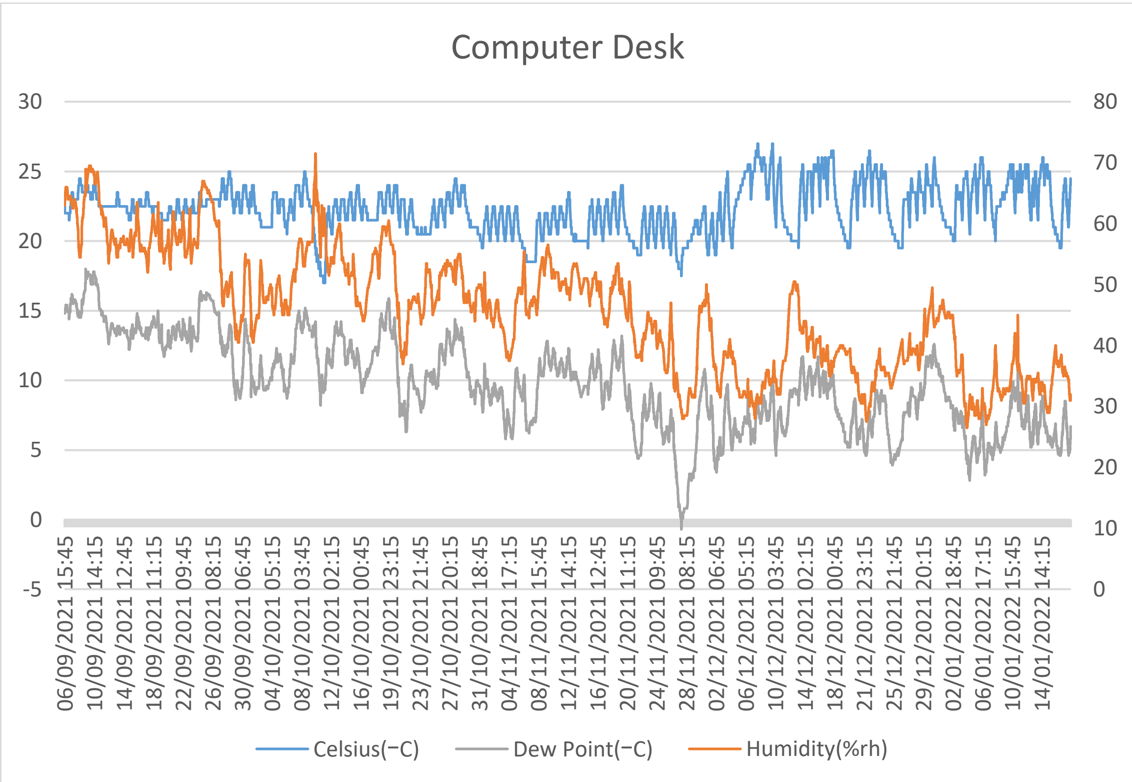



Figure 55. Temperature and humidity from the computer desk.

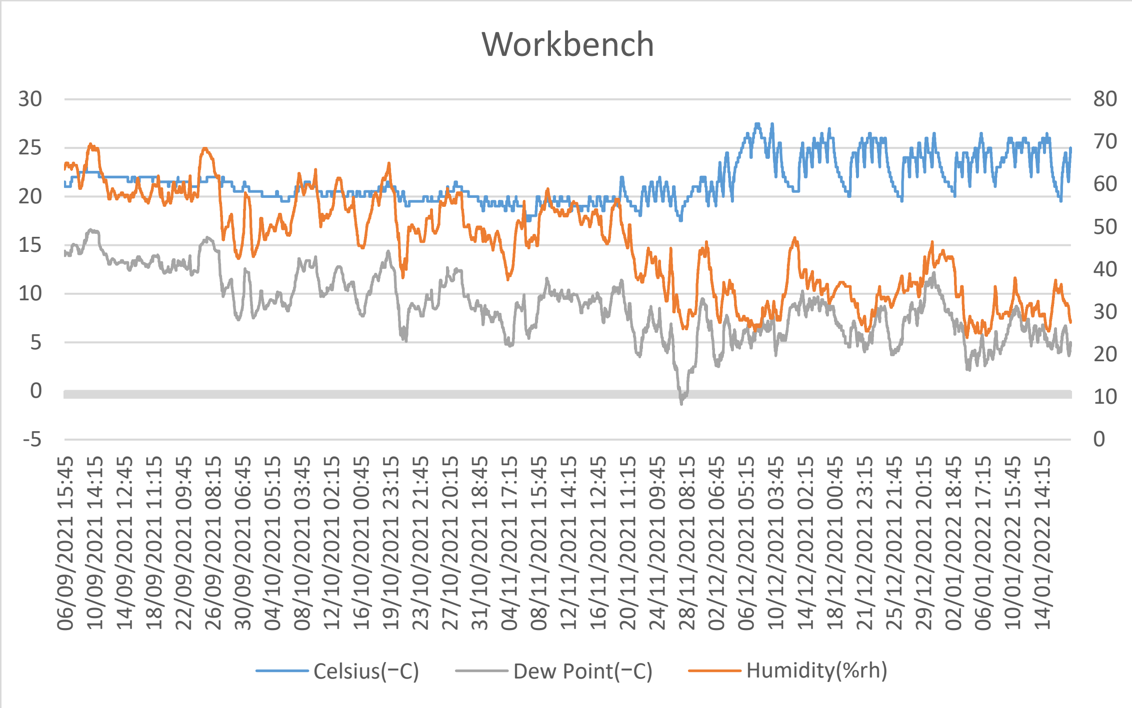



Figure 56. Temperature and humidity from the workbench.

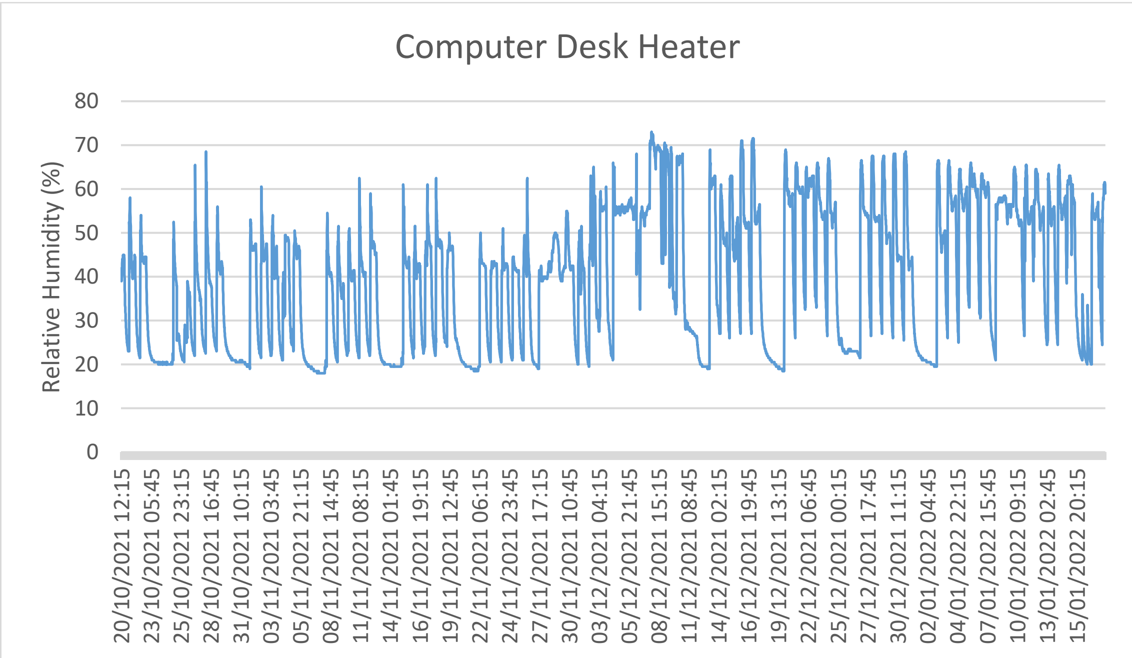



Figure 57. Temperature and humidity from the heater beside the computer desk.

### *7.2.2 Testing in the BRE house*

The data gathering sessions were divided into three major groups: the 'no people present', the 'people afternoon presence' and the night presence to capture the indoor condition related to the people presence and the impact on human thermal comfort. Sessions and periods were introduced to each group to capture the impact of different outdoor conditions and seasonal transitions from the winter to the summer. The sensors' location data and the first installation date and data collection are provided in Table 15. The obtained result from the BRE house for the first period is shown in Table 16. The chart related to the results in Table 16 is provided in Figure 58 for the temperature chart and Figure 59 for the humidity chart.

Table 15. Sensors location and first deployment date.

| Sensor | Location | Installation Date | 1st Data Processing |
|---|---|---|---|
| 01 | Outside room, stairs | 25/01/2022 12:00 | 10/02/2022 12:00 |
| 02 | desktop | 25/01/2022 12:00 | 10/02/2022 12:00 |
| 03 | window | 25/01/2022 12:00 | 10/02/2022 12:00 |
| 05 | desktop | 25/01/2022 12:00 | 10/02/2022 12:00 |
| TC011 | heater (surface) | 25/01/2022 12:00 | 10/02/2022 12:00 |
| TC024 | heater (top left) | 25/01/2022 12:00 | 10/02/2022 12:00 |
| TC025 | heater (top right) | 25/01/2022 12:00 | 10/02/2022 12:00 |
| TH002 | desk | 25/01/2022 12:00 | 10/02/2022 12:00 |
| TH004 | Outside room, stairs | 25/01/2022 12:00 | 10/02/2022 12:00 |

Table 16. Data were obtained from the first period for the sensors in the BRE house.

| Temperature(°C) | 01 | 02 | 03 | 05 | TC011 | TC024 | TC025 | TC02 | TC04 | TH02 | TH04 | Outdoor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Minimum | 11.98 | 12.13 | 11.10 | 12.34 | 11.00 | 10.50 | 10.50 | 11.50 | 12.50 | 13.00 | 12.50 | 2.00 |
| Maximum | 16.90 | 16.90 | 16.85 | 14.61 | 15.00 | 15.50 | 15.00 | 23.00 | 23.00 | 17.50 | 16.00 | 13.00 |
| Average | 14.10 | 14.53 | 13.72 | 13.93 | 13.22 | 12.97 | 12.86 | 14.15 | 14.51 | 15.91 | 14.39 | 8.53 |
| StdDev | 0.90 | 1.04 | 1.27 | 0.65 | 1.09 | 1.08 | 1.09 | 1.03 | 0.87 | 0.94 | 0.79 | 2.33 |
| Humidity(%) | | | | | | | | | | | | |
| Minimum | 47.69 | 47.40 | 48.17 | 44.72 | | | | | | 45.00 | 46.50 | 64.00 |
| Maximum | 60.99 | 56.98 | 60.98 | 57.50 | | | | | | 55.00 | 61.50 | 94.00 |
| Average | 55.43 | 53.33 | 56.11 | 53.51 | | | | | | 50.63 | 55.14 | 81.64 |
| StdDev | 2.92 | 2.07 | 2.20 | 3.21 | | | | | | 2.51 | 3.20 | 5.90 |

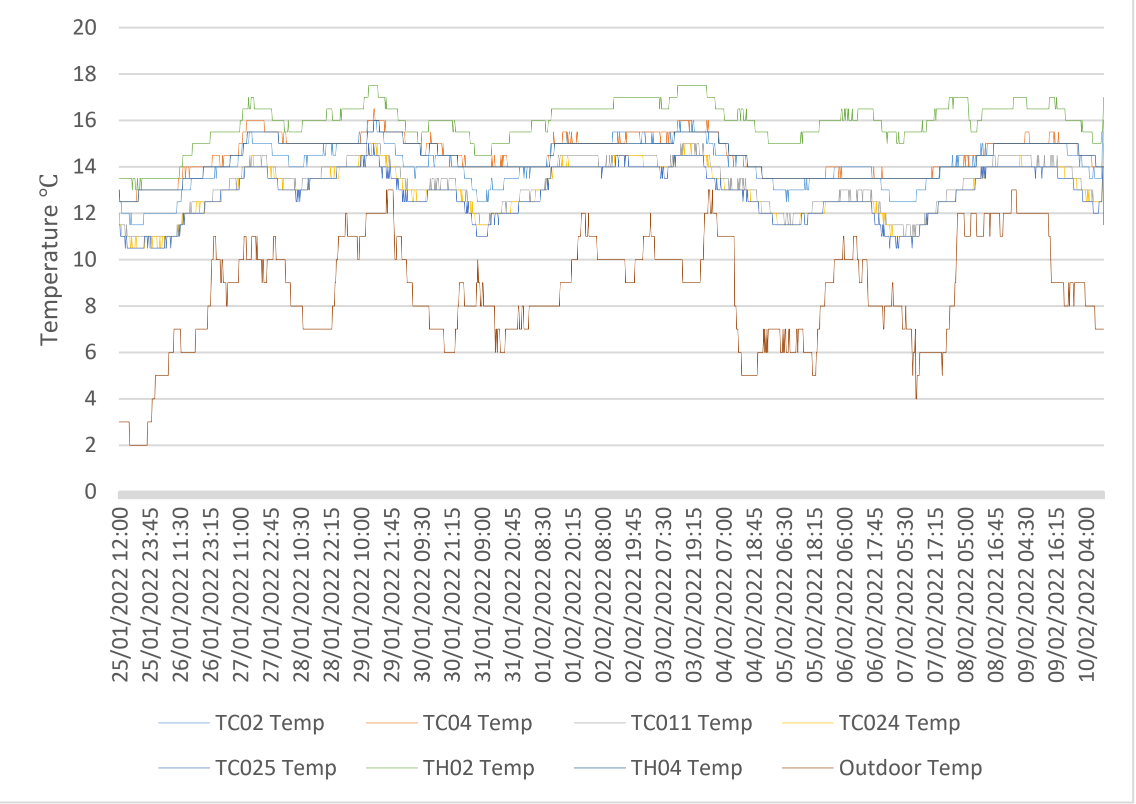



Figure 58. The temperature chart for the first-period data of the sensors in the BRE house.

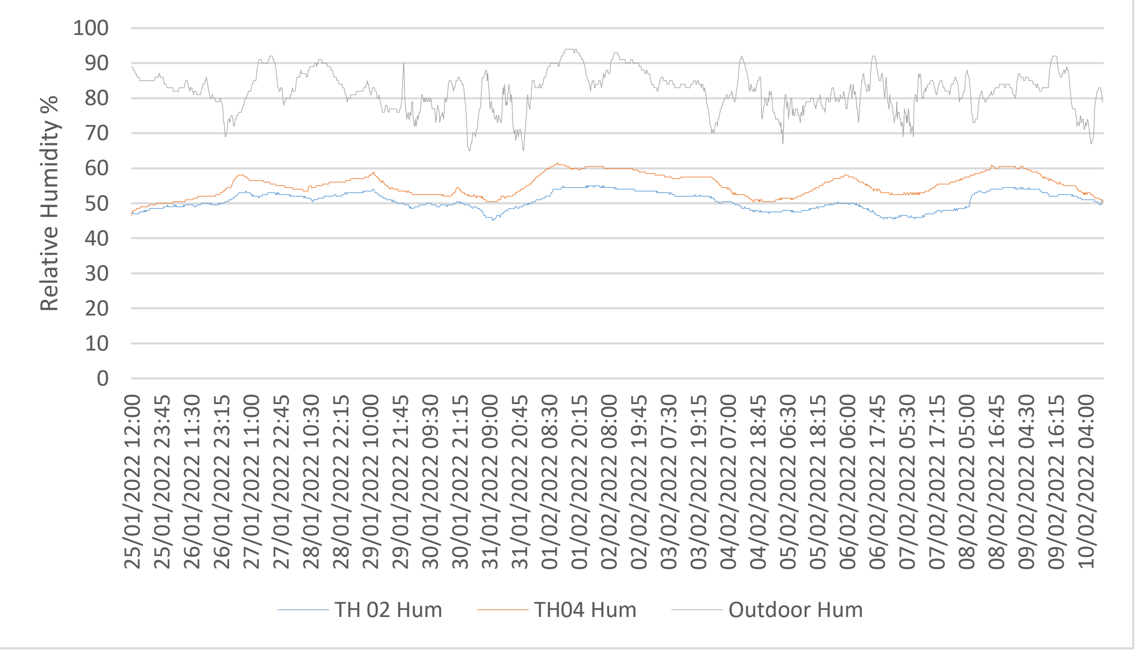



Figure 59. The humidity chart for the first-period data of the sensors in the BRE house.

The following groups and data periods can be referred to in Appendix 9.

## 7.3 Analysis

### *7.3.1 Testing in the laboratory*

This data result was analysed using the AI model based on the ASHRAE RP-884 and ASHRAE Global Thermal Comfort Database II. The result of all sensor 1 data is all in the range of comfort conditions. This sensor is placed on the workbench. The psychrometric mapping of all data is shown in Figure 60. This result is acquired with the assumption that the average clothing insulation is 1 clo. The activity value is set at 1.5, which is the average between the seating position and light work. The age parameter is set at an average of 30 years. The mapping shows that the indoor conditions are always within the range of comfort during the trial. The same parameters are also being used for other sensors.

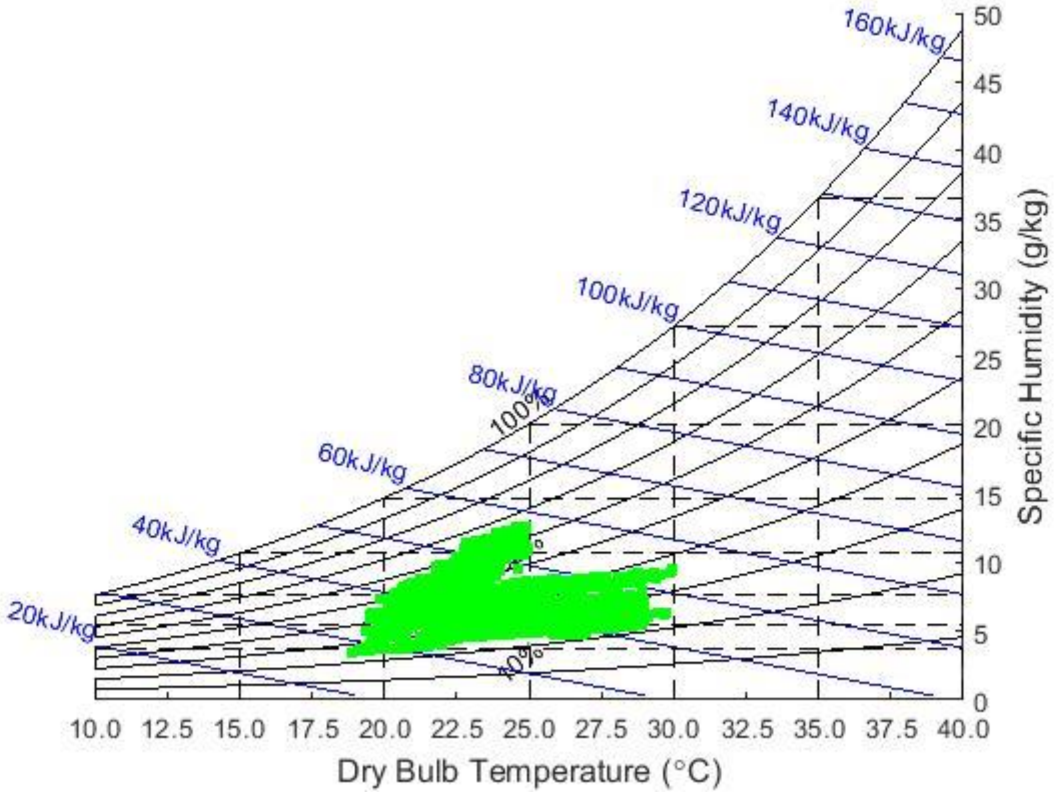



Figure 60. The psychrometric mapping of sensor 1 data (workbench).

The data for the computer desk is captured by sensor number 2. Similar to the result obtained by sensor number 1. Similar to the sensor number 1 result, all data shows that the conditions are in the range of comfort. The psychrometric mapping of the data from sensor number 2 is shown in Figure 61.

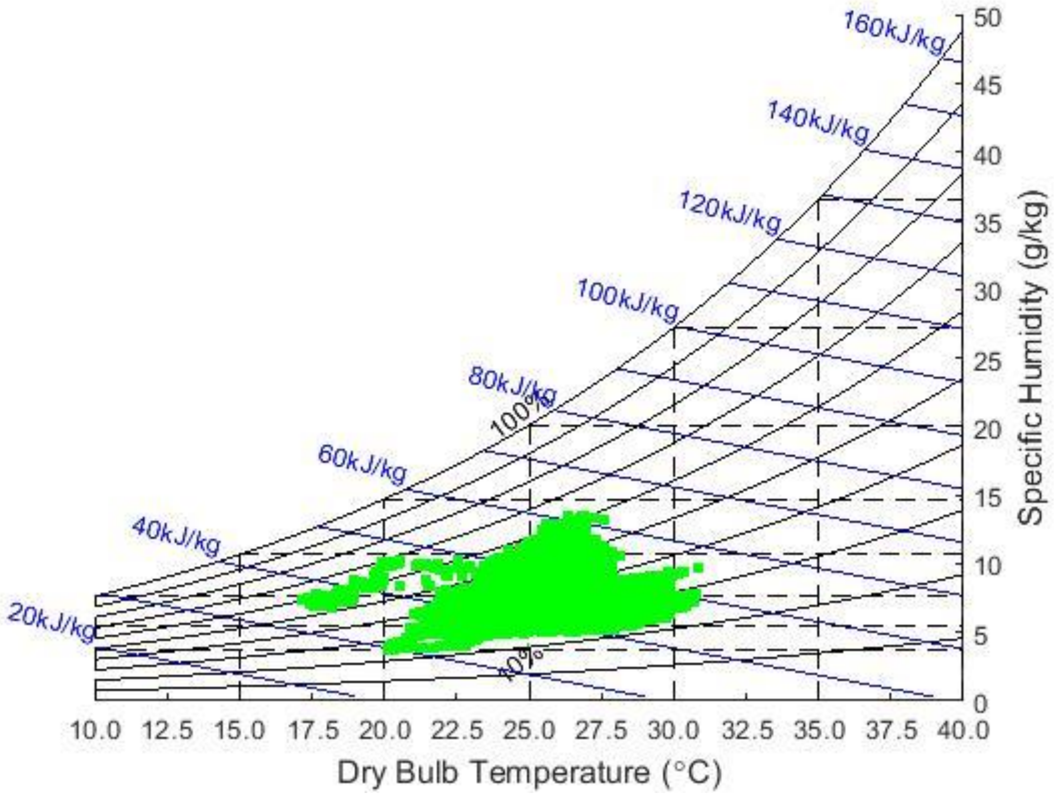



Figure 61. The psychrometric mapping of sensor 2 data (computer desk).

