NOTTINGHAM TRENT UNIVERSITY

THE DEVELOPMENT OF A REAL-TIME ENERGY PREDICTION FRAMEWORK IN DOMESTIC BUILDINGS

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Abstract

The construction industry consumed 35% of worldwide energy, with domestic buildings accounting for 22%. Providing a healthy, positive environment in domestic buildings raised energy demand by around 80% in building operations, with thermal comfort accounting for about half of that increase. Furthermore, building energy consumption is 5 to 10 times greater than predictions given during the design phase. The discrepancy between the actual and intended design is called the performance gap. Although the term is widely used in the context of energy performance, it can also be found in indoor environmental parameters such as temperature, relative humidity, air quality, noise, and illumination. This thesis connects building performance simulation to building operational performance, focusing on real-time energy prediction for space heating in an indoor environment of domestic buildings.

The work presented in this research is a technical implementation framework for examining the energy consumption of indoor space heating in real-time, focusing on energy-related thermal comfort conditions at the zone level. Unlike building performance simulation tools, The developed framework can be used beyond the design phase to encompass operations and assist in diagnosing and detecting building underperformance or performance discrepancy over time. Focusing on zone level can offer a greater understanding of the thermal state and energy usage of specific individual spaces, which can also assist in identifying performance disparity.

Buildings with good indoor environmental quality are objectively assessed using simulation tools. However, the indoor environmental quality, especially thermal comfort, is experienced subjectively, making the building energy and thermal performance evaluation task challenging. The developed framework extends the use of the energy model to the operational stage by predicting thermal and energy performance based on indoor and outdoor environmental parameters. Moreover, using a parametric energy simulation and machine learning approach connected to an IoT sensor system enable users to identify thermal comfort conditions in the indoor environment and the amount of energy consumed for space heating. Finally, the research identified several lessons that can potentially inform and improve the existing domestic buildings, especially winter space heating.

Following the framework, an innovative device was developed and validated using an experimental approach that focuses on real-time energy prediction of space heating. In this process, the experimental case studies' thermal comfort conditions and energy consumption were monitored and analysed to identify thermal-energy performance-related issues, also used for validating the proposed real-time energy prediction module.

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Glossary of terms

BE	Built Environment
GHG	greenhouse gas
CO2	carbon dioxide
EU	European Union
IEA	International Energy Agency
UN SDGs	United Nations Sustainable Development Goals
UK	United Kingdom
EPC	Energy Performance Certificate
DEC	Display Energy Certificate
BPS	Building Performance Simulation
IEQ	indoor environmental quality
BIM	Building information modelling
ML	Machine learning
IoT	Internet of things
IEQ	indoor environmental quality ()
NDT	non-destructive techniques ()
POE	Post-Occupancy Evaluation ()
HCI	human-computer interaction ().
HVAC	Heating, Ventilation and Air Conditioning
MEMS	micro-electro-mechanical system ()
VOC	Volatile Organic Compounds ()
TVOC	total volatile organic compound ()
RFID	radio frequency identification ()
GPS	global positioning system (),
UWB	ultra-wideband ().
WSN	wireless sensor network ()
FDD	fault detection and diagnostics ()
BAS	building automation systems
PMV	Predicted Mean Vote
PPD	Predicted Percent Dissatisfied
GUI	graphical user interface
USB	Universal Serial Bus
HTML	HyperText Markup Language
GPIO	General Purpose Input/Output
AzureML	Microsoft Azure Machine Learning Studio
IFC	Industry Foundation Classes
gbXML	Green Building Extensible Markup Language
XML	Extensible Markup Language
3D	Three dimensional
DHW	domestic hot water
IDF	EnergyPlus Input Files
RVI	Report Variable Input
CSV	comma-separated values
GB	gigabytes
BLR	Bayesian Linear Regression
BDTR	Boosted Decision Tree Regression
DFR	Decision Forest Regression
LR	Linear Regression
NNR	Neural Network Regression

MAE	Mean absolute error
RMSE	Root mean squared error
RAE	Relative absolute error
RSE	Relative squared error
CoD	Coefficient of determination
API	application programming interface
PRT	programmable room thermostat
TRV	thermostatic radiator valve
IHD	in-home display
MRT	mechanical room thermostat
EPW	Energy plus weather data
PID	parameter identifications

Chapter 1

Introduction

This chapter describes the research context, aim and objectives of how the energy use for space heating and cooling plays a critical role in the energy performance of domestic buildings and how real-time energy assessment can help bridge the performance gap of energy consumption. The Built Environment (BE) is considered one of the largest emitters of Greenhouse gas (GHG) emissions and a primary contributor to climate change (Architecure2030, 2018, DOE, 2010, Asadi et al., 2017). The total global energy consumption in the buildings and construction sector accounted for 35% of final energy use and 38% of total global energy-related carbon dioxide (CO2) emissions in 2019 see Figure 1.1. The International Energy Agency (IEA) estimates the construction sector emissions must decrease by 6% per year from 2020 to 2030 to be in line with the Paris Agreement and to reach the European Union's (EU) and the United Nations Sustainable Development Goals (UN SDGs) of being climate-neutral by 2050 (UNEP, 2020). In the United Kingdom (UK), the last amendment to the Climate Change Act 2008 (2050 Target Amendment) urged the UK government to cut down carbon emissions to at least 80% lower than the 1990 baseline by the year 2050 (HM Government, 2019). The construction industry has used various programmes, schemes, and tools to improve energy performance throughout the building life cycle to achieve this target. An example of this includes the Energy Performance Certificate (EPC) scheme for design quantification and the Display Energy Certificate (DEC) scheme for operational performance (RIBA, 2019).

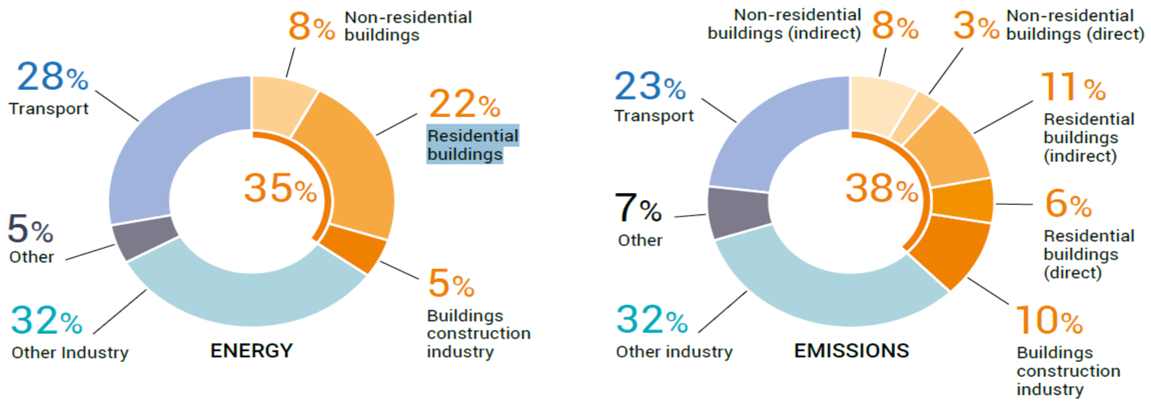


Figure 1.1 Total energy and emissions in buildings and construction sector (UNEP, 2020)

In the operational stage, providing comfort conditions (thermal, visual, acoustic and air quality) has increased energy demand to 80% in domestic buildings and about 70% in non-domestic buildings. Not to mention non-renewable energy sources are used to meet this increase in energy demand (Jason Palmer et al., 2016a, Jason Palmer et al., 2016b, DOE, 2010). Thermal comfort satisfaction is critical to building's users and has a significant impact compared to other comfort conditions (Frontczak and Wargocki, 2011). Previous studies have found that the thermal conditioning system is one of the most prominent energy end-uses in the BE, accounting for around half of overall energy consumption in buildings (Pérez-Lombard et al., 2008, Chua et al., 2013, Ma et al., 2019).

Furthermore, a series of case studies undertaken by the Chartered Institution of Building Services Engineers (CIBSE) and Post Occupancy Review of Building Engineering (PROBE) ran from 1995-2002, backed up by a recent building performance evaluation program by the innovative UK revealed energy consumption in buildings can be 5 to 10 times higher than energy prediction carried out during the design stage (CIBSE, 2012, Jason Palmer et al., 2016a, Jason Palmer et al., 2016b). This underperformance was evident in the building fabric, services, technologies, and user satisfaction and wellbeing, resulting in a performance gap. The performance gap is the difference between the anticipated design, usually calculated using Building Performance Simulation (BPS) tools, and the actual performance of the building. Many studies have attempted to identify the root causes of the performance gap and categorise it into design-related causes, construction causes, and operational causes. In many cases, however, it results from mixed factors (de Wilde, 2014, de Wilde, 2018, Carbon Trust, 2011, van Dronkelaar et al., 2016, Burman, 2016). In order to better understand the factors that lead to high or low building performance, this research has focused on developing a technical implementation framework to predict building energy performance in the operation phase of the building.

Building specialists use BPS tools to calculate thermal loads and energy consumption during design to anticipate building performance and other metrics, such as indoor environmental quality (IEQ) and thermal comfort. In the context of BPS, a model is an object that is simulated in a process where a simulation tool is utilised as a vehicle to analyse building performance. Any simulation depends on conditions and a range of variables where assumptions are made. Although variability in simulation outputs is expected, a wide scale of discrepancy diminishes the confidence level of simulation results (de Wilde, 2018). Thus, A realistic simulation model can accurately predict building performance by considering most of the complicated physical interactions and interrelationships.

1.1 Background

Understanding how effectively a building serves the needs of end-users is critical in evaluating building performance. Many construction codes place a strong emphasis on this, such as Government Soft Landings (Philp et al., 2019), British Standard 8536-1:2015 (BSI, 2015), with an aim to reduce energy use, cost and improve health and wellbeing. Building specialists construct buildings to give a comfortable living environment. Nevertheless, not all buildings meet this challenge due to various factors, such as human comfort, health and wellbeing, environmental issues, imperfections in the design and construction process, facility management and extreme events (de Wilde, 2018). It is also essential to consider every stage of a building's life cycle (inception, design, construction, commissioning, use, renovation and refurbishment and ultimately deconstruction and disposal). In addition, the role of occupants and technology in buildings is evolving, adding more challenges to the concept of building performance. In order to tackle these issues, the theory of building performance has to be further developed. A recent report to address building performance revealed that the delivery of Post-Occupancy Evaluation (POE) studies are patchy and the lessons learnt have not been consistently embedded into the knowledge of the construction industry and practice (RIBA, 2019). It also emphasises that if the UK is going to meet the 2050 net-zero carbon target, the operational performance gap in the existing and new buildings must be urgently addressed.

Computer simulation offers a unique opportunity to quantify building performance through experimentation and measurement (Shiflet and Shiflet, 2014). In addition, with the advancement of computer simulation, BPS has become one of the essential tools in the building industry (Hensen and Lamberts, 2012). Although BPS meets several challenges, one of the critical issues is the performance gap between predicted and measured performance (Carbon Trust, 2011, Menezes et al., 2012, CIBSE, 2012, de Wilde, 2014, van Dronkelaar et al., 2016, Fedoruk et al., 2015). In reality, few buildings perform similarly to the corresponding digital building model. Model uncertainties, operations that deviate from assumptions, and variations in physical factors all contribute to the differences. There is no easy way to address the performance gap; there are numerous underlying causes, such as fundamental model uncertainties, tool shortcomings, and training issues, aggravated by the building design, construction, and operation processes. Therefore, it is recommended that simulation jobs be performed by professionals knowledgeable about both the software and general calibration methodologies. Models should be aligned with actual data on the facility's loading as far as possible and then calibrated using metering data and utility bills.

In the context of the performance gap, building energy performance is usually the most prominent. However, the gap between actual and predicted performance is not limited to energy; it can also be found in IEQ parameters such as temperature, relative humidity, air quality, noise, and illumination (Tuohy and Murphy, 2015, Fabbri and Tronchin, 2015, Phillips and Levin, 2015, Harish and Kumar, 2016). Occupants' comfort, productivity and wellbeings have a direct influence on IEQ, any attempts to improve buildings' energy performance without considering IEQ may have a negative impact on buildings users, and improving IEQ might contradict with measures to improve energy efficiency (Wyon and Wargocki, 2013a, Chatzidiakou et al., 2014, Al horr et al., 2016). For example, If the focus is primarily on energy reduction or carbon emissions, poor indoor air quality in buildings can result in an unintended consequence. Lowers energy end-use is insufficient unless it allows buildings to serve their intended purpose, such as to be healthy, comfortable, and productive places to live and work. Therefore, a holistic approach to conducting building energy assessment, including IEQ, is required to avoid the unintended effect of degrading IEQ (Shrubsole et al., 2019).

This thesis links BPS to building operational performance, focusing on real-time energy prediction for space heating in an indoor environment of domestic buildings. It addresses the challenges of creating energy prediction models of existing buildings for real-time performance identification and mitigating building performance issues in the operation phase of domestic buildings. A framework and innovative device were proposed and validated using an experimental approach that focuses on real-time energy prediction of space heating. In this process, IEQ and energy consumption of the experimental zones are monitored and analysed to identify thermal-energy performance-related issues, which are also used for validating the proposed real-time energy prediction module.

1.2 Aim and objectives

The research aims to develop a technical implementation framework for a procedural examination of the energy consumption of space heating in real-time, focusing on energy-related thermal comfort conditions at the zone level. Using an integrated technique of emerging technologies in the operational performance assessment can effectively manage and control unintended energy performance. The following objectives were formulated to achieve the aim of the research:

- Create a digital replica of an existing dwelling and define the primary parameters for performance simulation.
- Devise and implement a framework that can predict the energy consumption of multiple scenarios for space heating at a zone level.
- Produce a real-time monitoring system to assess thermal comfort conditions in an indoor environment.
- Explore the developed integrated module and improve the validation approach for real-time implementation in the indoor environment when used for energy performance prediction.
- Examine the finding from different experiments and validate the prediction results against the actual performance.

The primary research method of this study to achieve these objectives is the experimental design approach to Five different zones in a domestic building in the UK: a lounge, a kitchen, a basement, a bedroom, and a loft. The selection and explanation of indoor zones are thoroughly explored in Chapter 5.

The approach utilised to construct the technical framework was based on a desk-based study of peer-reviewed publications and other industry specialists and professional body literature. On-site data collection was undertaken at two stages: one for model development and the second for framework validation for each experiment. In addition, data was collected through design documentation review, on-site measurement, and metering and monitoring. Different technologies and tools are utilised and integrated into an innovative device for real-time prediction of the thermal-energy performance of an indoor environment. Finally, in a desk-based study, the experimental analysis results were examined, the proposed framework was evaluated, and conclusions were drawn. The detailed explanation of the methodology in Chapter 3

1.3 Research approach

Given the context of the research, the following propositions have been made:

- Significant variations in energy use can be attributed to thermal comfort.
- Indoor thermal sensations are dynamic, and understanding thermal and energy implications narrow the building performance issues.
- Advanced technologies, such as the Internet of Things (IoT) and machine learning (ML), can play an essential role in reducing energy end-use.

This study also attempts to address the following research questions to have a deeper understanding of the presented propositions:

- What methods may be used to evaluate indoor thermal comfort? Standards and instruments?
- How to measure the impact of thermal comfort on energy consumption?
- What is the parameter that has the most significant impact on energy performance?
- How is IoT can be used to improve thermal comfort and energy performance?
- What is the difference between actual and anticipated thermal comfort and energy performance?

Figure 1.2 illustrate the conceptual outline of the research. The colours demonstrate how the research outline connects with the general structure of the thesis. The study is conceptually divided into four phases: Focus, establish the state of the art, development and Outcomes. Each phase of the thesis is addressed sequentially in several chapters.

Phase 1: This part explains the research approach, aim, and objectives and sets out the scope of the research. These include building performance simulations for predicting thermal comfort and energy consumption.

Phase 2: The thesis focuses on two areas: first, investigating building performance analysis methodologies and sensor technology for real-time prediction, and second, determining the root causes of the energy and thermal performance gaps and overtaking the challenges of energy modelling.

Phase 3: The process and steps to develop an innovative device following the proposed technical implementation framework. The phase covers the framework, the methodology, the development of the sensing device, and the thermal-energy performance prediction model.

Phase 4: Analyse the results and summarise the outcomes of the study. This final phase of the thesis focuses on the lessons learned. It presents a final technical implementation framework for real-time thermal-energy performance.

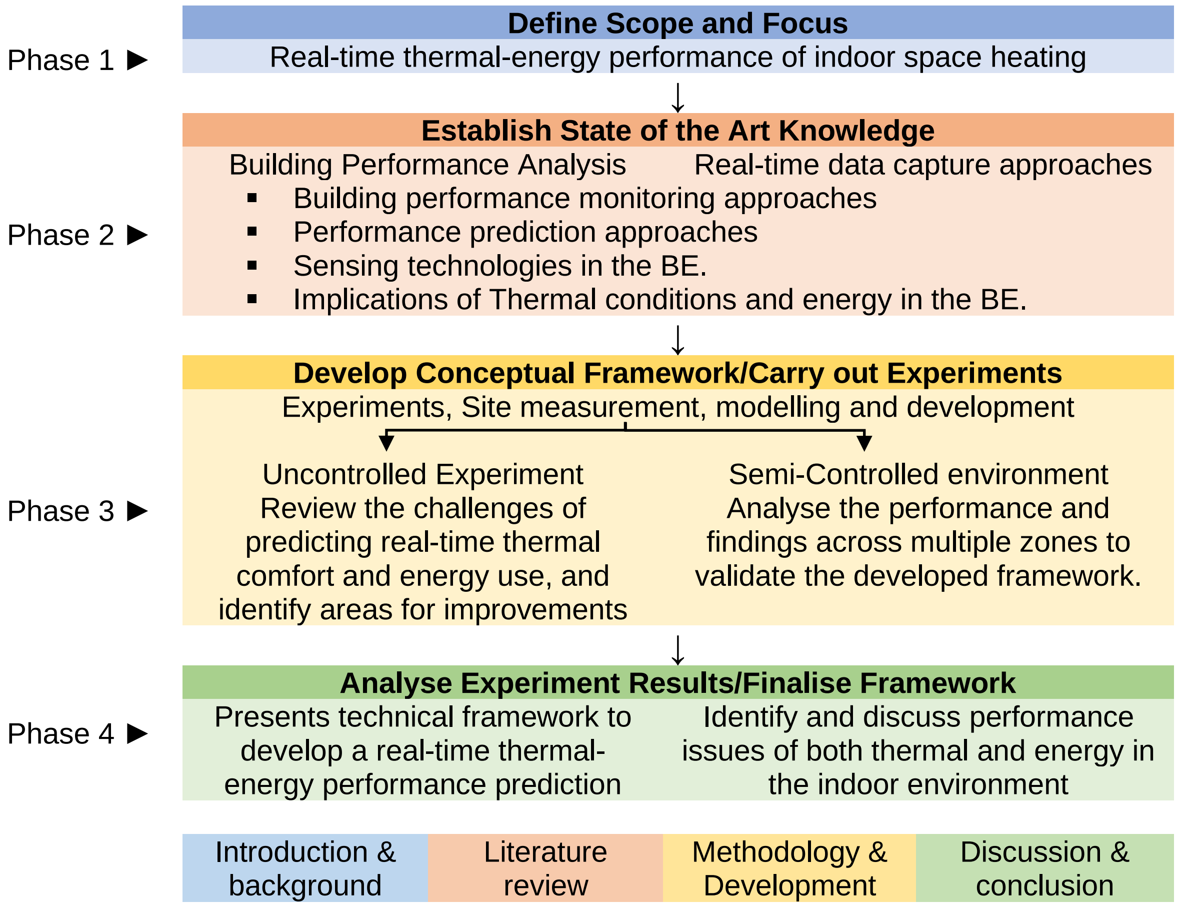


Figure 1.2 The research plan

1.4 Knowledge and contributions

Many researchers have looked into the impact of thermal comfort and energy consumption in buildings to bridge the actual and expected performance. Examining building performance during operation and identifying key challenges for domestic buildings can provide insight into endemic issues in the housing sector and help anticipate building performance more accurately. This thesis, including the current body of work, proposed a technical implementation framework for analysing and assessing building performance, focusing on real-time energy prediction for space heating in domestic buildings. The presented work addresses the performance issues in several experiments and provides lessons for building performance simulation practice. The key contributions of the current work are divided into theoretical and practical.

The theoretical contribution is accomplished by identifying and quantifying some of the impacts of thermal comfort on energy consumption, which cause inaccuracy prediction in the building energy simulation practices. Proposes a dynamic real-time simulation model for predicting energy consumption for indoor space heating. The proposed work to the current practices and building sector would enable the development of more robust simulation and improved building energy performance-based thermal comfort.

In addition, this research has influenced the development of a new tool for evaluating indoor environmental conditions and predicting energy consumption in real time. In the broader sense, the research expands the scope of BPS tools by quantifying building energy performance in the design and operational stages. The following practical contribution is also presented in this thesis.

- Synthetic data creation
- Real-time energy prediction model.
- Prototype of IoT prediction system.
- Technical implementation framework to extend the use of BPS beyond the design stage.
- Findings of this study Inform energy simulation practice concerning thermal comfort and energy consumption prediction.

1.5 Thesis structure

In line with the aim and objectives of the thesis, the following chapters are formulated. Table 1.1 maps the objectives to the sections and chapters to demonstrate how each of the objectives is met.

Table 1.1 Relationship between the study objectives and thesis chapters

<table>
<tr><th colspan="4">AIM</th></tr>
<tr><td colspan="4">Develop a technical implementation framework for a procedural examination of the energy consumption of space heating in real-time, focusing on energy-related thermal comfort conditions at the zone level.</td></tr>
<tr><th>Objective</th><th>Literature</th><th>Methodology</th><th>Chapters</th></tr>
<tr><td>1. Create a digital replica of an existing dwelling and define the primary parameters for performance simulation.</td><td rowspan="2">Building performance analysis approaches</td><td rowspan="3">Framework Development
Step 1: Data collection
Step 2: Data modelling</td><td>Chapter4</td></tr>
<tr><td>2. Devise and implement a framework that can predict the energy consumption of multiple scenarios for space heating at a zone level.</td><td>Chapter5</td></tr>
<tr><td>3. Produce a real-time monitoring system to assess thermal comfort conditions in the indoor environment.</td><td rowspan="2">Sensing technology</td><td>Chapter6</td></tr>
<tr><td>4. Explore the developed integrated module and improve the validation approach for real-time implementation in the indoor environment when used for energy performance prediction.</td><td>Step 3: Experimentation
– Whole house analysis
– Individual thermal zones</td><td>Chapter7</td></tr>
<tr><td>5. Examine the finding from different experiments and validate the prediction results against the actual performance.</td><td>Energy and Thermal performance</td><td>Step 4: Analysis</td><td>Chapter8</td></tr>
</table>

Chapter 1. Introduction: The research background, aims and objectives, the significance of the study, the scope of work, and limitations are all covered in this section. The research outline, contribution and structure are also explained.

Chapter 2. Literature review: A comprehensive review of building performance analysis approaches (tools and methods) focuses on real-time sensing technologies in the built environment. the chapter reviews the thermal comfort condition and their impact on the energy performance in the indoor environment. Moreover, it highlights the gaps in knowledge that need to be filled toward a better building performance monitories approach.

Chapter 3. Methodology: This chapter describes the framework development and experimental procedures for building energy performance and thermal performance issues for space heating in domestic buildings. It presents data collection strategy, and building performance modelling techniques, and explores the parameters for real-time energy prediction, including indoor environmental factors. In addition, this chapter serves as the foundation for the following chapters (4–7), covering the real-time thermal-energy performance, experimental research and their discussion and conclusion.

Chapter 4. Technical framework: this chapter introduces the technical implementation framework and provides a detailed description of the two proposed modules, thermal comfort and energy prediction.

Chapter 5. Development of sensing system: practical implementation of the proposed framework with the aim of producing a real-time sensing system that can measure indoor environmental variables and calculate thermal comfort conditions in real-time. This chapter discusses the system architecture, hardware and software, monitoring platform and the overall development process.

Chapter 6. Energy prediction model: This chapter introduces the methodology of developing an energy prediction model. First, it discusses the overall method of generating syntactic data of an existing building, and this includes digital modelling, energy simulation model, and parametric simulation. Then, it describes the framework of producing an energy prediction model based on indoor environmental variables.

Chapter 7. Experiments: This chapter practically implements the proposed framework in a field study of two typical dwellings. A mixed experimental approach of uncontrolled and semi-controlled experiments was conducted to understand the connection between energy and thermal comfort properties in the indoor environment, the cause and effects on energy use, and address building thermal comfort conditions and energy performance issues. Then, it describes the experimental buildings and setup, discusses the data collection procedure, and analyses the results. Furthermore, the chapter discusses the conceptual framework and validation process and draws the final framework to improve the accuracy of energy prediction based on thermal comfort conditions in real-time.

Chapter 8. Conclusions: This chapter contains the conclusion of the study line with research objectives. In addition, discuss accomplishments, shortcomings, limitations, and recommendations for future research.

1.6 Summary

Thermal comfort implications on a building's energy performance are not only essential to save energy and cut down bills, but a vital factor in improving indoor environment quality and mitigating buildings impact on the environment. This chapter introduces research by giving a context to essential aspects, including the research background, aims, objectives, and the research outline. This thesis intends to integrate building performance simulation to operational performance, focus on indoor climate conditions and energy consumption, extend the use of BPS, and address performance gap challenges. It also highlights the main contributions to the knowledge, including both theoretical and practical. The conclusion and findings of this research are intended to aid building users and professionals in understanding the implication of thermal comfort conditions on energy use, quantifying energy performance and assessing indoor thermal comfort conditions in the operational stage in real-time.

Chapter 2

Literature review

There is a growing concern about the source of energy use and its implication on the environment. Buildings are one of the primary energy end-use sectors in many developed countries, accounting for a larger percentage of overall energy consumption than both industry and transportation. Over the last half-century, many attempts have been made to make buildings and the construction process more environmentally friendly. In addition, concerns about energy and financial crises, global warming, pollution, and climate change have grown an interest in building performance and constructing more energy-efficient buildings. The lack of a clear definition of building performance leads to confusion, fuzzy designs, and complex software systems, such as employing building performance in the context of sustainability (Todorovic and Kim, 2012, Becker, 2008, Geyer, 2012).

The importance of lowering energy consumption in buildings become permanent. However, the complexity of building elements and the connections between various systems remains one of the serious challenges facing the construction industry. Reducing energy consumption and maintaining an acceptable thermal comfort condition in a building is even more challenging because it is directly connected to the building's users. Studies identified this decades ago and undertaken significant efforts to reduce energy use and improve indoor environmental quality (IEQ). In addition, computer simulations are utilised to anticipate and improve building energy performance, from initial design to operation and demolition. Existing studies on operational-stage building performance evaluation have found substantial flaws in the performance of energy and IEQ and a lack of consistency between design assumptions and actual on-site observations.

This chapter covers two primary subjects, building energy performance and thermal comfort conditions. Investigates building performance analysis methodologies, focusing on IEQ and energy consumption. The utilisation of advanced technologies, computer simulation and the internet of things. Finally, the review extends the understanding of thermal comfort conditions and energy performance. The literature review chapter is divided into three sections.

The first section reviews the building performance analysis approaches, focusing on data collection and measurement tools to assess and quantify building performance. The chapter reviews sensing technologies in the built environment, highlights sensors types and applications in the indoor environment, focusing on thermal comfort and energy saving related systems. Moreover, the chapter discusses the sensors data analysis method and processes. In the last section, the chapter reviews some of the studies related to energy and thermal performance issues in the built environment

2.1 Building performance analysis approaches

The term "building performance" is widely used in industry, academia, and governments. It plays an essential role at every stage of the building life cycle and overall decisions about the BE. However, there is no clear definition of building performance in the literature or a unified theory on building performance analysis (de Wilde, 2018). From a technological or aesthetic perspective, buildings are considered complicated systems. Generally, A building is a system of systems since it combines several systems, such as a structure, envelope, filling, and building services. The central principle of building performance is to meet the building standards for which they were designed. However, it is challenging to capture building performance and determine how well it meets the standards. The concept of building performance deals with quantification and measurement. Measurement is defined as the process of determining the size, amount, or degree of something by comparing it to a standard unit or an object with defined properties. Although measuring is a simple process, such as determining the length of an object, building performance measurement frequently requires the design of an experiment, the investigation of various observable states, and the aggregation of the data into a single metric. Measurement is also defined by using a specified method to determine the numeric level of a scalar attribute under specific conditions (Gilb, 2005). Thus, the term measuring is less appropriate for performance based on calculation or computation.

On the other hand, quantification is a process that translates observations into numbers and expresses or measures the quantity of anything (Oxford English Dictionary, 2010). Building performance can be quantified through actual physical testing, calculation, or a mix of both (Foliente, 2000). According to (Gilb, 2005) quantification is limited to 'articulating a variable attribute using a defined scale of measure and identifying one or more numeric levels on that scale'. This concept distinguishes quantification from measurement. However, building performance analysis can be grouped into physical testing and measurement, calculation and simulation, expert judgment, and post-occupancy evaluation.

2.1.1 Physical Measurement

A physical measurement is a direct method of determining how a building behaves using different instruments. Physical measurement instruments come in a wide range of qualities, prices, and various levels of detail, such as anemometers, illuminance meters, motion sensors, flow meters, thermocouples and pyranometers (Lirola et al., 2017). Although there are many existing techniques and approaches to physical measurement, accuracy is a crucial issue. Measurement precision can only be assessed if a reference can be determined (Oberkampf and Roy, 2010). Even though calibration and adjustment help reduce measurement errors, the quality of measurement depends on the control of random errors and systematic error, a random error is the quality of the instrument, and systematic error is the assumptions and analysis techniques (Efficiency Valuation Organization, 2014b).

In building performance studies, a typical temperature logger has an accuracy of ±0.2°C others may have a variation of ±0.6°C; depending on the case study, these numbers can be irrelevant to determine whether or not a room or building is overheating. As previously stated, equipment precision is critical for better measurement quality, but various other factors to consider (Gillespie et al., 2007, Friedman et al., 2011).

- The exact location of the device.
- Data acquisition or logging systems.

- Data transfer approach wire or wireless.
- Communications protocol among different devices.
- Calibration procedures.
- Data storage, in terms of location, capability and capacity.
- Conversions from analogue to digital.

Several approaches have been proposed for monitoring a measurement over time. For example, weekly measurements for energy monitoring was proposed by BSI, provide higher temporal measurement than the monthly data used for billing and easy to handle than the high-resolution hourly or half-hourly data (Vesma, 2009). In contrast, (Neumann et al., 2008) consider recording data on an hourly basis and providing an overview of the data that needs to be investigated in building services, including energy consumption at various system levels, outdoor and indoor environmental conditions, and data related to the system state. This approach is usually used for building monitoring projects. With regard to thermal evaluation, (Bolchini et al., 2017) provide an outline of some of the factors to consider when establishing a thermal monitoring assessment.

Physical measurement approaches are usually classified based on their applications to field studies and on-site measurement or laboratories in controlled and semi-controlled environments. For example, measuring actual buildings may require the removal of samples from the structure or gaining access to hidden sections such as cavity walls. Nevertheless, non-destructive techniques (NDT) are also utilised for physical measurements, such as laser scanners, 360 images and environmental sensors. Another example of NDTs includes taking direct measurements from building control and operation systems, such as data acquisition from buildings' energy management systems, and measurements focusing on a specific aspect of a building's performance, such as fault diagnosis in HVAC systems. Whole-building approaches and component or system-based measurements are two different types of psychical measurements (de Wilde, 2018).

2.1.2 Expert judgment

Field expert is another approach to assess building performance, especially when dealing with a complex situation, such as missing or insufficient data or the simulation is difficult to manage. Even though expert judgement is only one source of scientific evidence (Cooke and Goossens, 2008), it plays an essential role in decision-making in the industry

(Coussement et al., 2015). For example, expert field knowledge was combined with other data to improve model prediction (Wilson, 2017). In simulation and modelling, expert judgment is also a common strategy for reducing uncertainty in complex scenarios (Scholz and Hansmann, 2007, Kinney et al., 2010). Even though expert judgment is subjective by nature and may not be free from bias, it remains valuable, especially in a transparent and well-documented methodology (Coussement et al., 2015, Zhang and Hong, 2017). For example, determine which aspect is based on scientific data and which is based on personal preference (Dror, 2013). The general approach to expert evaluation is simple, a) identify the experts; b) obtain experts' assessments; c) post-processing and combine the results; d) record and quantify uncertainties in the assessment (INCOSE, 2015). Although expert judgment has a high value in the construction industry, few studies define an expert or how to elicit the best assessments. However, (Gann and Whyte, 2003) draw attention to the adaptivity of expert judgment in a design context as an advantage in dealing with uncertainty. According to (Blyth and Worthington, 2010), many qualitative performance aspects of buildings are subjective and require judgment.

Additional evidence shows expert judgement is used in building performance presented by (de Wit and Augenbroe, 2002), assessing uncertainties in building performance simulations, precisely the rate of ventilation in building areas and room air temperature distributions. (Galiana et al., 2012) point out the risk of expert judgement when utilising concepts and parameters that do not match the perception of actual buildings. (Carpio et al., 2015) utilise an expert panel to assess the quality of the documents used to certify energy efficiency**.** (Strachan and Banfill, 2017) rank retrofit measures of non-domestic buildings using expert judgment. In addition, the data collection and analysis for the Post Occupancy Review of Building Engineering (PROBE) studies were deeply dependent on experts (Blyth and Worthington, 2010)**.**

2.1.3 Post-Occupancy Evaluation (POE)

The Post-Occupancy Evaluation (POE) assesses building performance by asking and obtaining feedback from stakeholders about their perceptions of how well the building performs. User feedback is commonly employed in software and product design to study human-computer interaction (HCI). In building assessment, POE is considered part of a larger set of feedback procedures to evaluate building performance, including systematic study, panels with skilled observers, and direct surveying (Gibson, 1982). (Mlecnik et al., 2012) indicates that obtaining information from stakeholders such as occupants' perception and satisfaction are often considered in the domain of social sciences. Meanwhile, another study argues that people are the best tool for analysing a building's performance (Leaman et al., 2010). Obtaining occupants feedback varies depending on the study's objective, such as in a controlled environment or field study. It is also a common approach to assess IEQ. For example, (Wagner et al., 2007) investigate two approaches focusing on thermal comfort. (Blyth and Worthington, 2010) describes several methods for obtaining user feedback, such as questionnaires, interviews and focus groups, observation of building walkthrough, and comparisons to leading examples. Other areas of occupant evaluation are complicated and under investigation, such as the perception of a view from a window (Matusiak and Klöckner, 2016) and statistical correlation like using statistics to investigate the connection between occupant satisfaction and indoor environmental parameters (Candido et al., 2016, Frontczak et al., 2012).

Generally, in building performance assessment, the POE study is often used to determine occupant perceptions of a building, assess their level of satisfaction, suggest areas for improvement, and find unsatisfied occupants. Moreover, it can assist facility management and design processes in a broader sense (Jaunzens and Grigg, 2003). Preparation, data collecting, and data analysis are the three steps in the POE process. In the preparation step, the data collection technique is established and defines a target building and ensures that researchers/analysts have access to essential stakeholders such as building owners, facilities managers, and building occupants. The vast majority of research use questionnaires or a series of interviews to collect data. Likert scale ratings are frequently used to assess occupant satisfaction with elements such as thermal comfort. This information might also be linked with data from the building's systems and occupant profiles, such as age, gender, and education. Other information, such as building layout and location, building conditions and operating settings, building management, and design quality, may also be included. Furthermore, other data, such as temperature, humidity, noise level, lighting conditions, and ventilation system, can also be captured from rooms and zones in a building, depending on the type of study. The last step usually includes a thorough review of the data, a conclusion, recommendations, and suggestions for improvement.

The Usable Building Trust recommends evaluating a building's performance using a variety of techniques. There are several types of techniques, including a) audits, such as using the Energy Assessment in CIBSE TM22 and Reporting Methodology; b) review and discussions; c) questionnaire; e) process-supporting method such as the integrating of Soft Landings; d) the development of a comprehensive approach incorporates all of the above (Usable Buildings, 2021, Bordass and Leaman, 2005). Despite POE's general acceptance, it was subjected to some criticisms. In a literature review, (Hauge et al., 2011) discuss occupant experiences with various types of energy-efficient buildings, concluding the importance of acquiring the social context of building occupants and system operation. The findings of POE investigations that are limited to one or a few buildings are context-specific and difficult to generalise (Mansour and Radford, 2016). An example of this, a study that investigated the connection between occupants’ lifestyle and perception of building quality and then simulated occupants’ perception using a neural network approach (Rebaño-Edwards, 2007). Another study by (Nicol and Roaf, 2005) combines POE studies with field investigations in thermal comfort, emphasising that thermal comfort is influenced by time and environment, often overlooked in traditional POE surveys.

Some researchers believe that POE is about real-world research and that the absolute truth is measurable data. Therefore, they tend to overlook the significance of simulation and expert judgement in POE (Meir et al., 2009, Leaman et al., 2010). This concept, however, is inapplicable when developing an integrated strategy that fits all relevant approaches.

2.1.4 Computer Simulation

Computer simulation is another method of assessing and evaluating building performance through experimentation and measurement and is considered a key approach in the design and construction stages. For example, computer simulation was utilised to compare and evaluate different design options (Augenbroe, 2019). Building simulation tools creates a virtual experiment that mimics reality and is based on mathematical calculations that accounts for fundamental physical principles (de Wilde, 2018, Shiflet and Shiflet, 2014). Building simulation tools require a model representing a building, exist or imagined. Throughout the simulation, the model is exposed to several scenarios or experiments, which is based on an abstraction of physical entities, each used to monitor a phenomenon that helps to understand the performance of the model in that particular scenario (Augenbroe, 2019, Hensen and Lamberts, 2012, Zeigler et al., 2000). Setting up a virtual experiment is similar to performing physical tests, requires a careful plan of the experimental setup, boundary conditions, and measurement protocol to identify the required data capture, such as temporal and spatial resolution, where and when. The level of complexity is one of the advantages of utilising computer simulation instead of engineering calculations. Simulation can easily manage a large number of variables across several scenarios.

Building simulation tools come in various shapes and sizes, each with its own set of features. Some are based on research and are primarily utilised in academia, while others are used in the industry as a commercial product with complete backend support. Building simulation models cover different physical processes depending on the building simulation tool's functions. For example, the model may represent a whole building, including a complex combination of geometry materials and systems, or a one-dimensional section through a wall representing a section or small part of the building. Any building is subjected to a complex pattern of external and internal effects, making modelling an essential part of building simulation because it reduces real-world problems to a few variables, allowing for the analysis of a complex situation and a practical assessment of the building's performance (Gibson, 1982, Marques et al., 2011). There are different ways of classifying building performance models. A common way is based on a temporal dimension by differentiating between stationary, semi-dynamic and transient models. For example, a stationary model requires a mathematical solution of one set of equations, such as measuring heat transfer through a surface. In a semi-dynamic model, a set of equations need to be solved multiple times, such as several conditions representing the months of the year. The transient conditions are usually examined based on hourly data, increasing to 8760 steps per year.

Simulation models can also be divided into three categories, black box, grey box, and white box. In the black box model, the connection between input and output is based on machine learning, establishing the correlation using correlated datasets. The internal workings that cause the correlation are unknown. Regression analysis and neural networks are two common approaches to the black box model. A grey box prediction model provides insight into the system's basics, but unknown attributes and relations in these models must be estimated. In a white-box model, principles and rules are known, which allows for explicit modelling of the relation between input and output (de Wilde, 2018).

The scope and complexity of developing a building simulation model can also be defined based on the project life cycle stage and the purpose of the calculation into compliance modelling, performance modelling, and actual performance modelling (Jain et al., 2020). Compliance modelling is usually performed for regulatory compliance and comparative benchmarking during the design and construction stages (van Dronkelaar et al., 2016). Generally, the compliance model is not accurate enough to reflect the actual building operation conditions, such as temperature setpoint, occupancy and heating, ventilation and air conditioning (HVAC) system operation schedules. However, compliance modelling is well suited to policy applications that demand simplicity, replicability, verifiability, and applicability over the entire building stock and relative performance, such as comparing the energy performance of a building to that of a reference building. Nevertheless, compliance calculations are inappropriate for evaluating the energy use performance of buildings (Burman, 2016).

Performance modelling is used to estimate and anticipate building performance during the design and construction stages. (CIBSE, 2013) TM54 presents a framework for estimating the operational energy performance of buildings at the design stage, allowing designers to customise operating parameters according to the design document and predicted performance accounting for all end uses, including equipment loads. Actual performance modelling is carried out during the building's operating stage to assess the true performance and the potential for further improvement. The actual performance of the building is measured during a steady state of operation. Building performance modeller aims to calculate the actual performance during the design stage, achieve design requirements, and minimise the difference between prediction and actual performance.

In some cases, the building simulation method is ineffective. Some of the disadvantages of using building simulation are listed by (Basmadjian and Basmadjian, 2003).

- Serious modelling effort where modelling is time-consuming.
- Not valuable for solving inexpensive and straightforward experiments.

- Physical evidence is required.
- The modelling is too complex or fails to offer valid or useful information.
- The solution is self-evident

Even though building simulation has advanced significantly and is now recognised as one of the most key technologies provided to the construction industry, several challenges remain (Hensen and Lamberts, 2012). The discrepancy between predicted and measured performance is one of the serious issues that undermine the confidence of simulation results, and it is called the performance gap (Carbon Trust, 2011, van Dronkelaar et al., 2016, Fedoruk et al., 2015, Menezes et al., 2012, CIBSE, 2013, de Wilde, 2014). There are a variety of underlying variables that make the performance gap hard to address, such as fundamental model uncertainties, tool faults, and training challenges, which are increased by the complexity of the building design, construction, and operation procedures. Therefore, it is usually recommended to employ a calibration technique by aligning with actual data on the facility's loading and then calibrating using metering data and utility bills, if possible. Moreover, it is crucial to maintain track of the software used and establish a robust audit trail to the modelling and calibration effort (Efficiency Valuation Organization, 2014a). Another complicated issue is occupant behaviour because it involves anticipating occupant presence and activity. Previous studies state that a difference between modelled and actual occupant behaviour can be as high as a 40% gap (Donn et al., 2012, Duarte et al., 2015). (Prada et al., 2014) discusses the uncertainty of the thermophysical properties of building materials and how they affect simulation results; a Monte Carlo technique was used to run a sensitivity analysis on several walls in different climates. Nevertheless, interoperability and data exchange between different digital environments is another challenge, such as the connect of building simulation to building information modelling (Augenbroe, 2019).

Moreover, building simulation faces additional challenges related to the evolution of buildings and systems, which add more complexity to the simulation. For example, buildings with huge atria, odd shapes, complicated shading systems, radiant barriers, complicated HVAC systems, or cutting-edge technologies may push simulation to its limits, requiring new models (Efficiency Valuation Organization, 2014a). In a broader analysis of the field of building performance simulation, seven deadly sins of the simulation were listed by (Clarke and Hensen, 2015).

2.2 Sensing technology

Many sensors are utilised to determine the quality of the indoor environment, energy consumption, and occupants' satisfaction, collecting fine-grained information benefits in energy-saving and IEQ overall (Dong et al., 2018, Spataru and Gauthier, 2014, Ken Christensen et al., 2014, Klein et al., 2012). Proper management of energy consumption and indoor thermal comfort conditions is critical in the built environment (Choi et al., 2016a, Navada et al., 2013a). In addition, a variety of sensors were employed to measure occupant patterns and behaviour and thermal and visual preferences, allowing the building system to control energy usage and IEQ more efficiently (Andersen et al., 2015). To better understand the influence of sensing systems in the built environment, this section reviews various types of sensors and discusses the importance of sensors for energy-saving and occupant comfort and explains their impacts on the IEQ and occupant productivity. In addition, this section explores and analyses sensors applications in terms of energy-saving, thermal comfort.

2.2.1 Sensor’s overview

Understanding how building occupants perceive IEQ is critical to creating a healthy and productive environment. Analysing occupant behaviour and environmental parameters helps improve building comfort conditions and energy performance (Nguyen and Aiello, 2013, Li et al., 2012). Sensors and internet of things (IoT) have become more prevalent in the construction industry for a variety of applications. Different types of sensors and sensing systems are used in building operations to assess and control the building, such as smart metres, thermostats, environmental sensors, and personal sensors (Cheng and Lee, 2014, Cheng and Lee, 2016, Sim et al., 2016, Goyal et al., 2015, Kim et al., 2018a). Generally, sensors in the built environment can be categorised into personal sensors, environmental sensors and the presence sensors Table 2.1. Many sensors are used in the BE to measure indoor environmental parameters. The most common sensors are temperature, humidity, air velocity, Photometric, CO2, volatile organic compounds (VOC), and Particulate matter (PM). Environmental sensors or instruments usually need to be calibrated regularly to ensure stability.

Table 2.1 Sensors in the built environment

Sensors in the BE	purpose	Sensor type		
Environmental sensors	Measure indoor environmental parameters	Temperature	Humidity	Air velocity
		Sound sensor	Thermo-fluidic	Light sensor
		Volatile organic compound	Particulate Matter	CO_2
Personal sensors	Recognise human behaviour	Fingerprint	IoT based sensor	Heart Rate
		Wearable device	Smart Phones	
		Skin Temperature	Mobile pupilometer	
presence sensors	Detect occupancy presence	Passive infrared	Image-based	Radio-based
		Chair sensors	Camera	Photosensor
		Pressure mats	Ultrasonic ranging	Ultrasonic Doppler
		Microwave Doppler	Threshold and mechanical	

Environmental sensors

Temperature and humidity sensors are widely used in the BE with different precisions, quality, and price ranges. The most common temperature sensors have an accuracy of less than +/¬0.5 K (Snyder et al., 2013). Nevertheless, more precise sensors are also available with +/¬0.1. (Cheng and Lee, 2016) investigates sensor development, in particular thermo-fluidic sensors and occupancy detectors. A wireless sensor network (WSN) is used to measure the temperature and humidity of the indoor environment. (Kim et al., 2018b) explored occupants' thermal behaviour to develop personal thermal comfort models to predict occupant thermal satisfaction. A heating coil and a cooling fan attached to the chair along with a data logger to record temperature, humidity, and globe temperature in an office environment. (Jin et al., 2018) assess IEQ using a developed autonomous mobile robot system. A list of sensors integrated to monitor indoor environmental parameters, including temperature and humidity, light level, PM 2.5, CO2, and VOC. The study examined the effectiveness of air change by comparing static sensing with the dense sensor network required by the ASHRAE standard 129 (ASHRAE, 1997). The findings revealed that the automated mobile sensor accurately monitors environmental parameters at a low cost and minimal calibration work.

The airflow rate is measured using air velocity sensors, (Sardini and Serpelloni, 2010) proposed a self-powered wireless sensor to monitor air temperature and velocity in real-time. The developed sensor system includes an electromechanical generator, whose rotor frequency aids in measuring air movement. In another study, a micro-electro-mechanical system (MEMS) was developed to measure the airflow rate in the indoor environment; the system operates by monitoring changes in gaseous particles and particulate matter.

A light level sensor is another environmental sensor utilised in the BE. For example, a photometric sensor with the same sensitivity as a human eye assesses and controls lighting in the indoor environment can significantly reduce lighting energy consumption while maintaining visual comfort (Navada et al., 2013b). Nonetheless, Photometric sensors face several challenges, including positioning within the indoor environment and occupants' visual satisfaction with artificial and natural light; If the sensor is positioned next to a window, the artificial light will be dimmed following the daylight. However, if the occupant is positioned away from the window, the lack of natural light may be uncomfortable. For example, the typical average illuminance value in an office environment is 500 lx in the occupied zone and 300 lx in the unoccupied region (Halverson et al., 2014). Furthermore, to develop a control strategy employing photometric sensors, more factors, such as colour temperature ratio, glare, vertical to horizontal illuminance ratio, and light spectrum, need to be considered (Veitch and Newsham, 2000, Pandharipande and Caicedo, 2015).

The CO_2 sensors are widely used in the built environment, measure carbon dioxide concentration in the air by parts per million (PPM). Studies utilised the sensor to count the number of people in a zone by examining the correlation between CO_2 concentration and the presence (Nassif, 2012, Mumma, 2004). This approach is considered a non-individualised technique to measure occupancy presence. Some studies aimed to develop a low-cost CO2 sensor that could be used efficiently in an indoor setting. For example, (Park et al., 2003) Measured the CO_2 concentration in the indoor environment using a potentiometric CO_2 electrochemical sensor. In another study, a low-cost CO_2 sensor was developed using semiconducting oxides and thick film technology (Haeusler and Meyer, 1996).

Another typical sensor used in the BE is Volatile Organic Compounds (VOC) to detect the concentrations of gaseous material based on the interaction between the sensing material and the targeted gases concertation. Transducers translate environmental changes into electrical signals to assess indoor quality (White et al., 2012). A review of the concentrations of VOC in the building showed it is between 5 and 50 g/m3. On the other hand, the total volatile organic compound (TVOC) concertation concentration will be much higher than VOC (Brown et al., 1994). (Zampolli et al., 2005) developed a system that uses gas chromatography to monitor single volatile organic chemicals in the built environment.

Moreover, there are different VOC sensors, such as solid-state sensors (Ho, 2011). The VOC sensor is based on a micro-electro-mechanical system, which comes in different sizes, shapes, and materials (Kumar et al., 2016). Another type of sensor used in the built environment is the Particulate matter (PM) sensor to detect the concentration of particles in the air. The main challenge of PM sensors is to detect a low level of pollutants (Snyder et al., 2013).

Personal sensors

The personal sensors are human-related and are used to collect individual data. Personal sensors are relatively new in the BE domain, such as wearable devices and IoT sensor-based devices. Devices like smartwatches and bracelets were utilised to detect skin temperature, heart rate, and perspiration rate (Cheng and Lee, 2016). In thermal comfort studies, (Abdallah et al., 2016) outline the challenges of using wearable sensors to quantify occupants' thermal sensation. Throughout a series of environmental chamber experiments, (Choi and Yeom, 2017b) and (Yeom et al., 2019) investigated the potential use of skin temperature in establishing an accurate individual’s thermal sensation. In another study, personal and environmental sensors were integrated to control air conditions in the indoor environment. The developed system obtained a response from occupants using wearable devices and smartphones, which were used to adjust the temperature accordingly (Cheng and Lee, 2014).

Smart wearable devices were also used as an individualised system to detect occupancy presence in the building, such as a crowd detection and occupancy estimation (Viani et al., 2014). Smartphones and watches collect information about the occupant, such as identity, location, and tracking. In addition, smartphone applications were used to obtain feedback from occupants, potentially used to save energy and improve occupants productivity (Akkaya et al., 2015, Sim et al., 2016).

Presence sensors

The presence of occupants in the building is detected using a variety of sensors and techniques. In general, occupants' presence detection technology can be classified into two systems, individualised and non-individualised. Every person in the sensing zone is detected, identified, and tracked in the individualised system. In contrast, the non-individualised system detects the total presence of individual zones without knowing occupants coordinates or identity (Li et al., 2012). Accordingly, four major categories of sensors have been identified in the literature, Vision-based systems, Motion sensors, Radio Frequency Sensors, and Mechanical sensors.

Vision-based systems are individualised and non-individualised systems that rely on camera footage and video analysis techniques. The vision-based systems include infrared (IR) cameras, visible light, and luminance cameras (Seer et al., 2014). Cameras for occupancy presence can be considered an implicit detection system. For example, cameras are often used for security reasons. However, They could also be used as part of a presence detection system in the building, which helps decrease energy end-use and maintain better indoor environment conditions (Liu et al., 2013a, Erickson et al., 2013). Cameras can determine occupants' location, count, tracking, and recognition (Benezeth et al., 2011). In terms of reliability, (Yeom et al., 2019) states that visible light and luminance cameras are more common than infrared cameras as a presence detection system. However, they are associated with several challenges, such as a) the location where the cameras will be placed; b) To detect occupants' presence, count, tracking, position, and recognition, an individualised system requires expensive signal processing hardware and a complicated algorithm (Thanayankizil et al., 2012); c) the complexity of the installation; d) privacy issue (Abhijit et al., 2008); e) the high cost of the system prevents the use of additional sensors in a single zone.

Motion sensors are considered a non-individualised presence detection system, usually used to detect occupants for energy-saving applications, such as artificial light and HVAC system control (Guo et al., 2010). Nevertheless, any false signal can cause occupants' discomfort. The most common motion sensors are Passive infrared (PIR) sensors, photosensors, microwave Dopplers, and ultrasonic sensors (Hnat et al., 2012, Agarwal et al., 2010, Agarwal et al., 2011). The PIR sensors can detect occupants' presence using infrared technology. The disadvantage of the sensor, it records false signals when there is no movement for a while. Moreover, additional programming is required to count the number of people in a room. (Teixeira et al., 2010, Li et al., 2012). The Photoelectric sensor uses a light transmitter and receiver to detect an object's distance, absence, or presence. (Li et al., 2012) reported heating from the HVAC system can activate the sensor. Microwave Doppler radar is a sensor that uses electromagnetic waves to measure the speed of occupants moving toward or away from it. The sensor has a high sensitivity to minor motion in the indoor environment, which might overcount occupants of small movements (Dong et al., 2019). Ultrasonic sensors can measure the distance from the object by emitting ultrasonic sound waves. (Hnat et al., 2012) create an indoor tracking system using Ultrasonic sensors to count the number of people passing through a doorway in a domestic building.

Radio Frequency Sensors is an individualised system that employs a radio signal to detect occupants' presence and provides information, such as location, count, identification, and movement (Misra and Enge, 2011). Various radio-based systems are available to detect occupancies, such as Wi-Fi or Bluetooth, radio frequency identification (RFID), a global positioning system (GPS), and ultra-wideband (UWB). The RFID recognises and tracks tags attached to objects using radio waves and a unique identification number. RFID systems are divided into passive and active. The active system requires power to broadcast tags' signal continuously. It is mainly used as beacons to track an object in real-time accurately. It is considered an effective way for indoor localisation, such as measuring the distance, count, proximity, and estimate of occupants activities (Wu et al., 2009, Li et al., 2012). Other radio technology used to identify occupant presence in the built environment is Wi-Fi and Bluetooth. Both technologies have a limited wireless sensitivity range and an accuracy range of 2-10 m, depending on the localisation approach. Several studies investigate a short-range and low power sensor to monitor and control applications (Sabek et al., 2015, Anthony and Eyal de, 2008, Gomez et al., 2012). Another wireless system that transmits short signals to measure the distance of the occupant is the UWB, with a precision of 10-50 cm (Khoury and Kamat, 2009). Occupant identification and monitoring can also be detected using the GPS. The precision of GPS systems ranges from 1 cm to 10 metres depending on the technology (Misra and Enge, 2011). Using GPS involves using GPS-enabled devices, such as smartphones or wearables. Compared to WLAN and UWB, GPS technology provides a low level of uncertainty (1 to 2 cm) in the indoor environment (Khoury and Kamat, 2009).

Mechanical sensors are in different shapes and sizes, usually used to detect occupants while interacting with building elements, such as windows or doors (Agarwal et al., 2010, Caucheteux et al., 2013). It is considered individualised and non-individualised sensors depending on the system application. For example, the Reed switch and magnetic sensor is a low-cost non-individualised sensor that consumes low energy. The door badge and card sensor use a swipe to access the building's zone, allowing counting and recognising occupants. However, when a single swipe is used for several occupants, the system fails to deliver reliable data (Hay and Rice, 2009). A piezoelectric floor sensor is another approach to detect occupants' presence bypassing or standing on the piezoelectric sensor. However, the occupants must stand or walk long enough on the floor to detect them (Ranjan et al., 2013). The IR bean is another mechanical sensor that counts occupants by blocking the signal beam. A study found that the system is limited to the number of occupants because the device does not adequately detect several occupants passing at the same time (Yeom et al., 2019).

2.2.2 Sensor-based applications

In the BE, sensors are widely used to monitor, control, evaluate, and optimise building performance. Previous studies on sensor-based applications have focused on energy consumption and comfort control. The vast majority of applications are dedicated to reducing energy use while improving indoor environmental conditions such as thermal, visual, and indoor air quality (Choi and Yeom, 2017b, Cheng and Lee, 2014, Abdallah et al., 2016, Kim et al., 2018a). This research is focused on the sensor-based applications, focusing on energy performance and thermal comfort conditions in the indoor environment. Several sensors and applications used for thermal comfort and energy performance listened in Table 2.2

Table 2.2 Sensor-based applications of thermal conditions and energy performance

Study	Energy saving	Thermal Comfort	Sensor type				
(Labeodan et al., 2015)	X		Chair sensor				
(Williams et al., 2012)	X		Passive infrared	Photo sensor			
(Ekwevugbe et al., 2012)	X		Passive infrared	Pressure mats	CO_2	Sound	Camera
(Nguyen and Aiello, 2013)	X		Passive infrared	Camera sensor	WSN		
(Akkaya et al., 2015)	X		Passive infrared	Camera sensor	WSN		
(Cheng and Lee, 2016)	X	X	Passive infrared	Wearable sensor	Smart phones	Thermo-fluidic	
(Armstrong et al., 2007)	X		Passive infrared	Photo sensor	CO_2	Camera	
(Gentile et al., 2016)	X		Passive infrared	photo sensor	Pressure mats		
(Choi et al., 2016b)	X		Passive infrared	Photo sensor			
(Williams et al., 2012)	X		Passive infrared				
(Nagy et al., 2015)	X		Passive infrared	Thermostat	Humidity	WSN	
(Navada et al., 2013a)	X		Photo sensor				
(De Paz et al., 2016)	X		Photo sensor				
(Leephakpreeda, 2005)	X		Photo sensor				
(Sheikhi et al., 2016)	X		Wearable sensor				
(Abdallah et al., 2016)	X	X	Wearable sensor	Smart phones			
(Cheng and Lee, 2014)	X	X	Wearable sensor	Smart phones	Thermostat		
(Yun and Won, 2012)	X	X	Thermostat	Thermo-fluidic			
(Sim et al., 2016)	X	X	Thermostat	Heart rate	Humidity	Skin temperature	
(Viani et al., 2014)	X		Wireless sensor network (WSN)				
(Kim et al., 2018a)		X	Wearable sensor	Humidity	Thermostat		
(Yeom and La Roche, 2017)		X	Heart rate	temperature	Humidity	Air velocity	Skin temperature
(Choi and Yeom, 2017b)		X	Humidity	Air velocity	Skin temperature		
(Choi and Loftness, 2012)		X	Heart rate	Air velocity	Thermostat		
(Jin et al., 2018)		X	Wireless sensor network (WSN)				
(Dai et al., 2017)		X	Temperature	Humidity			
(Choi et al., 2012)		X	Heart rate	Humidity	Skin temperature		
(Goyal et al., 2015)		X	Fingerprint	CO_2	Thermo-fluidic		
(Choi and Yeom, 2017a)		X	Heart rate	Humidity	Air velocity		
(Zhang et al., 2010)		X	Air velocity				
(Andersen et al., 2015)		X	Wearable sensor				
(Ekwevugbe et al., 2012)		X	CO_2				

Sensors for energy consumption

Several studies investigate the use of CO_2 for energy saving. As previously stated, CO_2 sensors are frequently utilised as a presence sensor. Thus, it was found in applications to control ventilation connected with the HVAC system (Labeodan et al., 2015). For example, a study measures CO_2 concentration in the HVAC system's return duct and establish a multi-zone HVAC system control technique (Nassif, 2012). In a simulation-based and field study, CO_2 based demand-controlled systems can save 60% more energy than ventilation rate systems (Mysen et al., 2005, Lin and Lau, 2015). However, the sensor has a few flaws that influence the mixing of air and CO_2 concentration and result in incorrect storing of occupancy counts, such as opening and closing the door and the fluctuation of airflow rates of HVAC systems (Meyn et al., 2009). In another study, a chair sensor was used to detect occupancy presence and control lights and HVAC systems. (Li et al., 2012) developed a chair sensor that activates the HVAC system in the presence of an occupant, which can save energy, especially when it is not in use. A survey and detection system evaluation study stated several limitations of using pressure mats on chair sensors, such as a) the sensor does not detect standing person; b) the pressure must be applied at the precise location; c) the sensor is sensitive to a minimum weight; d) the sensor is sensitive to little movement such as adjusting seating position (Labeodan et al., 2015).

PIR motion sensor is a presence sensor usually used to control lights on in the indoor environment (Ekwevugbe et al., 2012, Akkaya et al., 2015, Nagy et al., 2015, Armstrong et al., 2007). For example, in a typical office room, the PIR sensor employs to switch lights on and off, depending on occupant presence, which can save energy when the room is not occupied (Emmerich et al., 2001, Linhart and Scartezzini, 2011). Both PIR and photo sensors were utilised in a cubical office environment, and two energy-saving measures were explored; first, lowering the timeout period of the PIR sensor from 20 minutes to one minute, which resulted in a 26% energy savings. Second, LED light with the photo sensor was used, and the findings revealed a 35% reduction in energy use (Choi et al., 2016b). The key challenges to employing PIR and photo sensors to save energy in lighting are the duration of the delay and dimming periods. a) short delay time cause disturbances to the occupants, especially when occupants are not moving for a while; b) long delay causes more energy waste (Nguyen and Aiello, 2013, Williams et al., 2012, Choi et al., 2016b). Thus, the delay time setpoint is critical for PIR applications.

Another sensor utilised in lighting applications in the indoor environment is the photometric sensor, which is used to adjust the luminaire intensity depending on daylight availability (Navada et al., 2013a, Gentile et al., 2016, Jin et al., 2018, Leephakpreeda, 2005, Williams et al., 2012, De Paz et al., 2016, Choi et al., 2016b). A study investigating three control strategies for light energy savings, occupant sensors, light sensors, and individual dimming controls revealed 42–47% light energy saved compared to luminaries operating when the three approaches were used together. The findings from individual strategies showed that the occupant sensor could save 35%, the light sensor 20%, and dimming control 11% of the light energy (Galasiu et al., 2007). Another study discussed three alternative light control systems for energy efficiency and occupant satisfaction, including the absence, presence, daylight harvesting technologies and a desk lamp to analyse the energy savings. The study's findings showed 79% energy saving from daylight harvesting with the artificial light and 75% energy saving using absence detector with the switch control. Moreover, the standard control offers better occupant satisfaction to the automatic control (Gentile et al., 2016).

The Internet of things (IoT) applications are used in the building to save energy. The IoT in the BE usually refers to a data collecting technique that use the internet or other communication networks to connect and share data. The sensors used for ToT applications include IoT-based thermostats and light control units, cloud-based applications, wristband-based feedback services, Smartphones and wearable technologies, such as GPS, NFC, schedules and applications.

(Sheikhi et al., 2016) developed an IoT-based sensor connected to structural health monitoring systems for adaptive energy consumption optimisation. Users' location and feedback, body temperature, and data from different energy monitoring systems were utilised to reduce energy use and increase comfort conditions. A study on energy reduction and comfort control utilised smartphones, wearable devices, temperature and motion sensors to control HVAC systems and maintain a better level of thermal conditions (Cheng and Lee, 2014). The IoT technology was used to obtain occupants position, behaviour patterns, and personal thermal preferences and send them to the intelligent control system. Furthermore, the wearable device's feedback helps determine occupants’ sleeping patterns and regulate the indoor temperature accordingly, resulting in 46.9% energy saving.

An app free method was presented by (Akkaya et al., 2015) to detect the occupant presence in the building, including Wi-Fi, camera, and sensor networks. A study used a wristband device for thermal sensation estimation, obtaining individual thermal comfort preference (Sim et al., 2016). An IoT device to measure heart rate was investigated by (Choi et al., 2012) to determine the personal factors for human thermal comfort calculation. The results can benefit the BE to improve thermal conditions and energy use.

Sensors for thermal comfort conditions

One of the most difficult aspects of studying thermal comfort is that human thermal comfort differs from to another, and there is no single point at which all occupants feel comfortable (Linhart and Scartezzini, 2011, Corgnati et al., 2008, Liu et al., 2013b, Abdallah et al., 2016). Nevertheless, several sensing technologies are employed to assess thermal comfort and its impact on building energy consumption. For example, a WSN monitors indoor environmental parameters to assess occupant thermal comfort. The indoor environmental parameters connected to thermal comfort studies are temperature, humidity, radiant temperature, and air velocity.

A study to address individual thermal comfort and energy saving proposed a microzone-centric approach using a chair as a personal comfort system. A heating strip and a fan are included in the chair and operated by the occupant's smartphone. The control system in the chair is equipped with temperature and relative humidity sensors. The findings of the study showed building control system and the personalised micro-environment, represented by the chair, work together to improve occupant comfort and reduce energy usage (Yun and Won, 2012). A self-powered WSN for temperature and air velocity is presented by (Sardini and Serpelloni, 2010); the developed system is connected to the electromechanical generator powered by the air velocity in the building. The sensor runs at a three m/s airflow rate, which is enough to power the system. The results showed a low energy use enabled the WSN to measure temperature and air velocity in the building.

Indoor air velocity measurement is challenging because the sensor must respond to real-time environmental changes and operate effectively. A combination of stationary and mobile sensing devices was employed in a study of a hybrid sensor system to monitor indoor air quality. The findings demonstrated a reduction in drift dependent and location-dependent measurement errors by an average of 40.8% (Xiang et al., 2013).

The impact of occupant satisfaction with air quality is discussed by (Choi and Moon, 2017). The study looked at age, gender, and the placement of the workstation in a typical office building. In addition, An IEQ measurement system was developed specifically for the study. The findings showed females were more satisfied with an air velocity of 0.2 m/s at 1.1 m height, and males felt dissatisfaction with the air velocity of 0.2 m/s, which comply with ASHRAE standard 55 for thermal environmental conditions (ASHRAE, 2017).

In an investigating study assessing human thermal comfort in the BE (Choi and Loftness, 2012), skin temperatures from various parts of the body, forehead, posterior upper arm, wrist, head, chest, abdomen, thigh, anterior and posterior calf, and foot, were measured to evaluate thermal sensation in different environmental conditions. Different environmental and personal sensors were used, including temperature, humidity, air velocity and heart rate sensor. The study found the best thermal perception captured from the skin temperature of the wrist. Their later experimental study found that skin temperatures from the arms, back, and wrist provide an overall thermal sensation of the occupant (Choi and Yeom, 2017b). In uniform and non-uniform, transient and steady-state situations, the skin temperature was also employed to construct a model of the occupant's local and whole-body sensation and comfort response (Liu et al., 2013b, Choi and Yeom, 2017a, Zhang et al., 2010).

Other studies utilised wearable devices and smartphones to measure heart rate and skin temperature to assess occupants comfort (Abdallah et al., 2016). Wearable sensors and mobile applications were used with Machine learning to predict thermal demands based on skin temperatures. The results showed that predicting personal comfort was 80 % accurate after collecting environmental and personal data (Dai et al., 2017).

2.2.3 Data analysis

The sensor is the initial step in collecting information from the built environment. However, data processing and analysis methods are needed to reach the end goal, such as reducing energy use and demand and producing a comfortable environment.

Figure 2.1 transforming sensors data into valuable knowledge requires turning the data into information and information to knowledge.

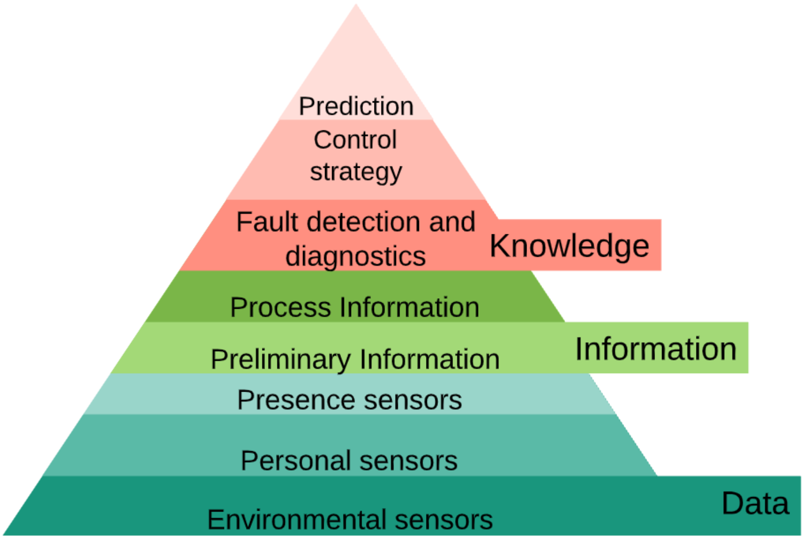


Figure 2.1 graphical representation of sensor data transformation

The data analysis process is demonstrated by the three essential aspects of data, information, and knowledge. Nevertheless, in many cases, these elements are frequently interconnected and interchangeable. The following are the definitions of these terms in the context of building operations.

The measured values directly collected from sensors are referred to as data regardless of the sensor type. The information gives value, implication, and input for valuable and relevant decisions or actions. Information can be subdivided into preliminary and processed. Preliminary data, such as temperature, humidity, and occupants’ count, are usually obtained directly from the sensor. The pre-processing stage improves the quality of information and transforms it into processed information. The knowledge step is based on the outcome of the information. Usually, it includes assessing a situation, such as energy performance, thermal condition, and air quality, and controlling strategies or actions to repair.

Extraction of information

There are two types of information extraction from sensor data. The first type does not require pre-processing or extraction methodology, as the sensor data immediately provides the desired measured values. An example of the first type of sensor data includes temperature, humidity, airflow, CO_2 level, luminance, heart rate, eye movement, and other physiological states of occupants, pressure, and energy consumption from metreing systems. In a study investigating the elements that influence the occupants' heart rates, the information was extracted from the sensor and analysed directly to understand the connection between heart rate and metabolic rates (Goyal et al., 2015). Pre-processing and extraction techniques are required to obtain useable information from the second type of sensor data. For example, various presence sensors are based on a different mechanism, requiring extracting and pre-processing techniques. Extracting data from CO_2 sensors is mainly based on establishing a link between CO_2 concentration and the number of occupants using a simple formula (Pérez-Lombard et al., 2008, Dodier et al., 2006)

In a wireless and wired environmental sensor network, a proposed sensor network was used to extract occupant information using three machine learning techniques, including Support Vector Machines (SVM), artificial neural networks (ANN), and Hidden Markov Models (HMM) (Dong et al., 2010). A proximity-based approach established on the K-nearest neighbour (KNN) technique was utilised in two similar studies extracting data from a radio-based sensor RFID (Zhen et al., 2008, Hallberg et al., 2003). Consequently, the quantity and location of occupants can be determined using data analysis tools, especially machine learning approaches.

Data pre-processing

There are multiple problems in gaining knowledge from a preliminary dataset. Thus, identifying and addressing these issues can help extract knowledge for better BE. Previous studies identified three key challenges: low data quality, the curse of dimensionality, and exponentially growing data volume.

Poor data quality leads to ineffective strategy and false reporting. Accuracy and completeness are two of the essential characteristics of data quality, which are determined by data that is missing, duplicated, consistent, and adheres to a standard form. (Liao et al., 2014)Data cleaning aims to clean and improve data quality by eliminating the poor records or estimating and replacing the missing values. Three typically methods usually deal with missing values include moving average, imputation, and inference-based methods. A primary source of inaccuracy is random errors in the measured data (Noise). There are several reasons for random errors, such as measurement uncertainty, operational uncertainty, environmental disturbance, and data transfer (Morris, 2001, Bellman, 2003). Binning and regression are two common data smoothing techniques for eliminating random errors. Duplication can be discovered using a distance analysis technique.

The curse of dimensionality describes a set of issues that arise when analysing and organising data in high-dimensional environments, which might have hundreds or thousands of dimensions (Bellman, 2003). Sensing systems are becoming more popular in modern buildings. Hence, buildings generate massive time-series data, leading to overgrowing the dimensionality of sensor data. For example, a medium-sized commercial facility generates more than 10,000 measurements over 500,000 timestamps at one-minute intervals. A Wavelet and PCA methods were proposed by (Li and Wen, 2014, Fan et al., 2015) to reduce the dataset's dimensionality.

The volume of sensor data generated by modern building systems is increasing rapidly. On the other hand, data cannot be utilised in its raw form. Therefore, the automatic detection of patterns aids the subsequent deployment of knowledge discovery from this enormous amount of data. To determine the underlying structure of building sensor data, researchers suggested a data processing method that uses Symbolic Aggregate Approximation (SAX), motif and discord extraction, and clustering methods (Miller et al., 2015). The suggested process divided quantitative raw data into qualitative subgroups based on daily performance similarity. Building commissioning, problem identification, and retrofit analysis techniques can benefit from the findings. Similarly, standard data mining algorithms, such as decision tree and association rule mining, can be employed in the knowledge discovery process, according to a clustering analysis approach used to determine the building's usual and non-typical operation patterns proposed by (Yu et al., 2012).

Knowledge

In most applications, finding knowledge is a context-aware computation process. After the pre-processing step, the information is analysed into a valuable form, turning occupancy behaviour and indoor environmental parameters into knowledge for effective energy control and maintaining a healthy indoor environment. Generally, databases and analytic methods used in various domains vary from one application to another. In a previous study (Dong et al., 2019), three main applications domain were identified on analysed sensors data: prediction, control strategy, fault detection and diagnostics (FDD). Nevertheless, a crossover in applications and data utilisation between domains. For example, (Benezeth et al., 2011) demonstrated fault-tolerant control technology for the HVAC system to detect potential errors in real-time, attaining the best energy consumption reduction levels. Using model-based predictive control (MPC), the control strategies were adjusted to the observed system failures. In the on-site study, the system demonstrates about 30% energy saving.

The data analysis methods that are discussed in the studies on building energy prediction include regression algorithms (Bauer and Scartezzini, 1998, Hong, 2009), support vector machines (SVM) (Hong, 2009, Niu et al., 2010, Kusiak et al., 2010), and artificial neural networks (ANN) (Dhar et al., 1999, Kalogirou et al., 1997). These studies cover many topics, from short to long term predictions, with several successful applications (Leephakpreeda, 2005, Kissock, 2008). In occupancy prediction applications, a grey prediction approach is implemented to predict the inactive period of occupants in an office environment (Erickson and Cerpa, 2010). Furthermore, the Markov Chain Occupancy Model is widely used. A WSN was used to collect data, and a Moving Window Markov Chain occupancy model was employed to predict occupant information (Erickson et al., 2014).

In the control strategy studies, sensor data is employed to design energy-saving and environment-friendly control systems (Fisk and De Almeida, 1998). Different studies demonstrate a demand-based control strategy designed based on occupancy information. For example, (Agarwal et al., 2010) presented a study on maintaining higher temperatures in unoccupied zones, while (Fisk and De Almeida, 1998) presented a study on maintaining lower ventilation rates. (Kuutti et al., 2014) tested different occupants counting techniques and proposed a demand-control ventilation system. Furthermore, the data from building automation systems (BAS) was extensively explored to design a control strategy. Physics-based, grey-box-based, and black-box-based models are among the basic models utilised in control system designs (Li et al., 2015). A review of the control strategies in the field of HVAC is presented by (Wang and Ma, 2008).