The data for the spot that was exposed to sunlight and located near the glazing was captured by sensor number 3. Unlike the previous two sensors, this sensor captures the conditions which are not in the range of comfort due to the exposure to the cold temperature outdoor. The number of data not in the comfort region is 0.60%. This result is also shown in Table 17, which shows the maximum, minimum and average of the temperature and relative humidity. The sensor detected a broader range of temperatures.

The lower temperature that is not in the range of comfort was detected. The psychrometric mapping of the data from sensor number 3 is shown in Figure 62. Two previous maps only show the green marked group, which is the comfort situation. In this sensor number 3 reading, the sensor detected the low-temperature group below the comfort temperature range. It was about 15 to about 17 °C. This low reading is due to the sensor being located near the glazing, which was exposed to the low outside temperature presented in blue.

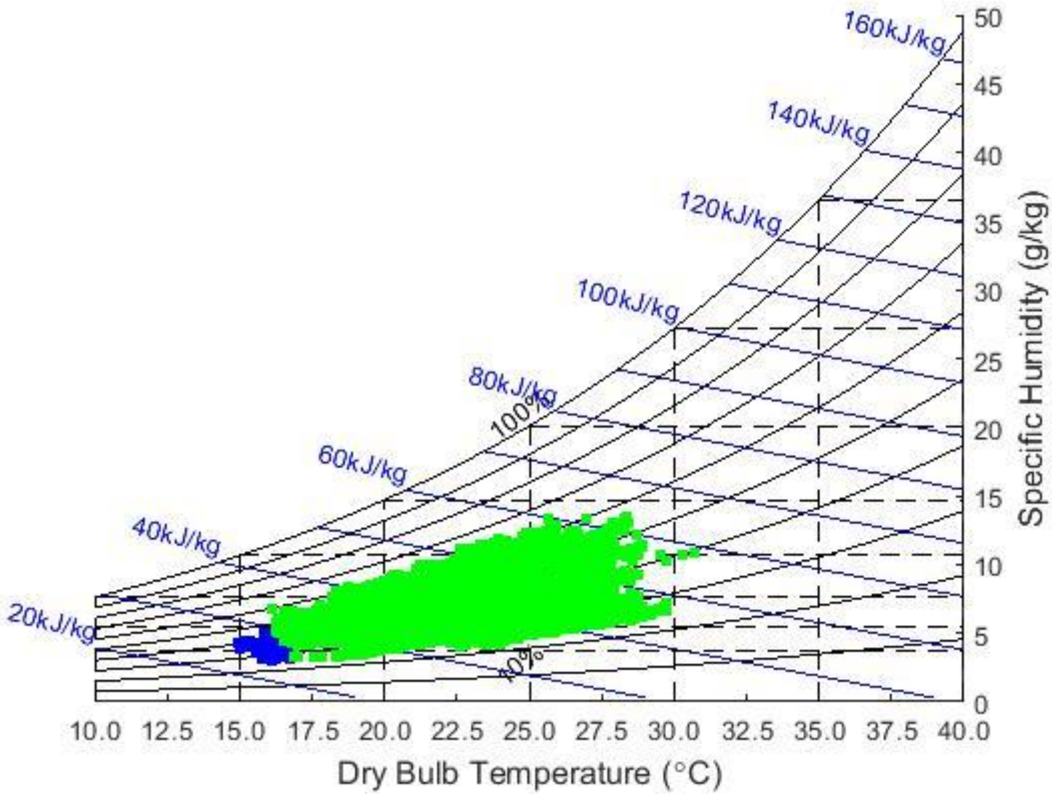



Figure 62. The psychrometric mapping of sensor 3 data (near glazing).

Table 17 also compares the comfort percentages that were interpreted using the PMV-PPD comfort zone, the Givoni comfort zone, the combination of PMV-PPD and Givoni comfort zone, and the developed AI model comfort zone in this work. The result shows that PMV-PPD acknowledged the narrowest comfort zone and the AI model has the capability to acknowledge a more expansive comfort zone.

### *7.3.2 Testing in the BRE house*

#### 7.3.2.1 First Period

The first phase of the test was intended to check and verify the result of the proposed sensors infrastructure against the offline commercial off-the-shelf (COTS) sensors. The check was needed due to the use of the dedicated Wi-Fi network with a frequency of 2.4 GHz, with the possibility of missing data. The more reliable quality of service (QoS) level can be used but will have a drawback in the power usage during transmission.

Table 17. The summary of the captured data from each sensor.

| Sensor Number | 1 (Workbench) | 2 (Computer Desk) | 3 (Near Glazing) |
|---|---|---|---|
| Max. Temp. Value (°C) | 29.95 | 30.83 | 30.71 |
| Min. Temp.Value (°C) | 18.92 | 17.14 | 14.94 |
| Average Temp. (°C) | 23.03 | 25.16 | 23.04 |
| StdDev | 1.86 | 1.96 | 2.84 |
| Max. RH. Value (%) | 65.93 | 69.44 | 65.21 |
| Min. RH Value (%) | 21.85 | 22.29 | 22.7 |
| Average RH (%) | 41.93 | 39.12 | 42.83 |
| StdDev | 11.12 | 8.63 | 8.97 |
| PMV-PPD Comfort Percentage (%) | 93.07 | 88.68 | 76.12 |
| Givoni Comfort Percentage (%) | 99.10 | 99.36 | 95.69 |
| PMV-PPD-Givoni Comfort Percentage (%) | 99.35 | 99.50 | 95.69 |
| AI Model Comfort Percentage (%) | 100.00 | 100.00 | 99.40 |

This phase can represent the regular use of the sensors and capture the differences between the data regarding the differences in sensor readings and the missing data due to the use of the default QoS level. The test was done from 25 January 2022 at 12:00 until 10 February 2022 at 11:00 AM (16 days) with the rate of sampling data interval of 15 minutes and collected data items are 1533.

The result shows that inside the room, the COTS sensor TH02 had an average temperature of 15.91ºC compared to the proposed sensor average, which was 14.53ºC (less than 1 degree C difference). The average relative humidity value was 50.63% for the COTS sensor and 53.33% for the proposed sensor 02. Outside the room (stairs), the average temperature reading from the COTS sensor TH04 was 14.39ºC, and the proposed sensor was 14.10ºC. The average relative humidity value was 55.14% for the COTS sensor and 55.43% for the proposed sensor. Since the COTS sensors reading also had their deviation, it was decided to include both sensor types in all the following phases for value comparison.

The first phase analysis also includes using the AI model to analyse comfort. Based on the sensor reading and fed into the AI model, the comfort inside the room was 36.03% and outside the room was 15.08% during the test periods. The other comfort area analysis with the PMV-PPD comfort zone and Givoni comfort zone returned 0% comfort. The uncomfortable situation was due to the low outdoor temperature (outdoor comfort was 0%) for all the comfort zone analyses. The AI model could still acknowledge a small percentage of comfort in a particular condition.

During this data collection, the capability of detecting the human presence (occupation sensor) was also activated in sensor 05 and showed that during people's presence, the indoor temperature dropped and put the room in an uncomfortable situation. This condition was due to the people's arrival habit, who entered the dwelling and went to check the trial, which led the sensor to be in contact with the cold outdoor air. The psychrometric chart showing the comfort map from sensor 1 (stairs, outside the room), sensor 2 (inside the room), sensor 3 (inside the room near glazing) and outdoor conditions are presented in Figure 63, Figure 64, Figure 65, Figure 66, and Figure 67 respectively.

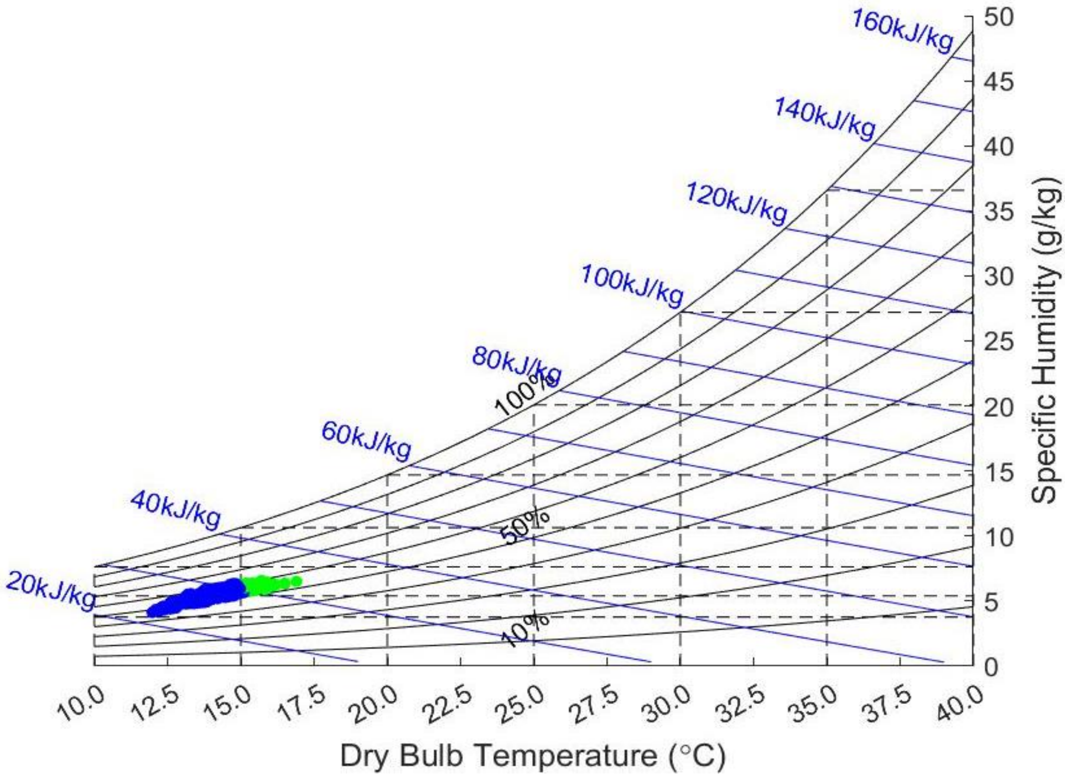



Figure 63. The comfort map for Sensor1 (stairs, outside the room) with a comfort level of 15.08%.

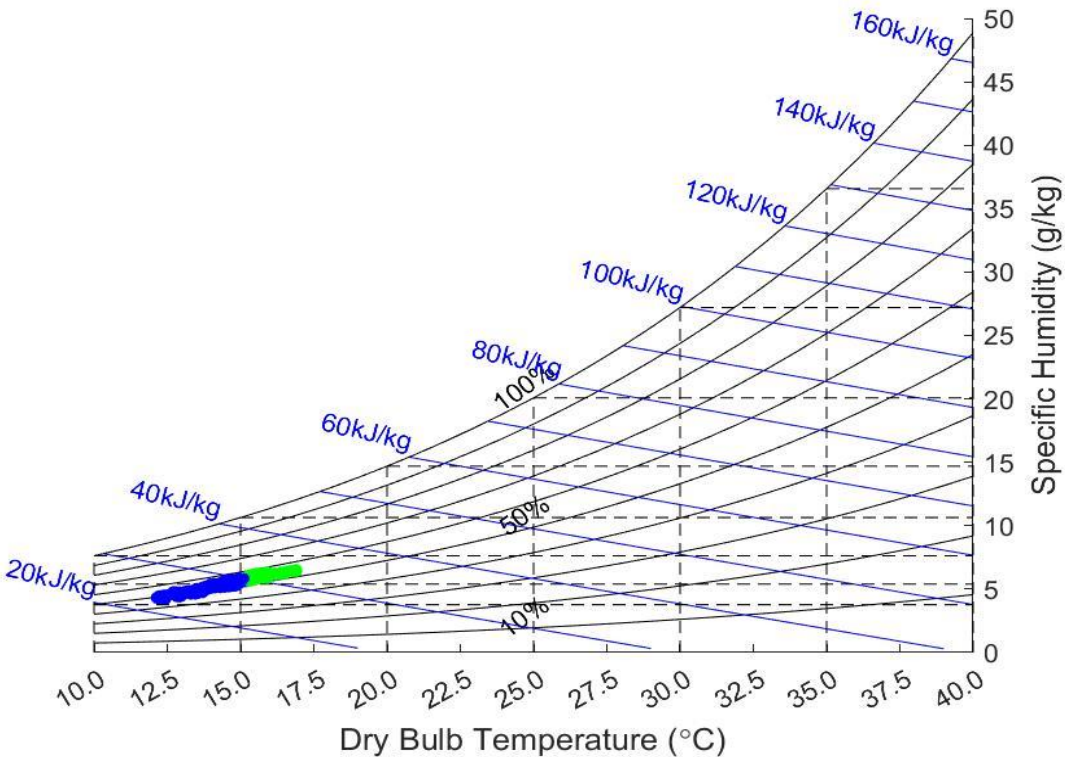



Figure 64. The comfort map for Sensor2 (inside the room) with a comfort level of 36.03%.

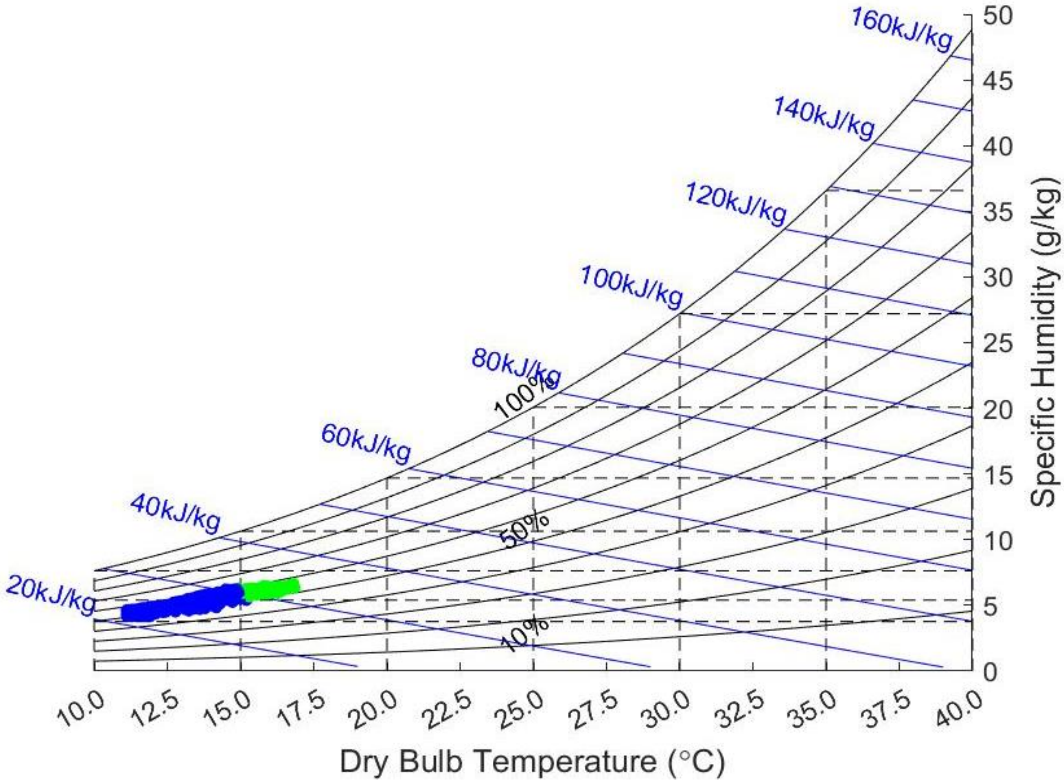



Figure 65. The comfort map for Sensor3 (near the glazing, inside the room) with a comfort level of 15.33%.

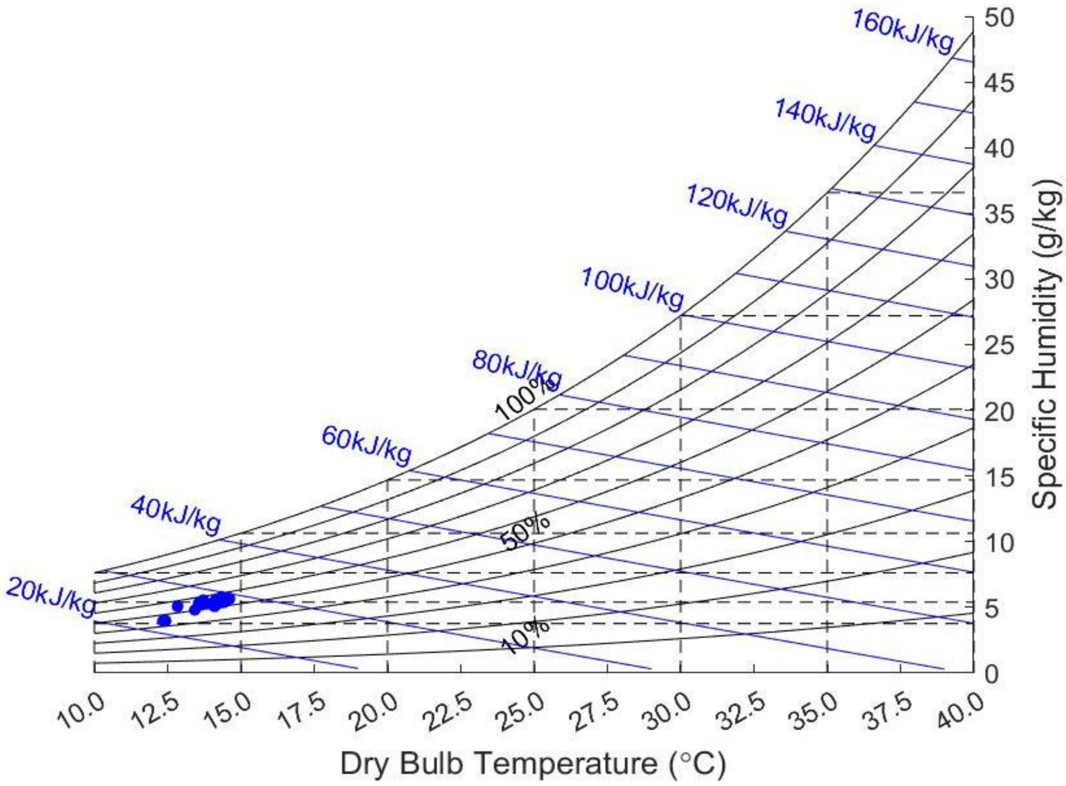



Figure 66. The comfort map for Sensor5 (people visit inside the room) with a comfort level of 0%.

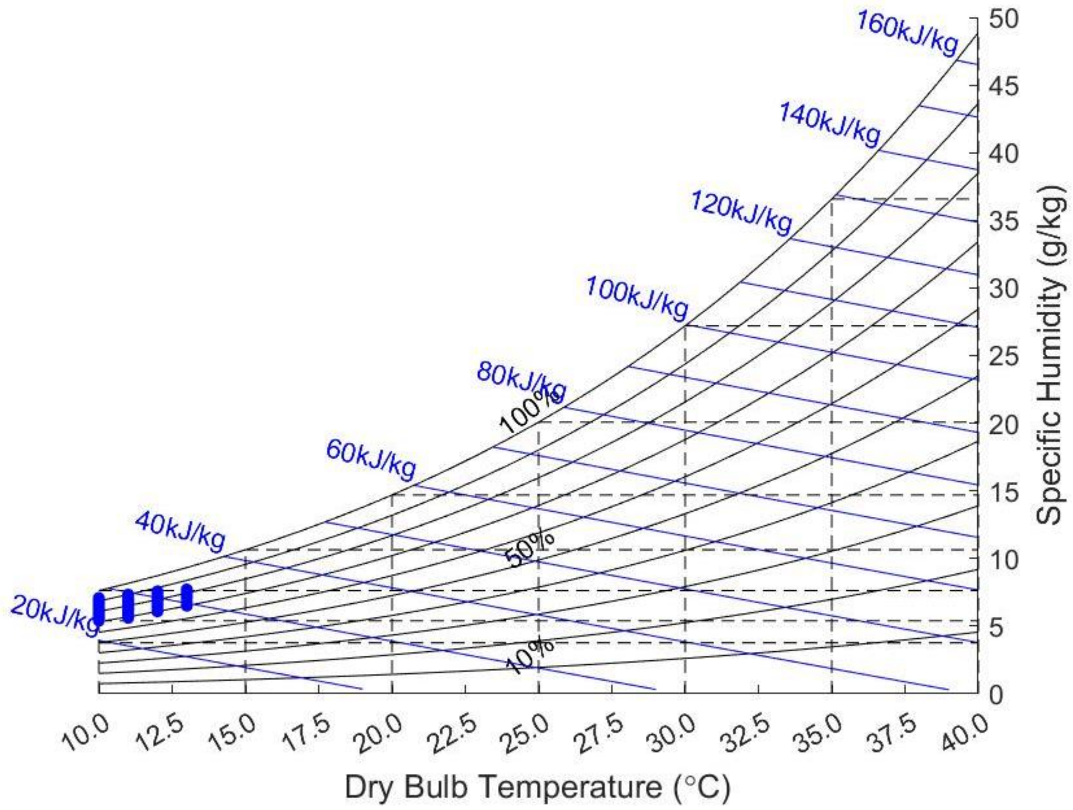



Figure 67. The comfort map for outdoor with a comfort level of 0%.