Another widely explored sensor data application is fault detection and diagnostics (FDD). The methods applied in these applications range from quantitative and qualitative model-based methods and history-based methods, where each can be subdivided (Rossi and Braun, 1997). For example, automated identification and diagnosis of faults in vapour compression air conditioners, a rule-based method, which is a typical qualitative method, was presented by (Bendapudi et al., 2002). As an example of quantitative model-based methods, (Kim and Katipamula, 2018) developed a dynamic centrifugal chiller model following the first principles for FDD. Data analysis approaches for process history-based methods include linear or multiple linear regression, artificial neural networks, and fuzzy logic. A review of data analysis methods for FDD is presented by (Miki et al., 2007). Table 2.3 summarises some of the most frequently used data analysis approaches in building operations.

Table 2.3 Data analysis techniques in building operation

Application	Analysis approach	Literature
Extraction	Bayesian probability theory	(Dong et al., 2010)
	Hidden Markov Model	(Ni et al., 2003)
	Support Vector Machine	(Hallberg et al., 2003)
	K-Nearest Neighbor	(Li et al., 2012, Zhen et al., 2008)
	Artificial Neural Network	(Ni et al., 2003)
Pre-processing	Regression	(Liao et al., 2014)
	Decision tree algorithm	(Yu et al., 2012)
	Wavelet transform	(Fan et al., 2015)
	Clustering algorithms	(Yu et al., 2012, Bengea et al., 2015)
	Principle Component Analysis	(Fan et al., 2015)
	Association Rule Mining	(Yu et al., 2012, Bengea et al., 2015)
	Binning method	(Liao et al., 2014)
Knowledge	Regression	(Bauer and Scartezzini, 1998, Hong, 2009)
	Markov chain	(Flett and Kelly, 2016)
	Artificial Neural Network	(Kalogirou et al., 1997, Dhar et al., 1999)
	Grey prediction	(Erickson and Cerpa, 2010)
	Support Vector Machine	(Hong, 2009, Niu et al., 2010, Kusiak et al., 2010)
	Rule-based method	(Bendapudi et al., 2002)

2.3 Energy and thermal performance

The discrepancy between actual measured performance and the result of the simulated performance of the building is referred to as the performance gap (de Wilde, 2018, Carbon Trust, 2011, Menezes et al., 2012). Several studies have looked into the performance gap in the building sector, but energy performance is the most evident and explored. The PROBE (Bordass et al., 2001) studies were the first to point out energy performance, and it was later backed by several other studies (Zou et al., 2018). In some buildings, energy performance can be twice higher than calculated in the design stage (Menezes et al., 2012).

Even though energy performance is the most emphasised in the literature, other parameters fall in the scope of building performance, including thermal comfort, air quality, lighting and acoustics. IEQ and energy performance are interconnected; obtaining high IEQ and energy use in buildings performance can be overlapping or conflicting goals.

For example, a significant proportion of the increase in energy use was due to the spread of the HVAC installations in response to the growing demand for better thermal comfort within the built environment. A recent literature survey of indoor environmental conditions has found that thermal comfort is ranked by building occupants to be of greater importance compared with visual and acoustic comfort and indoor air quality (Frontczak and Wargocki, 2011). Therefore, it is essential to understand thermal comfort conditions and the methods and standard approaches to evaluate indoor thermal conditions and their implication on energy performance.

2.3.1 Building energy performance

Different schemes and assessment criteria have been established to design and operate more energy-efficient buildings. These approaches are mostly related to energy consumption and can be quantified in both design (e.g., energy performance certificates (EPC) and part L calculations in the UK) and operational stage (e.g., display energy certificates (DEC) in the UK) of a building life-cycle (de Wilde, 2018). Accredited building performance assessment tools range from static calculations to dynamic simulation to meet regulated targets utilising standardised procedures. Significant variations are recorded on both classification schemes and standard calculation procedures for quantifying the energy end-use of a building in the operational stage, increasing the possibility of failing to reach regulated targets. This phenomenon is known as the performance gap.

One of the most comprehensive post-occupancy evaluation studies, the PROBE studies, found little correlation between design and actual building values (Bordass et al., 2001). As a result, the construction industry's model-based targets are unlikely to be met (Jason Palmer et al., 2016b, Jason Palmer et al., 2016a). Other studies conducted later were also revealed similar findings. (Norford et al., 1994) found a two-to-one mismatch between actual and expected energy performance in office buildings. Moreover, significant differences in measured performance from design predictions were discovered in studies on LEED-certified buildings (Turner and Frankel, 2008, Burman, 2016, Samuelson et al., 2014).

As explained earlier 2.1.4, compliance modelling is frequently used for regulatory performance, calculating the energy performance under specified operational settings, which is helpful to determine whether or not minimum energy performance are met under standardised settings (van Dronkelaar et al., 2016). Therefore, compliance calculations should not be used as a benchmark for real performance, which can misinterpret the energy performance (Burman et al., 2014). Theoretically, the performance gap can be reduced with a simulation model of real operational conditions. Man research investigates performance issues using a calibration approach to tune building energy model to actual operational conditions. In addition, the method can expose a building's operational inefficiencies and the root causes of disparities between design calculations and actual performance (van Dronkelaar et al., 2016, Burman, 2016, de Wilde, 2018).

Many reasons can affect the performance gap during the building life cycle, and knowing the causes is critical to increasing confidence in performance evaluations and tools (de Wilde, 2014). In the UK, a review study of 28 buildings concluded that 75% of buildings had poor performance due to severe flaws in the building sector practises (Shrubsole et al., 2019). Through a review of 10 years of research, (Zou et al., 2018) found the energy performance gap in buildings is a result of 8 factors, a) design parameters are weak; b) failure to account for uncertainties; c) lack of accountability; d) poor communication; e) lack of knowledge and experience; f) inefficient and over-complicated design; g) lack of post-construction testing; and h) lack of feedback (Zou et al., 2019).

Other researchers questioned the accuracy and adequacy of building performance simulation (BPS). A study investigates the use of different energy simulation tools to predict the energy end-use of full-scale multi-zone buildings. The study measured the energy performance of two identical buildings by 21 energy modeller using various energy simulation tools. The study revealed that prediction values and measured values confirmed the reliability of most energy simulation tools. The finding has also identified several user inputs errors, such as energy modellers interpretation of building zones, calculation of thermal bridges, and solar transmissions, which result in inaccuracies in energy predictions (Strachan et al., 2016). The use of abstract and simplified energy models has been identified as a source of disparity between expected and actual energy usage in buildings

(Marshall et al., 2017). However, energy modelling inefficiency is not the only reason for the performance gap; other studies have questioned the accuracy of the mathematical computations and the reliability of weather data, operation and occupancy pattern (Zou et al., 2018, Pollard, 2011). To summarise key performance gap issues, including modelling and calculation errors, limitation, complexity and lack of knowledge at the design stage, construction and commissioning issues, Inefficiencies in operations.

2.3.2 Thermal comfort conditions

Indoor environmental quality (IEQ) is a key factor in evaluating building performance (de Wilde, 2018). Occupancy productivity, health and comfort, and overall wellbeing are directly connected to the IEQ (Wyon and Wargocki, 2013b, Chatzidiakou et al., 2014, Al horr et al., 2016). The research community, policy-driven, and building industry, in general, have focused on lowering carbon emissions and making energy efficiency a crucial objective. However, energy efficiency is only one of the various performance aspects of buildings. In terms of performance, it is more likely to happen between predicted and measured indoor air quality, thermal comfort, acoustic performance, daylighting levels and others (de Wilde, 2014). The performance gap issues highlight the importance of meeting energy performance goals in practice. Nevertheless, for IEQ parameters is not always the case. Even though complying with IEQ performance standards is critical in the design process, energy and CO_2 emission reductions are primary and sometimes the only objective.

Indoor environmental parameters are linked to thermal comfort that is directly linked to human wellbeing. Generally, buildings with good IEQ are designed and evaluated objectively. IEQ, especially thermal comfort, are experienced subjectively by buildings' users. Thus, IEQ performance analysis and evaluation are challenging.

Thermal comfort in the indoor environment is a mix of personal and environmental factors. Personal factors include metabolic rate and clothing insulation, while environmental factors are air temperature, mean radiant temperature, air velocity and humidity (ASHRAE, 2017, BSI, 2007, Fanger, 1970). The most widely used thermal comfort models are the predicted mean vote (PMV) and percentage of people dissatisfied (PPD) by (Fanger, 1970), and adaptive thermal comfort (De Dear and Brager, 1998).

The PMV/PPD index is a classic steady-state model for indoor mechanically ventilated spaces and is based on a heat balancing model of the human body (Fanger, 1970). The main objective of the model is to predict the mean thermal sensation of a group of people and their respective percentage of dissatisfaction with the indoor environment. PMV is calculated using the six environmental and personal factors parameters over a 7 point scale. PMV scale ranging from ¬3 to +3 with Zero as comfortable. PPD is the percentage of people dissatisfied with the thermal environment at each PMV. The lowest PPD is 5% when PMV is Zero. The PMV/PPD was used to develop ISO 7730 (Standardization, 2005) and ASHRAE 55 (ASHRAE, 2017), which is still in use today.

The adaptive model is usually used to determine thermal comfort in naturally ventilated spaces. The model is based on adaptive principles (Nicol et al., 2012); for example, when a change causes discomfort, people react to restore their comfort. The adaptive model is built on three interrelated elements not considered in the PMV/PPD index, psychological, behavioural, and physiological (De Dear and Brager, 1998).

2.4 Summary

This chapter reviews the existing literature on the performance analysis approaches in the built environment, covering two primary subjects, building energy performance and thermal comfort conditions. Investigates building performance analysis approaches, focusing on IEQ and energy consumption. The general approaches included in this review are physical testing and measurement, calculation and simulation, expert judgment, and post-occupancy evaluation. Then, the review extended to investigate sensing technologies for real-time data collection. Several sensing technologies were identified and classified into three types, personal, presence and environmental. Different applications in the indoor environment were investigated after each sensor type, followed by data analysis techniques, which is categorised into two classes, data to information and information to knowledge. Then the last section discusses energy and thermal comfort performance issues and gaps between prediction and actual performance.

Chapter 3

Methodology

This chapter reviews the research methodology adopted in this thesis. It is evidenced from the previous chapter that the current building performance assessment approaches are not adequate for a procedural and repeatable systematic evaluation of building performance. Although existing processes are focused on quantitative requirements, they are not tied to a framework that can be validated. As a result, it is not clear that the technical flaws discovered in a building through on-site investigations, for example, reflect all or even most of the fundamental causes of the performance. Nevertheless, some critical issues are likely to be discovered throughout the investigations, whereas others remain undetected. Furthermore, in the context of thermal and energy performance, the human thermal comfort factors in the indoor environment and their implication on energy consumption are not thoroughly investigated. Understanding the link between indoor thermal comfort conditions and energy consumption will help us better understand the causes of the current significant energy consumption gap between actual and expected consumption.

This chapter describes the research process of the development of a technical implementation framework to identify, quantify, and validate thermal comfort conditions and energy consumption in the indoor environment. The work investigates the cause and effect of high or low energy usage based on indoor environmental conditions. In addition, an innovative IoT sensing system was developed, tested, and evaluated following the proposed framework. The effectiveness of the developed implementation framework is analysed using an experimental method. The framework was applied to multiple typologies of indoor environmental zones where the experiment was conducted naturally and in controlled environments. The development and evaluation of the framework, limitations, lessons learned, and applicability are all identified. The chapter discusses the steps taken to construct the technical framework—the selected parameters and the required data for the model development to the on-site implementation and evaluation. The method presented in this work is in three Phases, each of which involves a series of tasks linked in chronological order: Phase 1. framework development, Phase 2. experimental design, and Phase 3. Analysis and lessons. Figure 3.1 shows a diagrammatic representation of the methodological overview, which is then translated to the research objective in Figure 3.2.

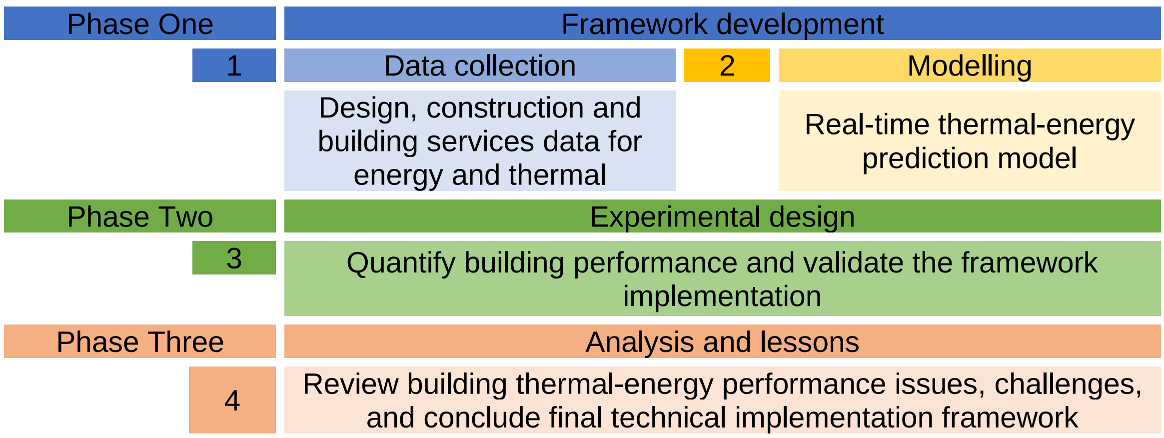


Figure 3.1 Methodological overview

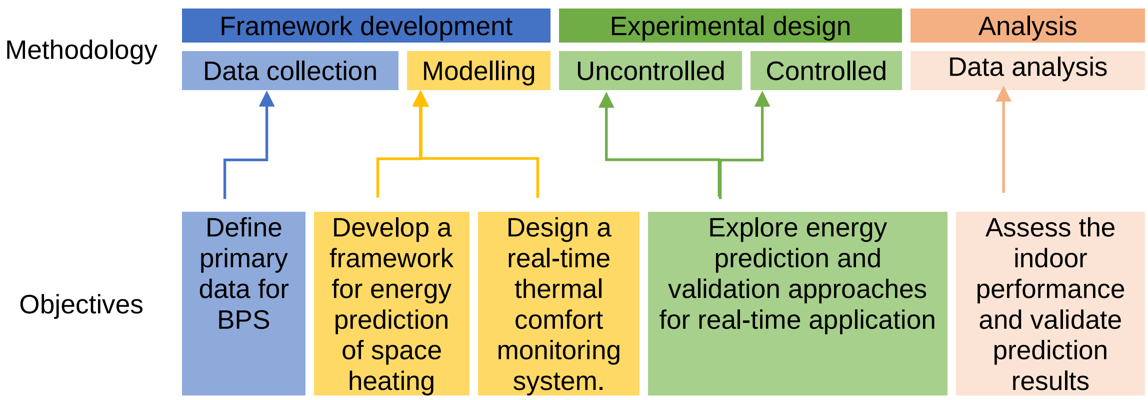


Figure 3.2 mapping research methodology to research objectives

3.1 Framework development

Following the previous chapter, many technologies are incorporated at various building life cycle stages to analyse and evaluate building performance. As the role of occupants and technology in buildings evolves, the concept of building performance faces new challenges. Hence, the theory of building performance must be further developed to address these challenges. The presented work is developing a technical implementation framework to extend the use of BPS beyond the design and construction stages, enabling building users and professionals to identify, quantity and evaluate building performance at the zone level. Real-time energy prediction at zone levels can provide a deeper insight into the building performance, thermal comfort and energy performance of individual rooms in the building, which can help identify performance discrepancies. Therefore, it proposed a new framework to utilise the BPS model in the operational stage to predict thermal-energy performance in real-time. The development of the technical framework consists of two stages: data collection and real-time prediction modelling. The overview of the framework is presented in Figure 3.3.

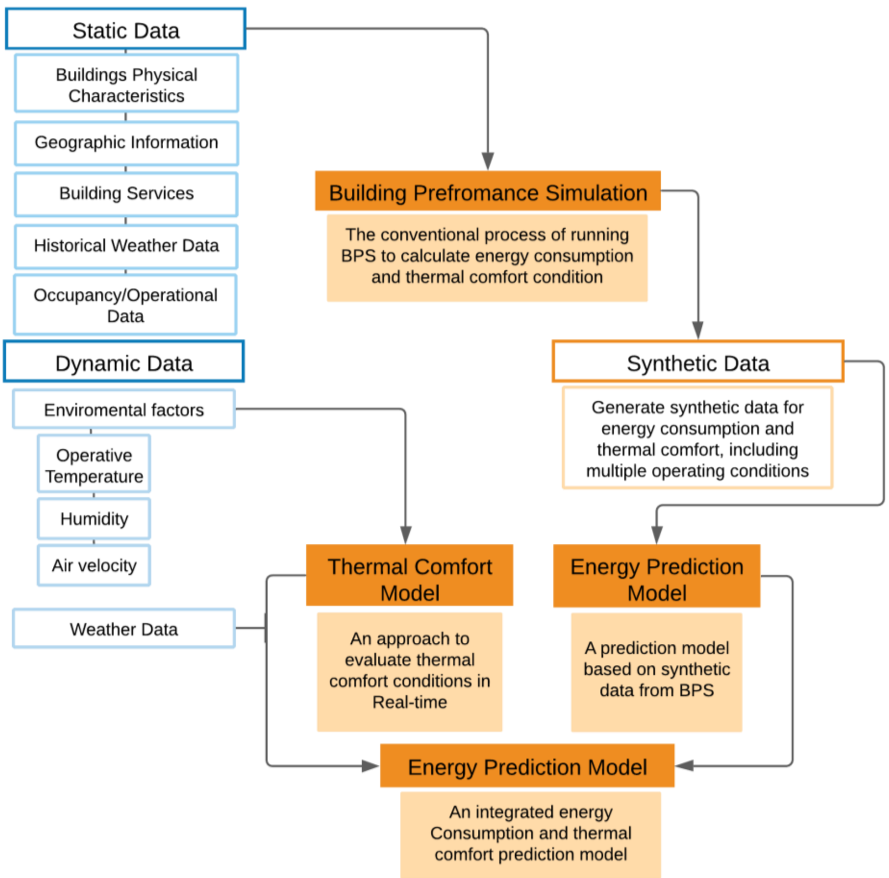


Figure 3.3 Overview of framework development stages

3.1.1 Data collection

Building performance relies on assumptions and intentions at the design stage. As the project progresses to the handover and operational stages, the assumptions and intentions become explicit and actual. Operational-stage performance evaluations necessitate comparing the intended outcome, data from the design, and the actual outcome from the operation. Although the proposed framework is not about achieving the intended performance goal, the required data collection is similar. As a result, data were collected in two stages to extend the use of the BPS model in the design stage and provide building users with insight into operational-stage performance issues: Stage 1. Data collection for BPS modelling (design data) and stage 2. Data collection for operational performance (actual data). In addition, two aspects of data collection were considered:

- Review the operational-stage performance assessment concerning energy consumption for space heating: the scope of this exercise is to explore thermal conditions factors that affect energy use in the indoor environment. For energy consumption, meter readings are collected, and for indoor thermal comfort conditions, data collection was explicit to the parameters related to indoor energy consumption for space heating. In addition, outdoor environmental factors were also recorded; these factors are directly linked to the BPS model, thermal comfort condition and energy consumption calculations.
- Data availability and quality: dwellings usually suffer from data available at design and operational stages; if available, these data are limited or outdated in most cases. Thus, the scope of this exercise is to determine the data quality required of design and operational data.

The collected data in this work were analysed and used based on the scope and availability aspects stated above. The essential data collection for each dwelling in the experimental section of the research is summarised in Table 3.1

Table 3.1 Overview of data collection

Data Type	Purpose	Data source	
		Design	Actual
Architectural drawings	Building geometries and construction details are necessary for BPS modelling	Drawings & documentation	Site survey, measurement
Building services	Determine the required parameters for space heating in both actual and virtual environments.	Drawings & documentation	Site survey, operation manuals
Hourly weather data	To accurately assess energy performance in both actual and virtual environments.	Historical weather data.	Data from the nearest weather station
Occupancy data	To set general occupancy density, activity, and insulation level.	Design assumption based on the activity and the season	NA.
Environmental control	To set indoor thermal condition factors and temperature ranges	NA.	Thermostat and heating control
Energy use for space heating	To estimate energy use of multiple scenarios over one year for every zone.	NA.	Meter readings
Indoor environmental parameters	To monitor thermal comfort condition in every zone	NA.	Environmental sensors

The study intends to develop a real-time prediction approach. Therefore, the design information collected primarily for creating the BPS models is considered static. In contrast, real-time data collecting to identify thermal comfort and energy performance patterns are dynamic. The following subsections explain the static and dynamic data collected for existing dwellings.

Design Data (static)

The design or static data refers to the data used to create the BPS model. The information embedded in the BPS model can be classified into building-related data, occupancy related data, and environmental-related data. Usually, these data are collected at different times and utilised in the BPS tools to predict building performance. Static data are linked to a) the geometrical and physical characteristics of the building, including building location, orientation, and surroundings; b) building services, include, lighting, heating, ventilation, and air conditioning (HVAC), and appliances; c) historical weather data; d) occupancy and operational data. Missing information was revised using measurement, site survey, observation, or other building standards/codes. Data collection and techniques for each dwelling are described in Chapter 7.

Operational data (Dynamic)

Operational data are the actual meter reading and environmental monitoring captured from the indoor environment over a specific period depending on the type of the conducted experiment, explained in Section 0. The dynamic data are data collected in real-time during the experiment, including predicted energy performance for space heating, actual energy consumption, thermal comfort condition, indoor environmental parameters, and outdoor environmental parameters.

For all experiments, energy use data was captured from home meters. The data for space heating was disaggregated. Thermal comfort-related data were captured from the experimented zones covering areas close and far from the heating system with 15 minutes intervals. In addition, the environmental-related data of the indoor and outdoor environment were computed using an innovative device developed precisely to capture and store IEQ and calculate thermal comfort conditions, following BS EN 15251:2007(BSI, 2007) and ASHRAE standards 55 (BSI, 2007, ASHRAE, 2017). The innovative sensing system was also used to capture the actual weather data dynamically and in real-time. The development of the sensing system is explained in detail in Chapter 5. The dynamic operational data collected for each experiment are described in Chapter 7.

3.1.2 Modelling

The scope of modelling in this work is to produce a digital replica of an existing building that can accurately evaluate thermal comfort conditions and energy use in real-time. Thus, the scope of modelling can be divided into two parts:

- Energy prediction model
- Thermal comfort condition model

Energy prediction model

The selected dwellings in this study had no energy model for performance prediction. Therefore, design drawings and on-site measurement is essential step to capture the existing state of the building for BPS modelling. The new BPS model was created using a mixed modelling approach, a building information modelling (BIM) tool for creating building's geometries, and a BPS tool for advanced energy modelling. In addition, modelling building zones necessitate a comprehensive understanding of the BPS hierarchy level. Designbuilder energy plus is utilised in this study, and the model is organised in a simple hierarchy, as shown in Figure 3.4.

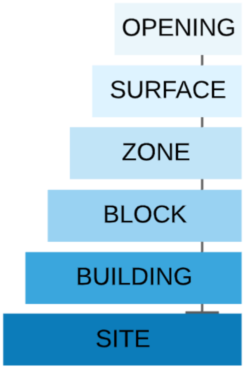


Figure 3.4 hierarchy level of DesignBuilder energy plus model

Moreover, the BPS model was explored in detail to identify thermal and environmental parameters that affect energy performance for space heating at the zone level. The objective of determining thermal and energy variables serve the aim of real-time prediction. In general, developing prediction models involves a large amount of data, with the source and quality of data being critical to the performance of the final model. Therefore, to meet the aim of the study, extensive data must be collected regularly to produce the energy prediction model. The data includes indoor environmental variables such as temperature, humidity, and air velocity, external environmental variables such as temperature, humidity, and wind speed, as well as the energy performance of the thermal condition system for every thermal zone. Furthermore, gathering this type of data from an existing building necessitates robust methodology, specialised equipment, and a significant amount of time.

The conventional process of BPS is not applicable of generate a broader range of scenarios with adequate data for developing a prediction model. Therefore, to overcome this challenge, synthetic data is proposed for data creation, where a parametric modelling method is used to fit the objective of this research. Although parametric simulation is a valuable tool for analysing multiple design possibilities, it is used in this study to give a dataset for the energy prediction model by applying a set of independent variables over thermal-energy related factors. The description of the environmental and energy-related factors in the BPS model and the utilisation of parametric simulation to generate synthetic data necessary for each experimental zone is explained in chapter 5, Section 5.5. Then, the next step is to create a prediction model in which the generated syntactic data is trained using a regression algorithm. Data pre-processing, model development, and evaluation are discussed in chapter 6.

Thermal comfort condition model

The research focuses on measuring thermal comfort conditions in the indoor environment. the existing thermal comfort models were investigated further for real-time calculations. As the research focuses on indoor space heating, Fanger's Predicted Mean Vote (PMV) index model is used (Fanger, 1970). Indoor environmental factors such as temperature, mean radiant temperature, air velocity, humidity, and personal aspects like metabolism and clothing insulation are required by Fanger's thermal comfort model.

Thus, the final step relies upon thermal comfort factors. In the beginning, constant measuring is essential to achieve the scope of real-time monitoring; environmental factors can be measured using environmental sensors where the internet of things (IoT) technology is utilised. Personal data, on the other hand, is presumed static. Therefore, for defining occupants' status, the metabolism and clothing insulation were set to predetermined values based on the overall activity in the space and the season. Finally, the details of the thermal comfort model factors, calculation, and real-time implementation are discussed in Chapter 5.

3.2 Experiments

The experimental design is constructed to identify, qualify, and assess thermal comfort conditions and energy performance in the indoor environment and validate the framework development. The experiments are divided into two stages: Stage one is a whole house execution, where an uncontrolled experiment is executed in a typical dwelling in the UK. The uncontrolled experiment consists of four steps: Implementation of the framework, sensor distribution strategy, simultaneous measurement of actual and predicted data, and analysis of performance issues and insufficiencies by comparing thermal conditions and energy performance of actual and predicted data. Ultimately, this experiment explored the implication of thermal comfort parameters on energy use for space heating.

The second stage is a detailed investigation of individual zones, including semi-controlled experiments in various domestic environments, including a lounge, kitchen, bedroom, basement, and loft. The semi-controlled experiment is a more detailed version of the first stage with further exploration of specific zones in the dwelling. The experiment consists of the same previously mentioned steps in the uncontrolled experiment with more control on thermal conditions in the studied zones. Finally, it reviews temperature distribution and energy performance in several indoor zones in detail. The following sections give an overview of each stage and the main objectives. Figure 3.5 illustrates research experimental plan steps and processes.

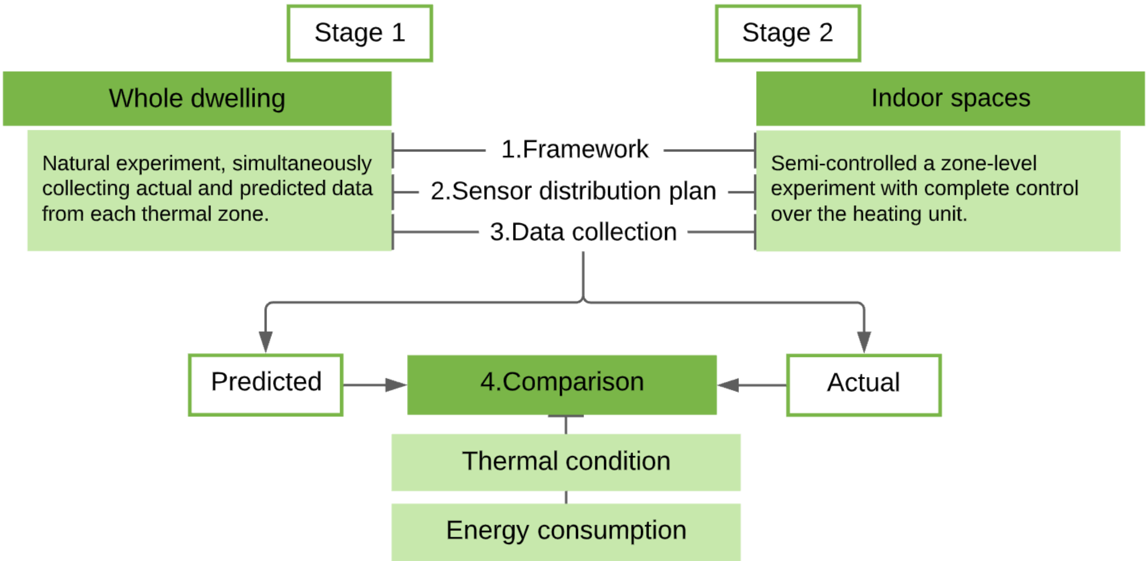


Figure 3.5 Research experimental plan

3.2.1 Uncontrolled experiment

This experiment was conducted naturally in a typical UK dwelling without any intervention focusing on gas consumption for space heating. The uncontrolled experiment dealt with the studied dwelling as one unit, performing a whole-house thermal-energy performance evaluation. The data collected for the actual energy use accounted for all gas activity, such as cooking, heating, and domestic water. This type of experiment involves the installation of prediction sensors throughout the dwelling and collecting data every 15 minutes for both actual and predicted. Because the framework works at the zone level, several prediction models must be processed and integrated using the proposed framework. In addition, two sensors were installed in every heated zone in the dwelling to measure temperature distribution and calculate comfort conditions. The first sensor was placed at least 1 meter inward from the centre of the heating unit, and the second sensor was placed 1 meter inward from the centre of the exterior wall.

This experiment aims a) to validate the implementation strategy and the performance of the produced real-time prediction system; b) to evaluate the studied thermal comfort and energy performance in the studied zones; c) to determine the gap between actual and predicted performance. The details of the experiment, including the chosen dwelling, capturing instruments and methodologies, experimental setup, findings, analysis, and validation, are explained in Chapter 7.

3.2.2 Semi-controlled experiment

This semi-controlled experiment was conducted in each room of a typical UK dwelling, where the framework was implemented to build up a prediction model for each room (thermal zone). The focus of this experiment was to investigate the thermal comfort condition and its implications on the energy consumption for space heating. Indoor environmental parameters, including temperature, humidity, air velocity, and thermal comfort conditions, are all measured using the developed system and compared with the actual data collected from the dwelling. The actual data was acquired from the smart metre system for energy usage in the house, which the energy providers installed. Room temperature was collected from two sources, the programmable room thermostat and the environmental sensors from the developed system. The data collected from the room thermostat is considered the actual data because it regulates the temperature within the dwelling. In contrast, the temperature measured from environmental sensors was used to evaluate temperature distribution and its relation to energy consumption.

This experiment continues to the previous experimental stage with an in-depth analysis of the implemented framework, indoor thermal condition, and energy use. The semi-controlled zone-level experiment aims to explain why people use more or less energy in connection to the thermal conditions and validate the implemented framework and the developed IoT system by comparing the actual and predicted energy consumption. The details of this stage of experimentation, the studied zones, room layout, experimental setup, and experiment conditions, and variables are all discussed in Chapter 8.

3.3 Analysis and lessons

The last phase explores and identifies differences between predicted and actual performance. The process and steps are taken in sections 3.1.1and 3.1.2 which were implemented on-site experiments. Then, the data collection in sections 3.2.1and 3.2.2 were analysed and compared to identify the critical area of the thermal-energy performance and verify the performance of the developed IoT system. The connection between each phase of research methodology; the data collection is fed into modelling, formulate a framework which is subsequently implemented on-site to measure thermal conditions and predict energy performance. The next step is to analyse experimental data from the site implementation to validate the system's performance and draw lessons linked to the study objectives.

3.3.1 Analysis

The analysis is in two stages. The first stage evaluates system setup, durability, and implementation strategy. This investigates the system's capability for real-time prediction over a long time, measuring indoor environmental variables, calculating thermal comfort conditions and predicting energy consumption. Then, it compares and evaluates the collected data by comparing prediction results from the system actual against energy consumption. Furthermore, identify the performance and technical implementation issues related to the framework development in sections 3.1.1and 3.1.2.

The second stage of analysis is framework verification. It focuses on comparing temperature and prediction data at different points in each room to the actual data. First, it investigates temperature distribution and differences at each studied point in the room and compares the results to the actual data collected from the controlled thermostat. Then, investigate the actual intended thermal performance and its energy consumption at various times, weather conditions, and indoor settings to understand thermal and energy performance. Finally, a connection between energy and thermal performance will be established and discussed.

3.3.2 Lessons

The experimental approach was used to meet the key objectives of validating the effectiveness and robustness of the proposed framework. Then, use the key findings from multiple experiments to establish a general understating of the cause and effect of performance gap issues for indoor space heating. The applicability of the experimental approach is first described in this section, followed by an explanation of the implications that can be formed after using this framework in several cases.

Justification of the experimental approach

Validation processes are required to reduce uncertainties when developing tools to estimate building performance (Ryan and Sanquist, 2012, Burman et al., 2012). In addition, the validation of an in-house developed BPS tool is essential to ensure the reliability and accuracy of the system and avoid misleading outcomes. Several general criteria and standard processes for validating BPS tools are available in studies (Coakley et al., 2014, Kalyanova and Heiselberg, 2006). These procedures involve empirical, analytical, and comparative approaches(Ryan and Sanquist, 2012, Judkoff et al., 2008, Neymark et al., 2002). The variation of these approaches is determined by the technique used to compare simulation outputs to the data considered a reference(Kalyanova and Heiselberg, 2006, Ren et al., 2018). For example, empirical validation analyses simulation results for a building or component by comparing actual data from an existing building, a test cell, or laboratory tests. Analytical verification procedures compare results to data obtained by established numerical methods or standard analytical solutions, such as heat transfer simulation under certain conditions. In the case of the comparative test, it compares simulation results from the existing established tool to the one under development, with current state-of-the-art tools considered more reliable and trustworthy to serve as a reference. The advantages and disadvantages of these procedures are detailed in (Ryan and Sanquist, 2012, Judkoff et al., 2008, Neymark et al., 2002). Although validation methods for BPS tools have improved significantly, the procedure is still time-consuming and difficult to achieve. Therefore, a robust method is needed to validate the proposed technical framework for extending the use of the BPS tool. Empirical validation procedures are often used to validate tools and mathematical models developed for simulating specific phenomena. Some studies have found this validation approach reliable because it is based on actual measuring and auditing data(Lomas et al., 1997). To this end, the method was used in several studies to validate BPS models for thermally activated building systems(Nageler et al., 2018, Zhu et al., 2016, Romaní et al., 2018), solar gain models and daylighting studies (Loutzenhiser et al., 2009, Malet-Damour et al., 2016), building envelope simulation studies and facades investigation (Zingre et al., 2017, Blanco et al., 2014, Anđelković et al., 2016, Alaidroos and Krarti, 2016) physical and behavioural approach (Sandels et al., 2016), and more.

Experimental validations of a single model are often more accessible than the entire BPS tool, which involves extensive testing procedures. Another concern of the experimental study is in the context of the validation of whole BPS requires the construction of full-scale buildings, which is relatively expensive and often impracticable (Attia and Herde, 2011, Todorović, 2012). As a result, experimental validation approaches used appropriate test units or existing scale building models (Lirola et al., 2017).

Lessons from the implementation

Extending the process outlined in Figure 3.6 for the individual room across the investigated dwellings, lessons are drawn related to the research's main focus areas. Figure 3.6 highlights how various stages of the proposed methodology, from framework development, experimentation to analysis, link to the key lessons.

1. **Framework implementation lessons**, Review the challenges of extending building performance simulation tools and the proposed framework, validation lessons for better on-site implementation.
2. **Common lessons and similarities** Review the performance issues found across all experiments, common themes and lessons that may occur to broader scenarios in the domestic sector.
3. **Thermal conditions and energy performance challenges** Report the performance issues in thermal comfort conditions and the root cause of higher energy performance.

3.4 Summary

This chapter provides a comprehensive description of the research method of developing a technical implementation framework to identify, quantify, and validate thermal comfort conditions and energy consumption in the indoor environment. The method is divided into three phases: framework development, experimental design, and analysis and lessons. The overall methodology is diagrammatically presented in Figure 3.6

The framework development starts by gathering building information, including architectural, structure, and building services; the modelling process creates an energy-based thermal prediction model. Then, the framework produces an energy prediction model implemented in many experiments where actual and predicted data were collected and compared. Finally, the analysis and lessons help draw the final technical framework, review common performance issues and lessons, and identify building performance challenges.

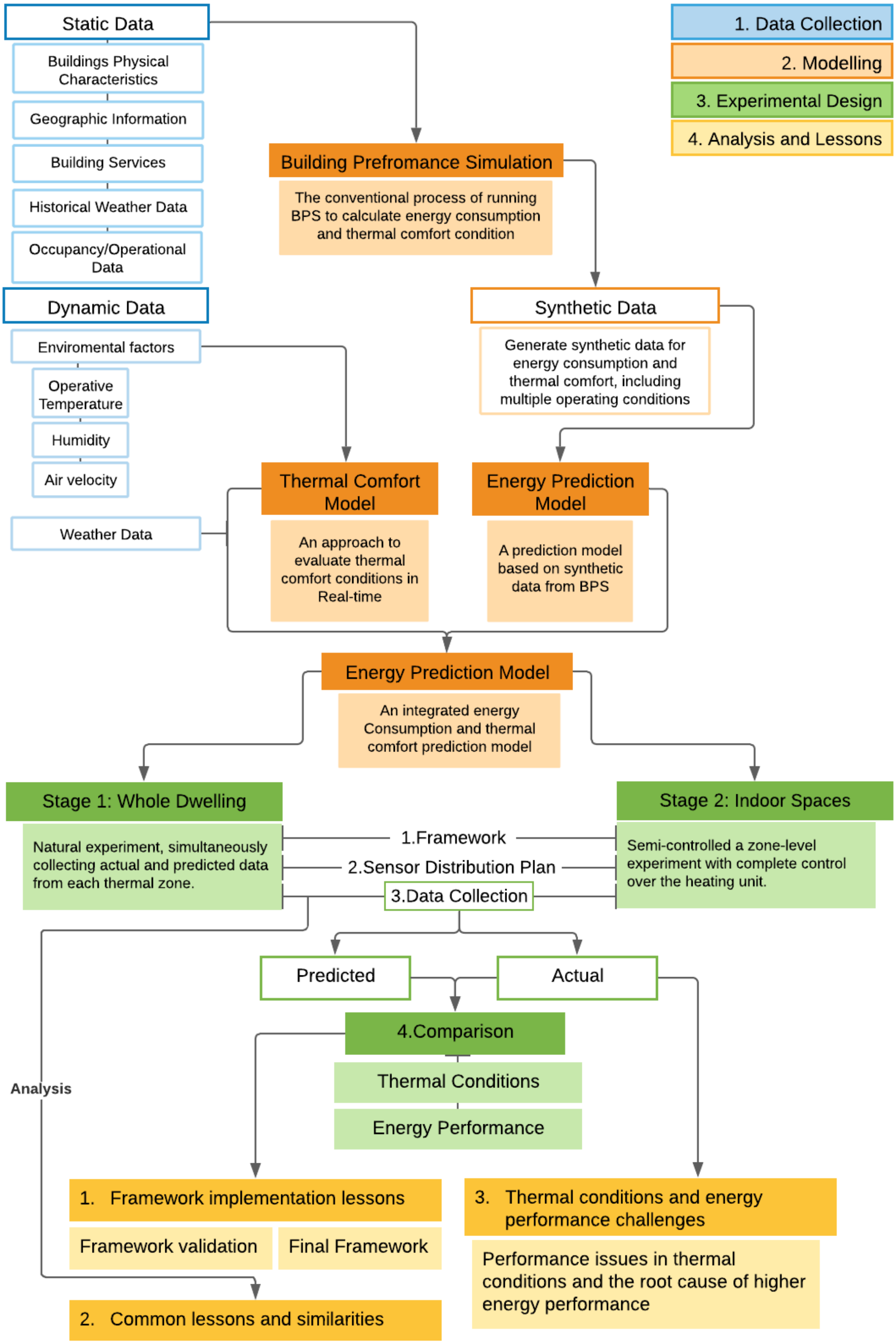


Figure 3.6 Graphical representation of the methodology

Chapter 4

Technical implementation framework

Buildings are complex and heterogeneous systems. Buildings energy consumption varies significantly depending on internal and external factors, making it extremely difficult to perform an in-depth assessment without appropriate technology and equipment. Building performance analysis applications have focused on evaluating specific designs based on static, uniform indoor environments. However, people live in a dynamic environment; neither indoor environments nor building occupants are static or uniform, making the thermal sensation experienced by an occupant in a building unstable, complicated, and nearly impossible to evaluate. In addition, assessing thermal-energy related performance requires a comprehensive understanding of how occupants perceive the indoor thermal environment and how much energy an indoor environment consumes to reach a certain level of thermal condition. Therefore, this study proposes a new approach of predicting energy end-use related to thermal comfort performance using a developed sensing system and data prediction technique based on machine learning in real-time. The system measures indoor and outdoor environmental parameters; then, the data is processed to predict the energy use and thermal comfort conditions of individual rooms in domestic buildings.

The proposed approach can assist building operators in determining the thermal comfort of individual zones in relation to the quantity of energy consumed; it can aid the process of energy prediction in the early design stages and POE; utilise the current thermal comfort model in standards to evaluate the indoor environment in real-time. Furthermore, to bridge the lack of understanding of the connection between thermal comfort conditions and energy use.

This chapter aims to propose a framework for extending the use of the BPS simulation beyond the design stage by integrating a real-time system that measures indoor thermal conditions and predict energy use accordingly. Thus, the proposed framework includes two modules which are described in the following sections.

4.1 Constructing the framework

This work intends to develop a framework for integrating an energy prediction model into a physical building to measure energy use for space heating depending on internal environmental conditions. In order to achieve this goal, the intended outcome was defined, and then the required input parameters and intermediate steps were established accordingly Figure 4.1. Thus, two modules have been proposed: the first module is environmental-related the second is an energy-related module. Because the study focuses on real-time prediction, the constructing framework utilised two data types for each module. Static data for creating an energy prediction model; and dynamic data to measure and assess indoor thermal conditions and enable a constant prediction. To start, it is crucial to understand buildings as systems of heterogeneous entities and how they are interconnected into the building energy performance model. This can be accomplished by a) exploring the energy performance tools, energy performance models, and the process of performing building energy simulation; b) distinguishing building physical characteristics and environmental variables that are thermal and energy-related; c) identifying static data for energy modelling and simulation; d) and the dynamic data for thermal calculation and real-time prediction.

The energy-related module requires a large amount of data to develop a zone-level prediction model. The data source of this development could come from a) monitoring existing buildings for a long time; b) or utilising BPS tools to cover a wider range of thermal conditions, indoor and outdoor scenarios. As mentioned earlier, collecting data energy information from an existing building is challenging, especially for this type of development. Therefore, BPS tools were an alternative method of acquiring building data. However, BPS tools are generally designed to predict energy use for the whole building and use schedules to understand occupants' patterns and building services' operational time. Even though both occupant and operation schedules are on an individual level, it is challenging to generate synthetic data of different operational conditions on zone-level without an advanced approach. Finally, a parametric simulation approach is proposed to create datasets for energy prediction models to overcome this challenge. Nevertheless, the parametric simulation approach can produce a large amount of data that could impact the intended goal of the study. Thus, to minimise the level of complication that comes with parametric simulation, a number of output parameters are defined. The environmental-related module is built on the prediction model and has several input parameters. The module includes several input parameters, capturing environmental data from indoor zones, and calculating thermal comfort conditions. The data input in the prediction model is classified into outdoor and indoor environmental parameters. The outdoor parameters help understand the local climate condition, while the indoor parameters evaluate room or space thermal conditions. Finally, the proposed environmental module captures, calculates and stores indoor environmental parameters, then passes the data to the energy prediction module. The proposed framework and the two modules are illustrated in Figure 4.1—further explanation in the next section.

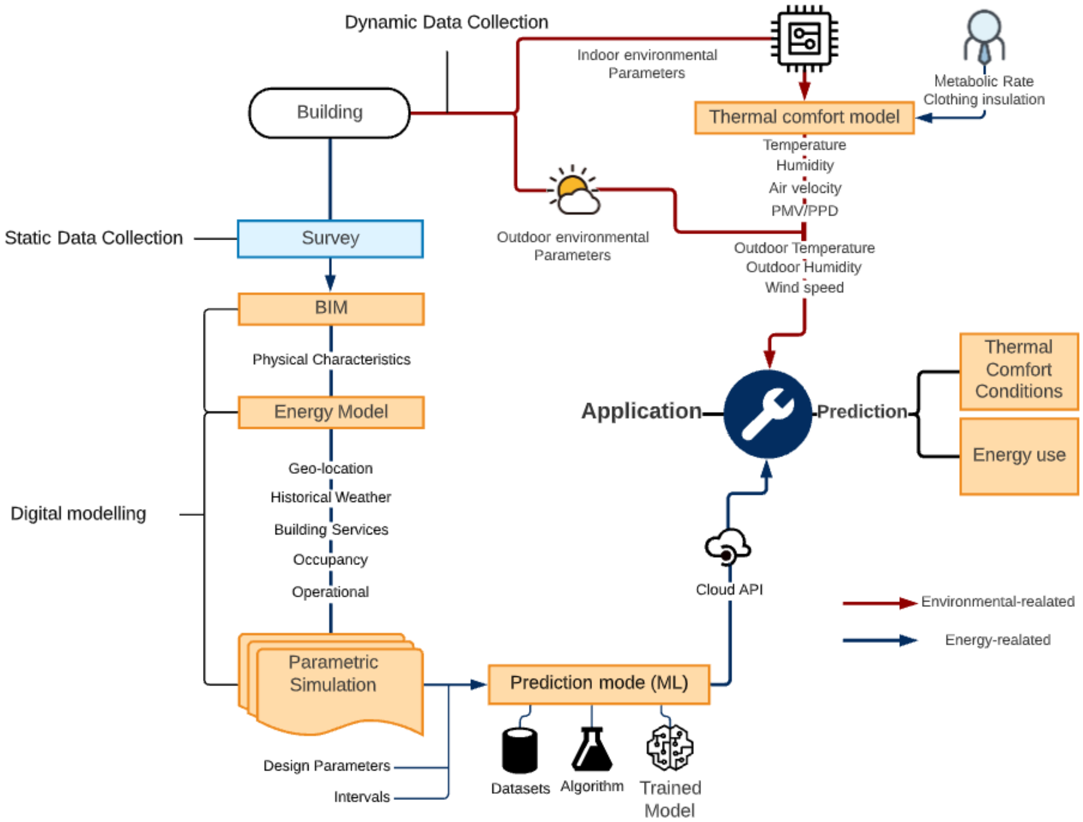


Figure 4.1 Overall proposed framework

4.2 System overview

As illustrated in Figure 4.2, the proposed thermal-energy prediction system comprises two modules, each of which serves as an input to the other.

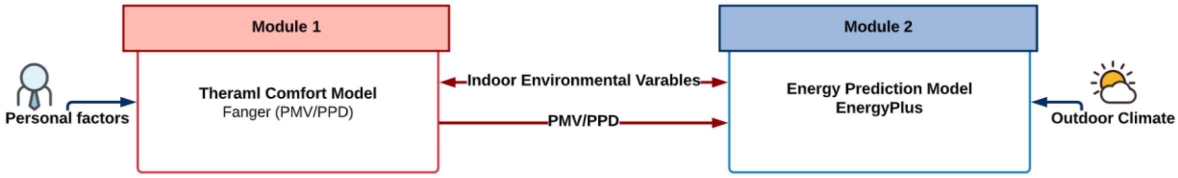


Figure 4.2 Thermal-energy prediction system

The first module collects data from the real environment to evaluate occupants' thermal comfort conditions, including the indoor environmental parameters, such as temperature, humidity and air velocity, and occupants' personal preferences associated with metabolic rate and clothing insulation. The data is divided into two categories: dynamic and static.

The static data is required for the BPS and energy prediction model development. In contrast, the dynamic data is acquired via wireless sensors and employed in a thermal comfort model to assess occupant satisfaction with the indoor environment.

Moreover, A function to calculate thermal comfort is adopted from the tool published by CBE University of California, based on ASHARE 55 standard (Schiavon et al., 2014). In general, to calculate thermal comfort conditions in the indoor environment, personal and environmental factors are needed. However, the research considered only environmental factors for the evaluation of thermal comfort. The personal factors are established based on the function of the space, to set the level of activity, and the time of the year, to set the type of clothing insulation—further details in the Chapter 5.

The second module consists of a machine learning algorithm to predict energy consumption in a single zone. The model has been developed using 18,396,000 worth of data generated from an energy simulation engine. The simulation is mostly relying on the physical characteristic of the building, weather information, and building operation and occupancy schedules—a detailed explanation in Chapter 5. The produced energy prediction model requires Eight parameters to predict energy use accurately. The input data are a) three environmental parameters collected from the indoor zone, temperature, humidity, and air velocity; b) two post-processed parameters of calculating thermal comfort in the indoor zone, Predicted Mean Vote (PMV) and Predicted Percent Dissatisfied (PPD); c) and another three parameters collected from the outdoor environment, temperature, humidity, and wind speed. However, this research focuses on the energy source from the heating system in domestic buildings. Thus, any parameters or energy sources unrelated to the space heating in the building have been excluded from the prediction model during simulation, such as lighting, computers, DHW, or other equipment.

4.2.1 Thermal Comfort module

The primary goal of the Heating, Ventilation and Air Conditioning (HVAC) system is to create a thermally comfortable indoor environment. To determine acceptable indoor thermal conditions, current standards such as international standard ISO 7730 (Standardization, 2005), the European standard EN 15251(standard, 2012), and the ASHRAE 55 (ASHRAE, 2017), use the Predicted Mean Vote and Predicted Percent Dissatisfied (PMV/PPD) model for air-conditioned buildings and the adaptive comfort model for naturally ventilated structures. Although the standards specify that at least 80% of the occupants in a building need to be satisfied with their indoor thermal environment, a large-scale survey showed that only 38% of the occupants are actually satisfied (Karmann et al., 2018). In the United States and Europe, HVAC systems account for nearly half of all building energy usage (Pérez-Lombard et al., 2008). This resulted in a massive failure of the building's HVAC systems, which failed to meet their primary purpose of creating a suitable indoor environment for the building's occupants despite their enormous energy consumption.

Thermal comfort is defined as the condition of mind that expresses satisfaction with the thermal environment, and it is assessed by subjective evaluation. The environmental parameters required for comfort are different from one person to another. Thus, it is challenging to satisfy everyone in space because there are significant variations between people, physiologically and psychologically (ASHRAE, 2017). The thermal comfort model for mechanically conditioned spaces in the international standards (PMV/PPD) is adapted from the seminal work of P.O. Fanger in 1970. It is still the official model to evaluate thermal comfort in buildings and energy simulation tools. The PMV/PPD thermal comfort model is based on the human body's heat balance (Fanger, 1970). The model relies on Six primary factors, four of which are conditions of the thermal environment: Air temperature, Radiant temperature, Airspeed, and humidity; and two factors are related to the characteristics of the occupants: Metabolic rate and Clothing insulation (Fanger, 1970).

Apart from metabolic rate, Fanger's model does not consider the behavioural, psychological and physiological factors that influence thermal comfort, which led to the development of the adaptive model in 1998 by de Dear and Brager (De Dear and Brager, 1998). The adaptive model heavily relies on physiological (acclimatisation), psychological (changing thermal expectations) and behavioural, such as operating windows and fans (Aryal and Becerik-Gerber, 2019). Hence, it urges occupants to accept a broader range of environmental factors, temperature and humidity, and adapt themselves to maintain thermal comfort. Nevertheless, the adaptive model is used in international standards to determine acceptable thermal conditions for naturally ventilated buildings.

This research has focused on domestic buildings (dwelling) to predict thermal comfort and energy consumption in mechanically conditioned settings based on PMV/PPD index in ASHRAE standard 55 (ASHRAE, 2017). Although the adaptive model is included in the standard, it has not been considered in the research because it deals with naturally ventilated environments. The PMV/PPD is calculated by using the six parameters, air temperature, radiant temperature, air velocity, humidity, metabolic rate, and clothing insulation, with the following formula:

$$PMV = (0.028 + 0.3033e^{-0.036M}) \times L \tag{4.1}$$

$$\begin{aligned} L = (M-W) - 3.05\times10^{-3}[5733 - 6.99(M-W) - P_a] - 0.42[(M-W) - 58.15] \\ - 1.7\times10^{-5}M(5867 - P_a) - 0.0014M(34 - t_a) \\ - 3.96\times10^{-8}f_{cl}[(t_{cl}+273)^4 - (t_r+273)^4] - f_{cl}h_c(t_{cl} - t_a) \end{aligned} \tag{4.2}$$

$$\begin{aligned} t_{cl} = 35.7 - 0.028(M-W) \\ - 0.155I_{cl}\{3.96\times10^{-8}\times f_{cl}[(t_{cl}+273)^4 + (t_{mrt}+273)^4] \\ + f_{cl}\times h_c(t_{cl} - t_a) \end{aligned} \tag{4.3}$$

$$h_c = \begin{cases} 2.38(t_{cl}-t_a)^{0.25} & ,if\ 2.38(t_{cl}-t_a)^{0.25} > 12.1\sqrt{V} \\ 12.1\sqrt{V} & ,if\ 2.38(t_{cl}-t_a)^{0.25} < 12.1\sqrt{V} \end{cases} \qquad 4.4)$$

$$f_{cl} = \begin{Bmatrix} 1.00 + 1.290l_{cl}for \\ l_{cl} \le 0.078\, m^2K/W \\ 1.05 + 0.645l_{cl}for \\ l_{cl} > 0.078\, m^2K/W \end{Bmatrix} \qquad 4.5)$$

Where:
M: metabolic rate (W/m^2)
W: external work (W/m^2) (assumed to be 0),

I_{cl}: clothing insulation
f_{cl}: clothing factor, ta: air temperature (°C)
t_r: mean radiant temperature (°C),
v: air velocity (m/s)
P_a: vapour pressure of air (kPa)
h_c: convective heat transfer coefficient (W/(m^{2}K))
t_{cl}: surface temperature of clothing (°C)
e: Euler's number (2.718)

The PMV index can be determined in two different ways: a) Use of the equation directly; b) Use tables of PMV values, including various combinations of activity level, temperature, humidity, and air velocity; c) Computer simulation using BPS tools. Furthermore, the PMV model has a seven-point scale, as shown in Table 4.1, and it is recommended that the PMV value be between -0.5 and +0.5 to provide the best thermal comfort for the majority of occupants. In other words, standards consider the indoor environment is thermally comfortable if no more than 10% of occupants feel unsatisfied.

Table 4.1: PMV thermal sensation scale

PMV	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

The PPD quantifies the number of dissatisfy occupants by calculating the percentage of thermally uncomfortable individuals as a result of the cold or heat (Fanger, 1970) using the following formula.

$$PPD = 100 - 95 \times \mathrm{e}^{-0{,}03353 \times PMV^4 - 0{,}2179 \times PMV^2} \quad 4.6)$$

Figure 4.3 illustrates the connection between PMV and PPD, showing the PPD = 5% even when the individual is thermally comfortable and the PMV = Zero. This indicates that even if ideal climatic conditions of temperature, humidity, and other factors were maintained, 5% of occupants were still dissatisfied with the indoor thermal environment.

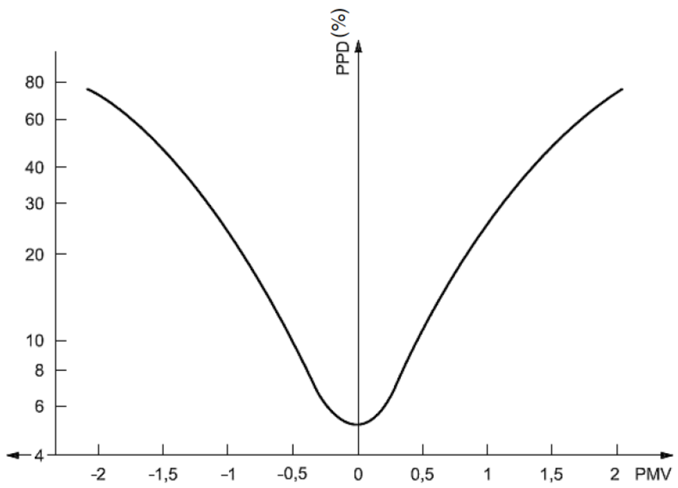


Figure 4.3 connection between PMV and PPD

To this end, the research has adopted the thermal comfort model PMV/PPD index, employing the formula mentioned above of PMV and PPD. The objective of the wireless sensor is to automate and personalise the prediction of thermal comfort conditions and then energy use for space heating in the individual zones of domestic buildings.

The intended system assesses the PMV/PPD in real-time, considering the environmental and personal factors. The environmental parameters are measured from the indoor space using wireless sensor nodes, including air temperature, humidity, and air velocity. The mean radiant temperature in mechanically conditioned spaces can be within (1°C - 2°F) of the air temperature, according to ASHRAE 55, unless it can be shown otherwise within the space (ASHRAE, 2017). Hence, the MRT has been set to 1 degree higher than the measured air temperature. The personal factors have been set to default values based on the activity and functionality of the space and the season of the year. For example, the metabolic rate set 1 met if the main activity of the studied space is stationary such as living room, and clothing insulation set to (1 clo) if the study is conducted in wintertime. Table 4.2 a sample of metabolic rates for typical tasks and clothing insulation values for typical ensembles (ASHRAE, 2017).

Table 4.2 Sample of metabolic rate and clothing insulation values

Activity	Metabolic rate (met)	Clothing insulation	values (clo)
Reading seated	1.0	**Typica summer indoor**	0.5
Typing	1.1	**Trouser, long sleeve shirt**	0.61
Standing/relax	1.2	**Jacket, Trouser, long sleeve shirt**	0.96
Walking	1.7	**Typical winter indoor**	1.0

The Overall approach to predict thermal comfort in real-time is illustrated in Figure 4.4. The wireless sensor node measures the environmental factors from the indoor space. The personal factors are fixed based on the function of the space and the season of the year. The data collected is used directly and in real-time in the PMV/PPD formula to evaluate the thermal condition of the indoor environment. The calculated thermal comfort conditions results will be stored in a cloud database following the 7 point formant of PMV and the PPD.

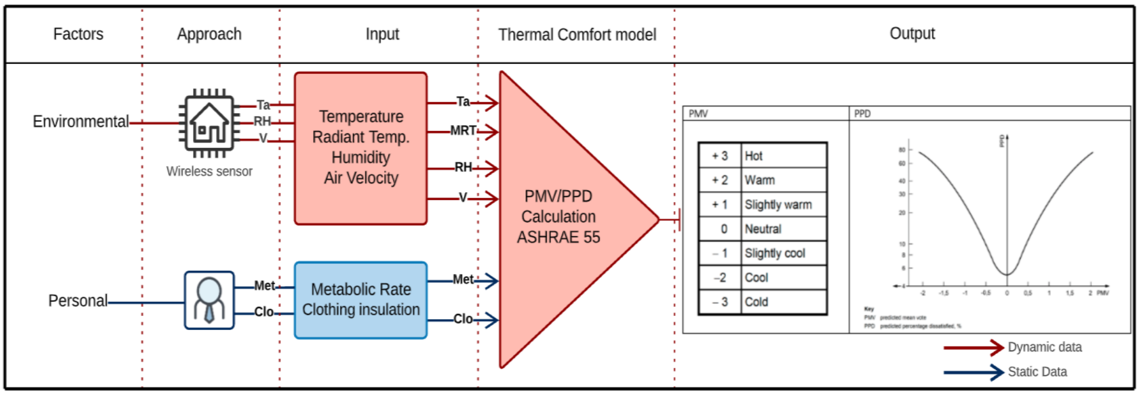


Figure 4.4 Illustration of the proposed thermal comfort module

4.2.2 Energy prediction module

Several tools and applications are used to predict buildings energy performance. Energy prediction tool is a mathematical calculation of building physical properties considering lighting and thermal aspects. There are hundreds of building energy modelling and simulation tools available. Some are standalone tools, and others are built upon energy engines, such as Energy Plus and APACHE; this category of tools provides a graphical user interface (GUI), default values, and preconfigured models. In this case, the shell application serves as a third-party interface. An example of these tools is Ecotect, IES-VE, DesignBuilder, and eQuest. Generally, energy simulation tools can be divided into two categories: whole building simulation and design-based studies. Despite the variety of the available building energy simulation tools, they required almost the same procedures and input parameters. For example,

i) Define building location, orientation, and climate data.

ii) Geometrical properties of building's zones.

iii) Thermal Properties of building's elements.

iv) Define the HVAC system and operation schedules.

v) Define occupancy schedules and activity.

The outputs of building energy simulation tools are similar, such as heating and cooling loads, electricity and fuel consumption, CO_2 emissions, lighting, thermal satisfaction, and some tools offer building energy certificates. Today with the rise of ML, many researchers have developed tools and approaches to optimise the energy performance of HVAC units or personalise thermal comfort tools. The current energy prediction mode looks to personalise the energy prediction of fuel consumption for heating in domestic buildings and based on individual zones. A machine learning prediction model has been developed using a regression algorithm to achieve that. The trained data in the machine learning model have been generated synthetically using the EnergyPlus energy engine. Even though the engine is widely seen as the most refined engine for running whole-building energy simulations, it has been utilised with a focus on individual zones. The designed machine learning model uses a range of input parameters classified into two categories: indoor and outdoor environments. A total of seven parameters are used for the prediction model to improve the level of accuracy. The first category is the indoor parameters consists of temperature, humidity, PMV, and PPD; these parameters are measured and processed using the wireless sensor from the indoor environment. The second parameter category is collected from the outdoor environment, including temperature, humidity, and wind speed. The outdoor parameter enhances the model prediction of perceiving the outdoor environment, regardless of the month, season, or time. Figure 4.5 illustrates the prediction model used in the proposed framework.

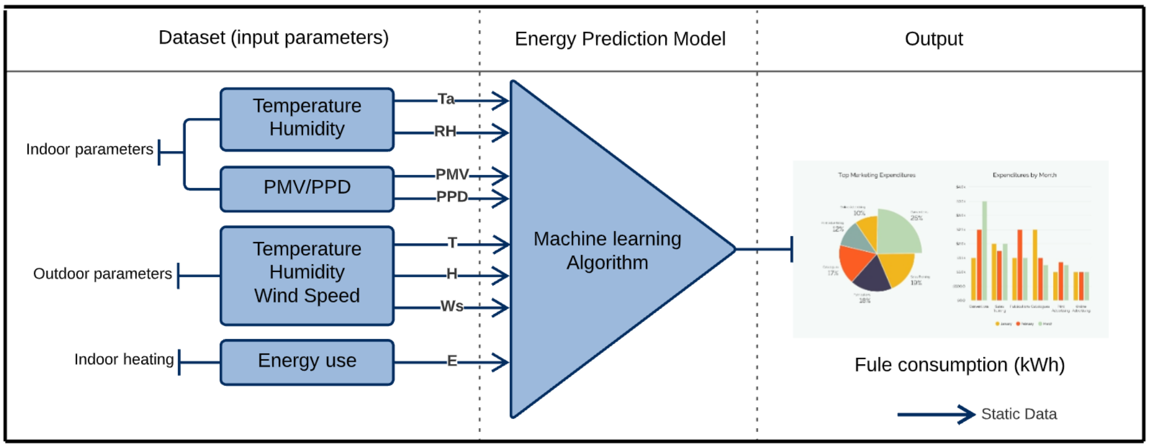


Figure 4.5 Illustration of the proposed energy prediction model

Several techniques and approaches are used to design a personalised energy prediction model for the indoor environment. The next chapter discusses the development of a wireless sensing system, including system architecture, hardware, and visual representation.

4.3 Summary

This chapter presents a proposed framework for real-time energy performance application with the ability to predict energy consumption based on defined environmental parameters in real-time. Several procedures, tools, and technologies were described, including two modules for calculating thermal comfort and predicting energy use. In addition, two types of data collection were presented; a) collecting data related to building's elements and systems for developing a prediction mode; b) Data collection of defined indoor and outdoor environmental parameters for real-time energy prediction. The following two chapters describe in detail the development process of both modules.

Chapter 5

IoT prediction system

This chapter aims to present a design and insight of a wireless sensor for measuring indoor environmental parameters to evaluate thermal comfort conditions and predict energy consumption. Earlier studies in this field have stated that wireless sensors have some limitations, including a) Developed systems are bulky and expensive; b) Exploit high level of communication protocols to create personal area networks, such as ZigBee requires the use of a gateway to communicate with existing computers within the building; d) They use protocols like HTTP, which have a considerable overhead and degrade performance. In contrast, the proposed approach can take advantage of the building's Wi-Fi network (IEEE802.11 protocol), which is widely available, and use PHP to manage dynamic content and databases. The following sections discuss design phases, from the choice of system architecture and requirements to the hardware device's realisation and the software development for the wireless sensor (for sending data) and the support nodes (for receiving data and reconfiguring the sensors).

5.1 System architecture

The proposed system is divided into three layers, a) Physical layer including data acquisition using environmental sensors; b) Back-end including data storage and data processing; c) and front-end layer for data visualisation. All system layers communicate wirelessly through the Wi-Fi network. The following sub-section summarises the purpose of the system layers.

5.1.1 System layers

The physical layer includes environmental sensors to measure attributes from the indoor environment. The implementation consists of commercially available sensors to capture environmental parameters related to thermal comfort conditions through a Wi-Fi module that provides two-way data transmission, sent and received. The sensors used in this development include environmental sensors and a Wi-Fi module, see Figure 5.1 . All environmental sensors are connected to the internet using the Wi-Fi module and powered by five voltages from a power bank using a standard Universal Serial Bus (USB) cable.

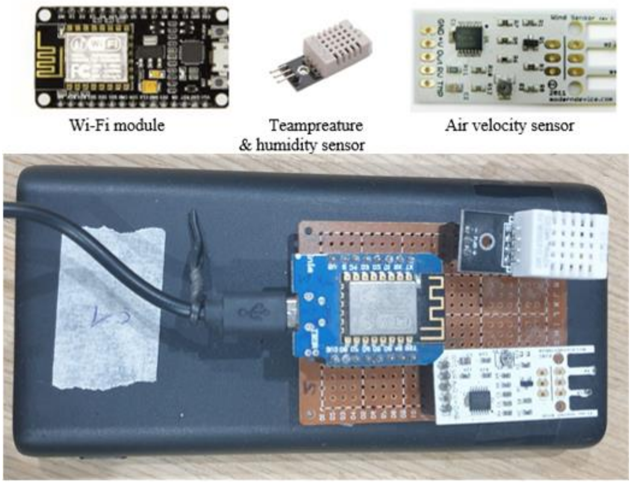


Figure 5.1 IoT prediction system

Clients read information from physical sensors through Wi-Fi in the back-end layer and transmit them every 30 seconds. Then, the captured data from the sensors is stored in a cloud database. Finally, the database has a separate table for each type of sensor in the cloud. The development also uses web page programming languages, HyperText Markup Language (HTML), JavaScript, and jQuery to control the data. Furthermore, this study developed a thermal comfort model adopted from CBE's thermal comfort calculator following ASHRAE standard 55 (ASHRAE, 2017). The developed model receives environmental values from sensors temperature, humidity, and air velocity and evaluates occupants' thermal satisfaction. In the developed thermal comfort model, personal factors, such as metabolic rate and clothing insulation, are fixed according to the general activity in the space and the season of the year.

The front-end layer utilised the stored data for representation and user interaction. An adaptable visualisation technique is required to accommodate real-time data. Thus, the study presents two visualisation approach that supports real-time applications, section 5.3. Figure 5.2 illustrates the system architecture, including system layers, workflow, and connections.

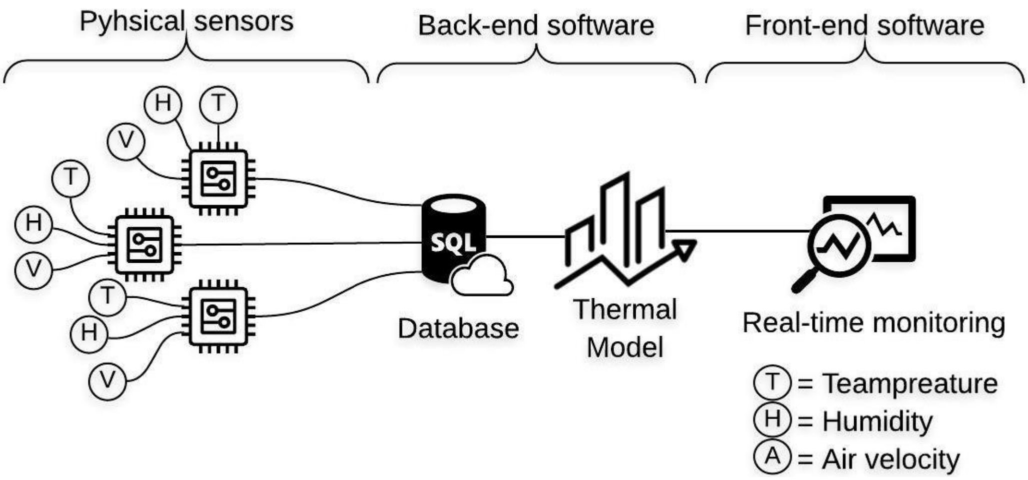


Figure 5.2: System overview

5.1.2 Communication Network

The developed IoT system connects and combines a number of sensors into a single node, resulting in asynchronous and distributed communication. Therefore, a POST/REQUEST method is adopted for PHP development and database exchange. PHP is a server-side scripting language widely used in web applications. The program is used to implement a simple message board that allows to read, write, delete, and update messages stored in the database. In addition, it provides a communication channel between the wireless sensor and the cloud-based server using pre-defined messages to send and receive data. Furthermore, to reduce the load on both the network and the sensors, the developed system has undertaken a minimum level of communication. In addition, the IoT system includes several pre-defined variables for different functions see Table 5.1. For example, a function to capture and store sensor's data, a calculation function for thermal comfort conditions, and a function that communicates with a cloud service for energy prediction, the detail of the energy prediction model in chapter 6.

Table 5.1 List of functions in the IoT prediction system

Function	Description
Insert	It is a post request to store sensors measured values in the database
Read	Read sensor measured data
PMV	Request to run a thermal model and calculate PMV and PPD
energy	Request to predict energy consumption against measured values
data	Read all stored data

Figure 5.3 emphasises the importance of pre-defined message exchange communication among system layers. The first communication (R1) is a request to capture the data from the indoor environment using the environmental sensors and then post the captured data into the database using a PHP request. The second request (R2) pulls the captured environmental data from the database to evaluate thermal conditions. The thermal comfort model was created with PHP and based on fanger's PMV heat balanced model explained in chapter 4. The third communication (R3) is a request to calculate thermal comfort conditions and send it to the database. Finally, once all environmental data and thermal comfort condition values are ready, two requests are made, (R4) to pass the data to the developed energy prediction model, then (R5) to send prediction results to the database—the prediction mode described in chapter 6.

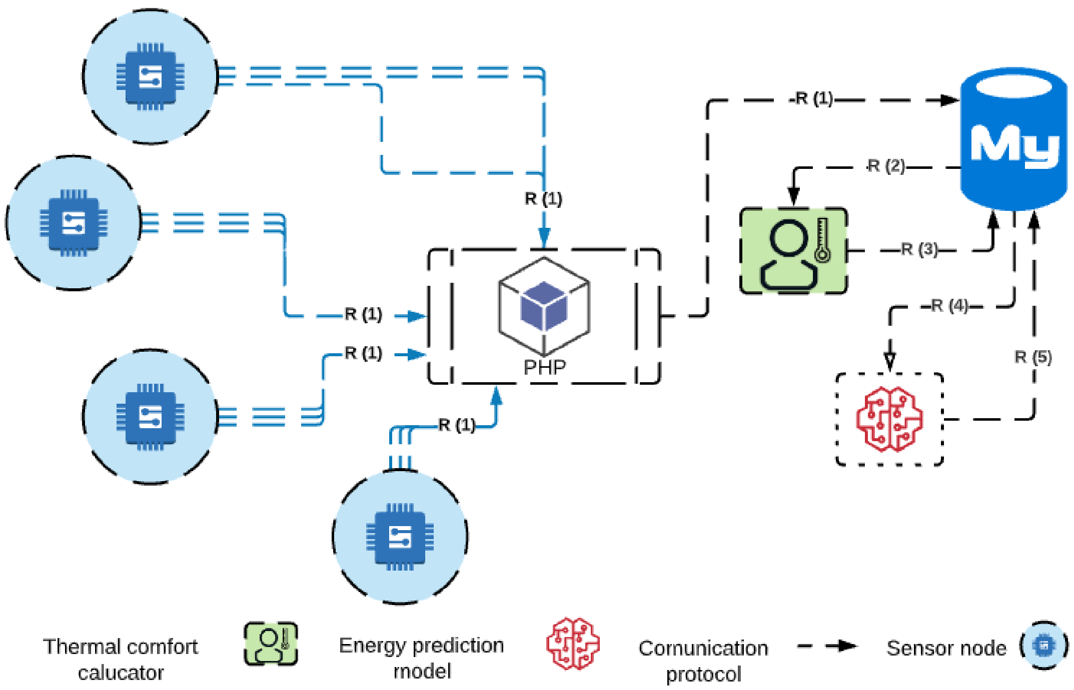


Figure 5.3 Communication protocol in the developed system

5.1.3 Requirements of the wireless sensor

Wireless sensors are made to be battery-powered, compact, and inexpensive. Each sensor measures and computes data separately, such as temperature, humidity, and air velocity. In addition, the wireless sensor needs to keep the timestamp of the measured data; this needs to be configured through the wireless sensor. However, to maintain a low level of communication in this development, the timestamp of the database has been configured to keep the current date/time and associated timestamp to the stored data. Finally, wireless configuration parameters must be stored in an Electrically Erasable Programmable Read-Only Memory (EEPROM) and updated remotely.

5.2 Hardware components

5.2.1 A platform for the sensor

Following the described requirement, the developed IoT system utilised a wireless module Wemos D1 mini. The proposed board is a low-cost Wi-Fi microchip on ESP-8266EX developed by Espressif Systems, including a low-cost IEEE 802.11b/g/n Wi-Fi chip with full TCP/IP support and a 32-bit RISC L106 microcontroller. In addition, it has 11 digital input/output pins and one analogue input pin. Compared to other available Wi-Fi modules, Wemos D1 mini has a small size of 34.2 x 25.6mm, good performance of ~20 MIPS, and cost about £5.00 (wemos, 2021). The technical specifications of the Wemos D1 mini are in Table 5.2.

Table 5.2 Wemos D1 mini specifications

Item	Specification
Operating Voltage	3.3V to 5V
Digital I/O Pins	11 GPIO pins with support for interrupts, SPI, I2C, and 1- Wire
Analog Input Pins	1(3.2V Max)
Clock Speed	80/160MHz
external flash memory	4M Bytes
Weight	3g

5.2.2 The hardware of the sensor system

The ESP8266 has a limited set of capabilities that are inadequate for this project. For example, the IoT system needs more than one analogue signal. Therefore, a CD4051 single 8-Channel multiplexer is used to maximise the module's input and output channels.

Moreover, the IoT system is powered up by a 24800mAh Lithium polymer rechargeable 5V/2.1A battery.