A better understanding of the comfort pattern was also acquired using a representation map of the data with hourly percentage comfort. The mapping can show the percentage of comfort inside the dwelling hourly throughout the day. The vertical axis (z) is the percentage of comfort, while the horizontal axis (x) shows the time (hour of the day). The other axis (y) shows the day relative to the trial period. The hourly comfort map from sensor 1 (stairs area outside the room) is presented in Figure 68. The other detail can be seen in Appendix 9.

#### 7.3.2.2 Second Period

The second-period data logging was intended to compare the sensor (S01B and S02B) with the black globe sensor (S01A and S02A). The black globe sensor will deliver a more stable reading which will be beneficial to be used in the thermal regulation system. In the case of the outside the room temperature reading, the sensor S01B shows an average temperature of 15.14ºC with a minimum temperature of 13.56ºC and a maximum of 16.98ºC. The same reading with the black globe sensor S01A showed the average temperature of 13.8ºC with a minimum temperature of 12.29ºC and a maximum of 15.9ºC. In the comparison, the COTS sensor average temperatures were 14.13ºC and 13.95ºC. The temperature inside the room showed an average of 16.21ºC with a minimum value of 13.69ºC and the maximum value of 18.57ºC. The black globe sensor installed inside room S02A showed an average temperature value of 13.74ºC with a minimum value of 11.74ºC and the maximum value of 15.9ºC. The values shown by the COTS sensors were 13.24ºC and 13.57ºC. Based on this result, the next phase elaborated on temperature and humidity and black globe sensors. The comfort level for each location is shown in Appendix 9. Based on the result, the black globe displays more sensible and accurate results.

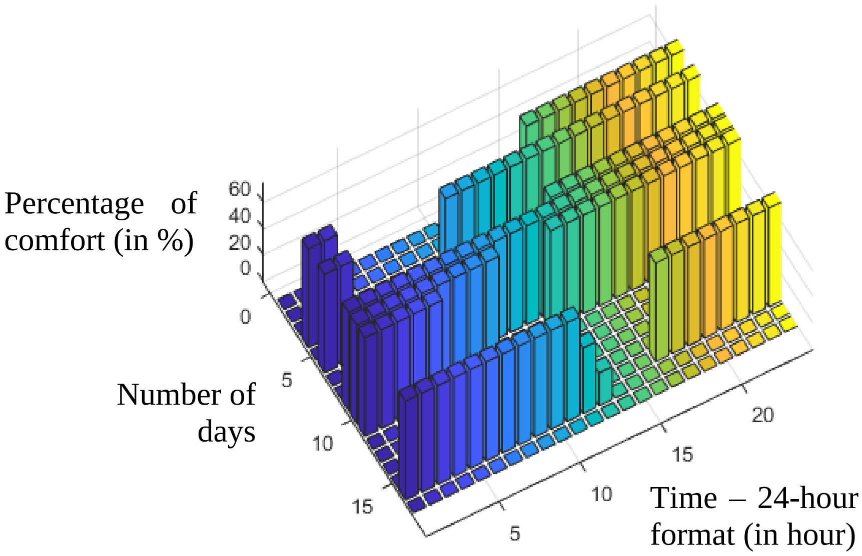



Figure 68. The hourly comfort map for Sensor1 (stairs, outside the room) with a comfort level of 15.08%.

If this comfort level is mapped hourly, the comfort pattern can be used to identify the condition that happened. If the outdoor temperature was not too low, it might be possible to get a comfortable condition inside the room. The sensor near the window detected a higher temperature than the temperature in the middle of the room but the lower temperature in the evening. Two possible reasons could trigger the faster decrease of the temperature. Firstly, the sunlight penetration through the glazing caused the temperature to rise. This condition causes the sensor near the window to detect the comfort level earlier than the sensor in the middle of the room. The second reason was the leakages in the glazing due to the lower insulation level of glazing compared to the wall materials.

The mapping also showed that the comfort level outside the room was lower due to the exposure to the lower outdoor temperature when the outer door was opened. This result also highlights the temperature decrease due to the heat loss outside of the room due to the internal doors that opened, and there were other windows with a lower insulation level compared to the wall materials that made the other rooms' temperature lower due to the thermal leakages. The hourly comfort map from sensor 2 (inside the room) is presented in Figure 69. The other detail can be seen in Appendix 9.

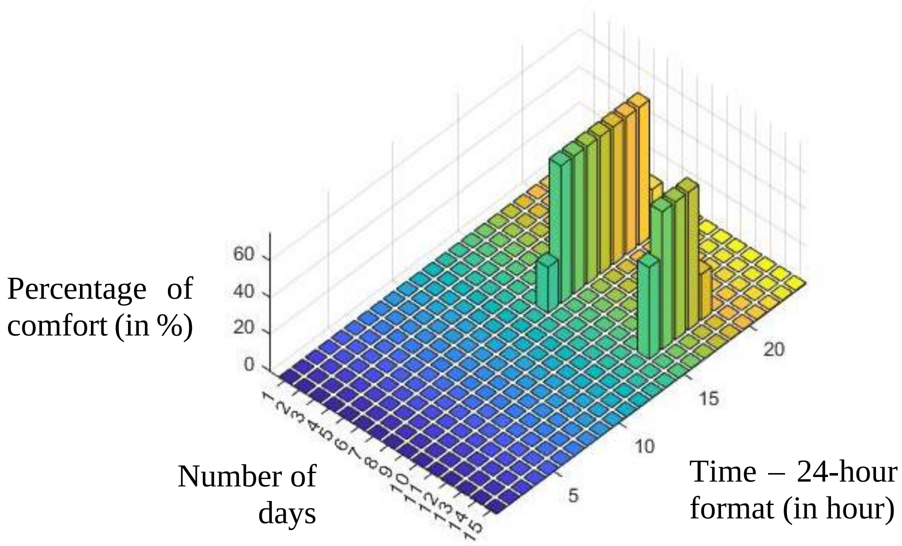



Figure 69. The hourly comfort map for Sensor2 (inside the room) with a comfort level of 3.50%.

#### 7.3.2.3 Third Period

The third phase was intended to check the influence of the human presence in the dwelling against the change in the temperature. Many thermal comfort assessments were being done before the occupancy periods in the absence of the occupants. If the occupants can be simulated, the temperature set point or control algorithm can be prepared to anticipate the human presence. Even if this value seems small and can be ignored, the energy reduction due to this fact can become a concern in the long run.

Based on the assumption of the average person sizing and the level of activities, the human thermal simulator was built with radial heating to represent the human presence. The human thermal simulator assumes the minimal thermal value of human metabolism that equals people sleeping or resting. If two human thermal simulators are present to represent resting, they can also represent one person's presence with a medium activity level.

The third phase uses two human thermal simulators placed inside the room and can increase less than 1 degree C if the human model were placed between 9:30 AM – 6:00 PM (8.5 hours a day). The outdoor temperature was not the same during the second phase, but since it was lower for the third phase, on average, it will be acceptable to claim that the human presence can impact the indoor thermal condition. The outdoor average temperature for the second phase was 7.96ºC, and the outdoor average temperature for the third phase was 7.23ºC. There were no other activities done in the house which could interfere with the result. The indoor room temperature increased from an average of 13.57ºC and 13.74ºC to 14.28ºC and 14.37ºC. The percentage of comfort charts for the third phase are provided in Appendix 9.

The exciting finding is the increase in the rate of comfort. It can elevate the comfort rate to 20.62% from about 4.02% to 3.50%. This reading might have happened due to the border condition that had less comfort and then could be elevated to comfort with the only slight increase in the temperature. If these conditions are likely to happen, a significant increase in energy performance can be achieved.

This result was acknowledged by reviewing the hourly comfort level data. The other comfort groups were in the morning to afternoon, whereas in the previous phase, these groups had no comfort even when the sensor near the window (that was exposed to sunlight) had comfort. There was also the possibility that the thermal increases were sustained until the evening after the people left the premises, but this issue still needs further proof since, at the same time, the comfort level outside the room also increased. The hourly comfort maps for each sensor's location are presented in

Figure 70.

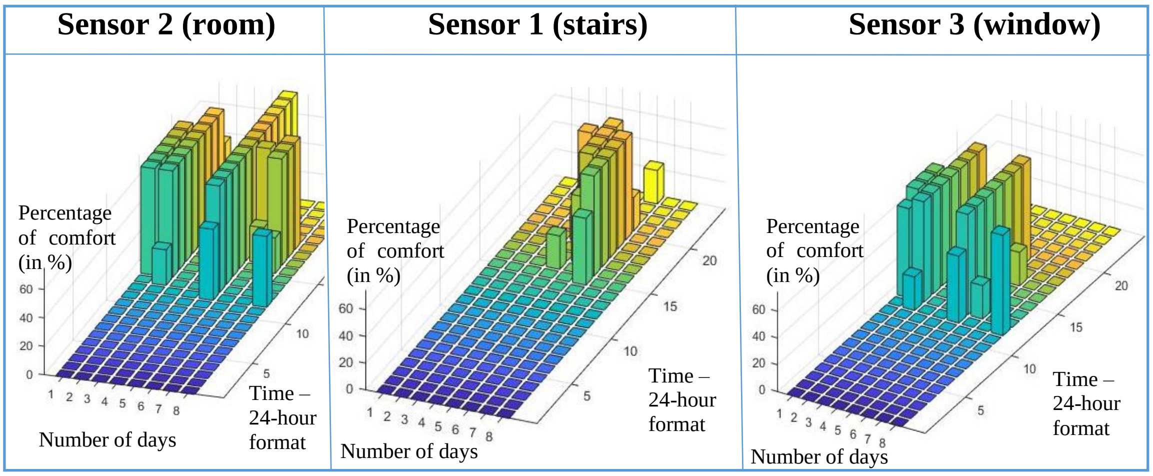



Figure 70. The hourly comfort map for Sensor2 (inside the room), Sensor 1 (stairs) and Sensor3 (Window). The vertical axis (z) is the percentage of comfort (in %), while the horizontal axis (x) shows the time in 24-hour format (hour of the day). The other axis (y) shows the day relative to the trial period.

#### 7.3.2.4 Fourth Period

Like the third phase, in the fourth phase, the average outdoor temperature was lower than in the third phase (from 7.23ºC to 6.89ºC). The average indoor temperature in the third phase showed a slight increase in the sensor temperature from 14.28ºC to 14.67ºC, but the black globe average temperature showed a slight decrease from 14.37ºC to 14.08ºC. In order to analyse further, the assessment of the sensor reading outside the room is necessary. The value of the average sensor temperature outside the room had a slight increase from 14.32ºC to 14.53ºC. The black globe average temperature from outside the room also slightly increased from 14.29ºC to 14.70ºC. This increase showed that some activities outside the room trigger the temperature increase even as the outside temperature decreases. Based on these conditions, the comfort level both inside the room and outside the room was increased to 23.85% of the time. The detailed comfort result psychrometric map can be seen in Appendix 9.

Looking further at the room's hourly comfort map indicated that it was affected by the temperature outside the room. However, the comfort map inside the room was also affected by the human presence that was identified by the increase in percentage level in the morning until the afternoon. The exciting data is also shown by the sensor near the window that is not affected by the condition outside the room. This phenomenon might be due to the low outdoor temperature that affected the sensor reading more than the condition of the room. The detailed map of these comfort zones can be seen in Appendix 9.

The periods were continued so that three periods of data were collected for each class; the measurement with no people present, people present in the afternoon and people present at night.

#### 7.3.2.5 Summary of the BRE House Trial

The result from three trial groups is tabulated to be able to be appropriately analysed and minimise the factors that have been simplified. In order to compare each group and minimise the error due to the simplification, the whole data on each group is compared with the corresponding data with similar properties. Since the indoor temperature data is affected by the outdoor and the adjacent room (stairs) temperature, the data are grouped into entries with the same outdoor temperature data and adjacent room data. With this approach, the error due to parameter simplification can be minimised. The analysis of the measurement result can be seen in Table 18.

Table 18. Field Measurement Result Analysis.

| | | Indoor Temp | Indoor RH | Stairs Temp | Stairs RH | Outdoor Temp | Outdoor RH | | Indoor Temp | Indoor RH | Stairs Temp | Stairs RH | Outdoor Temp | Outdoor RH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Min | No People | 13.10 | 44.11 | 13.00 | 46.47 | 4.00 | 60.00 | Day Presence | 11.54 | 41.14 | 13.00 | 44.83 | 4.00 | 49.00 |
| Max | | 20.90 | 57.77 | 18.92 | 60.95 | 15.00 | 92.00 | | 20.90 | 55.38 | 18.92 | 63.57 | 15.00 | 94.00 |
| Avg | | 14.20 | 53.87 | 14.26 | 54.34 | 7.63 | 79.41 | | 14.25 | 49.74 | 14.26 | 52.42 | 7.63 | 76.70 |
| StdDev | | 1.03 | 2.04 | 0.90 | 2.33 | 1.62 | 6.83 | | 1.65 | 3.05 | 0.90 | 3.79 | 1.62 | 11.95 |
| Percentage of Comfort | | **5.07** | | 4.88 | | 0.84 | | | **24.77** | | 4.88 | | 0.84 | |
| Min | No People | 13.10 | 41.46 | 13.68 | 44.12 | 5.00 | 43.00 | Night Presence | 12.46 | 35.75 | 13.68 | 38.86 | 5.00 | 38.00 |
| Max | | 20.98 | 57.81 | 20.60 | 60.17 | 20.00 | 92.00 | | 20.90 | 53.83 | 20.60 | 65.30 | 20.00 | 93.00 |
| Avg | | 17.28 | 48.60 | 17.43 | 50.03 | 10.47 | 75.73 | | 17.82 | 40.68 | 17.43 | 44.62 | 10.47 | 65.15 |
| StdDev | | 2.24 | 4.46 | 2.18 | 3.90 | 2.98 | 9.70 | | 2.39 | 3.88 | 2.18 | 5.25 | 2.98 | 12.33 |
| Percentage of Comfort | | **71.83** | | 71.83 | | 11.80 | | | **82.04** | | 71.83 | | 11.80 | |
| Min | Day Presence | 11.79 | 39.43 | 13.68 | 44.20 | 2.00 | 43.00 | Night Presence | 12.46 | 35.87 | 13.68 | 38.74 | 2.00 | 43.00 |
| Max | | 20.91 | 54.88 | 19.50 | 63.49 | 16.00 | 94.00 | | 20.32 | 53.58 | 19.50 | 63.33 | 16.00 | 92.00 |
| Avg | | 16.00 | 46.40 | 15.90 | 49.58 | 8.72 | 75.86 | | 16.73 | 43.20 | 15.90 | 46.82 | 8.72 | 73.12 |
| StdDev | | 1.84 | 4.16 | 1.19 | 4.11 | 2.30 | 12.36 | | 1.72 | 4.80 | 1.19 | 5.39 | 2.30 | 9.97 |
| Percentage of Comfort | | **51.97** | | 62.12 | | 1.01 | | | **79.93** | | 62.12 | | 1.01 | |

| **Percentage of Comfort based on** | **Indoor** | **Stairs** | **Outdoor** | **Indoor** | **Stairs** | **Outdoor** |
|---|---|---|---|---|---|---|
| | No People | | | Day Presence | | |
| PMV-PPD | 0.09 | 0.00 | 0.00 | 1.50 | 0.00 | 0.00 |
| Givoni | 2.53 | 3.00 | 0.00 | 3.00 | 3.00 | 0.00 |
| PMV-PPD-Givoni | 2.53 | 3.00 | 0.00 | 3.00 | 3.00 | 0.00 |
| AI Model | 5.07 | 4.88 | 0.84 | 24.77 | 4.88 | 0.84 |
| | No People | | | Night Presence | | |
| PMV-PPD | 2.99 | 0.70 | 0.00 | 4.05 | 0.70 | 0.00 |
| Givoni | 48.94 | 65.14 | 2.29 | 65.67 | 65.14 | 2.29 |
| PMV-PPD-Givoni | 48.94 | 65.14 | 2.29 | 65.67 | 65.14 | 2.29 |
| AI Model | 71.83 | 71.83 | 11.80 | 82.04 | 71.83 | 11.80 |
| | Day Presence | | | Night Presence | | |
| PMV-PPD | 2.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Givoni | 12.85 | 5.98 | 0.00 | 21.31 | 5.98 | 0.00 |
| PMV-PPD-Givoni | 12.85 | 5.98 | 0.00 | 21.31 | 5.98 | 0.00 |
| AI Model | 51.97 | 62.12 | 1.01 | 79.93 | 62.12 | 1.01 |

The average indoor temperature where no people are present is 14.2 °C, whereas the indoor temperature where people are present in the afternoon is 14.25 °C. The result showed a slight increase when there were people inside the room. Similarly, when there are people at night, it can increase the average temperature value from 17.28 °C to 17.82 °C. The exciting result was also acquired when the people present were compared with afternoon and night presence. The average indoor temperature data for the afternoon presence was 16 °C compared to 16.73 °C for the night presence. This result shows more borderline indoor temperature conditions at night compared to the afternoon. The people's presence will be having more effect on the indoor temperature conditions.

***7.3.2.5.1 Percentage of Comfort***

Table 18 also presents the percentage of comfort as the output of AI models that predict the percentage of comfort for each data item with corresponding temperature and humidity. This trial uses the median age of people in the UK, 40.5 years, clothes value of 1 clo, the recommended clothing value from ASHRAE for winter and activity value of 1.5 met, which is associated with light work. The percentage of comfort for the corresponding indoor condition where no people are present is 5.07 compared to 24.77 where there are people present in the afternoon. Similarly, when there are people present at night, the percentage of comfort can increase from 71.83 to 82.04. If the people are present in the afternoon compared with the night, the percentage of comfort will rise from 51.97 to 79.93. This value shows that the human presence at night impacts the most during winter's indoor conditions.

Table 18 also shows the comfort percentage defined by the AI model compared to the PMV-PPD comfort zone, Givoni Comfort Zone and the combination of both PMV-PPD and Givoni. The result shows that the AI model could capture a wider comfort area. The difference in the percentage comfort result is due to the acknowledgement of the comfort, especially in the border of temperature and RH values mapped in the PMV-PPD and Givoni, which were prescriptive and trenchant. These are shown in the last entry of the table, where the percentage of the AI model results far outperform both PMV-PPD and Givoni comfort zone acknowledgement. This test shows that in the case of the border condition, the comfort can be acknowledged by the AI model and, in return, will conserve more energy to obtain indoor comfort.

#### *7.3.2.5.2 Psychrometric Chart*

The psychrometric chart for the comfort map result of the indoor condition with the people present in the afternoon is shown in Figure 71 (a), and the people present at night are presented in Figure 71 (b). This chart shows the comfort condition in the middle part (green area), dominating the cold area (presented in blue). The cold area in Figure 71 (a) shows a broader area than Figure 71 (b) due to the more unsatisfied sensation in this condition. On the other hand, the more comprehensive comfortable condition is shown in Figure 71 (b), representing a higher percentage of comfort shown for the human presence at night.

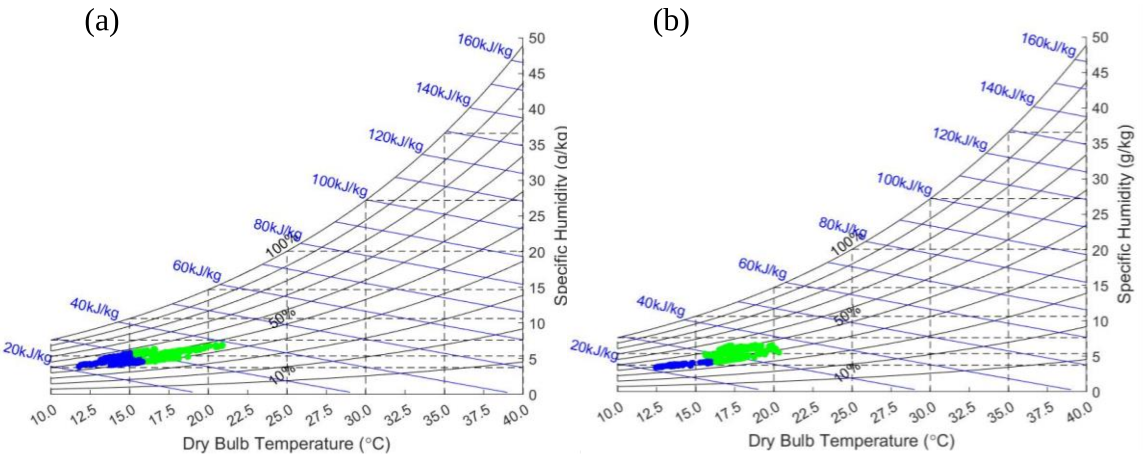



Figure 71. The Psychrometric chart for the comfort condition (a) with human presence in the afternoon (left) and (b) with the human presence at night (right).

#### *7.3.2.5.3 Sensor Reading Comparison*

In the IoT system, there is the possibility that the sensor reading does not reach the local controller or the server due to communication errors, especially when the QoS level is low. This work also compared the COTS sensors against the IoT sensor. The error generated can be from the communication error and sensor value deviation when used in the actual project. The comparison chart between the COTS temperature sensors and the comparison chart between the temperature and humidity COTS sensors and the IoT sensors can be seen in Appendix 9. The comparisons were made in the BRE house to simulate the actual sensor usage with 7,361 data readings with 15 minutes intervals.