A Wind Sensor Rev. C from Modern Device is used in the study as a low-cost anemometer to measure air velocity. The sensor is designed to be used with electronic projects. The sensor is a thermal anemometer that uses the hot-wire approach, a conventional method of detecting wind speed. The hot wire flow sensors involve heating an element to a fixed temperature and then calculating the amount of electrical power necessary to keep the heated element at that temperature when the airflow changes (Sparks, 2013, moderndevice, 2021). Low to medium wind speeds are ideal for the hot wire technique. This type of sensor is desirable for detecting air velocity in the indoor environment, as spinning cup anemometers, usually found on weather stations, are ineffectual. The technical specifications of the Rev. C wind sensor in Table 5.3.

Table 5.3 Rev. C wind sensor technical specifications

Item	specification
Dimensions	17.27 x 40.38 x 6.35mm
Supply Voltage	4 – 5 volts
Supply current	20 – 40 mA
Output signal	Analogue, 0 to Common Collector Voltage (VCC)

Finally, small size and low energy consumption sensors were employed to collect temperature and humidity information from the indoor environment. A DHT22 sensor is considered a low budget sensor to measure ambient air temperature and humidity with an accuracy of humidity +-2%RH (Max +-5%RH); temperature <+-0.5 Celsius. The sensor is widely used in electronic applications (Aryal and Becerik-Gerber, 2019, Liu, 2018), and the technical specifications of DHT22 are in Table 5.4.

Table 5.4 DHT22 technical specifications

Item	specification
Operating Voltage	3.3V to 6V
Output signal	digital signal via a single bus
Operating range	humidity 0-100%RH temperature -40~80Celsius
Sensing period	Average: 2 second
Size	14 x 18 x 5.5mm

5.2.3 Software components

The ESP8266 wireless module is developed in C/C++ using the Arduino IDE (Arduino) and ESP8266 libraries. The developed system contains two functionalities, setup and loop. The setup function is called during the system's startup, while the loop function is performed periodically after the system's startup is completed.

The startup initialises the use of serial port and General Purpose Input/Output (GPIO) pins, including DHT22 temperature and humidity sensor and Wind Sensor Rev. C. Then, the configuration parameters from the EEPROM establish the connection to the Wi-Fi network and the database. Environmental sensor readings and PHP requests that must be processed in a specific order are stored in the loop function, which is divided into five parts:

- Read and store the measured values from the temperature and humidity sensor.
- Read and store the measured values from Air velocity sensor.
- Post request to the database.
- Initialise thermal comfort calculator.
- Establish a connection with the developed energy prediction model.

5.3 Visual representation

The front-end layer includes data visualisation. Various methodologies and technologies were investigated to give a valuable means of visualising measured data in real-time, yet this was not the primary focus of the study.

Two types of real-time visualisation techniques are used in the front-end, simple and advanced. In Figure 5.4, the simple monitoring technique was utilised as a direct way of visualising the data from the sensor in real-time. This method incorporates a dashboard to inform the user of the local weather conditions, indoor thermal conditions, including room temperature, humidity, air velocity, PMV, PPD, and outdoor weather, including temperature, humidity, and wind speed. In addition, A 3D model displays the sensor's location within the dwelling, along with a 7-point scale of thermal comfort conditions. The PMV/PPD index was also represented by an illustration figure representing the thermal state of the zone; the view was coded using the Unity gaming engine, and web-GL then hosted on a server for easy access over the internet.

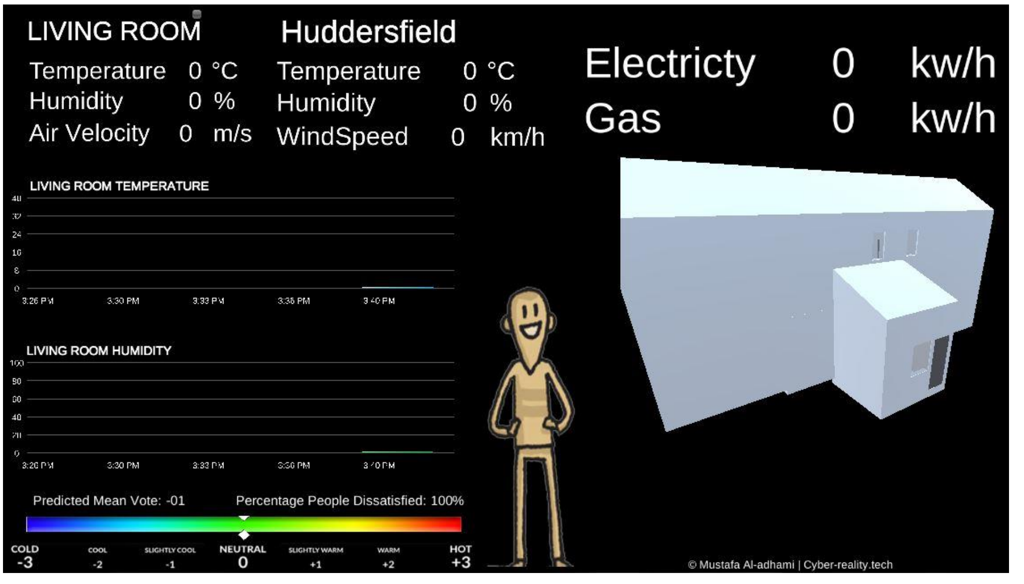


Figure 5.4 Simple monitoring technique

The advanced mode was a real-time analytic approach, programmed with power bi to read the data out from the database. The analytic dashboard includes a timeline slider and day range for visualising historical data. Several charts were incorporated to display PMV index, temperature, humidity, and gas consumption. In addition to the energy prediction data from every sensor.

Figure 5.5 Advanced analytic monitoring technique

5.4 Summary

This chapter describes an IoT prediction system, focussing on system architecture and layers of development. The work also focuses on the thermal comfort condition module and the environmental sensors needed to calculate PMV/PPD index in real-time; a microcontroller and a Wi-Fi module were utilised to receive and transmit data from the environmental sensors to a cloud database. In addition, the IoT system is integrated with the energy prediction model described in chapter 6. Finally, two visualisation approaches, simple and advanced, were also presented for real-time monitoring.

Chapter 6

Energy prediction approach

The energy prediction of domestic buildings has become a popular topic in the last decade, as it has the potential to improve building performance by lowering energy end-use and greenhouse gas emissions. One of the critical challenges is heating load and how it can save a significant amount of energy during wintertime. Determining the amount of energy required for a single space to maintain an acceptable level of thermal conditions is complicated and varies from one space to the next. Hence, a wide range of factors, such as building physical characteristics, location, occupant's behaviour, and HVAC system, must be addressed to develop an accurate energy prediction model. In addition, daily or hourly predictions are not helpful without applying a similar approach to the building and verifying individual room performance.

Furthermore, the real-time energy prediction approach for space heating and cooling requires advanced data collection and processing techniques, which is complicated given the nature and variety of elements that influence occupant comfort and energy consumption. Onsite measurements provide high-quality data for energy prediction. Nevertheless, it can only be used on existing dwellings and requires a substantial amount of time and sophisticated equipment to gather the necessary data. On the other hand, while each structure is unique, historical data from previous dwellings can be used to better understand energy use and thermal comfort. However, it cannot be used as a reference for other dwellings or to develop an accurate energy prediction. BPS is another method for generating high-quality dynamic data that can be used at various building life cycle stages. Despite the difficulties associated with BPS, many studies are nevertheless regarded as valuable methods for evaluating building performance. For example, a dynamic energy simulation engine, such as Energy Plus, DOE-2, or Apache, can successfully calculate energy consumption depending on a range of parameters. The most accurate outcomes come from the most detailed inputs. Thus, establishing a connection between energy consumption and thermal conditions requires a comprehensive simulation considering all changes in thermal operational performance. In order to fill this gap, this chapter presents a methodology for generating high-quality synthetic data along with the ML approach. The outcomes of this chapter, including the prediction model, are part of the innovative system presented in the previous chapter.

Literature found that ML has had a significant impact on smart buildings and energy management. Potentially it can minimise energy consumption in various structures, from residential to industrial. The ML prediction models are built on mathematical algorithms utilised to identify patterns in the source data and predict new values. Thus, this study used Microsoft Azure Machine Learning Studio (Microsoft, 2021b), a web service solution for developing prediction models. AzureML has been effectively used for the implementation of thermal-energy prediction, from data training to real-time performance evaluation. Microsoft Azure provides several advantages to other statistical software packages. First, it is user-friendly and straightforward, even if the user has only basic knowledge of cloud computing and ML. Second, a visual scripting drag-and-drop process to manipulate the workflow and navigate through a visualisation workflow. Finally, it supports the utilisation of external programming language, packages and algorithms (Shapi et al., 2021).

However, there are many challenges in developing an energy prediction model employing statistical analysis or learning methodology. For example, It was stated by (Attewell and Monaghan, 2015) that statistical prediction is limited in the case of large datasets with multiple features since modelling requires high computational power. Moreover, the statistical prediction method brings errors into the validation process and performs well only when time series are stationary and consumption levels are highly similar (Abdul Karim and Alwi, 2013). Additionally, time series analysis for energy performance has been proven to be insufficient in previous research due to irregularities in key variables (Newsham and Birt, 2010). The time series method is the typical approach of developing an energy prediction model, usually based on the trend of maximum energy demand (Xiangyu et al., 2019). Hence, other energy factors, such as energy fluctuations, would be ignored in the model development, resulting in the model being trained exclusively with historical data of maximum demand value. On the other hand, incorporating other aspects of energy can improve the accuracy of the prediction model (Wei et al., 2019). To this end, studies have recognised ML to be a suitable method for creating an energy prediction model.

Choosing the optimal strategy does not eliminate all of the challenges associated with energy prediction. For example, the source data, any missing or corrupted data negatively impacts the prediction model (Ahmad et al., 2016, Nugroho and Surendro, 2019). Missing data usually happens due to interconnection or sensor failure, which is one of the biggest challenges in innovative meter systems (Ahmad et al., 2016). Thus, syntactic data creation is utilised to deliver a reliable data source for the prediction model. Furthermore, using a cloud-based ML development service is preferable to avoid reliance on local hardware requirements. Generally, this chapter discusses three key areas of energy prediction: ML methodology, syntactic data creation, and cloud-based technology for the energy prediction model.

6.1 Methodology

This study used a cloud-based machine learning service to develop an energy prediction model. A dynamic synthetic data supplied by the BPS tool is the core of this development. The prediction model in this chapter was integrated into the real-time environmental sensing system discussed in the previous chapter. The method presented in this chapter consists of two phases: The generation of synthetic data and the development of prediction models.

Phase one establishes an approach to generate synthetic data of every zone in the building. The prediction model is extremely dependable on the raw data. Therefore, it is essential to prepare high-quality data for accurate prediction. The method used in this development includes three stages

- Building modelling

- Energy modelling
- Parametric simulation

Figure 6.1 highlights the procedures and actions required for data creation, including the connection to the next phase of the proposed methodology. In this process, several indoor environmental parameters, outdoor environmental parameters, and predicted thermal comfort and energy consumption are included in the synthetic data, all of which have the same timestamp. The outcomes of this phase are raw data comprising thermal and energy-related variables of every possible operational scenario for each zone in the building.

Phase two employs an ML algorithm to develop a prediction model for energy consumption. The generated synthetic data is used as the source dataset for creating a prediction model. A sample of the synthetic dataset is used to evaluate several ML algorithms to select the most accurate prediction algorithm for this development. The BPS synthetic data, including indoor operative temperature, relative humidity, PMV/PPD, outdoor environmental parameters, energy consumption, will be used as feature attributes for this prediction, with energy-based indoor conditions representing the desired output. As described previously, Microsoft Azure, a web service solution, was chosen for this development. The prediction modelling is done using the R programming language in Microsoft Azure Machine Learning Studio (AzureML). The raw data are analysed and pre-processed to reduce the model training complexity and manage any missing or corrupted data. Then, validation measures are used to assess each model. Accordingly, the energy prediction procedures are divided into three parts Figure 6.1:

- Data pre-processing
- Model development
- Model evaluation

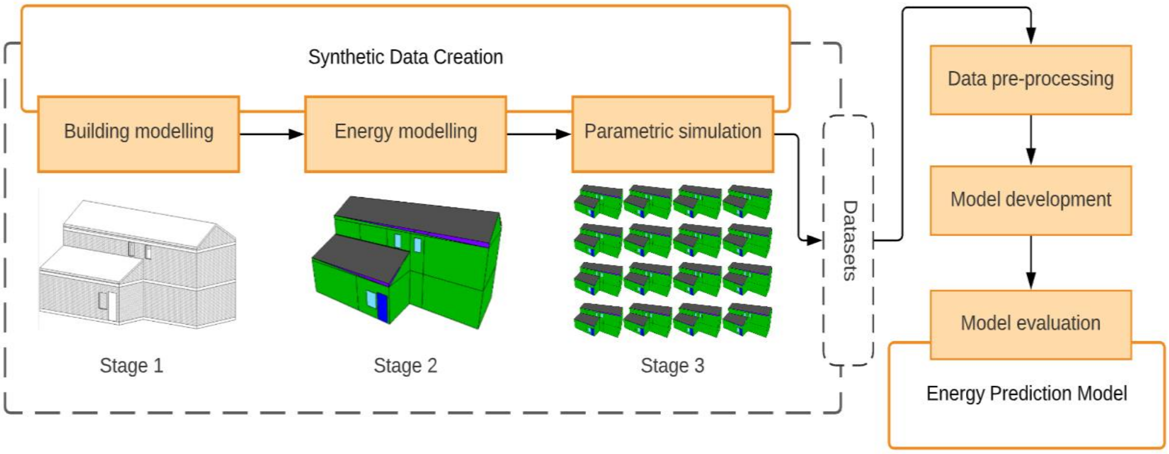


Figure 6.1 Energy prediction workflow

6.2 Phase 1: Synthetic data creation

Buildings are complex systems made up of several components that may interact directly or indirectly. Simulation software like BPS tools is most often used to built-up a connection between buildings' components and design parameters to create a more energy-efficient building. For example, whole-building energy simulation tools are a straightforward way to investigate energy performance through amending design parameters each at a time. This method, also known as the one-factor-at-a-time (OFAT) method, can be applied repeatedly to all building parameters several times. Building energy simulation software is typically constructed using a scenario-by-scenario approach, which is time-consuming and nearly hard to accomplish when generating high-quality dynamic synthetic data of different parameters. In this regard, a coupling approach includes building energy simulation tools, and parametric design is used to set up a complex parametric execution. Because of the iterative nature of this technique, they are generally known as simulation-based optimisation methods. Simulation-based optimisation methods explore alternative design options and find the best possible solution from extensive processed data. The data generated from the optimisation method are trustworthy to investigate to produce a reliable dataset to develop a prediction model that can interconnect thermal conditions parameters with the energy consumption of individual zones of a building.

Building energy analysis tools are based on mathematical calculations, and the process of utilising these tools, such as EnergyPlus, TRNSYS, ESP-r and DOE-2, is almost similar. The digital model of the building and design parameters are essential parts of every simulation. Design parameters include building location and orientation, geometrical and physical properties, building block or zone functions, building services, occupancy schedule and operation schedules, and simulation parameters such as simulation period and intervals. On the other hand, some energy modelling tools provide more detailed parameters, while others simplify the simulation process by using less detailed inputs. Thus, the selection of a simulation tool, the quality of the collected data, and the complexity of the model are the key elements of every simulation.

Figure 6.2 illustrates the three-stage approach of producing synthetic data from a new or existing building to create an energy prediction model. Building modelling is the first stage, which includes collecting and producing a digital replica of a building, focusing on building elements' geometrical and physical properties. The second stage, advanced energy modelling, is considered the most essential because it focuses on dynamic parameters in the building, such as occupancy and operating schedules, building services, lightings, and appliances. The energy model is mature to conduct a conventional energy analysis in this stage.

The final stage is using a parametric design optimisation tool. The energy model is used to create synthetic data based on pre-defined design parameters and a range of variables. The pre-defined parameters are environmental control and heating/cooling system control of every occupied zone with thermal activity. The outcomes of this stage, along with energy consumption data, are indoor and outdoor environmental parameters that were used in every energy simulation. Each stage is covered in detail in the following section.

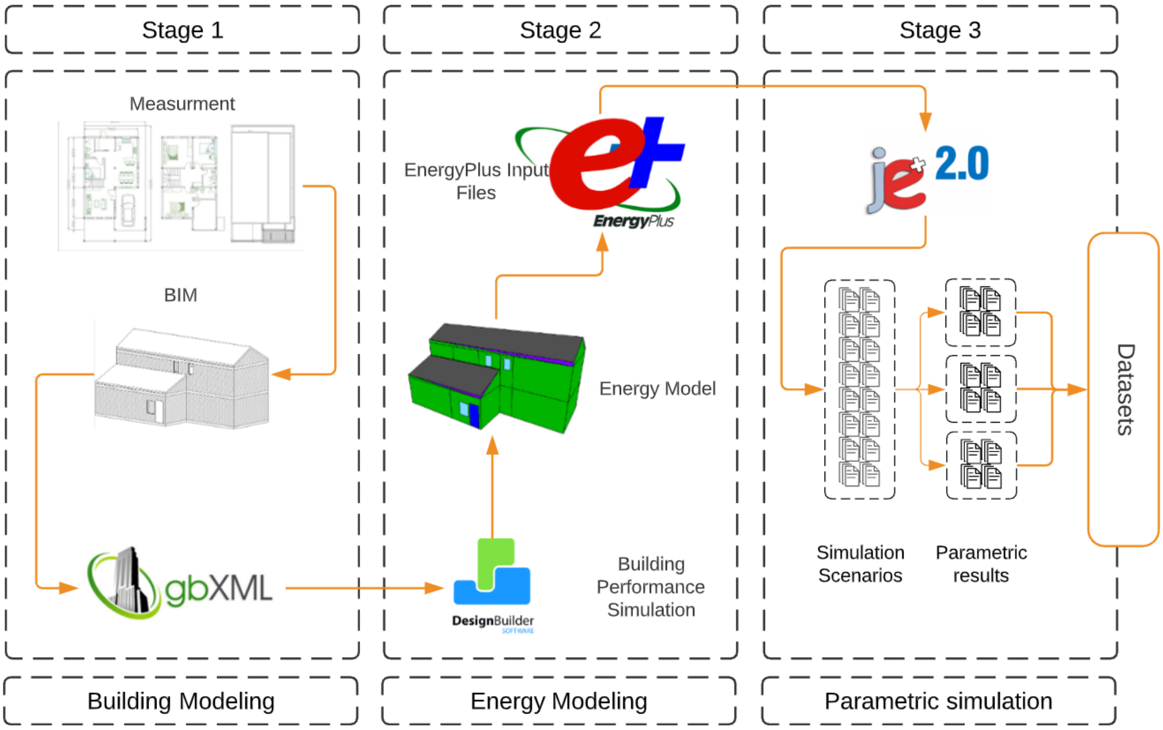


Figure 6.2 The process of generating synthetic data

6.2.1 Stage 1: Building modelling

Energy models have a special type of geometry and are used by building energy simulation tools like DOE 2.2 and EnergyPlus. The energy model is a computational network that abstracts the general structure of the building and encompasses all of the critical heat transfer channels and processes across the building (Harish and Kumar, 2016). There are numerous computer programs available today for building design and energy modelling. These modelling tools vary in complexity and level of detail. However, interoperability between building design and building simulation tools is a critical challenge (Guzmán Garcia and Zhu, 2015, McGraw-Hill, 2007, Chen et al., 2021). Previous industry reports estimate that interoperability issues account for 3.1% of the project budget; work duplication and manually data entry from one tool to another are one of the primary reasons (McGraw-Hill, 2007). According to (O'Connor et al., 2004), the cost of insufficient interoperability in the capital facilities business in the US might exceed $15.8 billion per year. Several research studies have highlighted a lack of interoperability between BIM and BPS tools. For example, a detailed identification and analysis study on the interoperability issues between BIM and BPS found a loss of geometric precision and a distortion of building information (Lam et al., 2012). An analysis of the interoperability challenges between existing BIM and BPS using a two-story office model case study indicated that each BPS tool has interoperability issues at different levels (Moon et al., 2011). The provision of open standard schemas is the basis to enable interoperability between different software applications. The Industry Foundation Classes (IFC) is one of the most widely used open standards in BIM-based projects (Buildingsmart, 2021). IFC is a vendor-neutral, object-oriented data format specification created by buildingSMART (formerly the International Alliance for Interoperability, IAI). However, it has a limited range of expression, and it is challenging to represent complex architectural geometries (Dong et al., 2007, Guzmán Garcia and Zhu, 2015). Green Building XML (gbXML) schema is another building language, uses the Extensible Markup Language (XML) format to allow disparate Three dimensional (3D) information models to be shared, such as building's geometries, material attributes, and elements (e.g., walls, floors, ceilings, doors, and windows). The gbXML schema has become a default industry standard that enables the transfer of the building information between building design tools and BPS applications (Dong et al., 2007, gbXML, 2021). In addition, several leading software firms, including Autodesk, Bentley, and Graphisoft, already support the gbXML format. The three essential components of the energy model, Spaces, Surfaces, and Zones, are depicted in Figure 6.3 and are based on the gbXML standard (gbXML, 2021).

- Spaces represent a discrete volume (masses) of air where heat loss or gain occurs. Temperature fluctuations are caused by internal processes and factors such as occupancy, illumination, equipment, HVAC, and heat transfer with other indoor and or outdoor spaces.
- Surfaces are the pathways that connect indoor and outdoor environments, and the heat transfer routes between them.
- Zones are groups of spaces linked together because they share a common feature, such as the same direction, function, or service.

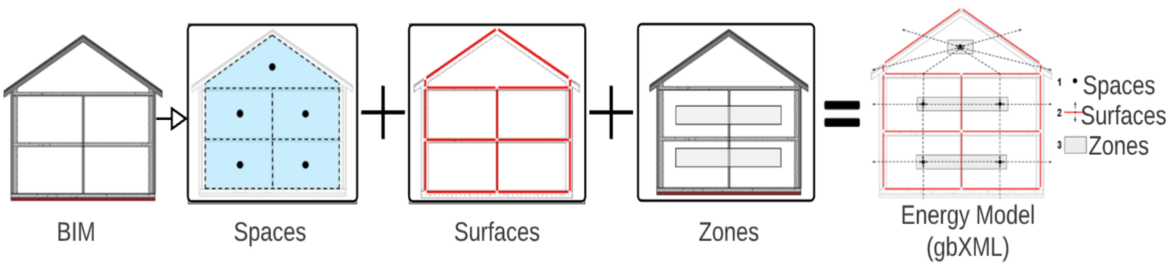


Figure 6.3 gbXML schema overview

The BIM model was created with Autodesk Revit, and the building energy simulation was done with DesignBuilder-EnergyPlus. Autodesk Revit provides two methods for exporting to gbXML. a) uses energy settings in Revit, and it exports the energy analytical model. The energy analytical model comprises analytical spaces and analytical surfaces generated by defining energy-related parameters in Autodesk Revit Energy Settings. b) export room or space volumes in the building model; the model's accuracy is determined by the precision with which rooms or spaces are added to the model. The exported file contains energy information for the building model following the gbXML file structure. Regardless of the export options provided by Autodesk Revit, understanding the range of modelling approaches and strategies is the key to successfully creating an energy model directly from a design model. Figure 6.4 illustrates the digital modelling workflow.

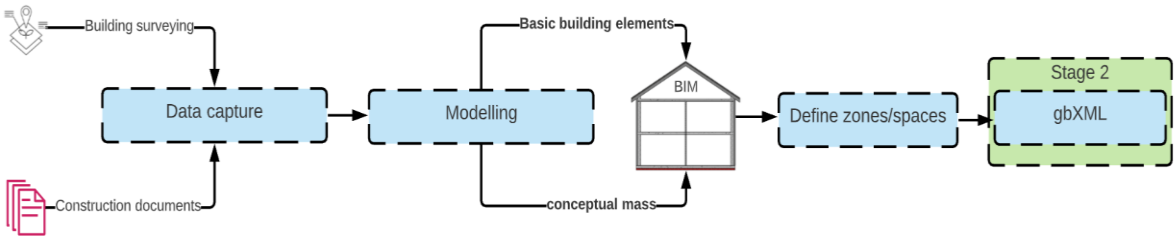


Figure 6.4 Digital modelling workflow in stage 1

6.2.2 Stage 2: Energy modelling

In stage two, the advanced energy model DesignBuilder-EnergyPlus is used to enhance the exported energy model from the previous stage. DesignBuilder is an energy simulation application that provides a graphical user interface built on the EnergyPlus engine and enables detailed inputs to study building energy performance. In addition, it has a user-friendly interface and has been used in numerous simulation-based investigations (Fathalian and Kargarsharifabad, 2018, Cárdenas et al., 2016, Streckiene and Polonis, 2014). For thermal comfort, DesignBuilder uses ASHRAE Standard 55 (ASHRAE, 2017), which is based on the Fanger comfort model (Fanger, 1970) and adaptive model (De Dear and Brager, 1998), discussed previously.

DesignBuilder has previously been utilised in many energy performance studies and has proven to be a reliable building energy simulation tool. For example, an energy management study on an office building validated the accuracy of the energy analysis of DesignBuilder EnergyPlus. The study showed an energy performance gap of less than 1.6

by comparing the monthly gas and electricity bills with expected energy usage (Fathalian and Kargarsharifabad, 2018). Even though the difference is too small to be a coincidence, it demonstrates DesignBuilder-EnergyPlus as a reliable tool for energy simulation.

Although DesignBuilder is a whole building energy analysis tool, it has been utilised for design-based study analysis research to perform a specific calculation. For example, an evaluation study of chimney stack effect utilised DesignBuilder to simulate various Computational Fluid Dynamics (CFD) scenarios to provide an insight on the effectiveness of natural ventilation through a chimney (Torre and Yousif, 2014). In a building retrofit study, a modelling approach and DesignBuilder were used to evaluate the effect of thermal bridges on the overall U-value of the building envelope (Boafo et al., 2015). It has also been used to study a double skin façade to improve the energy performance of the industrial buildings (Slavkovic, 2017). Furthermore, DesignBuilder can efficiently study individual elements of a building, such as one floor or a single zone. The energy model hierarchy is clearly defined by blocks, levels, zones, and surfaces.

To this end, DesignBuilder is utilised for advanced energy modelling due to its simplicity of working with multiple parameters provided by the EnergyPlus engine. DesignBuilder provides accuracy and detailed input related to thermal comfort and environmental control. It has a user-friendly interface with the ability to study different zones in a building. Interoperability with BIM models is provided through DesignBuilder's gbXML import capability, which allows users to encompass heating and cooling system sizes and environmental performance data developed in any BIM tool that supports the gbXML schema. Moreover, removing and correcting gaps between zone inner volumes is an essential aspect of DesignBuilder gbXML import capability. As a result, models lose relatively little geometric information during the transfer from BIM to EnergyPlus.

In the modelling process in BPS tools, activities need to be taken to carry out an energy analysis for a whole or part of a building. With minor differences in inputs and level of complexity, most energy simulation software follows the same procedure. The energy modelling approach of the case buildings in this research was prepared using DesignBuilder. Figure 6.5 illustrates the workflow of advanced modelling, and the process is as follows:

- Prepare project environment, including the site location, time and daylight, simulation weather data, and building orientation.
- Setup project data and create the 3D model of the building, which is in this research the 3D architectural model has already been created in BIM tools, such as Revit, ArchiCAD or MicroStation. The project was then imported to DesignBuilder as gbXML.
- Repair and remove the gaps between zone inner volumes.
- Assign building materials and openings, such as external walls, internal partitions, doors, windows, glazing type, and shading.
- Define the activity of the building's zones, such as zone type, occupancy, environmental control, and appliances.
- Define Lighting properties and building systems, including Mechanical ventilation, heating and cooling system, humidity control, natural ventilation, and domestic hot water (DHW).
- Set simulation period, intervals and define output parameters.

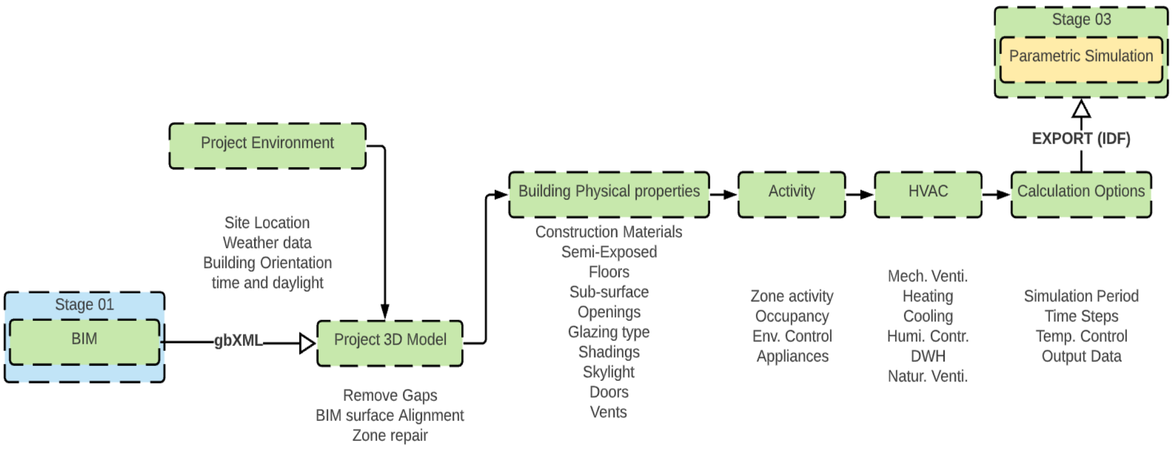


Figure 6.5 Advance energy modelling workflow in stage 2

In this stage of the energy modelling, the environmental parameters that influence occupants' thermal comfort in the indoor environment have been identified for the next stage of synthetic data creation. Every zone in the building has been dealt with individually using the process described above. Then, every thermal zone in the building are isolated and exported separately. Aside from establishing the building's physical and thermal attributes, the following assumptions have been made.

- Only the studies zone has been considered for every prediction model.

- The occupancy and operating schedules have been set to full 24 hours to ensure that the energy simulation generates energy consumption values for every potential change in the indoor and outdoor environmental parameters.
- Any electricity-related settings have been ignored and excluded from the simulation, as the research focused on gas use for winter space heating and natural ventilation for summer cooling.
- Any gas consumption settings unrelated to space heating have been ignored and removed from the simulation, such as gas usage for water heating and cooking.

This process produces an advanced energy model of a selected zone, exported as an EnergyPlus Input Files (IDF) file for use in the next stage of syntactic data generation.

6.2.3 Phase 3: Parametric simulation

Parametric analysis is a strong tool for evaluating alternative design options and establishing design variable interdependence. Parametric simulation is mainly used for design optimisation. Nowadays, hundreds of optimisation algorithms have been developed, and many design optimisation tools have become available for different purposes. Parametric energy simulation studies have proposed and developed different methods to optimise building energy performance. Tools such as Grasshopper and EnergyPlus are used to inform the early-stage of building design (Samuelson et al., 2016). Another study proposed a framework of integrating BIM with parametric simulation tools such as ladybug and honeybee to improve indoor thermal comfort (Amoruso et al., 2019). Other tools, such as MATLAB was employed to create an automated parametric simulator for EnergyPlus (Calafiore et al., 2017).

However, many additional studies utilised jEPlus for building energy simulation to study different design options. jEPlus is a parametric tool for EnergyPlus used for managing complex energy analysis (Zhang and Korolija, 2010, Zhang, 2012). Yi Zhang developed the tool in 2009, with the latest release in 2020, Version 2.1 (Zhang, 2020). jEPlus is intended to assist building designers in evaluating various design possibilities by allowing them to execute parametric simulations with EnergyPlus models. The software is open-source and free, and it has been used in a number of research investigations. For example, In (Chen et al., 2016) study, EnergyPlus and jEPlus are used to execute modelling experiments with varied parametric inputs to offer a passive design strategy and optimise indoor environmental quality. A multi-objective optimisation research also uses jEPlus to study bio-based thermal insulation materials in building envelopes (Torres-Rivas et al., 2018). A case study employs jEPlus by defining design parameters to analyse energy usage and thermal and visual discomfort (Naderi et al., 2020).

This study employs a sophisticated parametric design parameter. These parameters are processed using jEPlus. In general, the research focuses on adjusting the indoor environment parameters and energy-related values for different zones of domestic buildings in the UK. The procedure for parametric energy simulation is relatively simple by defining the parameters and their range of values, then jEPlus will automatically create multiple EnergyPlus simulation jobs. An IDF model generated from the DesignBuilder is used in this process. EP-Macro, an EnergyPlus tool, is used for energy model editing. The pre-processing tool is used to fix any errors in the exported IDF file for each studied thermal zone. For parametric simulation, JEPlus requires an IDF energy model file and weather data for the location of the building. EnergyPlus job simulation exports a number of output data that are considered processing-intensive and storage expensive. Furthermore, not all the output data are valid for the next phase of energy prediction. An advanced output variable reporting is used to generate a list of the report variables that are needed for developing the energy-thermal-based prediction model. A sample of the Report Variable Input (RVI) files in list 6.1.

EP-Macro is used to define the indoor environmental parameters for the parametric simulation. The input variables can be described in the EnergyPlus model as a single parameter at different places in the model, which are used for synchronous change of values. For example, list 6.2 shows the code used to control the humidity of a living room zone. Then, jEPlus will search for "@@ Humidity @@" and replace it with the intended values so that EP-Macro can import the values for parametric execution.

list 6.1 sample of the RVIs output file used in this study

```
eplusout.eso
eplusout.csv
Zone Thermal Comfort Fanger Model PMV
Zone Thermal Comfort Fanger Model PPD
DistrictHeating:Facility
DistrictCooling:Facility
Zone Mean Air Temperature
Zone Air Relative Humidity
Site Outdoor Air Drybulb Temperature
Site Outdoor Air Relative Humidity
Site Wind Speed
0
```

list 6.2 Humidity control parameters in IDF file

```
! Modified schedule: On 24/7
Schedule:Compact,
Block2:3LivingRoom Humidifying RH Schedule,
Any Number,
Through: 12/31,
For: AllDays,
Until: 24:00, @@ Humidity @@;

! Modified schedule: On 24/7
Schedule:Compact,
Block2:3LivingRoom Dehumidifying RH Schedule,
Any Number,
Through: 12/31,
For: AllDays,
Until: 24:00, @@ Humidity @@;
```

In order to prepare the synthetic data for the ML prediction model, the objective is to generate a set of data that includes the amount of energy consumption required for heating a specific zone along with the occupant thermal comfort index, indoor operational variables and outdoor environmental parameters. The RVI output list 6.1 contains the generated output data for this study. In addition, several parametric configurations need to be made before generating the parametric result.

- Operational schedules have been set to full, which means the heating system operates 24 hours.
- Occupancy schedules have been set to full, so the energy simulation can generate a thermal comfort prediction value assuming the space is occupied 24 hours
- The environmental control for heating and cooling is set to a fixed value for each simulation job.
- Humidity control, Humidifying and Dehumidifying are set to a fixed value for each simulation job.
- Temperature zone control for the thermostat ranges from 12 to 32.
- Humidity zone control for the humidistat ranges from 1 to 100.
- The interval of output results is set to hourly.

To this end, the study defines 2100 energy simulation jobs for every zone studied zone. 15 EnergyPlus input files and one EnergyPlus weather (EPW) file where required. The simulation runs hourly, resulting in 8760 worth of data for one simulation job, representing a one-year simulation energy analysis from January to December.

Figure 6.6 demonstrates the phase 3 process and the parameter structure for the simulation jobs. Each path in the design parameter tree represents a single EnergyPlus simulation. Then, jEPlus iterates through the arguments and runs all the simulation jobs of the pre-defined tree.

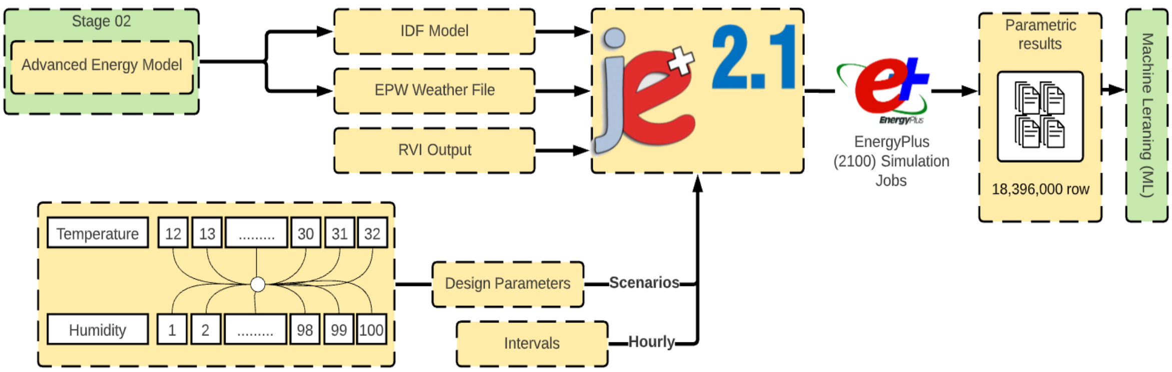


Figure 6.6 Parametric energy simulation workflow in stage 3

6.3 Phase 2: Energy prediction

6.3.1 Data pre-processing

Data pre-processing is an essential part of any ML project, and it takes a lot of time and computational power. This process is necessary because the dataset may contain missing or corrupted values or the scale of values between features are inconsistent (Barga et al., 2015). This process is to avoid problems that may arise during model training due to the insuffucnity of the datasets.