The values of R-Squared for the comparison between the temperature COTS sensors were 0.984, 0.974, and 0.990. The value of reliable R-Squared value should be more than 0.95. In this case, the COTS sensors were considered to be reliable. In comparing the black globe COTS temperature sensors and black globe IoT temperature sensors, the values were 0.990 for the centre room sensors and 0.986 for the stair sensors. These values were also considered reliable due to the values being higher than 0.95. For the humidity sensors, the values of the R-Squared COTS humidity sensor compared to IoT sensors were 0.974 for the centre room and 0.967 for the stairs. The IoT humidity sensors showed reliable results. Since the trials were done in the BRE house that simulated the actual condition, these IoT sensors are considered reliable to be deployed in the project.

#### *7.3.2.5.4 Conclusions for BRE House Trial*

This work shows that the data processed through the AI system demonstrate the following:

- The result shows a more expansive comfort zone than the standard comfort zone. This result shows the adaptive notion of human comfort.

- The comfort percentage increased to more than 10% with the human presence in the room. This value proves that the human presence should be considered in the heating system design, particularly in the low border indoor temperature.
- Human presence at night results in higher comfort than in the afternoon. This result shows the importance of the scheduling included in the heating control scheme.
- The IoT sensors are considered to be reliable when they are compared with the COTS sensors.

## 7.4 Case Studies for the Artificial Intelligence Model

The data collected in these case studies were done by a third-party using COTS sensors. Since the sensors are identical in output (sub-chapter 7.3.2.5.3), the data can be associated as similar to the proposed system output. Hence, the author has processed and analysed the data using the proposed model and presented the result in this chapter. Some cases might be interesting to include in this work because the case studies can represent real-world problems. Five case studies represent the problems most likely in the United Kingdom.

Where applicable, the questionnaire also had been given to the occupants to compare the thermal sensation of the occupants that was compared with the result obtained from the AI model. An example of the questionnaire was given in Appendix 11.

### *7.4.1 The Case of Humid Dwelling (Dwelling Prior 1970s)*

#### 7.4.1.1 The Data Acquired

This case is interesting because it is a typical case that happened in the dwelling pre-1970s with no insulation and cavity in the building envelopes. The example of the studied dwelling is shown in Figure 72. High humidity is most likely to happen. The data summary is presented in Table 19. As shown in the data summary, the humidity is very high, and the average relative humidity can exceed outdoor humidity due to the human activities inside the dwelling. The temperature chart for this data is shown in Figure 73, while the humidity chart is shown in Figure 74.

Figure 72. The picture of the studied dwelling with high relative humidity.

Table 19 Summary of the data acquired from the case of humid dwelling.

| Temperature (°C) | TH 06 Temp | TC 06 Temp | TH 12 Temp | TH 03 Temp | TC 05 Temp | Outdoor |
|---|---|---|---|---|---|---|
| Minimum | 10.00 | 11.00 | 10.50 | 12.00 | 11.50 | 3.00 |
| Maximum | 13.00 | 14.00 | 17.00 | 19.50 | 19.00 | 12.00 |
| Average | 11.65 | 12.33 | 13.07 | 13.74 | 14.27 | 7.44 |
| Std. Dev | 0.60 | 0.54 | 1.26 | 0.91 | 1.00 | 2.05 |

| Relative Humidity (%) | TH 06 Hum | TH 12 Hum | TH 03 Hum | Outdoor |
|---|---|---|---|---|
| Minimum | 79.00 | 76.50 | 62.50 | 53.00 |
| Maximum | 99.50 | 100.00 | 89.00 | 93.00 |
| Average | 93.91 | 86.41 | 80.57 | 78.66 |
| Std. Dev | 3.89 | 3.72 | 3.65 | 8.29 |

#### 7.4.1.2 AI Model Result

The AI Model for comfort shows that the comfort level in the living room was 13.28%, in the Bedroom was 0%, comfort in the kitchen was 9.70%, and the outdoor comfort was 0%. The comfort map from the Living room is shown in Figure 75. The other comfort map can be referred to in Appendix 10.

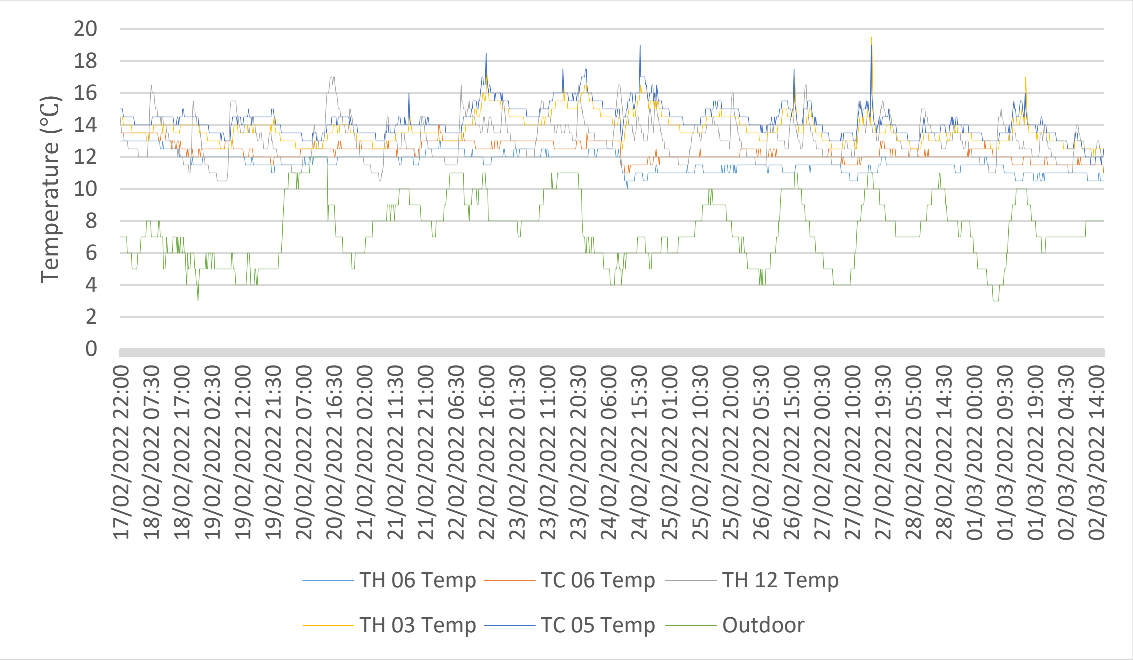



Figure 73 Temperature chart for the data acquired from the case of humid dwelling.

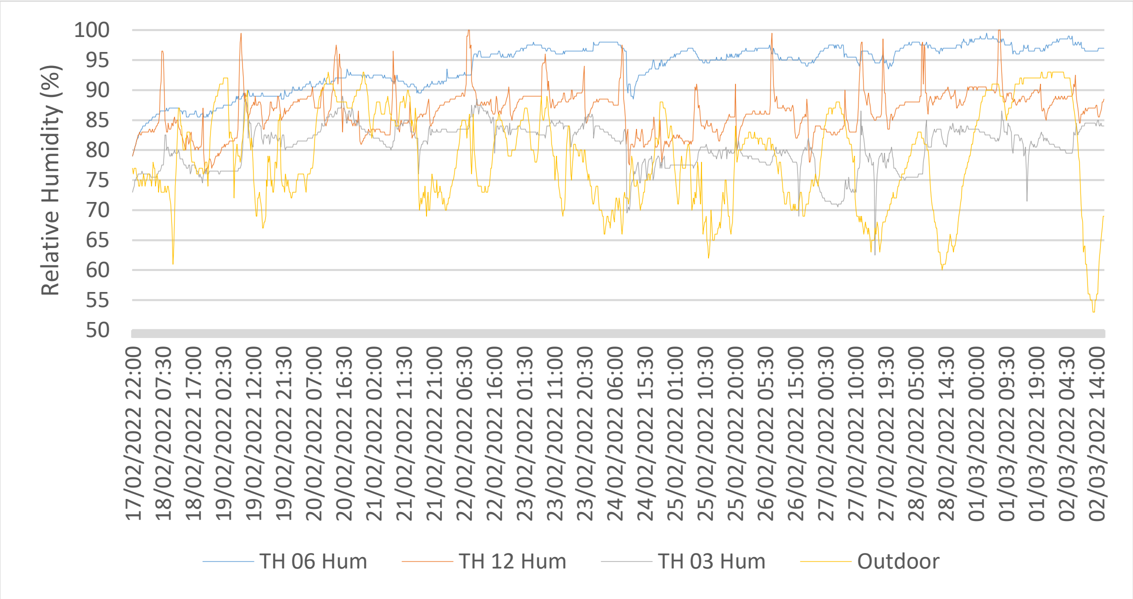



Figure 74. Relative humidity chart for the data acquired from the case of humid dwelling.

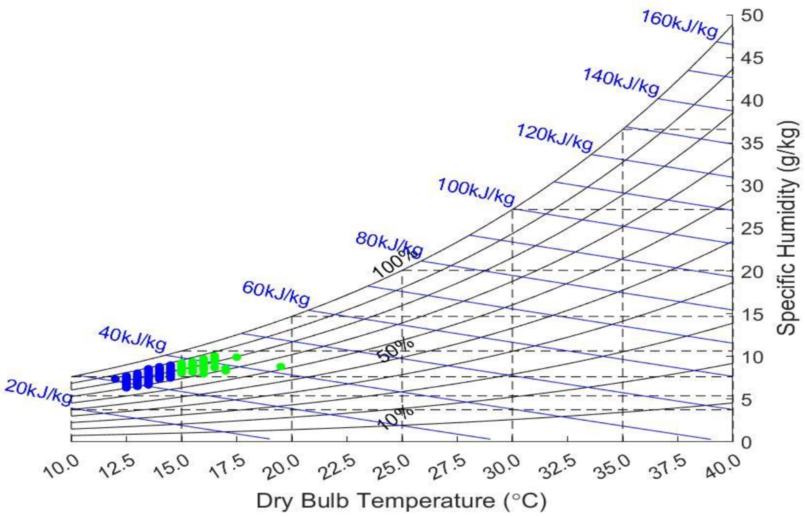



Figure 75. The comfort map from the Living room in the humid dwelling case.

#### 7.4.1.3 Analysis

The result of the AI model showed very low indoor comfort rates due to the relatively low temperature and the high humidity. The rise of the temperature in the living room and the kitchen was due to the cooking activity and the other activities being done by the occupants. Even though the outdoor temperature fell below 10ºC, the indoor temperature was higher due to the occupants' presence and activities. However, the indoor relative humidity showed a higher value than the outdoor temperature due to the occupants' activities that generated moisture, such as respiration, cooking, showering, and washing. This humidity value can be caused by poor insulation, ventilation, and heating.

#### 7.4.1.4 Conclusion

This trial proves that the model was able to highlight low indoor comfort due to the low temperature and the high relative humidity rate. The living room still had 13.28% comfort while the kitchen was 9.7% from all assessment time. In this case, the model will trigger the heater to be turned on in the low-temperature condition. The model was also able to acknowledge the comfort that was achieved due to the occupants’ presence and activities even when the heater was inactive. In this case, when the temperature reaches the predicted comfortable zone, the heater can be turned off to conserve the heating energy.

## *7.4.2 The New Dwellings*

### 7.4.2.1 Sensor Usage and Availability

The sensors were installed in the new dwelling, consisting of 5 sensor sets on each house. Each sensor can detect indoor temperature and humidity. Every house's set of sensors can detect the black globe temperature and relative humidity. Due to the missing sensors, only two homes had complete sensor reading and availability. The picture of the dwellings can be seen in Figure 76. The sensors' placements are described in Table 20.

Figure 76 The picture of the studied new dwelling.

### 7.4.2.2 Data Acquired for the New Dwellings

The sensors captured data from 19 October 2020 from 13:00 until 8 April 2021 at 04:15 (171 days or 4095 hours). The weather station installed in Liverpool John Moores University, Byrom Street Campus is used to obtain the outdoor temperature and humidity data. The distance of the weather station is still adequate to obtain similar outdoor temperature and humidity to the local premises.

Table 20. The placement of the sensors.

| House Number | 17 | |
|---|---|---|
| 1st Floor | AH15 | Landing |
| | AH14 | Bedroom 2 |
| Gnd Floor | AH16 | Hall |
| | AH02 | Lounge |
| | AC02 | Lounge |

| House Number | 19 | |
|---|---|---|
| 1st Floor | AH11 | Landing |
| | AH12 | Bedroom 2 |
| Gnd Floor | AH13 | Hall |
| | AH04 | Lounge |
| | AC04 | Lounge |

### 7.4.2.3 Analysis for the New Dwellings

#### *7.4.2.3.1 Temperature*

The indoor temperature for house number 17 during the assessed period was always in comfort. Only during the initial data gathering (23 to 27 October 2020) were the temperatures below the standard comfort temperature. Apart from the temperatures mentioned, the indoor temperature in each room monitored was always within the comfort zone. The low temperatures most likely happened due to no heater being turned on in the house. The summary of the thermal data can be seen in Table 21, and the chart which displays the outdoor and indoor temperature is shown in Figure 77.

As mentioned before, the minimum temperature values were reached due to the heater being turned off. The measurement shows that the value from the black globe sensor installed in the lounge was close to the outside temperature rather than the Lounge temperature. This result indicates that the thermocouple or the black globe sensor was touching the element of wall or glazing exposed to the external temperature.

Table 21. The summary of the thermal data for house number 17.

| Temperature (°C) | Lounge | Lounge BG | Hall | Bedroom 2 | Landing | Outdoor |
|---|---|---|---|---|---|---|
| Max | 25.50 | 21.00 | 27.50 | 28.50 | 28.50 | 21.00 |
| Min | 6.00 | -0.50 | 6.00 | 6.00 | 6.00 | -3.00 |
| Average | 18.77 | 9.08 | 22.40 | 22.43 | 22.59 | 7.56 |
| Std Dev | 1.89 | 1.46 | 2.63 | 2.52 | 2.64 | 3.67 |

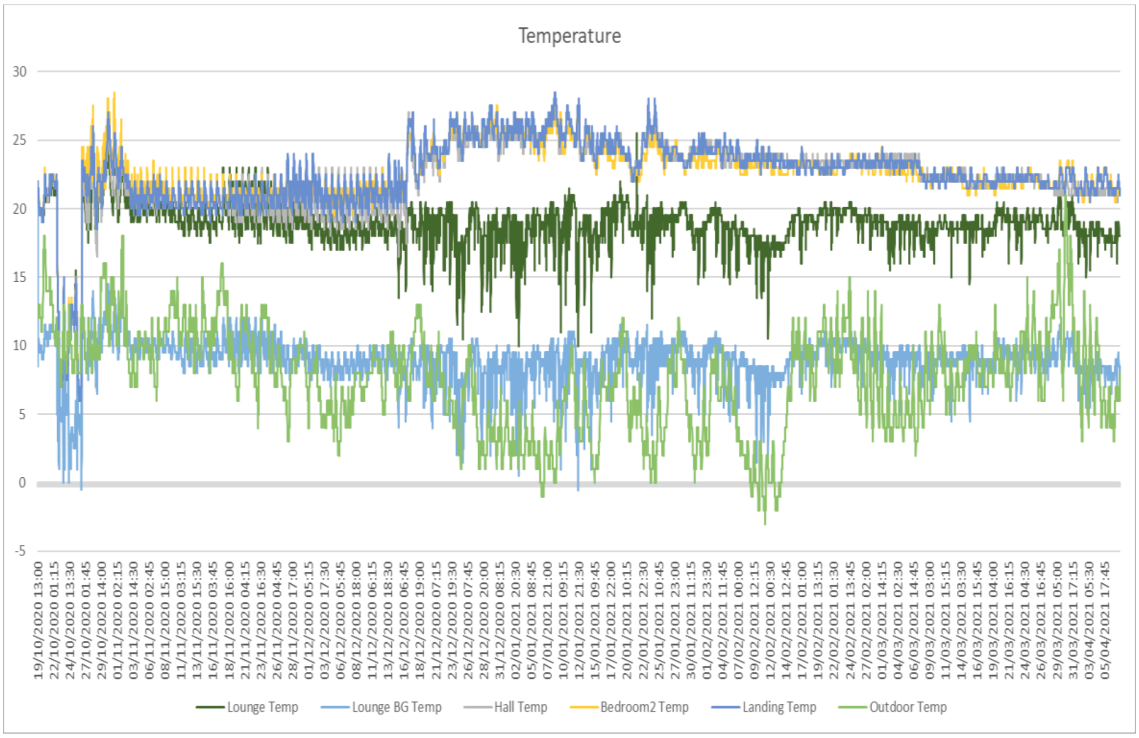



Figure 77. The chart displays the outdoor and indoor temperatures for house number 17. The Y-axis shows temperature (°C).

Assessing the maximum temperature value, the maximum temperature in the hall, bedroom 2, and landing might be too high during the peak of the external temperature. The heater/thermostat set point for these highlighted rooms is considered adjusted. However, the average indoor temperature for all the rooms was within the comfort zone. With the outdoor temperature average of 7.56 ºC, the indoor temperature can be maintained at about 18.77 ºC to about 22.59 ºC, which is still in the comfort zone. When the heater was turned off, the indoor temperature reached a value of about 6 ºC because the external temperature also showed a similar value.

In the early days of January 2021, the heater load was at the maximum. This load is because the outdoor temperature was around 0 ºC, but the room temperatures were at their peak. It is suggested to adjust the temperature set point or thermostat to save heating energy and have a better RH value, which will be explained in the next section. A lower room temperature set point is preferred.

At the end of March 2021, the outdoor temperature began to rise, with the room's temperature relatively stable. In this case, less energy was used for heating the rooms. In general, there was a gap between the lounge and other rooms. This gap might have happened due to the difference in the temperature set point between the lounge and other rooms. It is advised to balance the set point or the heater arrangement so that the temperature in the hall, bedroom 2 and landing room can be lowered, which can conserve the heating energy while maintaining indoor health and comfort.

Like the previous data set, the indoor temperature for house number 19 during the assessed period was always in the comfort temperature. Only during the initial data gathering (23 to 27 October 2020) were the temperatures below the comfort standard, which may be due to the absence of the heater. The Black Globe temperature in this data set shows correct values, unlike the previous data set. The chart which displays the outdoor and indoor temperature is shown in Figure 78, and the summary of the thermal data can be seen in Table 22.

The curve displays the average temperature values from the lowest to the highest: the lounge, bedroom, hall, and landing. With the outdoor temperature average of 7.56 ºC, the indoor temperature can be maintained at about 16.75 ºC to about 20.94 ºC, which is still in the comfort zone. Like the previous data set, in the early days of January 2021, the heater load was at the maximum. The outdoor temperature was around 0 ºC, but the room temperatures were more than 20 ºC. The values assessed show that the recommended temperature maximum setting during the observation period is less than 20 °C. It will result in the saving of heating energy and better RH value, which will be explained in the next section.

Table 22. The summary of the thermal data for house number 19.

| Temperature (°C) | Lounge | Lounge BG | Hall | Bedroom | Landing | Outdoor |
|---|---|---|---|---|---|---|
| Max | 22.00 | 22.50 | 24.50 | 25.50 | 24.50 | 21.00 |
| Min | 6.00 | 6.50 | 6.00 | 6.00 | 6.00 | -3.00 |
| Average | 16.75 | 17.65 | 20.07 | 19.86 | 20.94 | 7.56 |
| Std Dev | 1.72 | 1.72 | 1.98 | 2.05 | 2.15 | 3.67 |

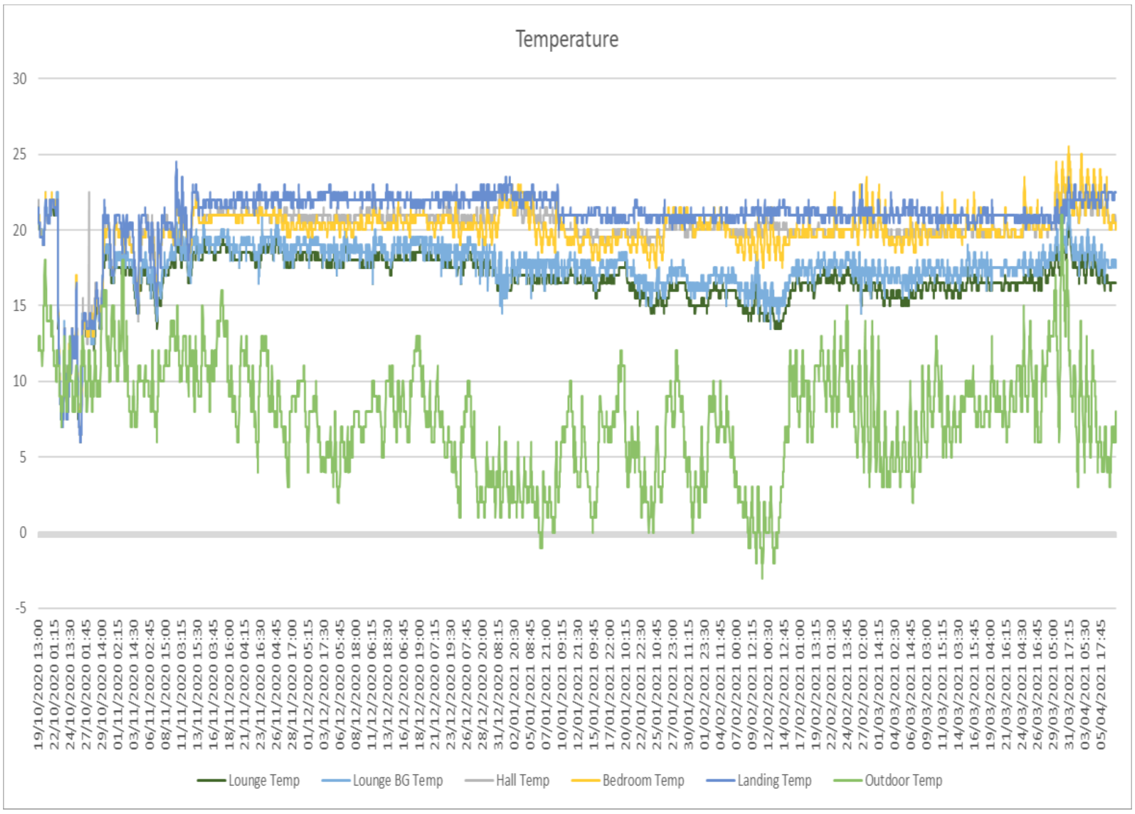



Figure 78. The chart displays the outdoor and indoor temperatures for house number 19. The Y-axis shows temperature (°C).

This data set also showed the same tendency as the previous data set at the end of March 2021. The outdoor temperature began to rise, keeping the room's temperature relatively stable. In this case, less energy was used for heating the rooms. There was a gap between the lounge and other rooms that may happen due to the difference in the temperature set point or the usage of the door, which brought lower temperature outdoor air to the lounge.

#### *7.4.2.3.2 Humidity*

Besides the temperature, relative humidity (RH) also plays a vital role in indoor comfort and healthiness. Based on the ASHRAE Fundamentals handbook 2017 (R. American Society of Heating et al., 2017), the healthy relative humidity range is 20 to 70 %. The RH value outside the mentioned range might trigger health problems. Furthermore, the RH value is advised to be 30 to 70% for a comfortable indoor environment. The summary of the relative humidity data can be seen in Table 23, and the humidity chart for House number 17 during the observation period is presented in Figure 79.

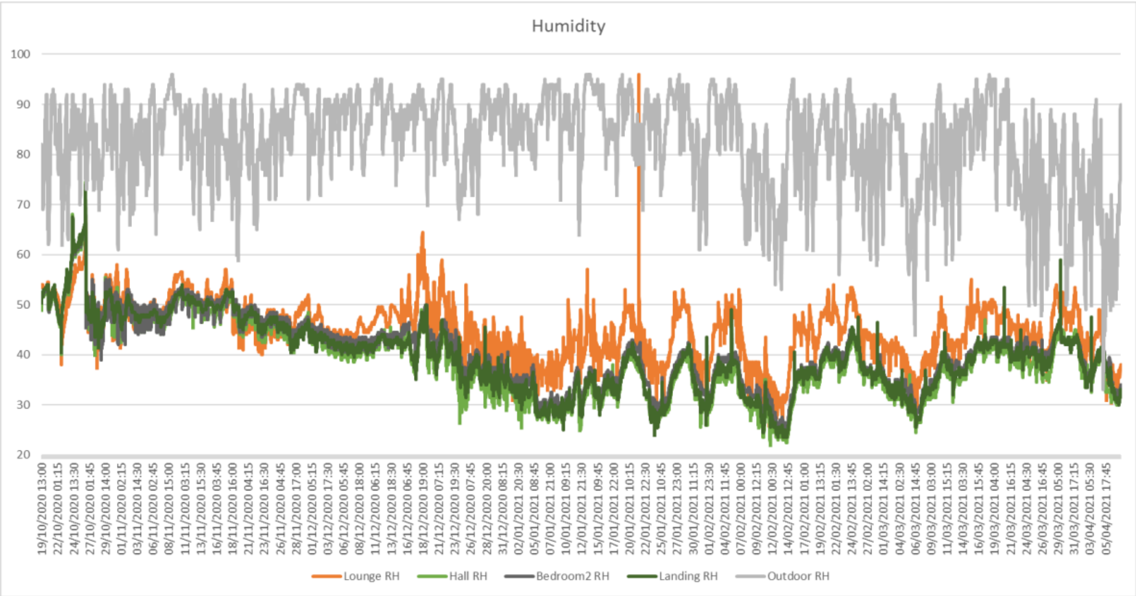



Figure 79. The chart displays the outdoor and indoor relative humidity for house number 17. The Y-axis shows relative humidity (%).

Table 23. The summary of the relative humidity data for house number 17.

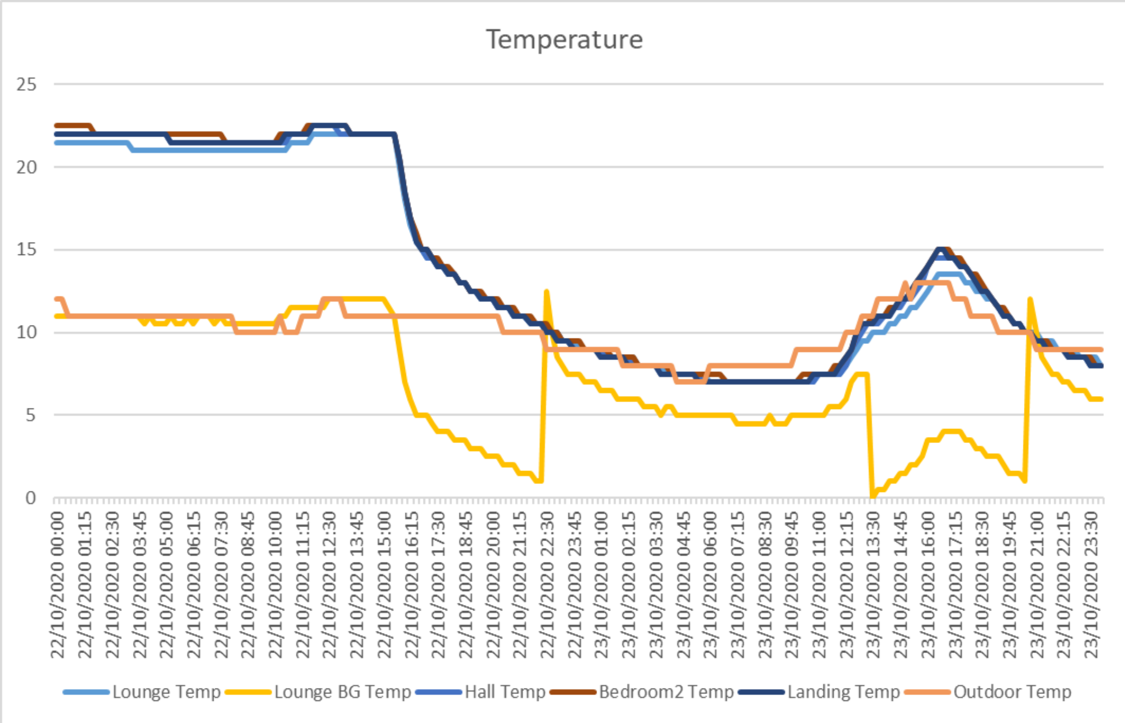
| RH (%) | Lounge | Hall | Bedroom2 | Landing | Outdoor |
|---|---|---|---|---|---|
| Max | 96.00 | 74.50 | 71.50 | 74.00 | 96.00 |
| Min | 25.00 | 22.00 | 25.50 | 23.50 | 33.00 |
| Average | 45.15 | 38.71 | 40.84 | 39.72 | 82.54 |
| Std Dev | 5.43 | 7.43 | 6.92 | 7.39 | 9.38 |

The table shows that the RH minimum value was still in healthy condition. The minimal RH value, close to 20%, is still healthy but might be causing discomfort. However, this value can be better when the temperature set point is adjusted to slightly lower values, as mentioned in the previous section. Assessing the average RH, the values are within healthy and comfortable conditions. Further analysis is being done to show how frequently the uncomfortable RH condition happened during the observation (4095 hours). The uncomfortable period is displayed in Table 24.

Table 24. Uncomfortable relative humidity values from the acquired data.

| Uncomfortable RH | Lounge | Hall | Bedroom2 | Landing |
|---|---|---|---|---|
| RH >70% (hours) | 0.75 | 1.25 | 0.75 | 1.25 |
| RH <30 % (hours) | 6.75 | 491.25 | 152.75 | 359.00 |
| Percentage | 0.16 | 12.00 | 3.73 | 8.77 |

Table 24 shows that the hall, bedroom2, and landing had 491.25, 152.75 and 359.00 hours of uncomfortable RH values from the total of 4095 hours. In percentages, they are 12%, 3.73% and 8.77% of the time that the RH values are not in the comfortable range. As mentioned in the temperature subsection, lowering the temperature set point for these rooms will lower the possibility of unhealthy RH conditions, as shown in the lounge chart and table. Decreasing the temperature gap with the lounge will also reduce the unhealthy RH to more than 30% to achieve healthier indoor conditions from the RH side. The indoor thermal and humidity condition during the time the heater is turned off is shown in Figure 80.



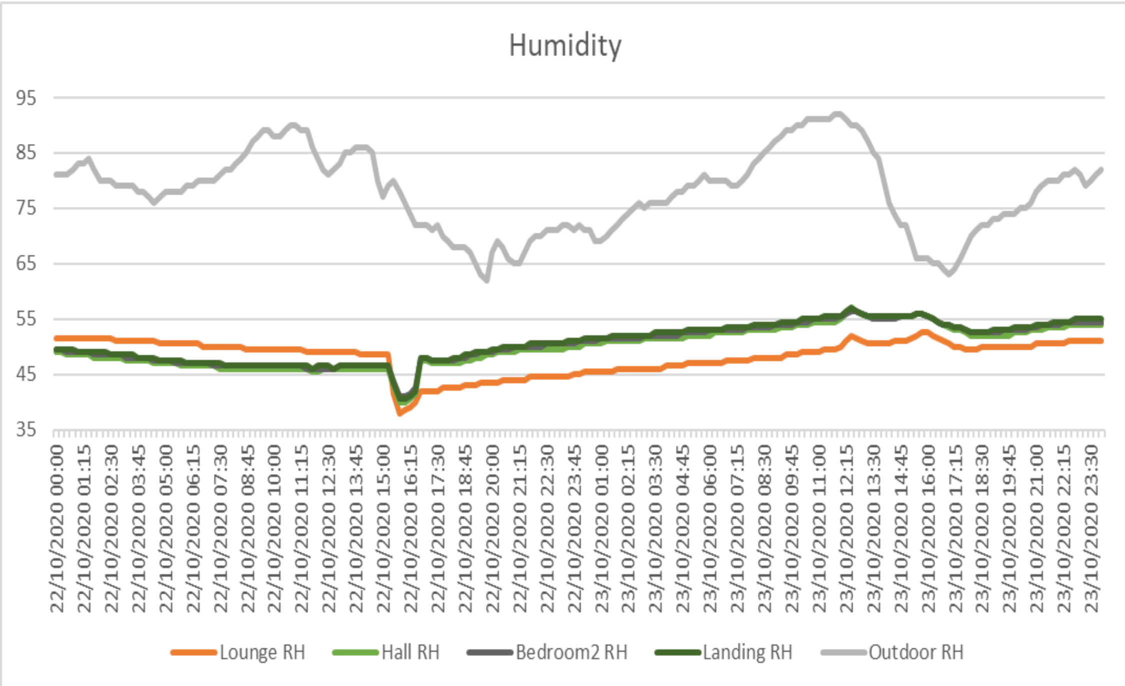




Figure 80. The indoor temperature (top) and humidity (bottom) condition during the heater turned off for house number 17. The Y-axis shows temperature (℃) (top) and relative humidity (%) (bottom).

Due to the low outdoor temperature, without a heater, the indoor temperature was not in a comfortable region. The humidity followed the outside humidity value, but the house materials buffer it. The indoor thermal and humidity conditions during the low outdoor temperature, during the high outdoor temperature and for house number 19 can be seen in Appendix 10.

When the heater is operational, the indoor thermal condition can be sustained within the comfort region. However, if the heater set point is too high, the humidity will fall to the uncomfortable zone (below 30% RH). It is advised to lower the heater set point temperature for better humidity value and heating energy saving. With the outdoor temperature raised, turning off the heater at some point will be needed or can be done automatically. The humidity value will remain stable even with the fluctuation of the external humidity value. The result from house number 19 can be seen in Table 25.

Table 25. The summary of the relative humidity data and the uncomfortable relative humidity percentage for house number 19

| RH(%) | Lounge | Hall | Bedroom2 | Landing | Outdoor |
|---|---|---|---|---|---|
| Max | 73.50 | 79.00 | 74.50 | 75.00 | 96.00 |
| Min | 34.00 | 30.50 | 33.50 | 28.50 | 33.00 |
| Average | 54.13 | 45.92 | 48.42 | 42.69 | 82.54 |
| Std Dev | 5.98 | 6.98 | 6.08 | 6.92 | 9.38 |

| Uncomfortable RH | Lounge | Hall | Bedroom2 | Landing |
|---|---|---|---|---|
| RH >70% (hours) | 53.5 | 2.25 | 2.75 | 0.25 |
| RH <30 % (hours) | 0.00 | 0.00 | 0.00 | 25.50 |
| Percentage | 1.31 | 0.05 | 0.07 | 0.62 |

The table shows that the RH minimum value was still healthy and comfortable. The temperature set point for the landing room should be lowered, and the set point temperature in the lounge should be raised. A temperature set point less than 20 °C is preferable.

#### *7.4.2.3.3 AI Analysis for Each Room*

The artificial intelligence model assumes that the occupants use clothing insulation value of 1 clo in the light or medium activity with a met value of 1.5 and the assumption of age 40.5 years. In House number 17, the lounge comfort level is 96.18%, hall 97.80%, bedroom 97.81% and landing 97.75%. These were achieved during an outdoor comfort level of 2.46%. For house number 19, the Lounge comfort level is 87.54%, the hall comfort level is 96.37%, the bedroom is 96.31%, and the landing is 96.20%, with the same outdoor comfort level (2.46%). The uncomfortable condition indoors happened due to the heater that was turned off and the indoor temperature falling below 15°C.

#### 7.4.2.4 Conclusion

The indoor condition was in a comfortable state for most of the time. Only when the heater was off, the indoor temperature was uncomfortable. The AI analysis was able to show that there is the possibility to lower the temperature set point and keep the occupants still in comfort. Lowering the heating or thermostat settings, especially in the hall, bedroom2, and landing room, to balance with the lounge will affect the more comfortable indoor environment and lower the usage of heating energy, which can lower the carbon footprint of the house. The case study reflects that if the model is implemented in the house, it can control the heater in a more impactful way for energy conservation.

### *7.4.3 The Refurbished Flats*

The case study of the refurbished flats was done with five flats being monitored from a 16-storey block of flats. There was Flat 89, which is located on the 15th floor, Flat 80 on the 14th floor, Flat 49 on the 8th floor, and Flat 41 and 38 on the 7th floor. This flat data was interesting to be analysed due to the refurbishment involving additional insulation installation and new electric heaters. The data readings were done at least three times during pre-, construction and post-construction. The picture of the flats can be seen in Figure 81. The range of data captured, and the intervals are listed in the table in Appendix 10. During the initial set-up stage, the sensor recorded data every 5 minutes for stages 1 and 2. On stage 3, it has been set to 10 minutes because from the observation on stages 1 and 2, not many different variants in terms of data set can be observed within the 5 minutes interval. The 10 minutes intervals allow for a longer duration. The precise date and duration can be seen in Appendix 10.

Figure 81 The picture of the studied refurbished flats; before, during, and after refurbishment.

Since the availability of tenants was different, the sensor installations were done at different times. The regulation change regarding the pandemic time also left the sensors out for a long time. The other challenge was the sensor's position which was moved so that it might be prone to invalid data because of direct contact with glazing with sunlight exposure like in the bedroom 1 sensor in Flat 80. The deviated sensors' readings were excluded from the results chart. Another challenge was the missing sensors. Some sensors were missing, with the significant loss in Flat 89 due to the occupant's passing away. The flats with the complete stages data were Flat 80, Flat 41, and Flat 38. The state of the sensors is presented in the table in Appendix 10. The indoor refurbishment was done by upgrading the electric heaters into new ones. In the result charts, this period can be detected by the absence of a heater high-temperature reading. Even with these limitations, the baseline data can still be obtained to analyse the refurbishment effects and the occupant's behaviour related to the indoor thermal conditions.

#### 7.4.3.1 Results and Analysis for the Refurbished Flats

The results and analysis are presented flat by flat. They will be concluded by presenting the tabulated data results since the weather station was not installed in this project; the available un-quality-controlled data from CEDA (MetOffice) for Liverpool (Crosby) was used to give a hint of the external temperature condition. The data can be found at https://data.ceda.ac.uk/badc/ukmo-midas-open/data/uk-daily-weather-obs/dataset-version-201901/Merseyside/17309_crosby. The Liverpool John Moores University weather station data which was obtained from the LJMU BRE Houses weather station located in the Byrom Street Campus was also used for the second and third stage. The data was in the format of 15 minutes intervals, which are linearly interpolated to match the sensor 10 minutes interval.

##### *7.4.3.1.1 Flat 80 Temperature*

The data shows that the occupants always turn on the entrance and hall heater and turn off the heater inside the bedroom. There was a trace of the bedroom heater turned on during the initial periods of data gathering, but that was the only time this heater was turned on. The most impactful heater in this Flat was the hall heater. It might be due to the position of the heater, which is in the centre of the flat, and the heat can be felt all around it. The bedroom doors were predicted to be open most of the time, which explains the similarity of the temperature result for the hall and bedrooms temperatures. Based on this chart, the occupants always get the indoor temperature relatively stable. The temperature chart for Flat 80 in the pre-refurbishment phase, pre and during-refurbishment phase, during and post-refurbishment phase and post-refurbishment phase are shown in Appendix 10.

Before the refurbishment, the indoor temperature was within the comfort temperature, but the energy to maintain the comfort temperature was high. This condition can be shown by the peak temperature and the number of peaks generated by the entrance and hall heater. Figure 82, Figure 83, Figure 84 and Figure 85 show the stable daily temperature in a day for all of the stages of the project from the pre-refurbishment until the post-refurbishment. The entrance heater and hall heater regulate the indoor temperature for the whole area of the flat. In the pre-refurbishment phase shown in Figure 82, the number of peaks was three, with the hall heater temperature peak reaching 80 ºC and the entrance heater temperature reaching 50 ºC. During the refurbishment process shown in Figure 83 and Figure 84, the number of peaks decreased to two, and the peak temperature also decreased. The hall heater temperature peak, which previously reached 80 ºC, was reduced to 50 ºC, and the entrance heater temperature from 50 ºC was reduced to 40 ºC. All of this happens with an outside temperature of around 10 ºC. Similar things happened with the post-refurbishment.

Figure 85 shows that the number of peaks is reduced to one. The hall heater's peak is about 50 ºC, and the entrance heater temperature was about 40 ºC, with the outside temperature around 10 ºC. This sensor reading shows the potential heating energy saving due to the refurbishment process. The temperature chart for the post-refurbishment phase shown in Figure 85 also showed a rise in the thermal performance when the heaters were switched off. The indoor temperature decreased slowly, indicating that the refurbishment can give the flat better thermal properties than before. Although these sensors cannot measure the precise amount of energy, the chart shows that energy saving is achieved after refurbishment.

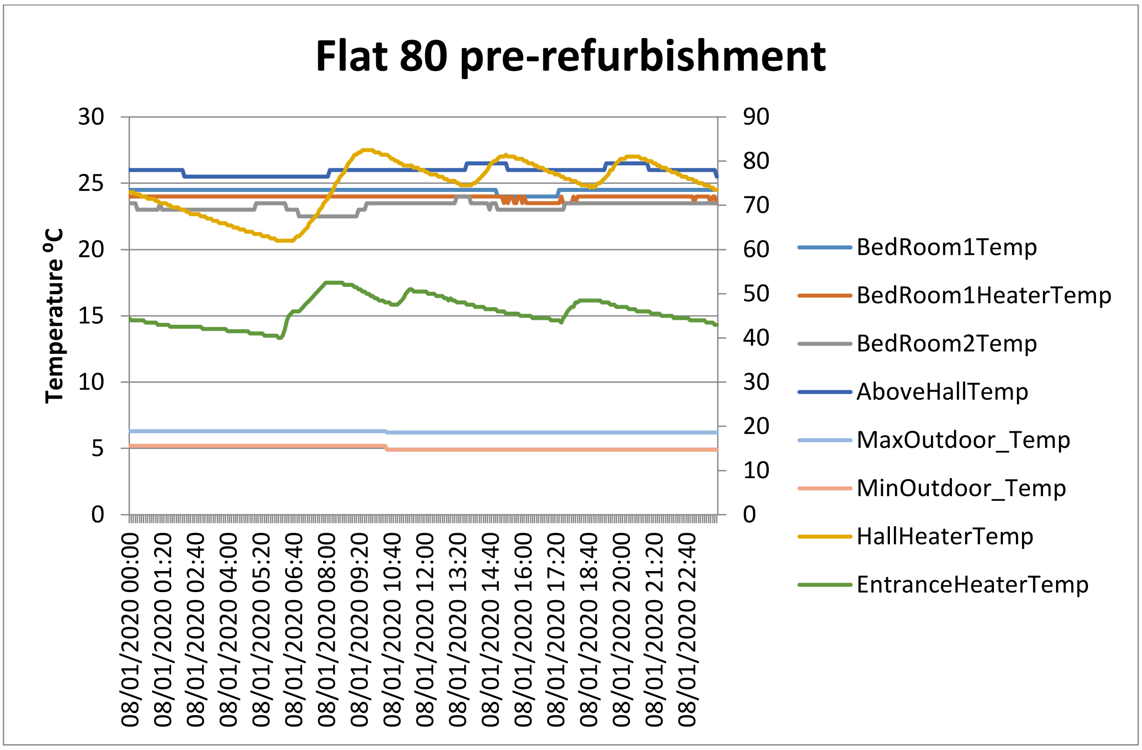



Figure 82. Daily temperature chart for Flat 80 in pre-refurbishment phase. Secondary y-axis is used for Heaters' temperature.