In addition, handling data capacity and the file size was another element that influenced the ML process in the current study. The synthetic data generated in the preceding phase is substantial. The data was generated in seven steps, each of which ran 300 simulation jobs, resulting in 2,628,000 rows of data in one large comma-separated values (CSV) file, which can make data pre-processing quite challenging. In addition, Microsoft Excel has a maximum capacity of 1,048,576 rows per worksheet, making even basic data cleaning impossible. As a result, data pre-processing was done in three stages: compiling, cleaning, and revising.

The seven parametric simulation results are combined into a single file during the compiling stage. The CSV file format was chosen because there is no row limit in CSV files. This stage produced a total of 18,369,000 rows and eight columns, with a file size of 3.1 gigabytes (GB) for every zone. The data was pre-processed using Azure ML's proprietary Clean Missing Data module to remove, replace, or infer missing values for the cleaning stage. This module includes a variety of "cleaning" operations for missing values, such as using a placeholder, mean, or other value to replace any missing value, discarding rows and columns with missing values, using statistical approaches to infer values. Even though this step included part of the pre-processing workflow, the results indicate no missing values from the generated synthetic data.

The last stage of the data pre-processing is amending the metadata. There is a scale unit mismatch between the simulation and the sensor data, which requires careful attention. Moreover, the raw generated data from the simulation contains different decimal places. As a result, two changes were required: first, to round the decimal places as needed, and second, to unify data units such as J to kw/h and km/h to m/s.

6.3.2 Model development

A supervised ML methodology was employed in this study to predict energy usage based on indoor thermal conditions. The data was generated, prepared, and fed into the learning algorithm. After data pre-processing, the following data were used for the ML training process, Thermal comfort PMV, Thermal Comfort PPD, Zone temperature, Zone humidity, Environment temperature, Environment humidity, and Environment wind speed, with Energy use for space heating and the desired output. Then, The data partitioning was done to segregate the data into two classes before developing and training the model: a training and a testing class. The training data was fed into a selected algorithm for model training while the testing group evaluated the output model. The evaluation process of the ML model and different testing algorithms are discussed in the following section. The overall workflow of energy prediction development is illustrated in Figure 6.7

In this development, a regression prediction model was employed to predict continuous quantity instead of classification. Regression is a commonly utilised methodology in various sectors, including engineering and education. The regression modules each use a distinct regression method, or algorithm, such as Bayesian Linear Regression (BLR), Boosted Decision Tree Regression (BDTR), Decision Forest Regression (DFR), Fast Forest Quantile Regression, Linear Regression (LR), Neural Network Regression (NNR), Ordinal Regression, and Poisson Regression. A regression algorithm attempts to learn the value of a function for a specific data instance.

To achieve the goal of this development, predict energy use for space heating the indoor environment based on the thermal variables, a DFR is used for data training. The DFR is used to develop a regression model based on an ensemble of decision trees. Decision trees are a prominent technique in ML and are often used in operation studies to assist or discover the best strategy for achieving a goal. Decision trees are non-parametric models that run a series of simple tests on each instance while traversing a binary tree data structure until they reach a leaf node 'decision'. The following are some of the advantages of decision trees for training and prediction: a) they are efficient in terms of computation and memory use; b) they can be used to indicate non - linear decision points; c) decision trees are durable in the presence of noisy features and can perform integrated feature selection and classification. The regression model in this research consists of an ensemble of decision trees. As a prediction, each tree in the RDF module produces a Gaussian distribution. The ensemble of trees is aggregated to obtain the Gaussian distribution that is closest to the combined distribution for all trees in the model (Criminisi et al., 2012).

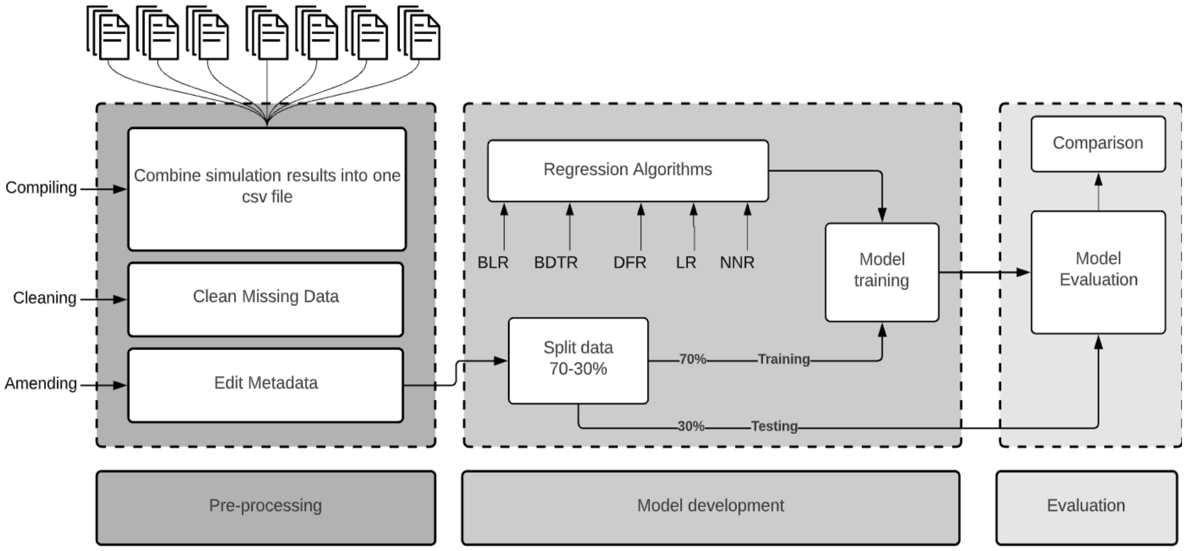


Figure 6.7 The overall workflow of energy prediction development

6.3.3 Model evaluation

The datasets were divided into two classes, as described in the previous section, with 70% of the dataset utilised for training and 30% for testing. AzureML data partitioning was used for training and testing to ensure that data partitioning was not a hassle or biassed. The partitioning process was simple, and the data were selected randomly. Consequently, overfitting, which could result in either an underestimating or an overestimation of prediction results, was avoided using this method. Then, the ML training process generates an energy prediction model that could output a value that matches the generated energy consumption in the syntactic data. Simultaneously, the rest of the data, testing dataset, was set aside to evaluate the trained model. In addition, the training dataset was used in the training and the evaluation of several regression algorithms and to ensure better performance. The process is illustrated in figure

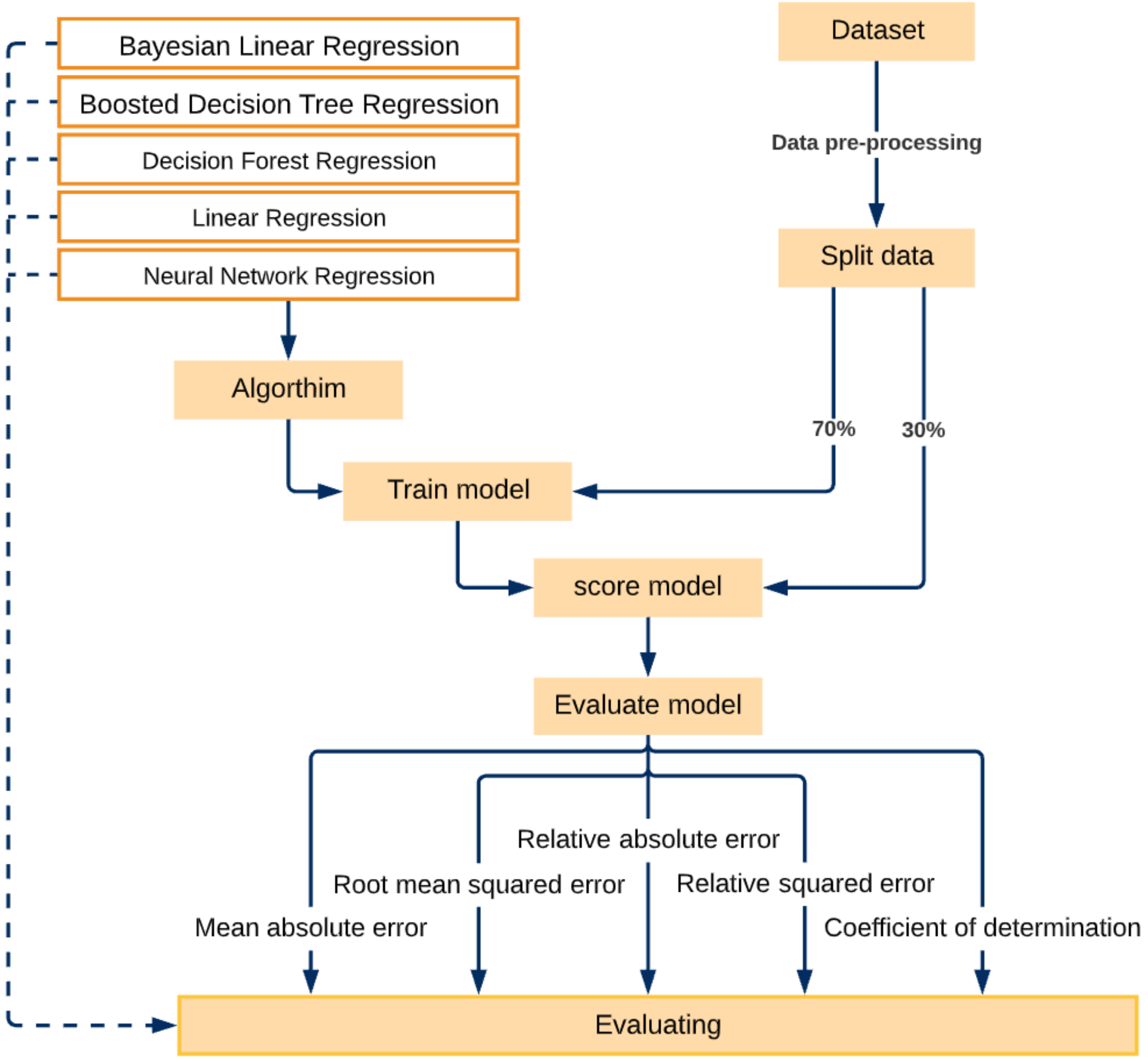


Figure 6.8 Testing and evaluating of prediction models.

Several metrics are used to evaluate regression models, and they are generally designed to estimate the amount of error. Therefore, a model is considered successful if it fits the data by measuring the difference between observed and predicted values (Botchkarev, 2018). Once the ML models were ready for each ML regression algorithm, they were evaluated to determine their performance and accuracy. Each regression model was evaluated based on Mean absolute error (MAE), Root mean squared error (RMSE), Relative absolute error (RAE), Relative squared error (RSE), and Coefficient of determination (CoD). The mathematical formula of model evaluation metrics are as follows:

$$MAE = \frac{1}{n}\sum_{j=1}^{n} e_j \qquad 6.1)$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}} \text{ or } RMSE = \sqrt{\mathrm{MSE}} \qquad 6.2)$$

$$RAE = \frac{\sum_{j=1}^{n} |e_j|}{\sum_{j=1}^{n} |A_j - \bar{\mathrm{A}}|} \qquad (6.3)$$

$$RSE = \pi r^2 \qquad (6.4)$$

$$CoD = R^2 = 1 - \frac{\sum_{j=1}^{n} (P_j - A_j)^2}{\sum_{j=1}^{n} (A_j - \bar{\mathrm{A}})^2} \qquad (6.5)$$

Where:
Aj : actual values
$\bar{A}$: the mean of the actual values
Pj : predicted values
ej=Aj− Pj –error
n : the size of the data set

Using AzureML, all regression performance metrics are evaluated using an Execute R Script and Add Rows modules to combine the results of all models. First, the Azure Evaluate Model module produces a table with a single row of the evaluation metrics. Then, an execute R Script module extracted the regression measures with the associated model. a sample of the scrip in list 6.1, The R Script create a table with a single row including the model name and evaluation metrics.

list 6.3 R Script to extract regression models performances

```
dataset <- maml.mapInputPort(1)
# Add algorithm name into the data frame
data.set <- data.frame(Algorithm=' regression_model_name ')
data.set <- cbind(data.set, dataset[1:5])
maml.mapOutputPort("data.set");
```

Figure 6.9 shows the results from the evaluation process of each model and compares them against each other to find the better performing model. The training and testing of the model revealed that each trained model performed differently for the same datasets. For example, measuring the gap between predictions to the actual outcomes, the MAE of the DFR model recorded the lowest score of (0.050946) compared to other models with a small gap to BDTR (0.07160) and NNR (0.083301). RMSE creates a single value that summarises the error in the model. Although the metric disregards the difference between over-prediction and under-prediction, the DFR model was lower, followed by BDTR and NNR. The relative absolute difference between expected and actual values RAE and the total squared error of the predicted values RSE supports the outcomes from previous metrics. The prediction power is indicated by the CoD or R^2 measure, which has values ranging from 0 to 1, with 1 representing a perfect fit. R^2 values should be evaluated cautiously since low numbers can be completely acceptable while large values can be suspicious.

To this end, using the data generated from energy simulation and developing an energy prediction model using five regression algorithms, the model evaluation process found that the DFR model has the best fit for this research. Although BDTR and NNR have good performance, BDTR requires a large memory footprint and NNR training time is quite substantial. Furthermore, the LR and BLR was the worst-performing model because it deals with small datasets (van de Schoot et al., 2015, Microsoft, 2021a).

Algorithm	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Relative Squared Error	Coefficient of Determination
Bayesian Linear Regression	0.264415	0.365438	0.557524	0.37456	0.62544
Decision Forest Regression	0.050946	0.110902	0.10742	0.034496	0.965504
Linear Regression	0.259478	0.355389	0.547114	0.354244	0.645756
Boosted Decision Tree Regression	0.071601	0.132567	0.150973	0.049291	0.950709
Neural Network Regression	0.083301	0.146127	0.175642	0.05989	0.94011

Figure 6.9 Evaluation of regression models

6.4 Summary

The primary goal of this chapter is to demonstrate a dynamic approach to produce synthetic data and cloud-based Machine Learning to design a real-time energy consumption prediction model that can assess energy use for space heating in individual rooms. In addition, the chapter discusses the creation of synthetic data, modelling approach and parametric simulation. Then it discusses and evaluates a number of ML prediction algorithms to produce a highly accurate energy prediction model. Finally, the workflow presented in this chapter utilised the next phase, onsite experimentation.

The synthetic data creation is varied from one building to another. Although many tools are available for digital modellings, such as sketch up ArchiCAD MicroStation, the basis of model development is the same in all these tools. In this research, Autodesk Revit is used, focusing on the physical characteristic of the building and the number of zones in each indoor space. Modelling for energy analysis is different from modelling for construction documents, as it is more oriented toward building thermal elements included in every zone and space. Furthermore, energy modelling does not deal with complex geometries and, in some cases, needs to be simplified by ignoring some architectural features to achieve an accurate result. Finally, parametric energy simulation is the key approach for dataset creation in this study; it allows the generation of multiple thermal conditions and energy consumption scenarios based on a range of indoor environmental control values.

Five supervised ML regeneration algorithms were chosen to develop an energy prediction model, including Bayesian Linear Regression and Decision Forest Regression. Linear Regression, Boosted Decision Tree Regression, and Neural Network Regression. The prediction performance of these five models was successfully compared. In addition, a cloud service AzureML was used for all ML development tasks in this study, including data pre-processing, model training and testing, and performance evaluation.

Furthermore, the cloud-based prediction system has the advantage of not relying on the performance of the machine on which it is operating; it avoids the failure of a sudden system shutdown; it supports the integration with the developed sensing system for real-time prediction through an application programming interface (API).

Chapter 7

Experiments

7.1 Introduction

The domestic sector consumes the most energy (22 %) compared to other sectors (UNEP, 2020). Indoor space heating is responsible for 76 % of the total energy use in the UK's residential sector (DBEIS, 2020). Therefore, there is an urge to track and reduce energy consumption. This chapter presents a field experiment utilising the proposed framework to monitor the energy use for indoor space heating based on the thermal comfort conditions in domestic buildings. The proposed work can potentially improve indoor environmental quality and lower energy demand for space heating. In the UK, 90% of dwellings have a central heating system, which allows people to heat all of their rooms at the same time. Combi gas boilers, the most common types of boiler in the UK, are are installed in approximately a third of the dwellings (Palmer and Cooper, 2014). Combi boiler complies with UK Building Regulations for existing dwellings. The control system of the central heating system includes a) a Programmable Room Thermostat (PRT), usually installed in the lounge; b) a Thermostatic Radiator Valve (TRV), installed to every radiator in the dwelling except where the PRT is located; c) and a by-pass valve, frequently found in the boiler (TACMA, 2018).

Nevertheless, around 70% of current dwellings do not fulfil the minimum control standards of the building regulations. For example, occupants do not use room thermostats, leading to excessive room temperatures. Dwellings lack individual temperature control in different rooms, such as TRV, resulting in the entire house being heated to the temperature set by the PRT, leading to heat or overheating unoccupied rooms. Additionally, some dwellings with a boiler have no controls at all (Beizaee et al., 2015, Force, 2010). Other factors, such as the type of dwelling, structure and materials, and location, all influence energy consumption for space heating in dwellings. Unless the building is retrofitted, the physical characteristics of the building, such as orientation, structure, and materials, are usually fixed factors.

On the other hand, weather conditions significantly impact energy performance for space heating. For example, UK households use less energy for indoor space heating in summer than in the winter, primarily used for domestic hot water (DHW) and food cooking. Therefore, the total energy used for space heating cannot be accurately measured without a proper approach. In dwellings, fluctuations in the heating load demand are expected, usually linked to occupancy profiles, especially during the winter. In most dwellings in the UK, a gas metre is used to calculate total energy use including, space heating, cooking, and DHW.

Consequently, it cannot adequately reflect the implications of occupants' thermal comfort conditions or the amount of energy required to achieve comfort. To that end, the total energy used for indoor space heating varies and is influenced by a variety of factors, making it difficult to quantify the amount of energy used for domestic space heating. In addition, thermal comfort conditions are highly subjective and complex to measure using BPS tools. Thus, the proposed framework was utilised in several experiments to address these challenges. The chapter introduces a field experiment to evaluate the proposed framework and identify thermal-energy performance on two test dwellings.

The first dwelling was used to study the implementation strategy and evaluate the performance of the real-time prediction system. The results are used to assess thermal comfort conditions and energy performance in the dwelling and identify the gap between actual and predicted performance. The second dwelling was used in a number of individual experiments where each room was studied intensively. The experiments in dwelling two provide an in-depth analysis of the implemented framework, indoor thermal condition, and energy use. The proposed method was used on the dwelling to predict the energy used for space heating. Since the central heating system powers both houses, a detailed description of how the central heating system operates in these two properties is explained in the following sub-section.

7.1.1 Central heating system

Central heating is the most common form of heating in UK's dwellings. A single boiler heats water pumped through pipes to radiators throughout the house and provides hot water to the kitchen and bathroom taps, Figure 7.1. The majority of boilers are powered by gas. Every radiator has a valve that controls the amount of hot water entering the radiator. The radiator's valve does not switch the boiler on or off, and they are not directly involved in energy consumption. The room thermostat or PRT is connected directly to the house's central heating system and is used to control the overall temperature of the system by monitoring the ambient temperature. The PRT controls the central heating system following the programmed setting by measuring room temperature, usually in the lounge, where PRT is installed. When the boiler is turned on, it provides hot water to all of the radiators in the dwelling.

The two primary thermostats are analogue (Mechanical Thermostats) and electronic (Digital Thermostats). A mechanical thermostat behaves similarly to a current switch, usually comprised of a knob and has a temperature range of 10 to 30 °C. The electronic thermostats are accurate, and most of them can be programmed, where occupants can set different temperature values based on their personal preferences. A third uncommon form of a thermostat is an electro-mechanical thermostat, which uses both electronic and mechanical mechanisms.

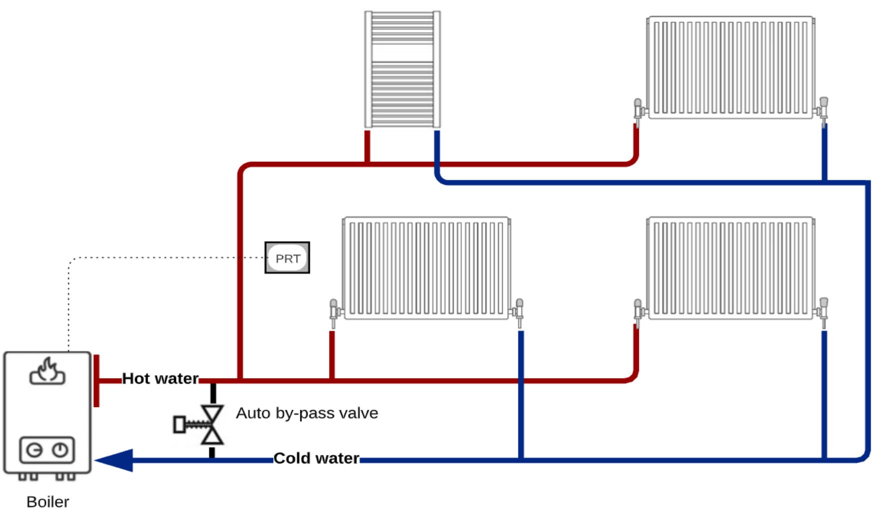
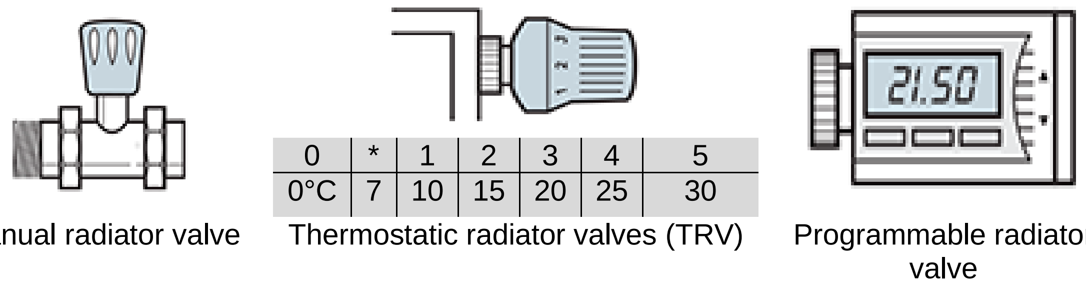


Figure 7.1 Illustration of the central heating system in most UK's dwellings.

Since each room operates differently, radiator valves are used to fine-tune the temperature of each radiator. The thermostat and the valve work together regardless of the controlling system, digital, smart, or manual, installed in the house. The thermostat heats the house to a pre-set temperature, while the radiator valve balances the temperature in individual rooms. Radiator valves are divided into manual, thermostatic, and programmable. Manual valves work similarly to a water spigot in that they are opened to allow hot water to enter the radiator. The thermostatic valve, also known as a (TRV), controls the volume of water that enters the radiator. The TRV, unlike a manual valve, can control room temperature throughout a range of temperature values rather than just on or off. Usually, this range is set between 1 and 7 see Figure 7.2. In addition, radiator valves that can be programmed to reach a specified temperature during different times of the day are also known as electronic programmable radiator valves.



0	*	1	2	3	4	5
0°C	7	10	15	20	25	30

Figure 7.2 radiator valves

7.2 Experimental building

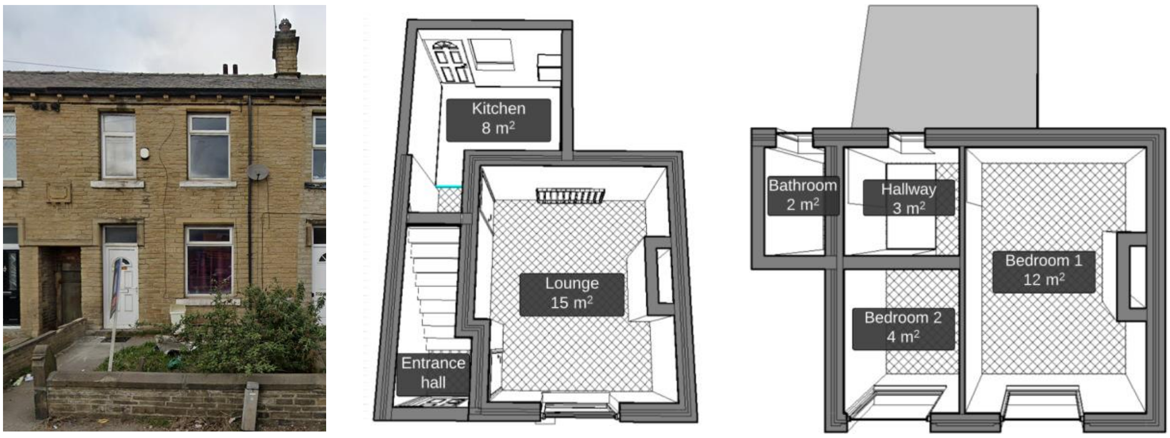
7.2.1 Characteristic of the building

The selected dwellings in this experiment are shown in Figure 7.3, a mid-terraced house located in the centre of Huddersfield. Huddersfield is a town in the Metropolitan area of Kirklees in West Yorkshire, England. It is classified as Cfb by the Köppen climate classification, with an average high temperature of 15.5 °C and a low temperature of 5.3 °C.

Location: N, 1.7850° W53.6458°

Figure 7.3 Geo-location of the dwellings

Dwelling One is a 67 m^2 conventional house selected primarily to pilot the implantation of the framework, from the data collection, energy modelling and ML training to the thermal-energy prediction system. Figure 7.4 the two-storey dwelling comprises an entrance hall, a lounge, a kitchen, two bedrooms, and a bathroom. The dwelling has double glazing windows, Low E, argon filled with thermal transmittance (U-value) of 1.3W/m^{2}K. The external wall is a 300 mm cavity wall with insulation and gas central heating to keep it comfortable in the winter. Each room has its own radiator operated by TRVs for space heating. The dwelling is cooled by natural airflow instead of air conditioning or mechanical ventilation in the summer. The energy sources for this dwelling include electricity and gas. Artificial lighting and electrical appliances are powered by electricity, while cooking, DHW, and radiators are powered by gas. For water heating, the property uses a fully automatic gas-fired wall-mounted combination boiler, Main Combi 24 HE.



Dwelling One Ground Floor First Floor

Figure 7.4 Plans and elevations of dwelling one

Figure 7.5 illustrates the equipment and type of appliances installed on the property for indoor space heating. The dwelling is equipped with a smart meter, Smart Metering Equipment Technical Specifications 1 (SMETS1), and Pipit 500 in-home display (IHD), which was utilised in this study. Moreover, the Pipit 500 is part of a line of IHDs produced by Secure Meters to meet UK smart metering standards. Pipit was designed to display energy consumption, both gas and electricity, by providing data in a numerical display and monitoring current and historical energy usage. In addition, TRVs are installed in all radiators in the dwelling and a manual radiator valve in the lounge where a mechanical room thermostat (MRT) is used to indoor control temperature.

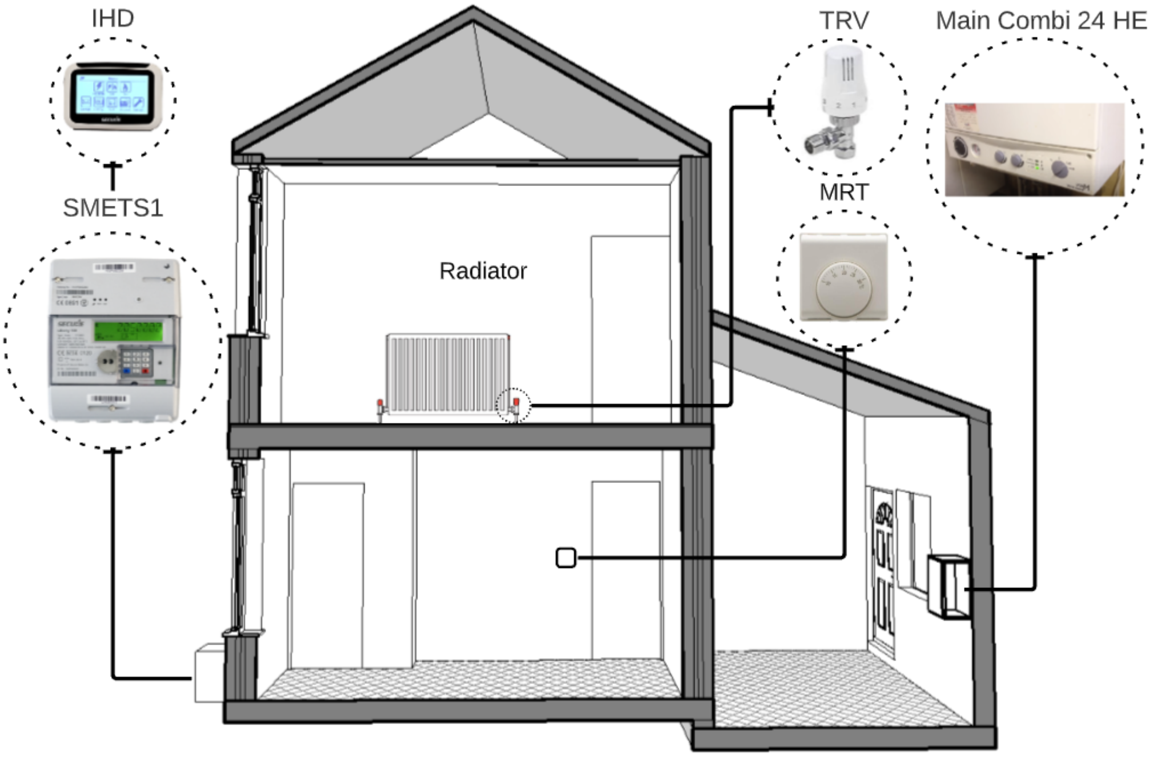


Figure 7.5 Dwelling one, Space-heating tools and devices

The second dwelling is 130 m^2, a two-story house with a loft and basement. Figure 7.6 The house was refurbished in 2018 and comprised a lounge, a kitchen, two bedrooms, two bathrooms, a studio, and basement storage. The property was selected for a more in-depth investigation, with each room serving as a semi-controlled environment.

Figure 7.6 Plans and elevations of dwelling two

The property benefits from double-glazing windows, a 300 mm cavity wall with insulation, and a gas central heating system with radiators fitted in every room. Electricity and gas are the only sources of energy in this dwelling. The electricity in this house for operating lighting and appliances, while the gas is for cooking, heating and providing the property with hot water. Moreover, this property has no mechanical ventilation system for summer cooling.

The dwelling is equipped with a fully automatic gas-fired wall-mounted boiler Gold Combi 28kW Gas Boiler (Potterton, 2021), and it has a SMETS2 and IHD6-PPMID in-home display for monitoring electricity and gas consumption (Chameleon, 2021). The equipment and type of appliances illustrate in Figure 7.7.

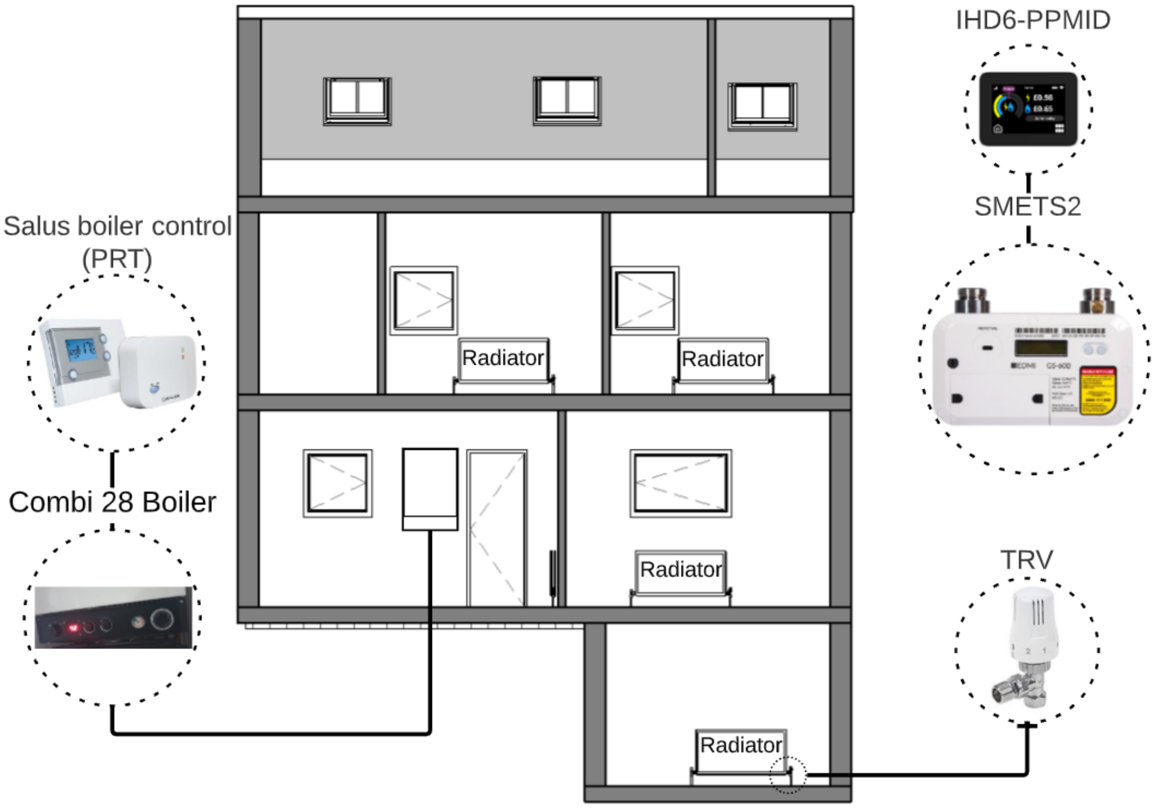


Figure 7.7 Dwelling two, Space-heating tools and devices

7.2.2 Data preparation and modelling

At the start of the study, the test dwellings were digitally modelled, and their floor plans were prepared. For digital modelling, physical measurements of both properties were taken due to the lack of an as-built drawing or a previous model. An initial model was created using Autodesk Revit, which was then utilised to create a digital representation of the house's geometrical shape. Advanced energy modelling was carried out primarily for parametric simulation using the proposed framework, as explained in chapter 6. In a series of steps, a BPS tool, DesignBuilder-EnergyPlus, was used for synthetic data creation, first dealing with data exchange and file format. Then, replicating the existing state of the tested dwellings, including the site location, local environment and surroundings, historical weather data, and thermo-physical features of building's elements, such as materials properties, building services, windows, doors, openings, and artificial lighting.

Next, to follow the framework of generating synthetic datasets based on indoor thermal conditions, occupancy and operations schedules are modelled to reflect a full occupancy 24 hours, seven days a week, during the simulation period. Furthermore, to ensure the produced datasets only calculate energy consumption associated with indoor space heating using the radiators, equipment and appliances that are not gas-related to the thermal conditioning system in the studied dwelling are excluded from the simulation. Thus, any energy sources that are not relevant to real-world conditions or the framework's aim are discarded, such as artificial lighting, computers, kitchen appliances, mechanical ventilation, and DHW. The only environmental controls provided in this development for indoor environmental factors are temperature and humidity. Consequently, the utilised HVACs replicate the current state of the dwellings, which are naturally ventilated in summer and heated with a central heating system in the winter. Finally, advanced energy modelling requires each room to be exported individually for parametric simulation; rooms were modelled as independent zones in DesignBuilder, isolated, then exported as an IDF file.

In the parametric simulation, EP-Macro is used to determine output parameters and intervals for the exported IDF of each zone. The reported output parameters are the PMV, PPD, Zone Mean Air Temperature, Zone Air Relative Humidity, Site Outdoor Air Drybulb Temperature, Site Outdoor Air Relative Humidity, Site Wind Speed, and Zone Heating. Then, to prepare a dataset for ML training, jEPlus, a parametric simulation tool, runs a number of simulations (batch simulation). The output results from the simulations combined to create a dataset for ML model development. The created datasets are based on several indoor and outdoor environmental parameters. The process of jEPlus began by defining the historical weather data (EPW), the IDF of the simulated zone, parameters of the simulation, and a range of values for every parameter. Two parameter identifications (PID)s were made, one for temperature changes and the other for humidity. The simulation encompasses pre-defined parameters related to thermal performance and conditions in the indoor environment. Table 7.1 displays the values of pre-defined parameters that were changed automatically during the parametric simulation.

Table 7.1 PID variable and IDF parameters

IDF elements	PIDs
Heating Setpoint	@ variable A @
Cooling Setpoint	@ variable A @
Zone Cooling Design Supply Air Temperature	@ variable A @
Zone Heating Design Supply Air Temperature	@ variable A @
Maximum Heating Supply Air Temperature	@ variable A @
Minimum Cooling Supply Air Temperature	@ variable A @
Humidification Setpoint	@ variable B @
Dehumidification Setpoint	@ variable B @

The framework proposed a cloud-based service for ML modelling. Microsoft AzureML was utilised and integrated with the IoT environmental-related system developed in Chapter 5. The ML process is initialised once every examined room (zone) dataset is ready, including data pre-processing, model building, evaluation, and cloud deployment. Finally, an energy prediction model was created for every zone based on Decision Forest Regression (DFR) algorithm, as explained in Chapter 6. The cloud-based service was implemented for all models and integrated with the thermal-energy prediction system. The prediction models were configured by sending a request with the pre-defined input environmental parameters captured from the indoor environment.

7.3 Experiment setup

The proposed framework with the IoT prediction system is evaluated in two stages experiment conducted in 9 different zones in test dwellings, uncontrolled and semi-controlled. The uncontrolled experiment is a whole building investigation in dwelling one, including 37 days of real-time data collection. The objective was to investigate the framework implementation and the system's capability of real-time prediction performance. The outcome of the uncontrolled experimental study in dwelling one was to identify system errors, including missing values, bugs, and an initial evaluation of the energy prediction module, quantify thermal comfort conditions and energy consumption, and enable more detailed investigation for the second stage. Stage two is a semi-controlled room-based experiment in which every zone in dwelling two was thoroughly investigated in terms of energy performance, environmental condition and framework validation. The following sub-sections explain the experimental setup, including the IoT prediction system implementation, TRVs and PRT control settings, and the real data capture approach.