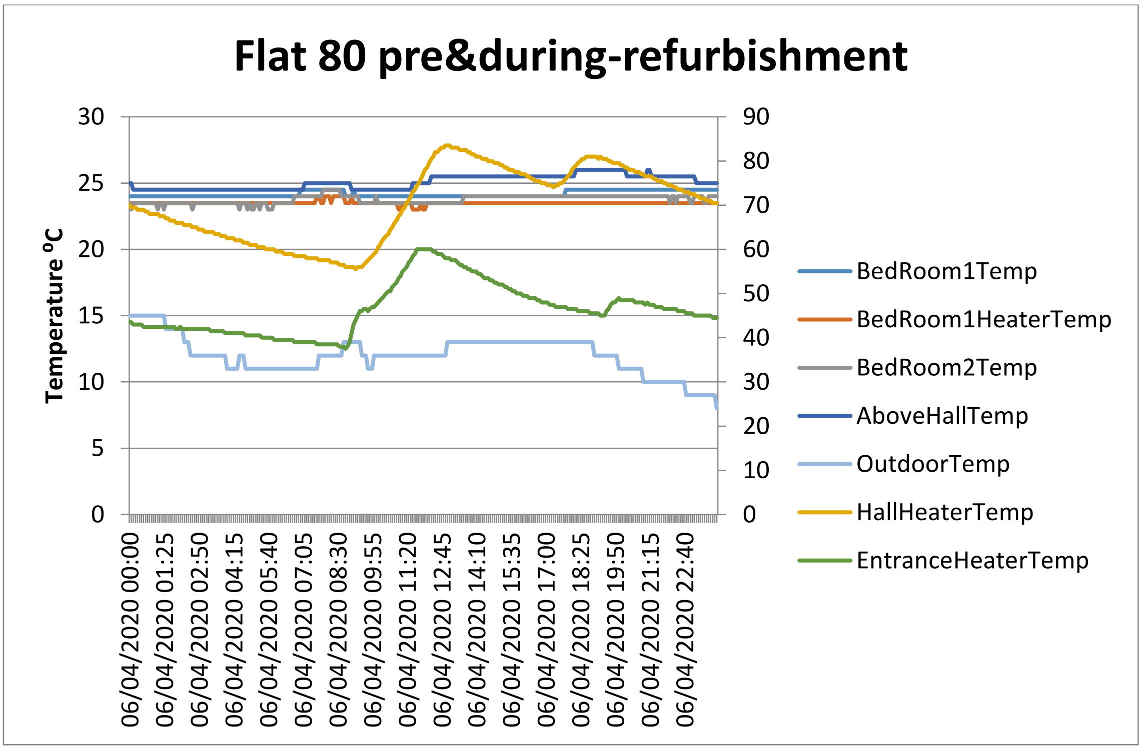



Figure 83. Daily temperature chart for Flat 80 in pre and during-refurbishment phase. Secondary y-axis is used for Heaters' temperature.

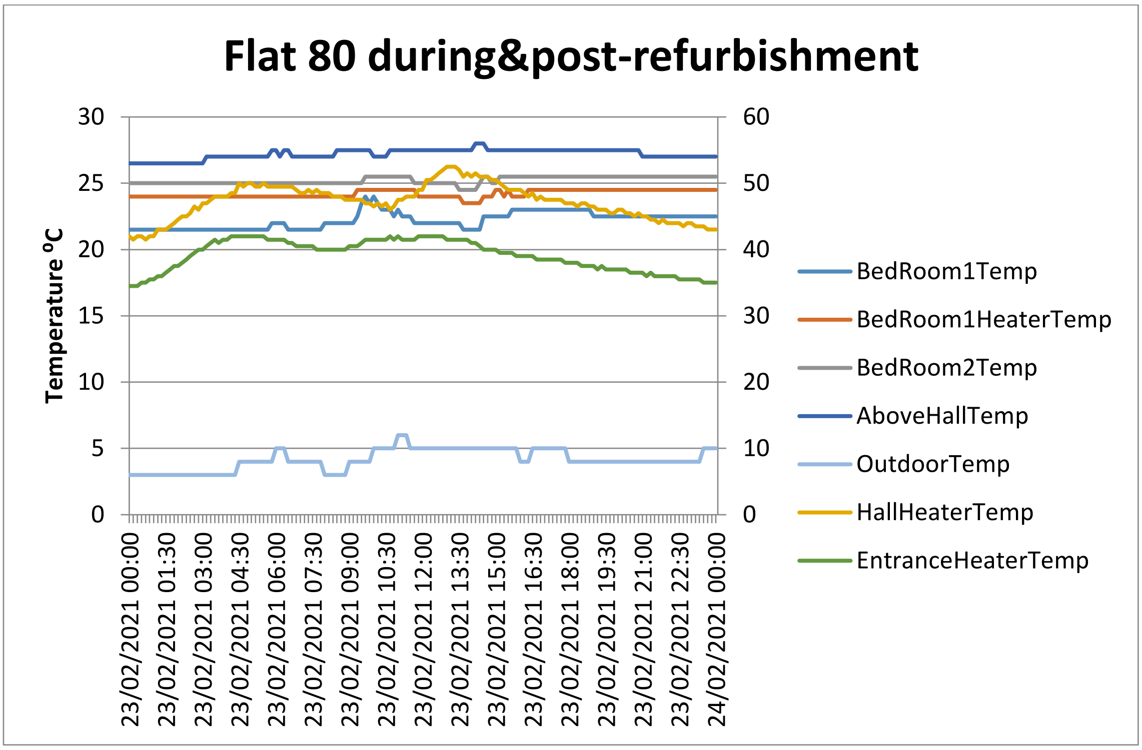



Figure 84. Daily temperature chart for Flat 80 during and post-refurbishment phase. Secondary y-axis is used for Heaters' temperature.

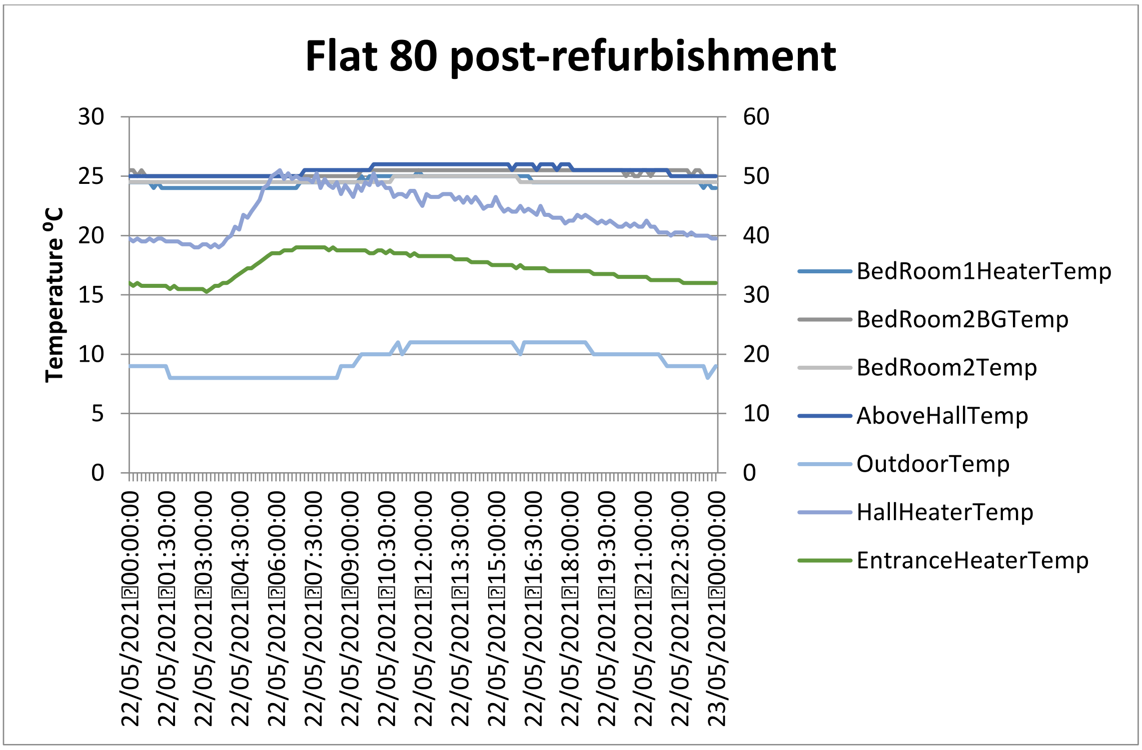



Figure 85. Daily temperature chart for Flat 80 in post-refurbishment phase. Secondary y-axis is used for Heaters' temperature.

The Sign of the thermal energy efficiency increase is also shown in Table 26. The hall heater's average temperature decreased from 74 ºC in the pre-refurbishment to 64 ºC, 43 ºC and 39 ºC in the post-refurbishment. The average temperature of the entrance heater is decreased from initially 47 ºC down to 45 ºC, 38 ºC and 35 ºC in the post-refurbishment. Based on this value, the potential energy saving can reach about 36% on average. The value is based on the outdoor temperature value of 6 ºC, 13 ºC, 5 ºC and 10 ºC, which in this case is assumed to be constant for simplification. Table 26 shows the summary of the sensor reading.

Table 26. The parameters summary for Flat 80

| Summary for Flat 80 | Pre refurbishment | | Pre&During refurbishment | | During&Post refurbishment | | Post refurbishment | |
|---|---|---|---|---|---|---|---|---|
| **Parameters** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| BedRoom1 Temperature (ºC) | 23.981 | 0.407 | 24.538 | 0.859 | 19.825 | 1.886 | 24.226 | 3.250 |
| BedRoom1Heater Temperature (ºC) | 23.692 | 1.983 | 24.004 | 0.963 | 22.029 | 1.606 | 24.591 | 1.609 |
| BedRoom2 Temperature (ºC) | 23.067 | 0.698 | 24.027 | 0.927 | 23.032 | 1.408 | 25.225 | 1.517 |
| Hall Heater Temperature (ºC) | 73.996 | 5.992 | 64.167 | 17.383 | 43.233 | 7.833 | 39.085 | 9.329 |
| Above Hall Temperature (ºC) | 25.380 | 0.485 | 25.083 | 0.871 | 25.033 | 1.114 | 24.796 | 5.051 |
| Entrance Heater Temperature (ºC) | 47.466 | 4.139 | 45.319 | 6.140 | 37.989 | 2.479 | 34.594 | 5.194 |
| Outdoor temperature (ºC) | *6.459 | *1.897 | *12.609 | *4.224 | 5.027 | 2.917 | 10.927 | 4.528 |
| Outdoor Relative Humidity (%) | *93.36 | *1.87 | *66.934 | *12.809 | 86.864 | 5.601 | 72.386 | 13.247 |
| Indoor Relative Humidity (%) | 40.120 | 2.328 | 33.984 | 3.688 | 31.507 | 4.040 | 34.214 | 4.196 |

NOTE: * incomplete data

### *7.4.3.1.2 Flat 80 Humidity*

Even with the outdoor relative humidity, which can reach about 90% and cause discomfort, the indoor relative humidity value was not exceeding 70% and stayed in the healthy range. The indoor relative humidity is relatively stable, with a standard deviation value of about four and an average value of about 40% in pre-refurbishment, 33%, 32%

and 34% post-refurbishment. The outdoor humidity value is about 80%. In the pre-refurbishment phase, the outdoor humidity data from the weather station was unavailable, and the humidity data were obtained from the daily humidity data from CEDA (MetOffice).

The humidity chart for Flat 80 in the pre-refurbishment phase, pre and during-refurbishment phase, during and post-refurbishment phase and post-refurbishment phase are shown in Appendix 10, including the example of the daily humidity chart comparison between pre-refurbishment and post-refurbishment. The result of the post-refurbishment relative humidity value is slightly lower than the pre-refurbishment, which shows that the post-refurbishment relative humidity value will most likely not exceed 70%, which is considered to be in a healthy range.

#### *7.4.3.1.3 Flat 38 Temperature*

Similar to the case of Flat 80, the increase in thermal efficiency can be seen through the lower peaks in the heater temperature. Unlike in flat 80, where the peaks and peaks number are easily recognisable, the pattern was not simple in the case of flat 38. The daily temperature chart for the pre-refurbishment phase, during refurbishment and post-refurbishment can be seen in Figure 86, Figure 87, and Figure 88, respectively. The thermal efficiency can be seen more easily in Table 27, which shows that the hall heater and the entrance heater have lower temperatures in the post-refurbishment phase while maintaining the indoor comfort temperature of around 24 $^{o}$C.

#### *7.4.3.1.4 Flat 38 Humidity*

The relative humidity value from Flat 38 shows a similar tendency to that in Flat 80. The outdoor relative humidity value fluctuation would not directly affect the indoor relative humidity. After the refurbishment process, it is shown that the internal humidity value has a health advantage: it rarely reached 70% and was within the healthy requirement and not too low. The chart showing the relation of the outdoor relative humidity against the indoor relative humidity in Flat 38 can be seen in Appendix 10.

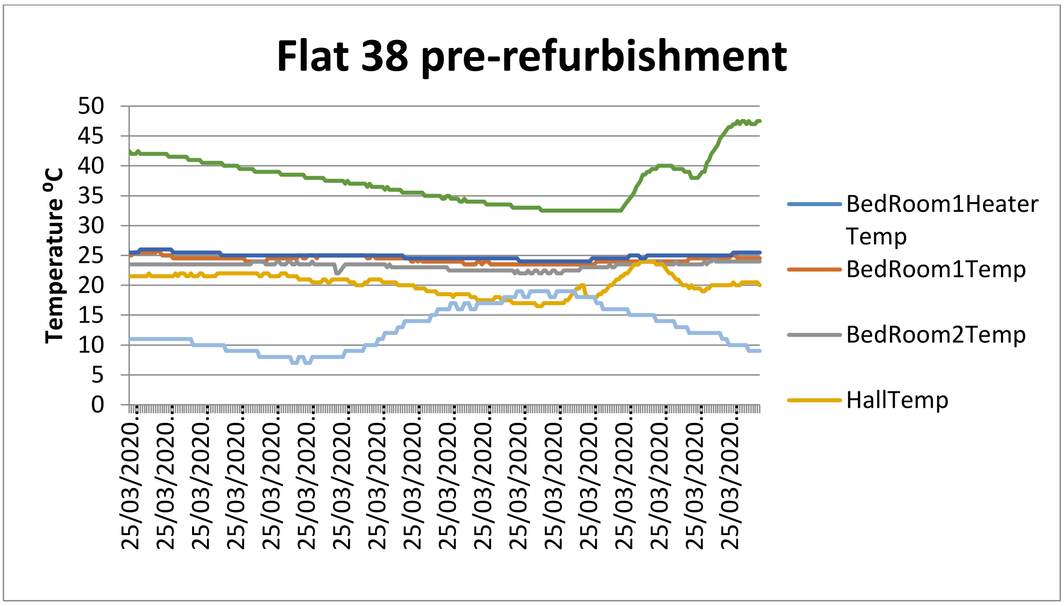



Figure 86. Daily temperature chart for Flat 38 in pre-refurbishment phase.

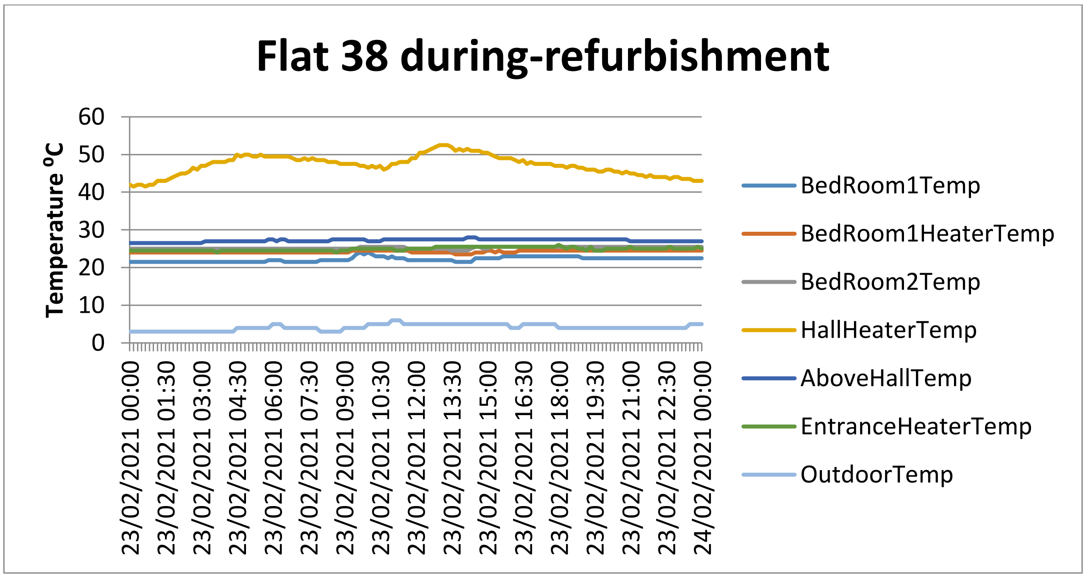



Figure 87. Daily temperature chart for Flat 38 during-refurbishment phase.

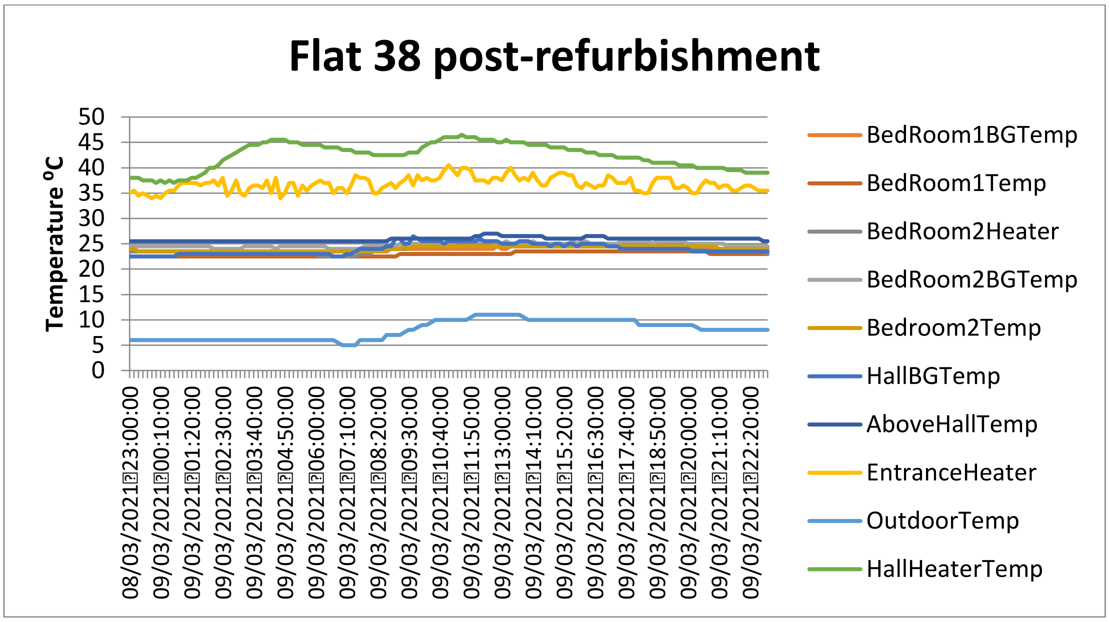



Figure 88. Daily temperature chart for Flat 38 in post-refurbishment phase.

Table 27. The parameters summary for Flat 38

| **Summary for Flat 38** | **Pre refurbishment** | | **During refurbishment** | | **Post refurbishment** | |
|---|---|---|---|---|---|---|
| **Parameters** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| **BedRoom1Temperature (°C)** | 24.625 | 0.848 | 19.825 | 1.886 | 23.498 | 1.444 |
| **BedRoom1HeaterTemperature (°C)** | 24.405 | 0.859 | 22.029 | 1.606 | 24.158 | 1.594 |
| **BedRoom2Temperature (°C)** | 23.981 | 1.177 | 23.032 | 1.408 | 23.843 | 1.792 |
| **HallHeaterTemperature (°C)** | 37.260 | 23.125 | 38.806 | 11.783 | 29.083 | 7.045 |
| **AboveHallTemperature (°C)** | 25.075 | 0.611 | 25.033 | 1.114 | 25.676 | 0.652 |
| **EntranceHeaterTemperature (°C)** | 42.776 | 5.873 | 42.689 | 10.132 | 35.701 | 5.397 |
| **Outdoor temperature (°C)** | *12.609 | *4.224 | 5.027 | 2.917 | 10.927 | 4.528 |
| **Outdoor Relative Humidity (%)** | *66.934 | *12.809 | 86.864 | 5.601 | 72.386 | 13.247 |
| **Indoor Relative Humidity (%)** | 42.555 | 5.954 | 40.794 | 4.409 | 36.518 | 5.603 |

NOTE: * incomplete data

#### *7.4.3.1.5 Flat 41 Temperature*

Although Flat 38 and 41 are located on the same floor (7th floor), the indoor thermal value in Flat 38 was not identical to Flat 41. The pattern difference was related to the metabolism of the occupants and the occupants' behaviour, for example, the heater setting and the activity that impact indoor thermal conditions like cooking. However, with the refurbishing process, the thermal efficiency would increase and can be seen through the lower peaks in the heater temperature. The daily temperature chart for the pre-refurbishment phase, during refurbishment and post-refurbishment can be seen in Appendix 10. Table 28 shows the reduction in the hall heater and the entrance heater value after the refurbishment phase, with the indoor temperature remaining constant at around 24 ºC.

Table 28. The parameters summary for Flat 41

| Summary for Flat 41 | Pre-refurbishment | | During refurbishment | | Post refurbishment | |
|---|---|---|---|---|---|---|
| **Parameters** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| **BedRoom1Temperature (ºC)** | 24.709 | 0.797 | 22.780 | 1.229 | 24.179 | 0.977 |
| **BedRoom1HeaterTemperature (ºC)** | 23.944 | 0.689 | 22.541 | 2.271 | 24.993 | 1.165 |
| **BedRoom2Temperature (ºC)** | 24.648 | 0.734 | 22.849 | 0.861 | 24.387 | 1.237 |
| **HallHeaterTemperature (ºC)** | 54.150 | 9.931 | 58.214 | 11.671 | 48.505 | 6.746 |
| **AboveHallTemperature (ºC)** | 25.259 | 0.730 | 25.819 | 0.872 | 25.801 | 0.839 |
| **EntranceHeaterTemperature (ºC)** | 36.720 | 8.861 | 39.728 | 4.320 | 30.134 | 6.527 |
| **Outdoor temperature (ºC)** | *12.609 | *4.224 | 5.027 | 2.917 | 10.927 | 4.528 |
| **Outdoor Relative Humidity (%)** | *66.934 | *12.809 | 86.864 | 5.601 | 72.386 | 13.247 |
| **Indoor Relative Humidity (%)** | 32.514 | 2.854 | 31.507 | 4.040 | 32.475 | 4.755 |

NOTE: * incomplete data

Comparing the data from Flat 80, 38 and 41 shows that after the refurbishment process, the tendency of overheating was not detected. Flat 80, located on the 14th floor, shows a higher reduction in the heating peak temperature by 47% and 27%. This reduction was higher than Flat 38 and 41, located on the 7th floor. This difference cannot be claimed due to the Flat's location but was also related to the occupants' activities and metabolism. It is shown by the Flat 38 and 42 result, which was different even though they are located on the same floor. The reduction in Flat 38 heating percentages was 22% and 17%, while in Flat 42 it reached 10% and 18%. The reduction of the heating on average is 24%, and the percentage can be seen in Table 29.

Table 29. The heating reduction percentage for flats 80, 38 and 41.

| Flat no | Heater | Pre-refurbishment | Post-refurbishment | Reduction |
|---|---|---|---|---|
| **80** | Hall Heater Temp | 73.996 | 39.085 | 47.18% |
| | Entrance Heater Temp | 47.466 | 34.594 | 27.12% |
| **38** | Hall Heater Temp | 37.260 | 29.083 | 21.95% |
| | Entrance Heater Temp | 42.776 | 35.701 | 16.54% |
| **41** | Hall Heater Temp | 54.150 | 48.505 | 10.42% |
| | Entrance Heater Temp | 36.720 | 30.134 | 17.94% |
| | Average | | | 23.52% |

#### *7.4.3.1.6 The AI Model Result*

The assumption for the AI model is clothing value 1 clo, light work/activity 1.5 met and age 40.5 years. Figure 89 shows the comparison of the comfort conditions before and after refurbishment.

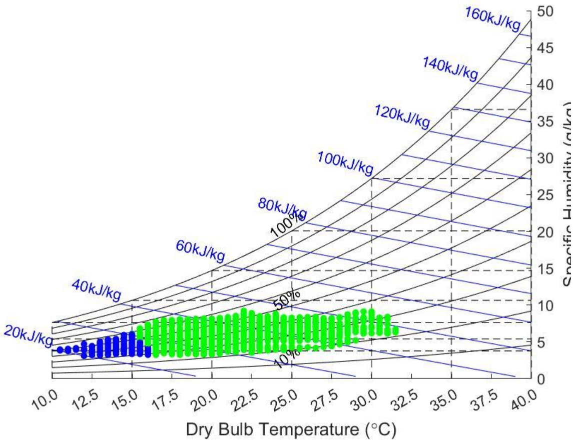
The AI model was able to acknowledge that after the refurbishment, the condition of overheating was most likely to happen. Overheating can occur due to the old habit of the occupants that use the pre-refurbishment setting to gain comfort while their dwellings are having a better energy performance.

### 7.4.3.2 Conclusion

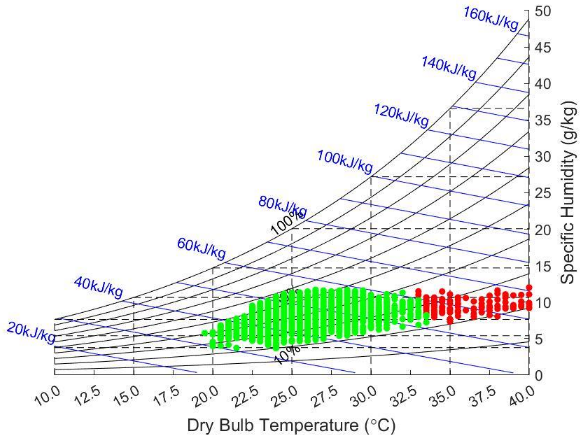
The temperature and the number of peaks of the hall heater and entrance heater decreased while the indoor temperature remained stable after the refurbishment. This reduction was a sign of energy saving due to the refurbishment. However, the amount of energy saving cannot be calculated precisely based on this value. Comparing this value only, the rough estimation of the energy saving can reach about 24% on average.

Flat 38, Hall:

before: 92.19% in comfort condition

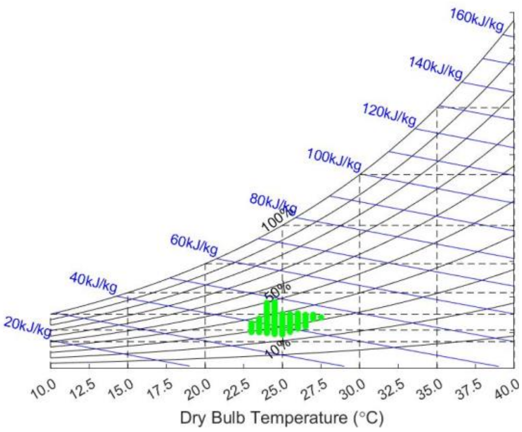



after: 98.97% in comfort condition

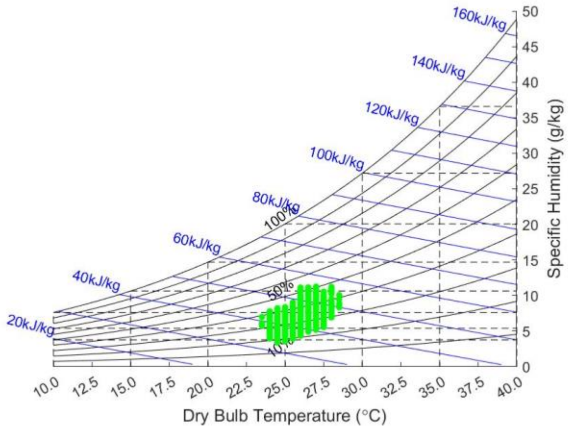



Flat 41, Hall

before: 100% in comfort condition

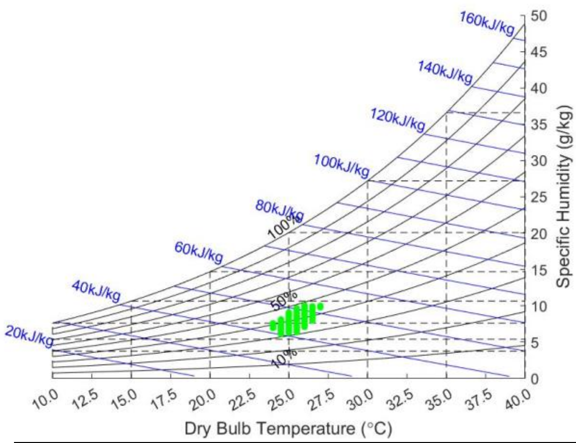



after: 100% in comfort condition

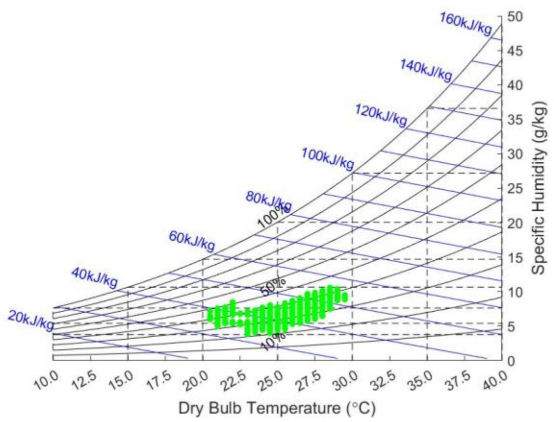



Flat 80, Above Hall

before: 100% in comfort condition




after: 100% in comfort condition



Outdoor comfort: 20.96% in comfort condition

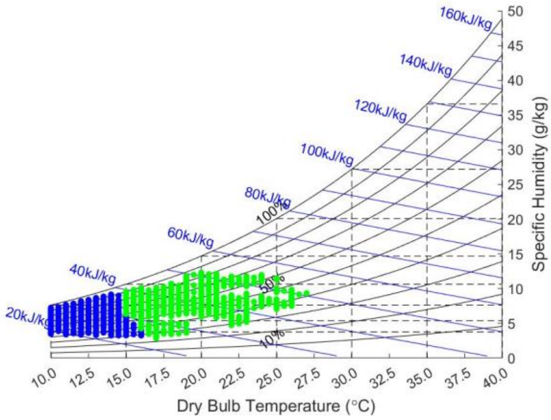



Figure 89. The comparison of the comfort conditions before refurbishment, after refurbishment and outdoor conditions.

The value of relative humidity also decreased after the refurbishment. This fact represents that the probability of humidity exceeding 70% (unhealthy limit) is also decreased. After refurbishment, indoor health and comfort levels also increased.

The use of the model can give a further benefit to energy saving. The model was able to detect the tendency of overheating. Elaborating the model in the dwelling heating control can result in the conservation of the heating energy. The model will give better control so that the temperature set point can be lowered to avoid the overheating problem.

### *7.4.4 The Implementation of the New Materials for Thermal Improvement*

This case study compares the use of the latest material to increase the thermal performance in dwellings. The trial was done in four dwellings, with one room using the improved materials and one left as it was. The occupants filled in the questionnaire regarding their behaviour that might impact the trial. The sensor installation summary, sensor reading and chart for the temperature and relative humidity and the thermal comfort percentage can be assessed in Appendix 10.

#### 7.4.4.1 Analysis and Comparison of Comfort Model with Occupants Questionnaire

**House #1 Phase1:**

Based on the heater temperature data, the average temperature for the heater in the bedroom is 22.32°C, while the average heater temperature in the living room (equipped with the materials) is slightly lower at 21.95°C. Even with this lower setting, the average temperatures detected by other sensors in the living room are slightly higher than the condition inside the bedroom (living room: 19.40 °C and bedroom 18.23°C). The peak temperature detected for the bedroom heater was 60°C compared to the living room, heater which was 49.5°C. The difference indicates that the energy needed to maintain a comfortable temperature is less with the new materials.

In terms of humidity, there was no indication of the change in the humidity upon the installation of the material since the two sensors have different average value readings. Based on the Artificial Intelligence (AI) model, the percentage of comfortable time in the living room is also higher compared to the bedroom (95.4% compared to 91.2% of the time).

Compared with the data from the questionnaire, the occupant has an electric fire, but it is just for decoration and not to be turned on. The occupant always kept their internal door, and the external front door closed most of the time during the test. Similar things happened with windows. The occupant only occasionally opens the kitchen window and never during winter. This show that the data gathered are valid. However, based on the questionnaire, the occupant has not changed behaviour after installing the materials.

Even though the sensors did not detect the humidity improvement, the occupant sensed less window moisture for the window equipped with the materials. The thermal sensation that the occupant felt was comfortably warm, acceptable temperature, and the occupant was satisfied with the condition and did not want to alter it (no change condition). The occupant felt the humidity was proper and only felt too humid on the porch. This perception was also reflected in our average humidity measurement, below 70%, while the average outdoor humidity was 81%.

**House #1 Phase 2:**

In the second period of data gathering, the average temperature for the heater in the bedroom was 20.79°C, while the average heater temperature in the living room (equipped with the material) was slightly lower at 19.22°C. The highest temperature detected by the heater sensor for the bedroom was 65°C, whereas the living room was 49°C. These temperature values were similar to the first phase of data gathering.

Analysing more detail for the maximum outside temperature and outside temperature, it is also apparent that the material positively impacted heating energy reduction. The heater temperature in the room equipped with the material had less value than the existing room, with the indoor temperature relatively the same for both rooms. This second phase shows a better chart profile than the chart generated from the first.

The humidity values for the second phase showed no improvement. Even though our sensors did not detect the humidity improvement, the occupant sensed less window moisture for the window equipped with the material. The thermal sensation that the occupant felt was comfortably warm, an acceptable temperature, and the occupant was satisfied with the condition and did not want to alter it (no change condition). The occupant felt the humidity was proper and only felt too humid on the porch. The average relative humidity value for the second phase was also below 70%. The average outdoor humidity value from the second phase was 74.39%.

Based on the Artificial Intelligence (AI) model, the percentage of comfortable time for the outside weather condition was just 7.82%. The comfort level in the living room with material installed inside was 75% compared with the bedroom, 69%. The comfort level was lower in the second phase due to the lower temperature set point. The occupant will benefit from the lower energy needed for the heating. More precise energy usage can be checked by comparing the energy bills before and after material installation.

**House #3 Phase1:**

The indoor condition in this house is different compared to the previous house. The dwelling is a one-bedroom bungalow. Based on the questionnaire, the occupants have an electric fire, and the internal doors are always open (the occupants only close the internal doors at bedtime). The occupants also use their gas cookers daily. This habit makes the living room's average temperature slightly higher than the bedroom equipped with the material. The heater temperature in the bedroom also showed a higher average number compared to the living room due to these reasons. The habit of opening their windows for a few hours during autumn and winter might affect the result.

The benefit of the installation of the materials, in this case, was only shown when the black globe temperature was compared between sensor EH20, which was in the bedroom (with the materials) compared sensor EH17, which was in the living room. During the lowest outside temperature, sensor EH20 shows that the temperature was slightly warmer than detected in sensor EH17. Both sensors showed a similar temperature level during the highest outside temperature (about 30°C). This result indicates that the materials help buffer the indoor temperature and reduce glazing leakages.

The bedroom sensor and the relative humidity data showed a lower average value than the living room. These average values are in the healthy zone. The questionnaire result acknowledged this measurement that the occupants only feel the moisture on the kitchen windows and bathroom, mainly in the winter.

From the AI model result, it can be said that the occupants were always in their comfortable situations (94.38%, 99.97% and 100% of the time). This result justified the questionnaire results that the occupants feel warm and comfortable and do not want to alter the thermal condition (no change).

**House #3 Phase 2:**

Like the first phase, the benefit of the material installation, was shown when we compared the black globe temperature between sensor EH20 in the bedroom installed with the material compared to the sensor EH17 located in the living room. Sensor EH 20 shows that the temperature is slightly warmer than detected in sensor EH17. This value indicates that the material helps buffer the indoor temperature and reduce glazing leakages.

The average relative humidity values were always in the healthy zone for the second period. The questionnaire result acknowledged this condition that the occupants only feel the moisture on the kitchen windows and bathroom, mainly in the winter. This moisture was due to the occupants' activities that generated water vapour. From the AI model result, it can be said that the occupants were always comfortable (almost all cases had 100% comfort of the time). This value justified the questionnaire results that the occupants feel warm and comfortable and do not want to alter the thermal condition (no change).

**House #4 Phase 1:**

Similar to house 1, the average temperature of the heater in the living room equipped with the materials was lower compared to the bedroom (21.91°C compared to 22.72°C), resulting in a slightly lower room temperature. The living room's average temperatures are 18.48°C and 18.10°C, while the average bedroom temperatures are 19.40°C and 19.31°C. The occupants seldom open the window, and their internal and external doors are always closed. The occupants also do not own a fireplace.

The effect of the materials installed in the living room can easily be identified during the minimum outdoor temperature. The heater sensor detected that to achieve a relatively similar indoor temperature, the heater temperature inside the living room (EC16) showed a temperature of less than 40°C. The bedroom (EC15) showed a temperature of almost 60°C. This case showed that the materials help to maintain the indoor temperature during winter.

The sensor reading also shows the temperature reached more than 30°C, even 36°C. This reading was acknowledged in the AI model, which had a wider red-coloured area representing overheating, although the overall comfort based on the AI model was mainly comfortable. This condition reflects in the questionnaire result that the occupants felt slightly or comfortably warm but still acceptable (no change). The overheating might be reflected by the fact that the occupants need to increase air movements.

Although the relative humidity in the living room (with the materials) is slightly higher than in the bedroom, the average values are still in the healthy range. The occupants also state in the questionnaire that the humidity is just right.

**House #4 Phase 2:**

Similar to the first phase, the average temperature of the heater in the living room equipped with the material was lower compared to the bedroom. The average temperature of the heater in the living room was 20.93°C, and in the bedroom was 21.46°C. This case is also an excellent environment to test the impact of the material due to less noise impacting the measurement results. The chart with minimum outside temperature showed a bold difference in the heater temperature that showed the heating energy conservation.

Like in the first phase, there was a possibility of overheating in the living room. This case was acknowledged in the AI model, which has a wider, red-coloured area in the psychrometric chart. This condition reflects that the occupants felt slightly or comfortably warm (mentioned in the questionnaire). The overheating might also be reflected by the statement in the questionnaire, which needs to increase air movements. The occupants were advised to reduce the temperature set point.

Although the relative humidity in the living room (with the material) was slightly higher than in the bedroom for both phases, the average values are still in the healthy range. The occupants' questionnaire results also acknowledged this.

**House #5 Phase 1:**

This house is different from the other houses because the heater was either on or off, and no thermostat was installed. The electric fire was also installed in the living room with the materials installed. This condition made the bedroom average temperature heater higher than the living room heater (22.87°C compared to 17.57°C), which can highlight the benefit of using the materials but might be due to the electric fire. This extreme figure was shown during the minimum outside temperature periods. Due to this higher heater temperature, the average value of the indoor temperature in the living room is slightly lower than in the bedroom.

The result might be affected by the cooking done twice daily and the internal doors that are never closed. The low temperature in the room could be due to the effect of the window opening. The occupants mention that the windows are usually open in summer and autumn and often in winter and spring. This condition explained the questionnaire result: they felt cool but still comfortable, and the indoor temperature was acceptable (no change). This statement also justifies our AI model that captures the comfort level at 67.6%, 93.74%, 87.91% and 99.37% during data logging. The average relative humidity is also just about 60% which is a healthy level, and the occupants feel the humidity was just right.

**House #5 Phase 2:**

The second-period bedroom average temperature heater was higher than the living room heater (21.46°C compared to 15.71°C). This value was due to the occupants' behaviour. Due to this higher heater temperature, the average value of the indoor temperature in the living room was slightly lower than in the bedroom. This condition makes the house not an ideal case study for the use of the material. The average relative humidity for this period was in the healthy level condition below 70%. The Ai analysis showed that the comfort percentages were below 89.83%.

The AI model assessment results captured a wide area of indoor thermal conditions. It reflected that the heating controls were not done properly. Even though most of the time occupants were in comfort situations, the use of the AI model can increase the comfort level of the occupants. There might be still a possibility in this case to conserve the heating energy.

### 7.4.4.2 Conclusion

Although not all the tests can show clear evidence of the impact of using the materials to increase thermal performance, each test shows that installing the materials improved the indoor thermal condition, especially during winter. The installation of the materials can reduce the heater temperature or energy usage for heating.

The use of an AI model can properly fix the heating profile and minimize the uncomfortable situation in both “too hot” and “too cool” conditions. The heating energy conservation can also be obtained with the use of the model to focus the comfort zone to the lower comfort temperature during winter.

### *7.4.5 The New Modular House with Advanced Heating Controls*

The analysis is based on the data generated by third-party sensors for indoor and the Weather Station located in Byrom Street Campus LJMU for outdoor data. The picture of the modular house is presented in Figure 90. The data was obtained from 19 October 2021 to 29 November 2021. The data is grouped based on the sensor position. Due to the sensors' nature that they will send the data when there are changes in the value, the data needs to be arranged into 15 minutes intervals using the epoch timestamp from the data. The information about the data on each group is shown in Table 30. This data is then displayed in the chart with the left axis showing the temperature and the right secondary axis showing the relative humidity. The result can be accessed in Appendix 10.

Figure 90 The picture of the studied modular house.

Table 30. Summary for data measurement in the Modular House.

| Area | Outdoor | Stairs | Backdoor | Master Bedroom | Living room | Kitchen | Landing | Bedroom | Dining room |
|---|---|---|---|---|---|---|---|---|---|
| Temp. Max (°C) | 20.00 | 22.83 | 18.87 | 26.69 | 22.70 | 26.99 | 21.35 | 21.82 | 21.70 |
| Temp. Min (°C) | 0.00 | 14.29 | 13.98 | 19.15 | 16.53 | 18.97 | 17.34 | 18.77 | 16.52 |
| Temp. Average (°C) | 10.65 | 19.05 | 17.08 | 21.14 | 19.56 | 23.31 | 19.57 | 20.15 | 19.32 |
| Std Dev | 3.35 | 1.90 | 1.36 | 1.16 | 1.10 | 1.64 | 0.82 | 0.65 | 1.31 |
| RH Max (%) | 95.00 | 35.42 | 33.36 | 32.61 | 32.87 | 32.37 | 33.58 | 32.29 | 31.96 |
| RH Min (%) | 51.00 | 19.54 | 17.83 | 17.58 | 18.50 | 16.92 | 15.97 | 18.50 | 12.18 |
| RH Average (%) | 81.50 | 26.68 | 24.79 | 25.56 | 25.47 | 24.24 | 24.29 | 25.74 | 23.58 |
| Std Dev | 8.58 | 2.82 | 2.94 | 2.93 | 2.43 | 2.86 | 2.65 | 2.73 | 3.22 |
| % Comfort | 10.27 | 80.07 | 68.08 | 100.00 | 99.90 | 100.00 | 100.00 | 100.00 | 99.78 |

The data is then processed with the AI Model to show the comfort condition percentage over the data for each group of sensors. In the model, the clothing insulation value is assumed to be 1 clo, the recommended clothing insulation value in the winter. The activity value is assumed to be 1.5 met, representing the activity of sitting and light work. The age entry for the model was 30 years.