7.3.1 Uncontrolled Whole-building Experiment (Dwelling One)

The designed IoT prediction system was tested in real-time, including both prediction modules, thermal comfort conditions and energy prediction. Three zones have been used in this dwelling: a Lounge, a kitchen, and a bedroom, where the experiment was conducted on all three zones simultaneously, during winter over 37 days from 07/12/2020 to 13/01/2021. The captured data from the environmental sensors and the prediction modules were gathered from indoor spaces and outdoor environments at 15 minutes intervals spontaneously and without any intervention. Even though the experiment was uncontrolled, the MRT in this experiment was set to a fixed value of 30°C at all operation times to ensure data collection consistency and guarantee that the central heating system is running at full capacity to heat up all rooms, regardless of size. In order to control operation time for space heating, built-in boiler controls were used to set heating time. The timer on the boiler was programmed to heat the whole house at a specified time every day. The TRV was used to control the heating set-point in individual rooms during the day. However, it was set to 5 most of the time.

Following the framework, an energy prediction model was developed for every room. The IoT prediction systems were distributed in the kitchen, lounge, and bedroom to monitor the changes in the indoor environmental parameters, including temperature, humidity, and air velocity. Then, calculate thermal comfort conditions and predict energy use for every room. Two rules were applied to locate the IoT prediction system in each zone: a) IoT prediction system should be placed one meter away from building features, such as floors, walls, windows, and doors in compliance with the standard (ASHRAE, 2017); b) Every zone is equipped with two IoT prediction systems, one on each side. Figure 7.8 shows the location of the IoT prediction system within the indoor environment in plan view.

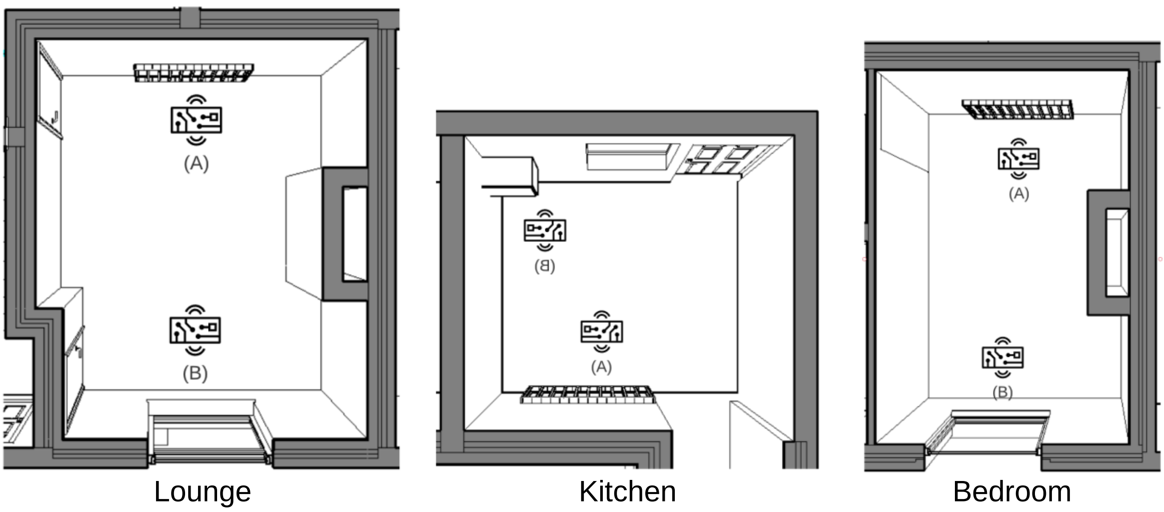


Figure 7.8 plan view of the IoT prediction system distribution in the dwelling 1

To Measure thermal comfort conditions in the indoor environment requires two factors: environmental and personal factors. As previously explained, the environmental factors were captured directly from the IoT prediction system. In contrast, the personal factors, including clothing insulation and metabolic rate, were fixed. Table 7.2 shows the

Metabolic rate and clothing Insulation values used in this experiment. The clothing insulation was set to 1 clo, equal to the typical insulation of winter clothing. The metabolic rate was set to 1 met for bedroom and lounge, and 1.8 met for the kitchen, representing the general activity of the investigated rooms (ASHRAE, 2017).

Table 7.2 The metabolic rate and clothing insulation values in the dwelling 1.

Zone	Activity	Metabolic rate (met)	Clothing insulation	Values (clo)
Lounge	Seated, quite	1.0	Typical winter indoor	1.0
Kitchen	cooking	1.8	Typical winter indoor	1.0
Bedroom	Relaxed	1.0	Typical winter indoor	1.0

7.3.2 Semi-controlled Zone-based Experiment (Dwelling Two)

The dwelling includes six rooms, a lounge, a kitchen, a basement, two bathrooms, two bedrooms, and a loft (studio). For the second stage, eight experiments were conducted in all rooms individually, excluding the two bathrooms. Each physical room in this dwelling was represented digitally by a single zone in the energy modelling. Rooms were used as a semi-controlled environment where every zone has been investigated individually to evaluate prediction results and quantify thermal conditions and energy performance. The experiment took place in April, and each room was treated separately.

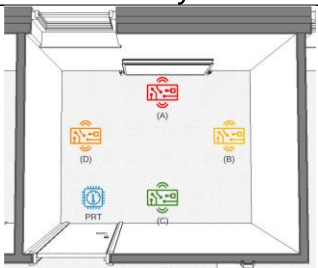
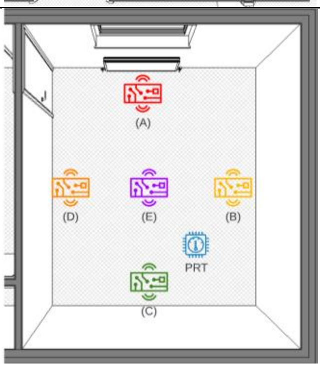
Several independent variables were used at this stage of the experiment to evaluate multiple scenarios: a) fixing room temperature with the PRT; b) changing the location of the PRT in respect to the radiator and the IoT prediction system; c) IoT sensor distributions in relation to the radiator in each room. Furthermore, there are several tools were utilised for the objective of the experiment, which are:

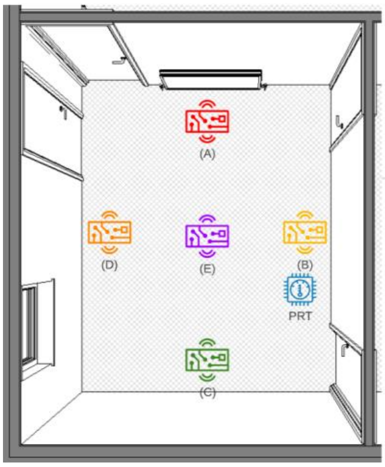
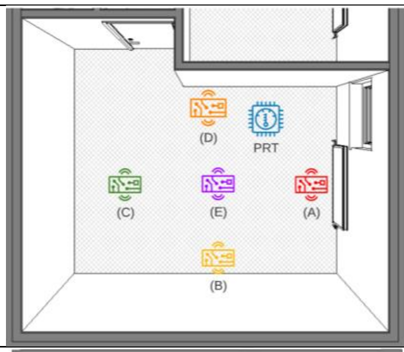
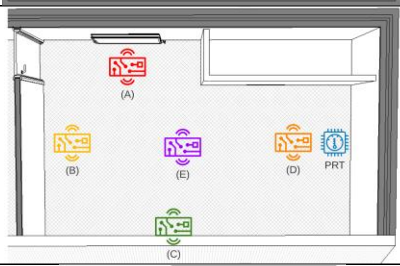
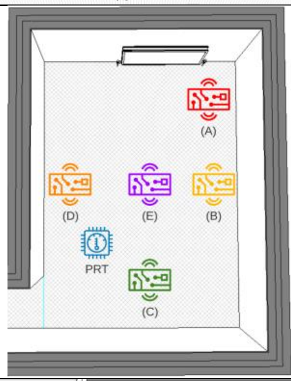
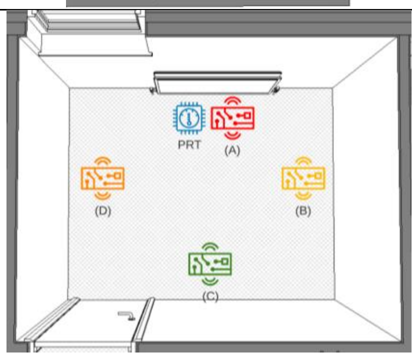
- IHD to monitor actual gas consumption at 30-minute intervals.
- A portable PRT to control the central heating system (boiler).
- TRV to control room temperature.
- 4 to 5 IoT prediction systems capture environmental parameters and predict energy consumption at different locations in the room.
- An outdoor environmental sensor to measure local weather conditions.

Since each room in the property was handled as a semi-controlled environment, the following boundary conditions were imposed:

- The duration of the experiments on every zone is 12 hours, starting at midnight and ending at noon; This period was determined in stage one to be appropriate for investigating aggressive temperature changes between indoor and outdoor environments.
- TRVs were switched off throughout the house, with the exception of the studied zone, which was set to 5 (maximum).
- All other energy sources, including the use of a gas oven and DHW, were switched off during the experiment to ensure the actual record energy was only for the examined zone.
- The portable PRT was set to 23°C during the experiment; it was recognised by previous studies and standards the comfortable range of room temperature within 20°C to 26°C (Tulus et al., 2018, Melikov et al., 2013, ASHRAE, 2017, standard, 2012, Standardization, 2005).
- Table 7.3 shows the number and position of the IoT prediction system in every experiment.
- The actual and predicted data were captured at 15-minute intervals.
- The configurations of personal factors were set to 1 met for metabolic rate and 1clo for clothing insulation to comply with the average clothing insulation in the winter.

Table 7.3 experiments layout and setup, dwelling 2

ID	Date	Zone	Plan layout	IoTs
1	07/04/2021	Bedroom two		4
2	08/04/2021	Lounge		5

3	09/04/2021	Kitchen		5
4	10/04/2021			
5	11/04/2021	Bedroom 1		5
6	12/04/2021	Studio		5
7	14/04/2021	Basement		5
8	29/04/2021	Bedroom two		4

7.4 Results and analysis

7.4.1 Uncontrolled Whole-building Experiment (Dwelling One)

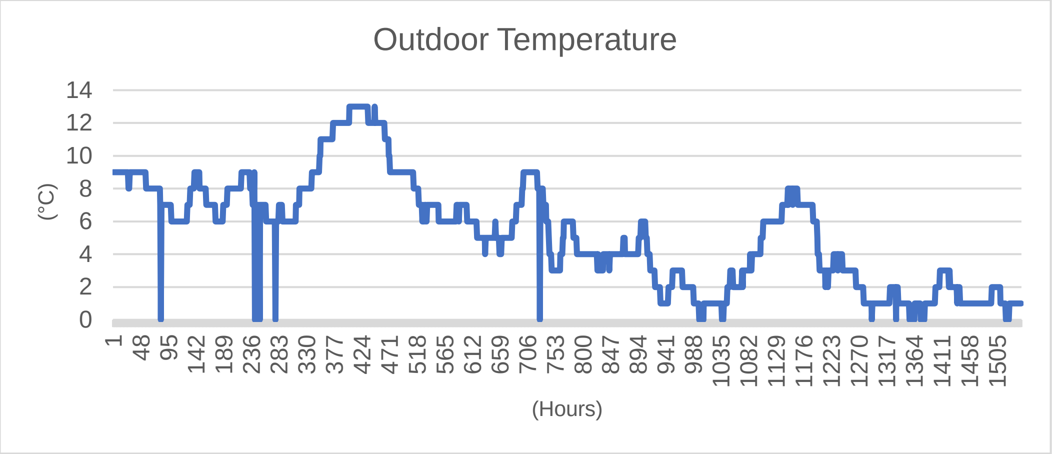
The IoT prediction system was implemented and operated on 07/12/2020. The environmental sensors in the system start collecting the temperature, humidity, and air velocity of the indoor environment and collecting the outdoor temperature, humidity, and wind speed of local weather from "weather.com" simultaneous. The two-module system calculates thermal comfort conditions and predicts energy usage in real time. Then, data were stored and visualised using the developed system. Finally, the actual gas consumption of the whole dwelling was recorded from the IHD. The following are the results and discussion of the uncontrolled experiment:

System setup and real-time evaluation, the IoT prediction system was in operation for 37 days, continually running and evaluating thermal comfort conditions and predicting energy consumption in real-time. The stored data from the local weather station and indoor environmental sensors, temperature, humidity and air velocity were analysed to verify any errors or missing values. Then the data were further investigated by analysing the thermal comfort calculation results and the energy prediction model results.

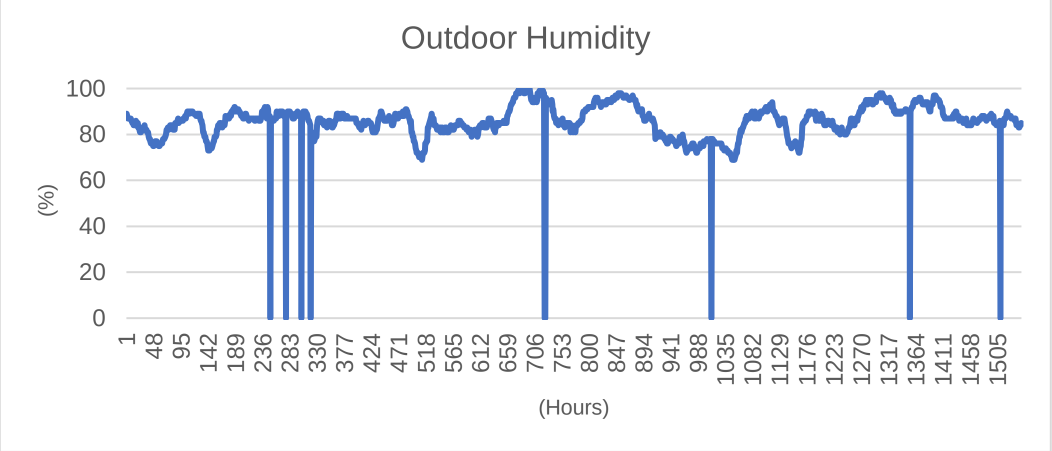
Analysing the recorded data from environmental sensors, DHT22 and the Rev. C sensor showed no errors or missing values in all deployed sensors. However, it has been observed that the approach used to measure the outdoor environment was failed to record the actual value of the local weather a few times; this was due to the system API could not fetch the data from the weather channel. Table 7.4 shows the errors recorded from collecting outdoor environment conditions from all sensors in the experiment over 37 days of operating. In addition, a line graph indicates outdoor environmental parameters that change over time during the experimental period, Graph 7.1 temperature, Graph 7.2 humidity, and Graph 7.3 wind speed.

Table 7.4 Record of missing values in weather data for dwelling 1

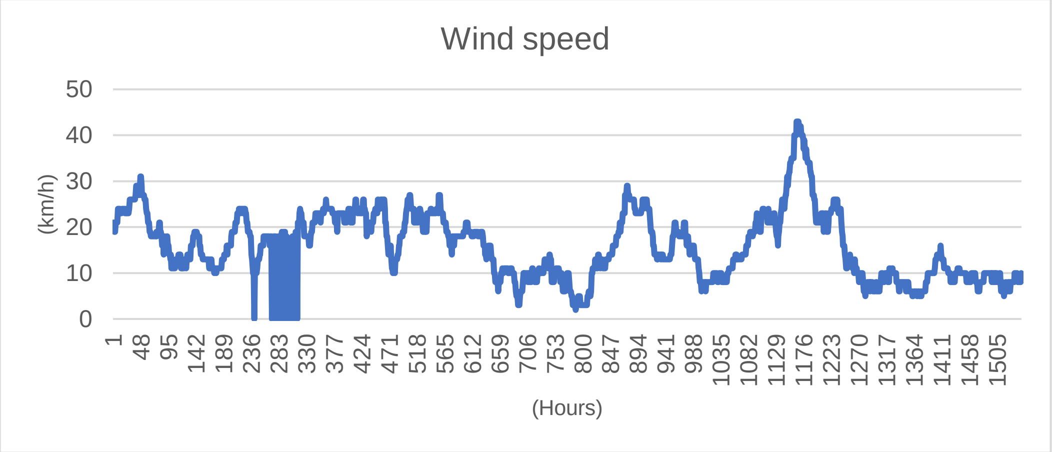
Outdoor environmental parameters	Missing values
Wind	12
Humidity	9
Temperature	7



Graph 7.1 Outdoor temperature in dwelling 1



Graph 7.2 Outdoor humidity in dwelling 1



Graph 7.3 Outdoor wind speed in dwelling 1

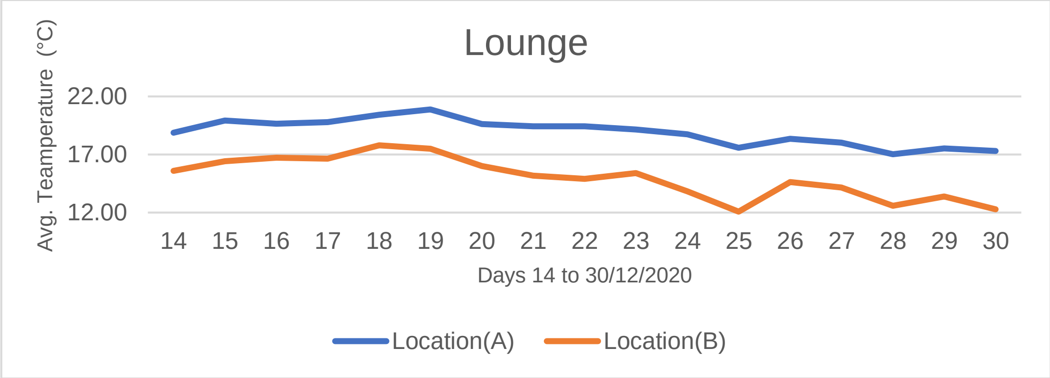
The data captured from the environmental sensors entirely controls the output of the thermal comfort module, PMV and PPD calculation. Thus, the results of thermal calculations showed no faults or missing values. Although no errors were recorded from the integrated sensors, any failures will impact the entire prediction system, not just the thermal comfort calculations. To this end, the energy prediction module's findings contained incorrect predictions due to the missing values from the outdoor environment. Nevertheless, the system continuously evaluated indoor thermal conditions and predicted energy consumption, apart from the limited flaws.

With all six sensors operating in real-time at 15-minute intervals, six days were selected for prediction results and a preliminary assessment to study the cause and effect of thermal comfort and energy performance and help validate the outcomes of the developed system concerning the proposed framework. During the experiment, actual gas consumption records were obtained from the IHD and used to analyse and compare the data from the energy prediction system. It is worth mentioning that because the uncontrolled experiment was conducted without any intervention, the actual energy consumption data include gas use for space heating, food cooking, and DHW. The data were analysed and compared as follows:

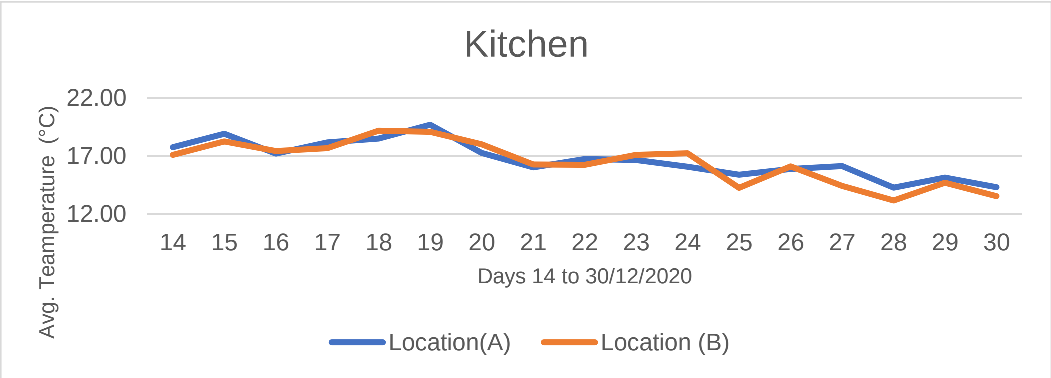
a) Analyse and compare results of sensors in the same room including, temperature, thermal comfort conditions and energy prediction.
b) Analyse and compare the actual energy consumption with the energy prediction and determine the energy performance gap.
c) Identify the energy performance differences between the prediction system close to the radiator, far from the radiator and actual gas consumption.

In the lounge room, the findings from thermal comfort conditions and indoor temperature revealed a four-degree difference between sensors in location (A) and sensors in location (B). In addition to less than 0.5 degrees temperature differences in the other rooms. The average daily temperature difference between sensors in locations (A) and (B) is displayed over time in Graph 7.4 lounge, Graph 7.5 kitchen, and Graph 7.6 bedroom.

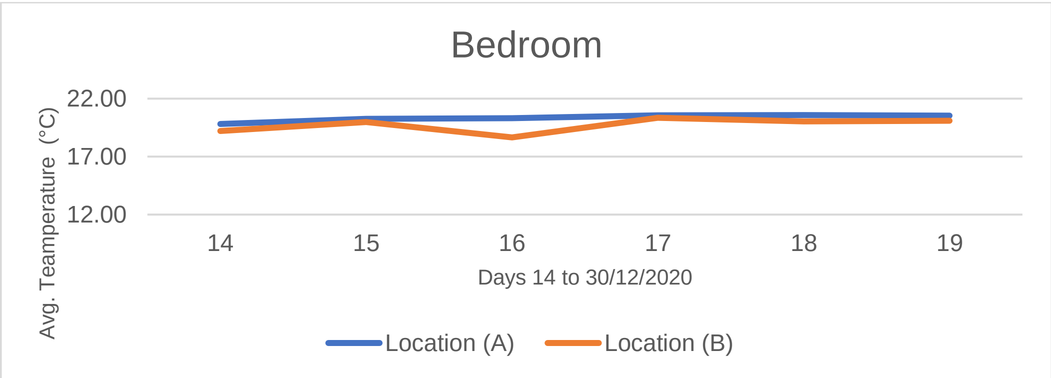
Thermal comfort (PMVs) calculations are also influenced by temperature differences between locations (A) and (B). This gap was also observed clearly in all rooms, especially the lounge.



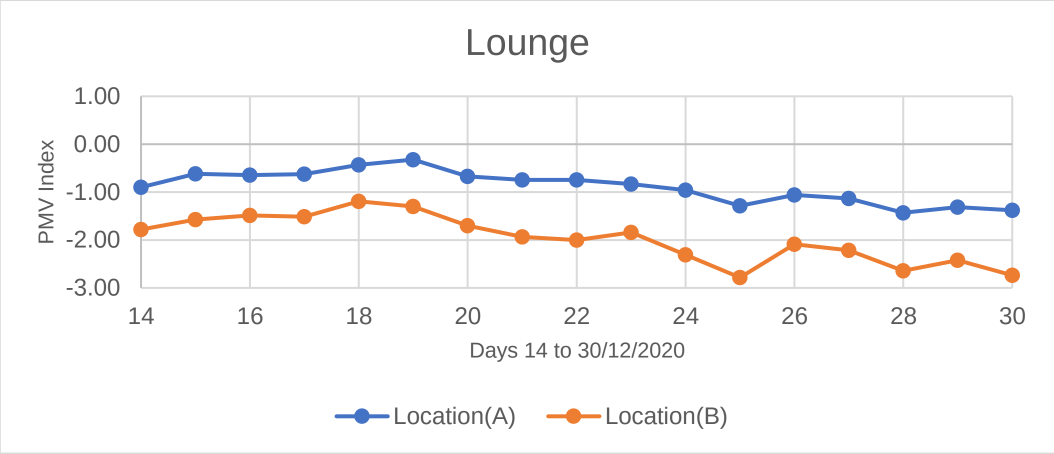
Graph 7.4 Average daily temperature difference (lounge) - dwelling 1



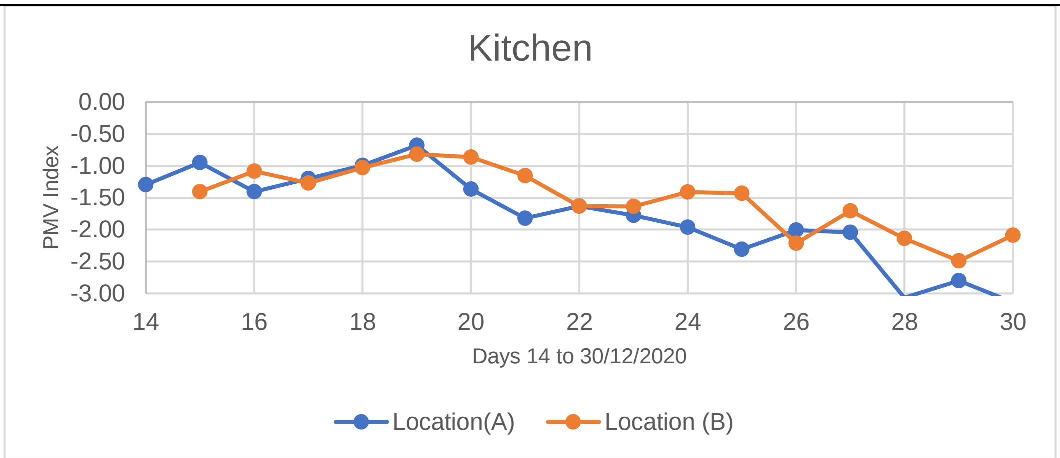
Graph 7.5 Average daily temperature difference (kitchen) - dwelling 1



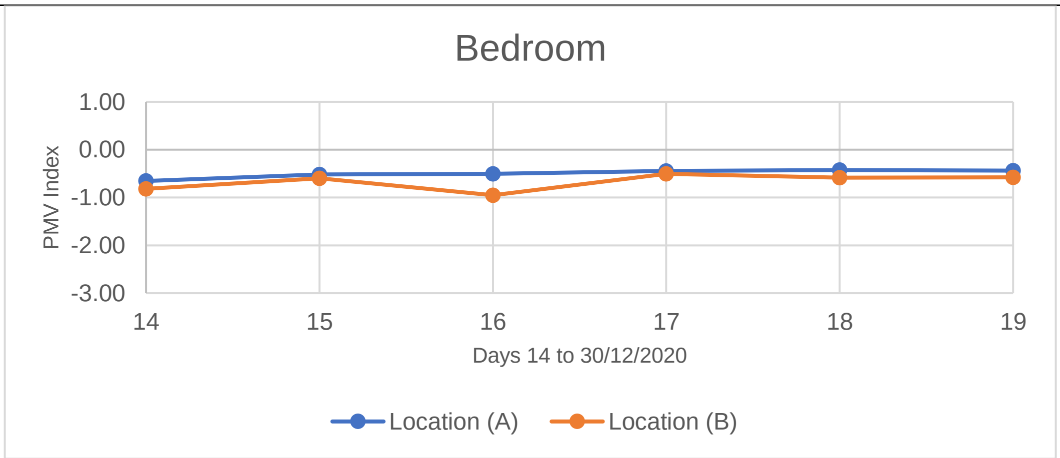
Graph 7.6 Average daily temperature difference (bedroom) - dwelling 1



Graph 7.7 Average daily PMV (lounge) - dwelling 1



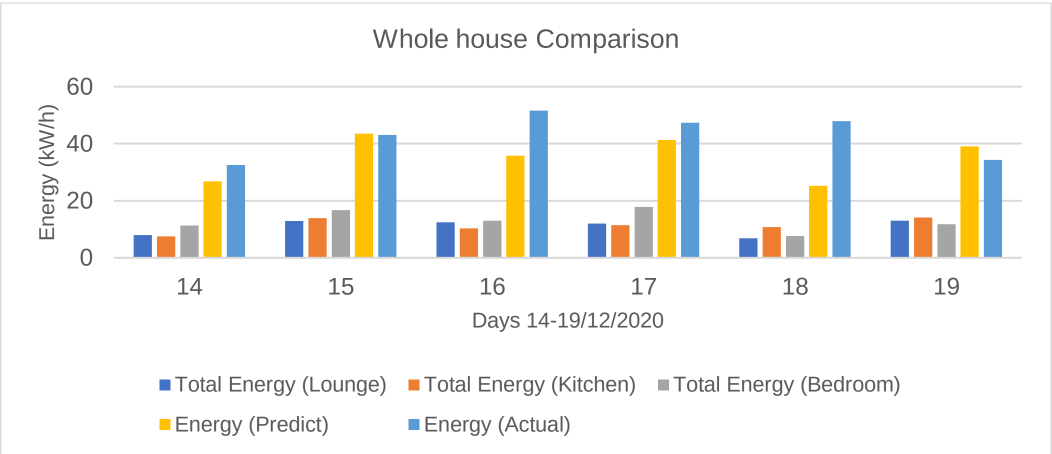
Graph 7.8 Average daily PMV (kitchen) - dwelling 1



Graph 7.9 Average daily PMV (bedroom) - dwelling 1

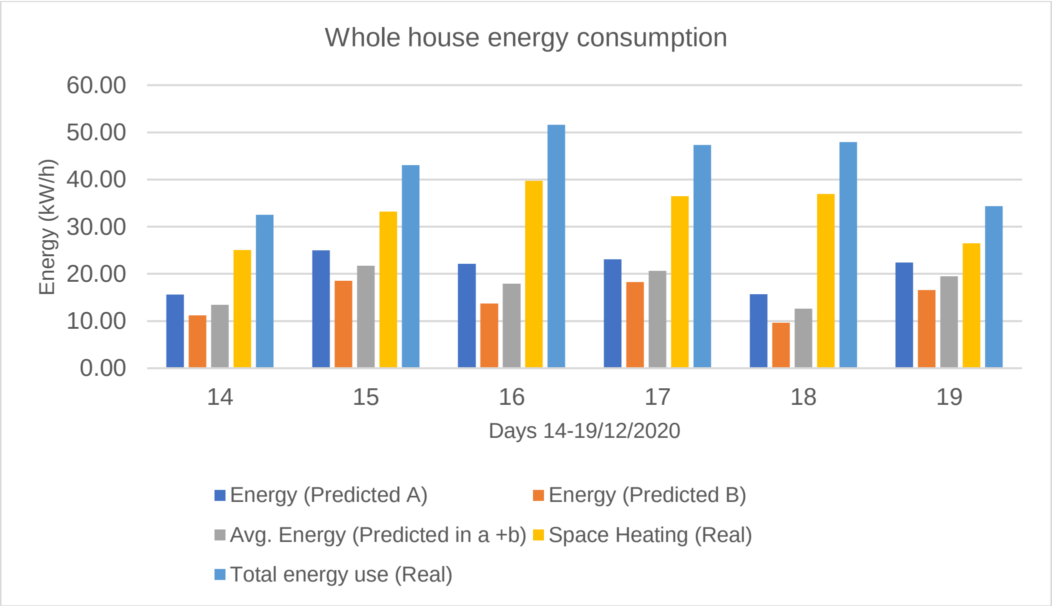
As shown in Graph 7.7 PMV readings in the lounge, thermal comfort conditions in location (A), close to the radiator better than location (B), far from the radiator. However, the PMV values in Graph 7.8 kitchen and Graph 7.9 bedroom were stable, primarily because the temperature distributions were even in the indoor environment during the experiment. Analysing rooms layout and measuring the distance between sensors showed that the distance between sensors in location (A) and location (B) was around 3.5 m in the lounge. In contrast, the distance was about 1.5 m in the kitchen and 2.5 m in the bedroom; this could explain why there were relatively substantial variations in the thermal condition of the lounge. Regarding energy prediction, higher energy consumption was observed in location (A) than in location (B) in the lounge.

It is important to point out that in this experiment, the actual energy consumption recorded from the IHD is for the whole house, including space heating, DHW, and food preparation. With that being mentioned, the energy prediction results were examined in three different approaches to detect and highlight the performance discrepancy. First, analyse the average daily energy consumption of both locations in the studied rooms and compare it with the actual energy use captured from the IHD. As shown in Graph 7.10, there is a small gap between a total of 16 % between prediction and actual energy consumption. In this experiment, in addition to the energy use for DHW and food cooking, data were not obtained from two other rooms with operated radiators, a bedroom and a bathroom, due to a shortage of IoT sensors. Even though the actual energy is higher than predicted by 16%, the results of the average daily prediction might overpredict energy consumption. Therefore, this method of analysis might be unreliable.

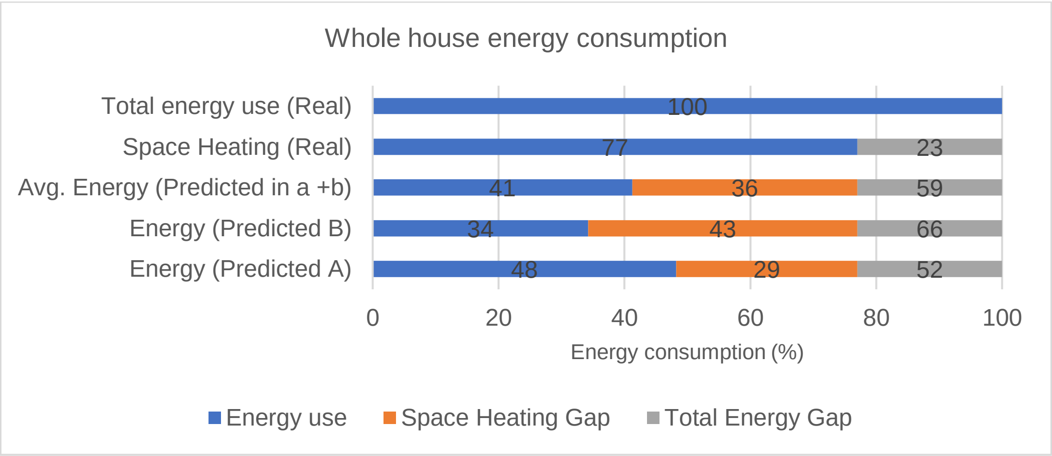


Graph 7.10 Comparison of Avg. Daily energy consumption & Actual energy use.

Second, a daily average of energy prediction in location (A) and location (B) was used to analyse and compare the data with actual energy use separately. Graph 7.11, this method revealed a 51% energy performance difference with the IoT prediction system in location (A) and a 65% energy performance gap in location (B). Furthermore, domestic gas usage for space heating accounts for about 77% of overall gas consumption (Statista, 2021, DECC, 2013). Thus, the third approach was to estimate the total actual gas consumption for space heating and compare it with the prediction results from the system, and the results are shown in Graph 7.11. The average performance of the studied zones during the focus period is calculated and compared to the actual energy use for space heating in Graph 7.12. The results showed a 29 % performance gap in location (A) close to the heat source, 43% gap in location (B) far from the heat source, and 36% by comparing the average of both locations to the actual energy for space heating.



Graph 7.11 Findings from a whole-house Energy consumption (Actual and predicted)



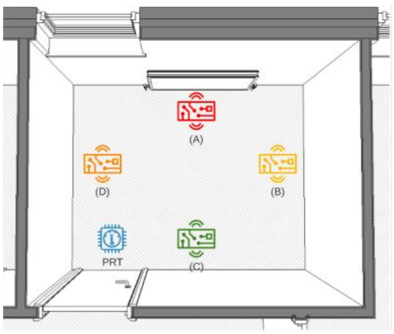
Graph 7.12 whole-house Energy performance (Actual and predicted)

7.4.2 Semi-controlled Zone-based Experiment (Dwelling Two)

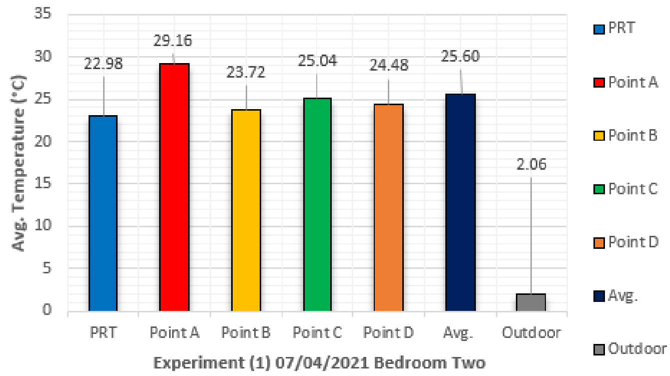
In the second dwelling, eight experiments were carried out across six zones, in which the actual and predicted energy consumption results were analysed and compared. The SMETS2 transmits a signal every half an hour; thus, the actual gas consumption data were captured every 30 minutes. Although the developed system recorded the data every 15 minutes, an average of the recorded data was calculated to follow SMETS2 transmits time for analyses purpose. In order to evaluate the performance of the predicted system, actual energy usage and ambient temperature were recorded. Temperature readings were acquired from portable PRT and gas consumption from IHD for space heating to represent the actual performance. The results of the experiments were analysed into two main groups: a comparison of indoor temperature and a comparison of energy consumption.

The first part of the analysis, a comparison of indoor temperatures, throughout all experiments, the heating setpoint was set to 23°C using PRT, and the TRV was set to maximum, equal to 28-30°C. This step was essential to ensure the portable PRT controls the thermal conditions of the studied rooms. Even though the heating strategy was the same, the recorded air temperature and the radiator performance varied in all the experiments. However, depending on the position of the PRT in the room in relation to the radiator location, there were distinct temperature differences across rooms. In addition, thermal comfort conditions in the indoor environment are affected by excessive temperature distribution, resulting in higher energy use and poor thermal satisfaction.