The psychrometric charts were drawn based on the AI model to show the comfort condition. The green dot represents the comfort class group. The blue and red coloured dot represents the uncomforted class group. The red represented the occupants that needed the cool temperature. The blue represented the need for a warm temperature. This result can be seen in Appendix 10.

#### 7.4.5.1 Results for the New Modular House

The measurement and comfort analysis shows that the comfort level was 10.27% for the outdoor data, while the indoor comfort levels are relatively good. The comfort percentage in the backdoor was 68.08%, the main bedroom 100%, the living room 99.9%, the stairs 80.07%, the kitchen 100%, the landing 100%, the bedroom 100%, the dining room was 99.78% in comfort condition.

The backdoor had the lowest comfort due to the exposure to the outdoor condition when the door was opened. The stairs also still had acceptable comfort, although the area does not have a dedicated heater, and the heating was taken from the convection of the air in the room. Although the heating schemes were being altered, due to the excellent insulation of the house and the minimal leakages, the heating can be efficient.

Based on this analysis, all rooms were in comfortable conditions, with the humidity value sometimes below the recommended value. In this case, the room humidifier is recommended to decrease the probability of the relative humidity falling under the lower healthy limit. The relative humidity value in the dining room was the lowest and should be prioritised for the room humidifier. This low humidity value was also due to no one living in the house, so no vapour was generated by the constant respiration, bathing, or cooking. The comfort value of the backdoor was the lowest due to the direct exposure to the outdoor condition.

The AI model still can contribute to this case, especially related to the comfort analysis of each area even though it was already having an advanced control system. The model was able to give the comfort map for each location to give a better comfort situation for the occupants.

#### 7.4.5.2 Conclusion

In the case of advanced heating, although the heating system was already able to give comfort to most of the area of the house, the model still contributes to better comfort mapping for each monitored location in the house, so that the comfort can be evenly distributed throughout the monitored area.

# Chapter 8 Conclusions

## 8.1 Summary of findings and conclusion

Fuel poverty in some areas of the UK has reached 25% and this issue is currently of interest to UK policymakers and stakeholders. This problem arises along with the energy crisis and Global Climate Change which put thermal comfort research into the focus of interest. This work introduced a novel base system model that better reflects the user condition for the future indoor thermal control system to be able to solve the mentioned gaps. The system model has the compatibility to control the heating panels based on the real-time sensor network with the adaptive thermal comfort acknowledgement capability in a low-cost system to suit residential needs.

About 87% of the population spends their time indoors. Human comfort is a state of mind expressing satisfactory adaptation to the immediate environment. The comfort zone can be widened to accommodate a special group of people and lower the energy use for comfort. There has been a great improvement in building standards, techniques, and materials since the early twentieth century. This has led to improved energy efficiency and as a result housing built in the 1920’s will have very different heating requirements from housing built in the period from the 1970’s. to the present day. Using heating contributes to approximately 61% of total energy consumption for UK homes, so a better heating strategy is needed to lower the energy use for comfort. There is a clear correlation between fuel-poverty homes and the building envelope typology.

A software physical model was developed to better understand thermal comfort, resulting in a model that can justify the thermal comfort in the building with the variations in building materials and the occupant’s presence. This model focuses on two main housing typologies which represent about 12.78 million houses and covers about 53.4%

of the total dwellings in the UK. The model analysed three locations: Kent, Liverpool and Aberdeen, using each location's hourly data and predicting the percentage of heater usage state. This analysis recommends lowering the thermal set point, which is still proven to deliver a healthy indoor environment.

The housing typology will significantly impact thermal comfort when the temperature set point is below 16ºC, a level that generated high humidity. When the temperature set point is above 19ºC, the dwelling typology becomes no longer important to comfort but only impacts energy usage. Therefore, recommending a temperature set point around 16ºC-19ºC to become the comfortable standard temperature would be desirable.

If the heater used state was used to measure the dwelling typology improvement, the energy-saving value will be about 2%. With the assumption of 16,500 kWh - 22,000 kWh on annual heating energy consumption per household per year, the energy-saving per house per year will be in the range of 330 - 440 kWh. If it is multiplied by the number of '1920s' homes which are approximately 36.6% of the total dwellings (approximately 8.76 million homes), the total energy conservation across the UK will reach about 2.89 - 3.85 billion kWh. The carbon reduction per year can reach approximately 635.8 - 847 thousand tonnes with 220 g $CO_2$ eq/kWh. This result can be higher if the heating energy simulation is considered. More than half of the heating energy can be saved with the lower temperature set point and the use of modern construction materials as used in the modern housing typology. The carbon reduction per year can reach 21 million tonnes.

In the development of the novel prototype, a new algorithm to recognize the comfort zone was introduced. The revisited thermal comfort development produced the map of two groups of researchers based on human physiology and human psychology/behaviour. This work addresses those comfortable temperatures that are changeable rather than fixed. Comfort can be reached if there are sufficient opportunities for people to adapt. Only with the adaptive approach, all parts of the whole system can become part of the comfort solution.

This algorithm utilised the benefit of using AI for the main feature to recognize the comfort zone. The artificial neural network was chosen because the shallow supervised learning process can be done in a more powerful machine with multiple ASHRAE databases. Once the training has been done in an artificial neural network, this huge training data set is no longer needed, and the trained network can be deployed in a less powerful machine such as a local server or controller. The multi-layer feed-forward fully connected neural network with 100 nodes/neurons (wide neural network) was used for the model.

The multiple ASHRAE database consists of ASHRAE RP-884 and ASHRAE Global Thermal Comfort Database II for the learning process. The shallow supervised learning for the base ANN introduced better portability compared to using XAI. The ASHRAE RP-884 consists of 25,616 entries, and ASHRAE Global Thermal Comfort Database II includes 81,967 entries. Previous research used part of the data to represent each label to have a better training result but will not perform well, especially on the edge of the comfort zone. The plain data set will only result in less than 50% of accuracy. To overcome the problem, this work used the filtering process and data augmentation process for the learning data.

This work proposes simple yet powerful methods to filter the data based on human perception consistency. The need for filtering is because the data was based on precise measurement, but the human perception data was based on the questionnaire which was more prone to error and subjective judgment than the measured data. This filter worked based on the comparison of parameters and omitted the data that was inconsistent. After filtering, the ASHRAE database has 65,256 entries or 60.66%. Six parameters are mandatory for thermal comfort. This work also addresses the possibility of considering five parameters, including acknowledging human adaptive, which can be deployed in the IoT infrastructure.

Semantic data augmentation was introduced to overcome the overfitting problem in the AI learning process. The class "no change" remains untouched while the "warmer" and "cooler" classes are augmented with the new data. In order not to introduce error and bias, the semantic direction of the value was applied in the area that is not covered by the ASHRAE database. The "warmer" class is augmented with the lower temperature value under the value of mapped ASHRAE data. On the contrary, the "cooler" class is augmented with the data, which is higher than the mapped ASHRAE data. The benefit of this method is that the data obtained from the ASHRAE database is unaffected due to the non-overlapped semantic augmentation direction. In this case, the data related to the psychological aspects are still maintained, and the essence of using the ASHRAE database is sustained. The data then can be used to properly train the ANN model.

Checking the learning against overfitting issues is not easy. This work proposes using psychrometric chart mapping to validate the supervised learning result. This method is based on the comfort zone map in the psychrometric chart. The overfitting results will lead to the map not showing the correct pattern if the system is fed with the data series.

The algorithm results in wider comfort acknowledgements by acknowledging adaptive thermal comfort. With the winter parameters, the acquired comfort percentage is 98.03% from all of the ASHRAE multiple databases, compared to the PMV-PPD value of 69.91%, the Givoni comfort zone value of 89.19% and the combination of both with the value of 92.84 %. There is an increase of 5.19% in the acknowledgements of the comfort zone. With the summer parameters (clothing value of 0.5 clo), the acquired comfort percentage is 98.49% from the ASHRAE multiple databases. There is an increase of

5.65% in the acknowledgements of the comfort zone compared to the combination between the PMV-PPD and Givoni. If the clothing parameters are combined (summer and winter), the value of comfort percentage rises to 98.90%, an increase of 6.06% of the acknowledgement.

The value of the comfort percentage can be increased to 99.46% for multiple input parameters such as multiple age groups, compared to all the ASHRAE multiple databases, which is an increase of 6.62% of the PMV-PPD and Givoni acknowledgement. If the $CO_2$ emission factor used is 0.309 kge / kWh ((BEIS), 2018), this work will contribute to the reduction of 4,842 thousand tonnes of $CO_2$ equivalent. If the emission factor used is 50 g$CO_2$eq/kWh, which is the target for 2030 (Technology, 2011), the contribution of carbon reduction from this work will be about 783.5 thousand tonnes of $CO_2$ equivalent. These values show that using an AI model to acknowledge thermal comfort can significantly conserve energy and help reduce carbon emissions.

This model shows that the thermal comfort zone can be widened from the ASHRAE comfort Zone and Givoni Comfort zone based on the reliable ASHRAE multiple thermal comfort database, which can lower the energy use for thermal comfort. The shallow supervised learning is feasible to be included in the real-time controlling model and capable of coping with the adaptive approach for thermal comfort and giving the ability for the model to compensate for the special occupants' needs.

This work uses sensor networks to capture real-time data. The performance of these sensors was compared with the COTS sensors. The value of R-Squared for the comparison between the black globe COTS temperature sensors and black globe IoT temperature sensors was 0.990 for the centre room sensors and 0.986 for the stair sensors. For the humidity sensors, the values of the R-Squared COTS humidity sensor compared to IoT sensors were 0.974 for the centre of the room and 0.967 for the stairs. The comparisons were made with 7,361 data readings with 15 minutes intervals. These values were considered reliable due to the values being higher than 0.95.

This work also proposes to address the people's presence in the heating assessment to achieve lower energy use since the people will dissipate their body heat. This work shows that at least 10% of the comfortable condition can be achieved by involving the people's presence. The learning validation based on the comfort zone mapping in the psychrometric chart is also proposed to avoid AI learning errors in the AI-based system. This validation uses a broad range of temperature and humidity data fed into the AI system and maps the comfort zone to validate the learning result.

Validating and testing the model using the BRE houses at LJMU shows that the AI model can be used to analyse indoor thermal comfort. The case studies of different real case situations also strengthen the model use. This work delivers:

- An overview of the thermal comfort research map and the highlight of its importance
- An indoor thermal model which can be tuned to capture the behaviour of the indoor thermal environment to assist the research in human comfort.
- The possibility to lower the temperature set point to reduce the energy consumption for comfort while still maintaining the healthy indoor environment.
- The AI-based framework uses filtered and semantically augmented ASHRAE multiple databases for shallow supervised learning (ANN).
- The validation of AI learning results is done using psychrometric chart mapping.
- The acknowledgement of a more expansive comfort zone based on multiple ASHRAE databases, compared to the ASHRAE 55 standards (PMV PPD approach) and Givoni comfort zone.
- Proof that the presence of the occupation has a strong impact on the indoor comfort evaluation.

- The physiological, psychological, and behavioural approach acknowledgement was implemented in the novel base system and shares the benefit of lowering energy use.

## 8.2 Limitations

- Trials are not directly done with an actual human who can introduce errors or biases into the result.
- AI model cannot deliver 100% accuracy but still introduces false positives and negatives.
- The human thermal model only focuses on human presence's thermal impact and does not add $CO_2$ and water vapour to the system.
- The prototype does not implement a complete user application. The prototype only shows the base model for the base model of AI implementation for thermal comfort.
- No real user interaction and gamification with the system was implemented.
- The research focused on the heating control and not the cooling.
- The algorithm for controlling the heater currently does not implement the trigger mapping zone. With the trigger mapping zone, the heater control can have a different action between the trigger near the AI thermal comfort zone's borderline, in the middle of the comfort zone, or far out of the comfort zone.

## 8.3 Recommendations and Future works

Based on the findings from this work, the recommendations are:

- Revise the thermal comfort zone in the standard to accommodate broader thermal preferences and behavioural and psychological aspects of humans, which can lead to better comfort, acknowledging the special groups of people (young, elderly, disabled, and temporary ill) and or lower the energy use.

- Using the thermal comfort map in the psychrometric chart to justify the AI learning result and validate and justify the result.
- Introduce the use of the AI model for indoor comfort evaluation.
- Consider the occupants' presence under the indoor comfort evaluation.

The future works:

This work can be extended to achieve a better result in the database for AI learning by extending the semantic augmentation for precise humidity. This work is not focused on giving the augmentation for humidity value but giving the augmentation for the humidity value might be possible to increase indoor comfort. The augmentation data should be generated correctly to not alter the humidity values based on actual measurements from the ASHRAE multiple databases.

Implementing the entire system that all rooms are registered in the system, all user and user preferences can be registered, and their preferences can be stored and associated with their activities and clothing values.

Implementing different schemes for controlling the actuator according to user preferences. This scheme can prioritise minimising energy use or maximising the comfort factor with sensible energy use.

The use of gamification integrates the heating energy spending and the heating energy cost. The gamification can encourage users to be concerned about their energy spending for thermal comfort. The user can compare their daily, monthly, or yearly and be given an incentive if they can lower their energy use for comfort. The user achievement can also be posted and ranked to constantly endorse the user.

The system can have the ability to reduce the temperature setting in the long run. Based on the data stored in the system and user preference, the thermal setting can be reduced annually, for example, half a degree Celsius in a year; with this temperature reduction, heating energy can be saved without the user realising and affecting their comfort perception.

The system can be tested with an actual user (human), and the users are given a questionnaire for feedback to check the system performance and user satisfaction. The user application interface example can be seen in Figure 91.

The system can be tested in other parts, such as tropical areas. The actuator will use the fan and air conditioner instead of the heater to achieve thermal comfort.

Thermal comfort depends not only on the temperature and humidity but is also affected by the other human senses, as seen in Figure 91. In this case, the lighting comfort can also affect thermal comfort. Further research is needed to study this relation and the strategy to increase thermal comfort using lighting comfort, which might have the benefit of less energy achieved.

The thermal camera has been adapted for detecting the human skin temperature to capture the human thermal comfort state. The example of the image captured by the thermal camera can be seen in Figure 92.


Figure 91 User interface example for the application.

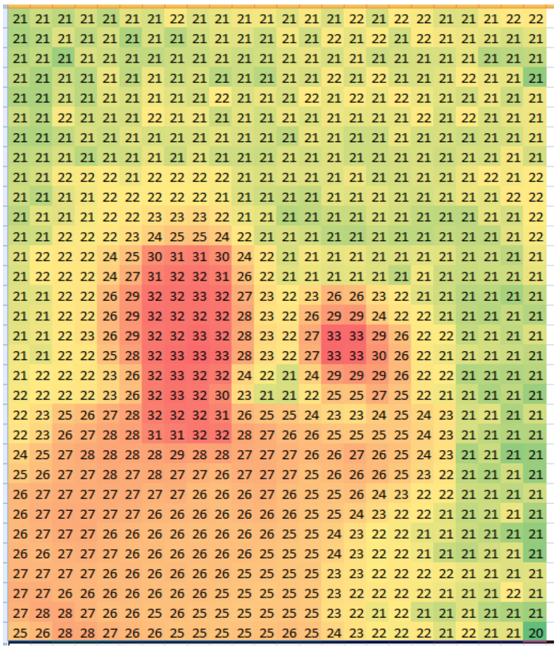


Figure 92 The output of the thermal camera with the colour mapping.

Elaborating the thermal camera image of the human skin to predict the human comfort and temperature set point. The skin temperature relation with the human body temperature is shown in work by Burton (Burton, 1935). It states that skin temperature is 4° or 5° C lower than the core temperature. The accurate average temperature can be obtained by combining the rectal and surface temperatures. The average temperature equals 0.65 × rectal temperature plus 0.35 × average surface temperature. The average error is reduced from 7½ per cent using rectal temperature alone to 5½ per cent using the formula. Rectal measurement is the most reliable way to obtain a core temperature value due to the low variation. The normal temperature range is approximately between 36.6 °C and 38.0 °C(Corporation). Rectal measurement is a reliable method to measure body temperature, but it is not practical. Measuring using zero heat flow in infants can also be as reliable as the rectal method (Van Der Spek, Van Lingen, & Van Zoeren-Grobben, 2009).

Body temperature should be measured with precautions. The measurement should be:

(1) convenient, harmless, and painless

(2) not be affected by local blood flow or by environmental changes.

(3) temperature changes should reflect quantitatively small changes in temperature (Fox, Solman, Isaacs, Fry, & MacDonald, 1973)

The average temperature of the peripheral thermal compartment is 2°–4°C less than the core temperature. The difference depends on the severity of the environment and the consequent vasomotor responses to substantial changes in the core-to-peripheral tissue and internal distribution of body heat. The hypothermic condition usually has a core temperature of approximately 34.5°C. Peripheral tissue temperatures vary widely depending on the region, environmental characteristics, and thermoregulatory vasomotion. The MBT formula is as follows:

$$MBT = a \cdot T^{Core} + (1 - a) \cdot T^{Skin} \quad (6)$$

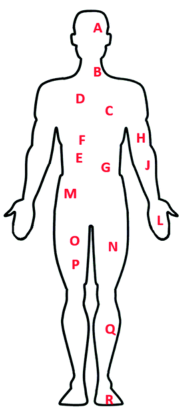
Where 'a' is the coefficient 0.64 derived from the measurement, $T^{Core}$ is the temperature of human body core temperature and $T^{Skin}$ is the temperature of human body skin temperature.

For a neutral and hot environment, 'a' can be defined as 0.7, while additional muscular work in a hot environment can raise 'a' value to reach 0.8. The value of 0.79 can also be assigned in an extremely hot environment (Lenhardt & Sessler, 2006).

An oral measurement (in the cheek or under the tongue) is below the measured value of a rectal measurement (up to 1.1 °C). The normal oral temperature range is approximately between 35.5 °C and 37.5 °C. Another axillary measurement type (in the armpit) is only possible up to a particular body mass and takes a long time. This method also results in a lower temperature than a rectal measurement (up to 1.9 °C). The normal axillary temperature values are between 34.7 °C and 37.3 °C. Measuring temperature n the ear using an IR thermometer normally will result in a value between 35.5 °C and 37.7 °C. For IR thermometer with the forehead measurement values are approximately between 35.4 °C and 37.4 °C (Corporation).

Forehead IR thermometer will not predict axillary temperature reliably, but is comfortable, rapid, and non-invasive. Fever is defined as an axillary temperature greater than or equal to 37.5°C. For the children aged 2 to 6 years, the forehead measurements had a sensitivity of 88.6% and a specificity of 60% in patients with temperatures ≥36.75°C. The sensitivities of the neck measurement at cut-offs of ≥37.35°C and ≥36.95 were 95.5% and 78.8% (Ataş Berksoy, Bağ, Yazici, & Çelik, 2018).

The effect of the ambient temperature in IR thermometer reading is shown in Figure 93 (Suarez, Nozariasbmarz, Vashaee, & Öztürk, 2016), (Webb, 1992). The skin temperatures can also be used to determine the overall thermal sensations people experience (J.-H. Choi & Loftness, 2012).




| Skin Location | Cold (15°C) | Room (27°C) | Hot (47°C) |
|---|---|---|---|
| Forehead (A) | 31.7 | 35.2 | 37 |
| Back of Neck (B) | 31.2 | 35.1 | 36.1 |
| Chest (C) | 30.1 | 34.4 | 35.8 |
| Upper Back (D) | 30.7 | 34.4 | 36.3 |
| Lower Back (E) | 29.2 | 33.7 | 36.6 |
| Upper Abdomen (F) | 29.0 | 33.8 | 35.7 |
| Lower Abdomen (G) | 29.2 | 34.8 | 36.2 |
| Tricep (H) | 28.0 | 33.2 | 36.6 |
| Forearm (J) | 26.9 | 34.0 | 37.0 |
| Hand (L) | 23.7 | 33.8 | 36.7 |
| Hip (M) | 26.5 | 32.2 | 36.8 |
| Side thigh (N) | 27.3 | 33.0 | 36.5 |
| Front Thigh (O) | 29.4 | 33.7 | 36.7 |
| Back Thigh (P) | 25.5 | 32.2 | 36.0 |
| Calf (Q) | 25.1 | 31.6 | 35.9 |
| Foot (R) | 23.2 | 30.4 | 36.2 |

Figure 93 Skin temperature reading using IR thermometer (Suarez et al., 2016), (Webb, 1992).

The thermal camera result for the forehead is in the range of 32 °C to 33 °C. The axillary temperature reading is 36°C. The room temperature is 24 °C. The temperature reading difference is 3 to 4 °C. Based on the result and the literature review; the thermal camera module should be compensated if it is used to measure the thermal sensation. The thermal camera module is factory calibrated for the temperature reading. The detection of the thermal sensation will have to be corrected when it is used at a cold or hot temperature.

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# Appendix