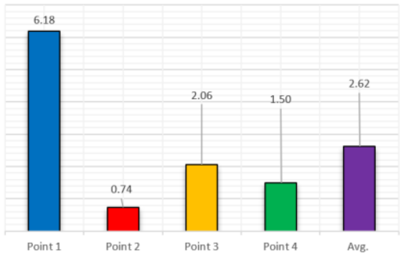
The first experiment was conducted in bedroom 2, which is relatively small, 6.75 m^2. Four sensors were set up. The portable PRT is located in the corner of the room between point (C) and point (D), as shown in Figure 7.9 (a). Even though the portable PRT attempted to maintain the heating setpoint across the room, the room heated up to an average of 25.6°C, which is 2.6°C higher than the set value Figure 7.9 (b). However, the temperature difference was 6.18°C higher in point (A) where the sensor was closest to the radiator Figure 7.9 (c). The variance indicates that the radiator heated the room continually until the portable PRT reading reached the desired temperature, as shown in Figure 7.9 (d).



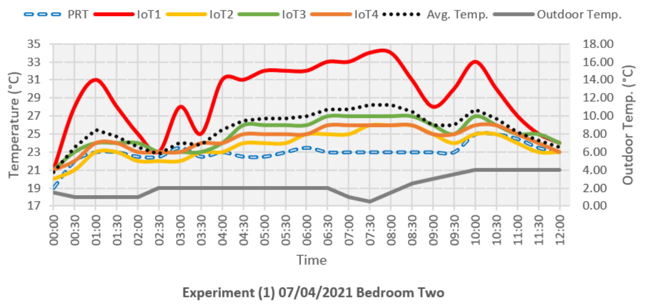
(a) Room layout



(b) Average air temperature



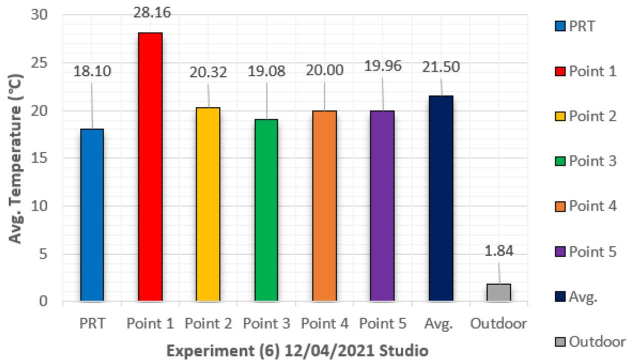
(c) Temperature differences



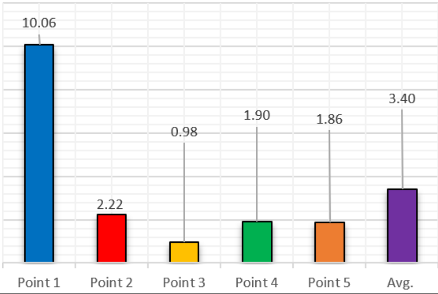
(d) Temperature readings

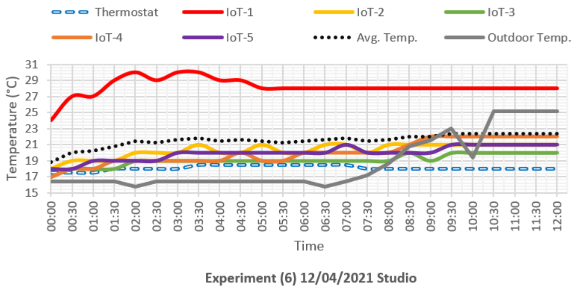
Figure 7.9 Results of the experiment (1), dwelling 2

In a large-scale room, experiment Six, the studio 22 m^2, the same phenomenon occurred. The portable PRT was located around 4 metres away from the radiator, where five IoT prediction systems were used, as shown in Figure 7.10 (a). The portable PRT reported the lowest average temperature of 18.1°C in the room, indicating that the heating setpoint of 23°C was not attained during the experiment. The average temperature was 21.5°C, with a 3.4°C temperature difference from the PRT, the higher temperature difference reported in all experiments. Moreover, the temperature reading in point (A) was the highest temperature difference with an average of 10.06°C. Since the TRV in the studio had reached its maximum level (28-30)°C, the average temperature recorded in point (A) was 28.16°C. A moderate result in temperature differences between portable PRT and the environmental sensors readings was found in experiments 2, 5 and 7. The average temperature difference was 1.10°C, 1.21°C, and 1.5°C, respectively; see Figure 7.12 (c), Figure 7.13 (c), and Figure 7.11 (c).



(a) Room layout **(b) Average air temperature**

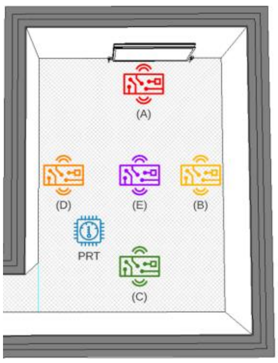


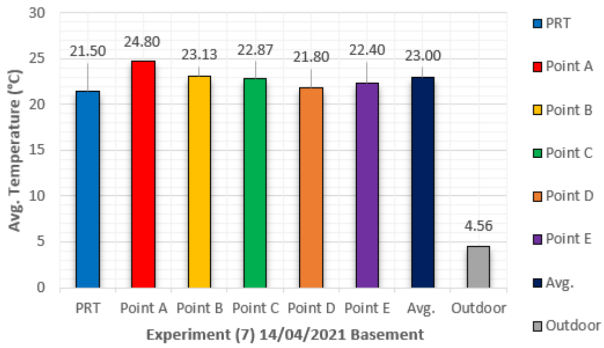


(c) **(d)**

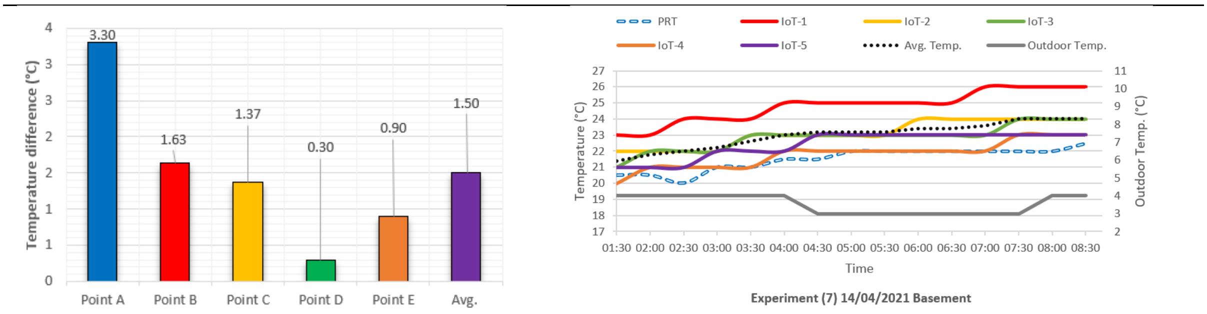
Figure 7.10 Results of the experiment (6), dwelling 2

In experiment 7, in the basement 12.5 m^2, five sensors were used, and the portable PRT was located 3 m away from the radiator, Figure 7.11(a). Despite the variations in temperature at different locations over time, the average temperature was 23°C during the experiment, as shown in Figure 7.11 (b) and (d). Although the portable PRT was not able to reach the setpoint temperature, the radiator could heat the room. In point (a), the reported temperature was 24.8°C with an average gap of 3.3°C to the PRT, see Figure 7.11 (b) and (c).





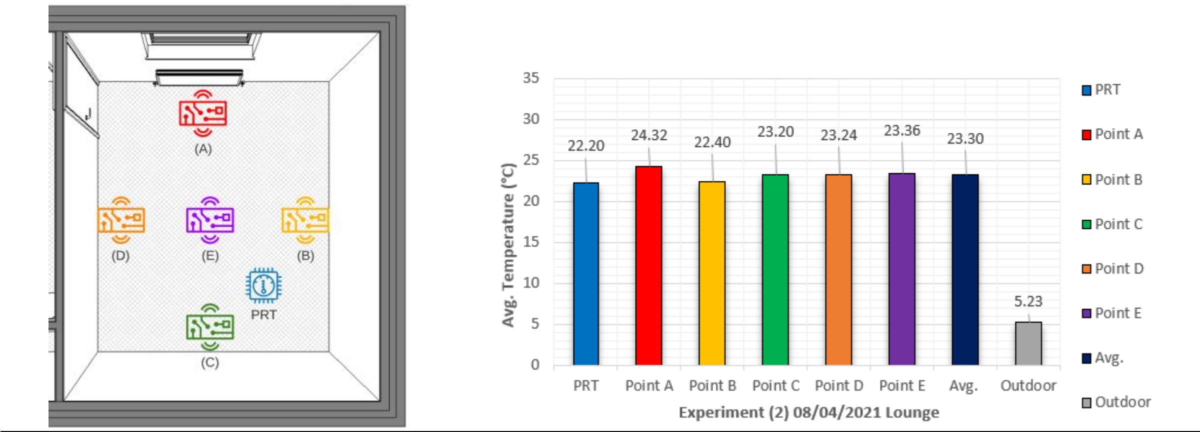
(a) **(b) Average air temperature**



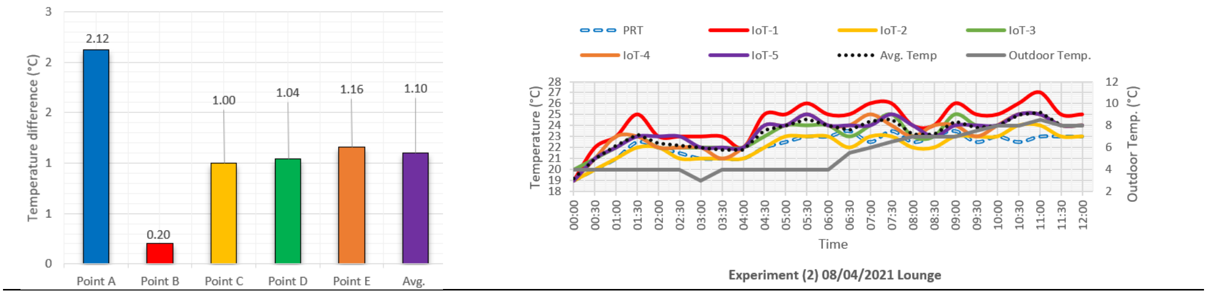
(c) **(b)**

Figure 7.11 Results of the experiment (7), dwelling 2

The results of experiment 2 (the lounge) and experiment 5 (the bedroom one) are extremely comparable. For example, both rooms are about the same size, with 14.5 m^2 in the lounge and 13.5 m^2 in the bedroom. The bedroom is on the first floor, right on top of the lounge. Moreover, the experimental setup is similar. The portable PRT was placed close point (D), with a distance of 2.5 m^2 in the lounge and 2 m^2 in the bedroom, see Figure 7.12 (a) and Figure 7.13 (a). The average temperature readings in point (A) were 24.32°C in the lounge and 25.2°C in the bedroom, with temperature differences of 2.12°C and 2.58°C to the PRT, respectively, Figure 7.12 (b and c) and Figure 7.13 (b and c). The thermal conditions were also maintained across the room in both experiments Figure 7.12 (d) and Figure 7.13 (d).

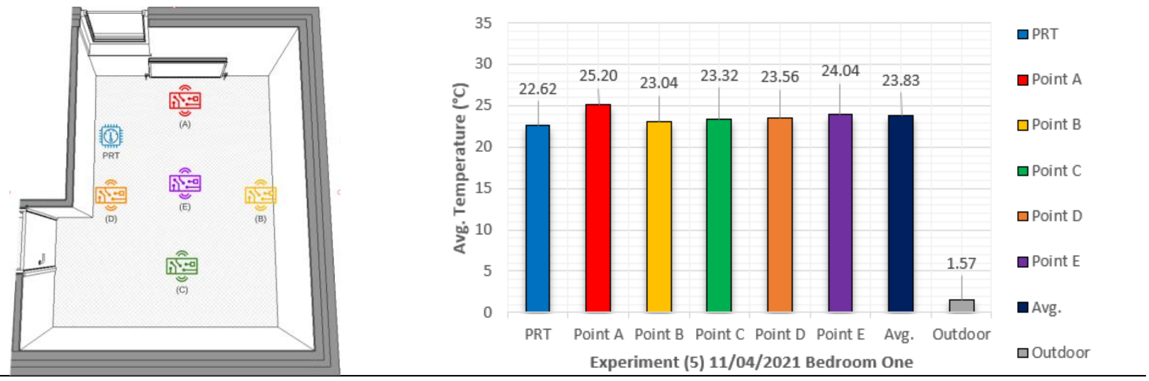


(a) Room layout **(b) Average air temperature**

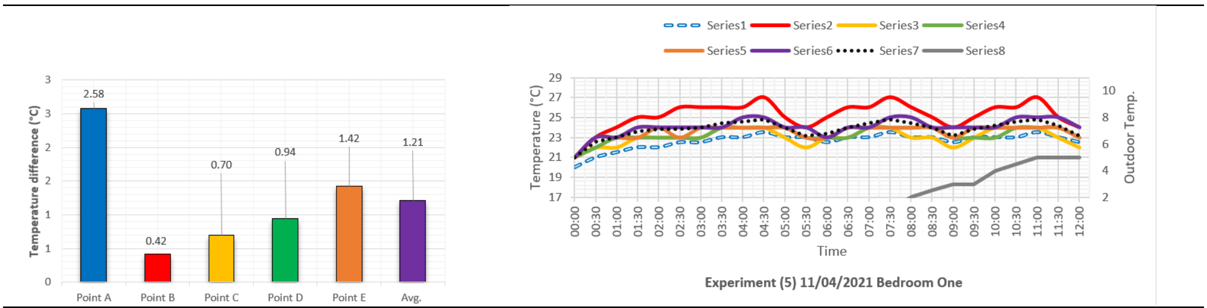


(c) Temperature differences (d) Temperature readings

Figure 7.12 Results of the experiment (2), dwelling 2



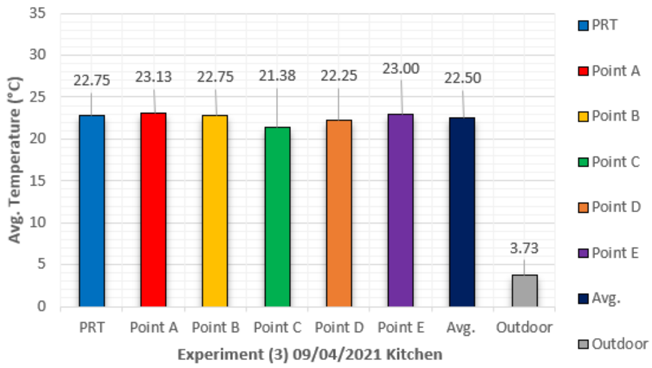
(a) Room layout (b) Average air temperature



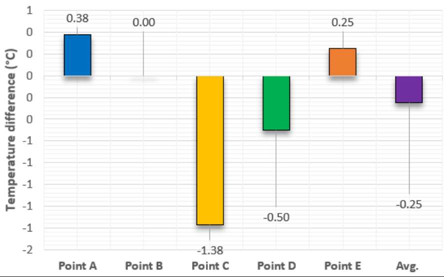
(c) Temperature differences (d) Temperature readings

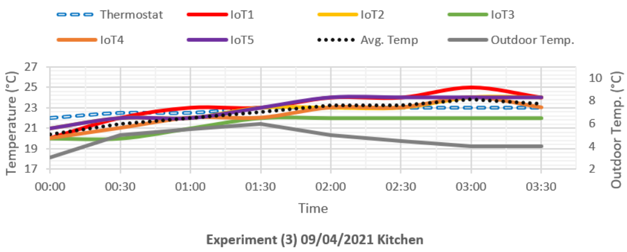
Figure 7.13 Results of the experiment (5), dwelling 2

Experiments 3 and 4 were carried out in the kitchen employing the same setup. Experiment 3 lasted 3.5 hours, and experiment 4 lasted 12 hours. Figure 7.14 (a) and Figure 7.15 (a) the PRT was located near point (B), about 2 m away from the radiator, and IoT prediction systems were utilised. Both experiments showed comparable results, with an average temperature of 22.5°C in experiment 3 and 22.7°C in experiment 4, Figure 7.14 (b) and Figure 7.15 (b). The temperature difference of -0.25°C and 0.24°C was the most intriguing finding of the kitchen's experiments; this explains the temperature variation was distributed equally across the room Figure 7.14 (c) and Figure 7.15 (c). As indicated in room layout, the sensor in (B) is close to PRT, and the reported average temperature differences were nearly identical. Furthermore, the average temperature recorded in point (A) was 23.13°C in experiment 3 and 23.72°C in experiment 4, which was too close to the heat setpoint by the portable PRT, Figure 7.14 (b) and Figure 7.15 (b).



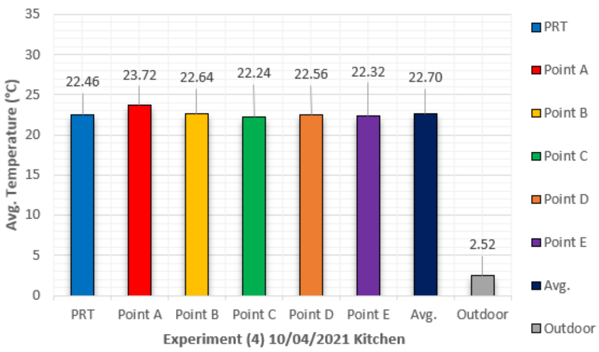
(a) Room layout **(b) Average air temperature**



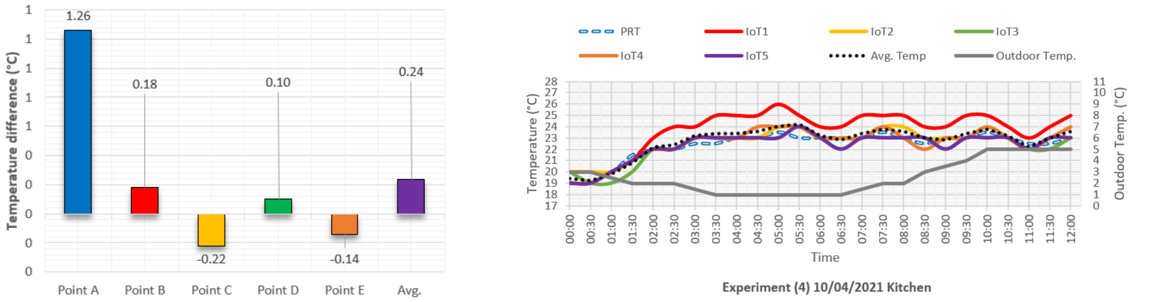


(c) Temperature differences **(d) Temperature readings**

Figure 7.14 Results of the experiment (3), dwelling 2



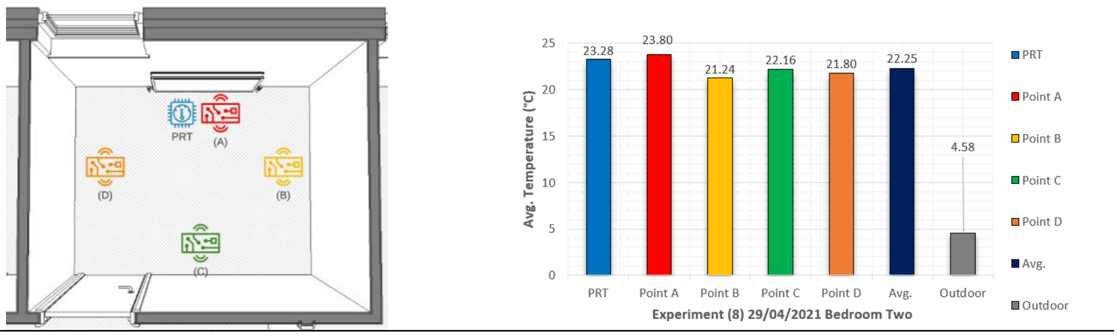
(a) Room layout **(b) Average air temperature**



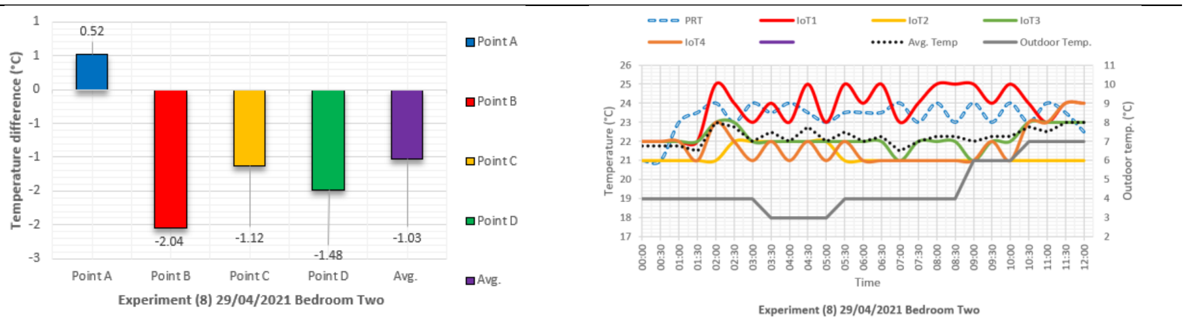
(c) Temperature differences **(d)Temperature readings**

Figure 7.15 Results of the experiment (4), dwelling 2

Experiment 8 is the second experiment in bedroom two. The portable PRT was placed near the radiator in point (A), as shown in Figure 7.16 (a). The average temperature difference was -1.03°C and 0.52°C between the portable PRT and the temperature reading in point (A) Figure 7.16 (b). Temperature readings reveal a lower temperature beyond the location of portable PRT Figure 7.16 (d). The temperature differences were -2.04 in point (B), -1.12 in point (C) and -1.48 in point (D), Figure 7.16 (c).



(a) Room layout **(b) Average air temperature**



(c) Temperature differences **(d)Temperature readings**

Figure 7.16 Results of the experiment (8), dwelling 2

The second part is an analysis and comparison of energy consumption. Figure ## shows the results from all eight experiments regarding energy performance. The figure contains two rows, a) average gas consumption, indicate findings from individual IoT prediction systems and the average prediction, b) and finding of energy performance, compearing actual and predicted results to quantify the gap between average and individual IoT prediction systems. Experiments 1 to 5 revealed that the energy gap between average prediction performance and actual use ranged from 20% to 39%, while the performance gaps from experiments 6 to 8 were much higher, 61% to 75%.

The big average performance gap in these experiments was analysed and explained. During experiments 6 and 7, as shown previously in Figure 7.10 (d) and Figure 7.11 (d), the portable PRT could not reach the setpoint of 23°C, and the radiators could not maintain a consistent temperature across the room. This can be explained in Experiment 6 since the studio is quite large, and a single radiator is not enough to heat the entire space. In addition, analysing results in experiment 7 showed that the same scenario occurred because of the room layout; there was a low air temperature coming from the stairway. Thus, the radiators in both rooms were insufficient to heat the entire space. However, the big average performance gap in experiment 8, bedroom two, was due to the portable PRT being placed close to the radiator point (A), preventing the rest of the room from reaching the setpoint, see room layout Figure 7.16 (a), temperature differences and Figure 7.16 (c).

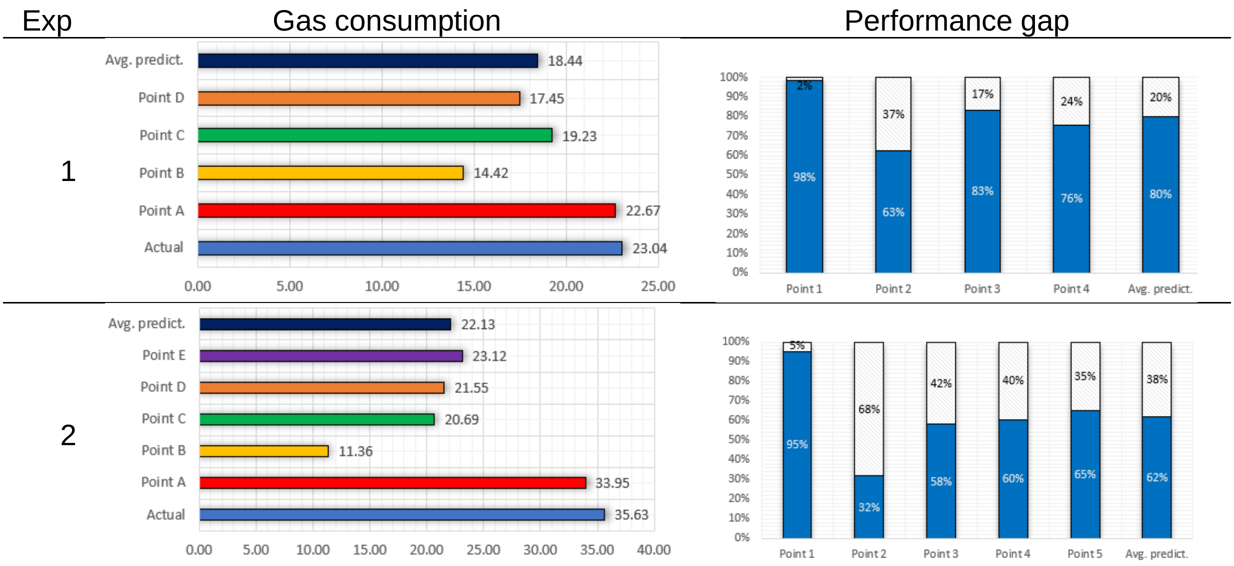


Figure 7.17 Gas consumption and performance gap in all experiments, dwelling 2

Following the analysis of indoor average temperature discussed previously, the setpoint value of 23°C was achieved cumulatively in the majority of the analysed zones. Nevertheless, the hourly chart indicates the setpoint was not always reached in all sensors at the same time. Accordingly, evaluating the energy performance gap based on the average performance of all sensors in the room is miss leading. The actual energy consumption the boiler uses to heat the water in the radiator's pipes is most likely reflected by the device close to the radiator regardless of the position of the PRT.

To this end, Figure 7.17 findings from all sensors in point (A) reveal interesting results. For example, in six experiments, the performance gap was less than 10%, experiments 1,2,3,4,6 and 8. In experiment 7, the basement was 24%, and in experiment 5, bedroom one was 44%. Therefore, the majority of the experiments reach a 10% performance gap. The data collected from the IoT systems in point (A) reveal that the performance gap is better the closer the IoT prediction system is to the radiator.

However, in one experiment, the IoT prediction system failed to perform well in point (A). Figure 7.17 experiment 5, the bedroom one, a higher gap was recorded from point (A) in all experiments. By analysing the data, two key findings emerged; first, experiment 5 was the only experiment that overpredicted gas consumption by 11.86 kWh over the actual usage; second, point (A) in the same experiment indicated a higher temperature than other sensors in all experiments. The source of the poor performance was identified by investigating the experimental setup and room layout in bedroom one; it was discovered that the bedframe was blocking the radiator, which was the reason for locating the sensor on top of the bed frame. Thus, the IoT prediction system was placed 10 cm away and height of 30 cm from the radiator.

Furthermore, the overall temperature and energy prediction findings revealed a clear connection between the location of the IoT prediction system, temperature, and performance gap. For example, analysing average temperature differences in experiments 1, 6, and 7 showed the highest temperature difference among other experiments with 2.62°C, 3.4°C, and 1.5°C. In addition, points (A) in the same experiments reported the highest temperature difference, 6.18°C, 10.06°C, and 3.30°C. Reviewing the room layout and the location of the PRT revealed that it was located from the radiator. To this end, Table 7.5 and Table 7.6 showed that point (A), which was reported to be the nearest to the radiator, have a better performance gap with a higher temperature. Meanwhile, a maximum performance gap was detected at a remote location with inadequate temperature distribution.

Table 7.5 Performance gap (Minimum and Maximum)

Experiment	Room	Min performance gap		Max performance gap	
1	Bedroom two	2%	Point A	37%	Point B
2	Lounge	5%	Point A	68%	Point B
3	Kitchen	10%	Point A	62%	Point C
4	Kitchen	0%	Point A	52%	Point C
5	Bedroom one	15%	Point E	44%	Point A
6	Studio	10%	Point A	100%	Point E
7	Basement	24%	Point A	80%	Point D
8	Bedroom two	8%	Point A	87%	Point B

Table 7.6 Room temperature (High and Low)

Experiment	Room	High temp. (°C)	Location	Low temp. (°C)	Location
1	Bedroom, two	29.16	Point A	23.72	Point B
2	Lounge	24.32	Point A	22.4	Point B
3	Kitchen	23.13	Point A	21.375	Point C
4	Kitchen	23.72	Point A	22.24	Point C
5	Bedroom one	25.20	Point A	23.04	Point B
6	Studio	28.16	Point A	19.08	Point C
7	Basement	24.80	Point A	21.8	Point D
8	Bedroom two	23.80	Point A	21.24	Point B

7.5 Summary

The proposed framework is implemented in two-stage experiments (uncontrolled and semi-controlled). The uncontrolled experiment investigated the durability and applicability of implanting the framework for real-time prediction over 37 days. The uncontrolled experiment was a whole building investigation in a typical terrace house in the UK. The semi-controlled experiment conducts a zone-based investigation by implementing the framework in individual rooms. Eight experiments were conducted to evaluate the accuracy of the prediction system and generally identify the thermal comfort conditions and performance issues in domestic buildings. The chapter discusses the implementation including, the physical characteristic of the building, parametric modelling and ML development. Present the experimental setup, including room layout, IoT distribution plan and other equipment and tools uitlised for data capture. Then, analyse the collected results of both experiments to conclude.

Chapter 8

Discussion

Buildings underperform when compared to predictions in the design stage. The discrepancy between actual and intended design is called the performance gap (Carbon Trust, 2011, de Wilde, 2018). The term performance gap is widely used in the context of energy performance, but its meaning is unclear. The extent and source of the gap can vary depending on the reference standard or the calculating protocols used (Burman, 2016). The variabilities in simulation outputs are expected due to assumptions made during the design stage. However, the discrepancy scale is extensive and reduces the confidence in simulation outcomes (van Dronkelaar et al., 2016). An energy prediction model, an accurate virtual representation of a building, operates as a real-time simulator and can be used to investigate and identify building performance issues.

Following this background, the chapter introduces the key findings with links to the scope of the study, aim, and objectives described earlier. The primary aim of this study was to develop a technical implementation framework for exam the energy consumption of space heating in real-time, focusing on energy-related thermal comfort conditions at the zone level. An approach to integrating different technologies, computer simulation, machine learning, and the internet of things was utilised to achieve that aim. In this section, framework development is first presented in the next section, followed by a discussion of the individual objectives, chapter 1.

1. Create a digital replica of an existing dwelling and define the primary parameters for performance simulation.
2. Devise and implement a framework that can predict the energy consumption of multiple scenarios for space heating at a zone level.
3. Produce a real-time system to assess thermal comfort conditions in the indoor environment.
4. Explore the developed integrated module and improve the validation approach for real-time implementation in the indoor environment when used for energy performance prediction.
5. Examine the finding from different experiments and validate the prediction results against the actual performance.

8.1 Framework Implementation

The framework was developed to be structured, procedural and replicable, was applied to multiple experiments. The energy performance and the comfort conditions were analysed by focusing on key aspects: a) The durability and applicability of framework implementation and the developed system; b) Analysis of performance gap findings to validate the prediction results and to identify the common issues across experiments which cloud be applied to other domestic buildings; c) Report the performance issues related to the thermal condition in the indoor environment and the cause of higher energy performance in space heating.

8.1.1 Data collection and digital modelling

Objective 1. Create a digital replica of an existing dwelling and define the primary parameters for performance simulation.

The real-time energy consumption prediction based on the thermal comfort conditions approach that was developed in this study was implemented in two domestic buildings. The buildings selected include a range of representative rooms found in most UK homes, which can provide insights into the causes of performance issues in the domestic sector. First, the study conducted an initial investigation focusing on the energy sources and modelling approach connected to space heating, especially gas consumption, since it is a common type of space heating in the UK. Several BPS tools, energy engines and digital modelling tools were investigated, focusing on digital energy modelling, energy-thermal related parameters, and environmental control parameters. Then, to acquire the data needed for digital modelling, a site survey was done for both buildings. Physical measurements of building layout, geo-location, orientation, building services and other utilities that may cause or influence space heating are included in the data collection.

Different approaches and methods of energy modelling were also investigated to find the proper practice to replicate the existing state of the dwellings. For example, two modelling techniques were investigated using Autodesk Revit. The first model was produced using Revit's standard components, while the second was created using basic and customised geometry. The main objective was to determine the most appropriate modelling approach to support the gbXML schema for data exchange. In addition, to replicate the dwellings' current state, basic geometries representing the site surrounding was considered in the model. Both models are exported to DesignBuilder-EnergyPlus for advanced energy modelling using the gbXML schema, as described in Chapter 6. The findings of the first model revealed that throughout the data exchange process, geometric information was lost, gaps between inner volumes were developed and misformed and misaligned surfaces were created. Thus, the model must be fixed before it can be used in energy simulations. The second Modelling approach was found to be simpler and had fewer issues than the first approach, Figure 8.1. Accordingly, this approach was selected as the primary modelling technique for the next stage of advanced energy modelling.

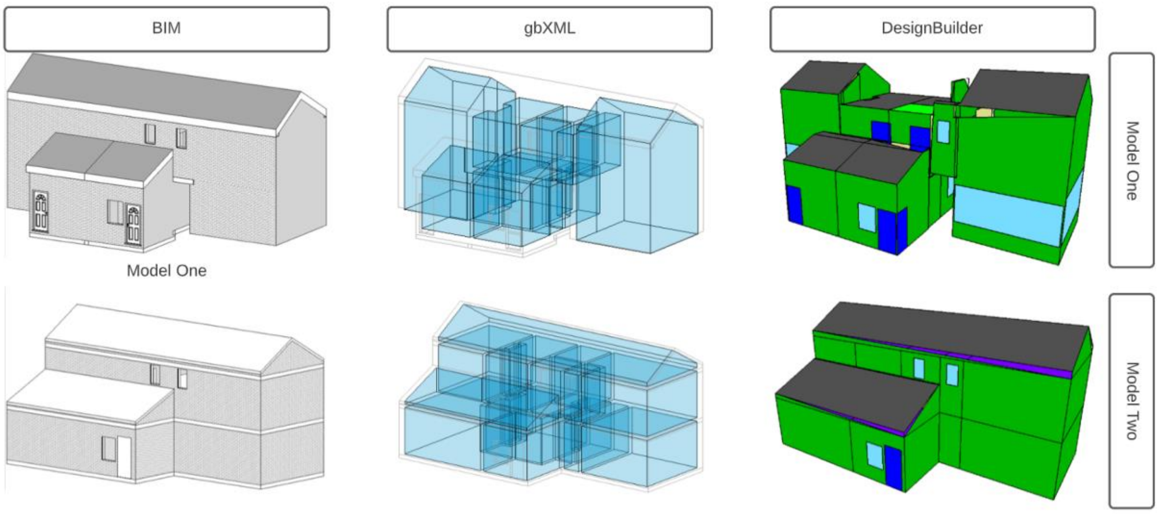


Figure 8.1 investigating modelling and data exchange using gbXML

8.1.2 Energy modelling and parametric simulation

Objective 2. Devise and implement a framework that can predict the energy consumption of multiple scenarios for space heating at a zone level.

The framework utilised energy modelling to create a dataset necessary for the aim of this study. Building energy analysis tools are used in the design stage to anticipate Building performance. Energy modelling is different from modelling for architectural design or construction documentation. It is mainly focused on the thermal characteristic of building's elements. Despite various energy analysis tools, they are fundamentally based on the same mathematical calculation—the level of complexity is mainly related to the precise information input they offer to the user. As described in chapter 6, EnergyPlus is one of the popular tools utilised by the industry and the research community. In addition, because of the poor interface that EnergyPlus provides, many other tools are built on top of EnergyPlus to enhance user experience, and DesignBuilder is one of them. Therefore EnergyPlus, based on the DesignBuilder interface, was utilised in this research

DesignBuilder-EnergyPlus is used to develop advanced energy modelling to create a dataset for energy prediction using ML. Although the performance gap issues in EnergyPlus well documented, the research used performance gap as a metric to evaluate the proposed approach. A number of steps were followed to create the dataset; first, energy modelling usually works with simplified geometries to produce reliable results; after data exchange, a healing process was performed to simplify geometries and fix modelling gaps, such as the gaps in the roof in Figure 8.1. Second, project outdoor environmental conditions were defined by the location, building orientation and providing weather data. Finally, the model uses the software's standard template for the building material, and the values were selected carefully to replicate the thermal transmittance of the building's elements.

Energy simulation tools are usually used to perform a whole building energy analysis, in which the output of the tools includes the overall energy consumption of the building. However, the research focuses on the changes of thermal conditions in the individual rooms and the amount of energy usage accordingly. Therefore, to overcome this issue, a zone-based simulation was performed to calculate energy consumption for every room; zones in the energy model represent rooms in the building. In DesignBuilder-EnergyPlus, all zones are included in simulations by default. Nevertheless, it offers the possibility of excluding a zone or series of zones and focusing on some part of the building. During the simulation, Surfaces between the included and excluded zones were considered adiabatic, which constrain the heat exchange between building's zones; for example, heat exchange through the wall mass occurs as if the temperature of the excluded zone is the same as the temperature of the included zone (DesignBuilder, 2021). To this end, the output simulation of the zone-based simulation was a simulation report only for the zones included in the thermal calculation.

DesignBuilder utilised a user interface to amend the EnergyPlus input data file (IDF) in this study. Thousands of energy simulation jobs were run using a parametric design tool, JEPlus. A complete dataset was created using JEPlus-EnergyPlus, which included all potential operational scenarios. In addition, examining EnergyPus data input for indoor environment control assist in determining design parameters that influence indoor thermal conditions and account for energy consumption, Table 7.1. These parameters were employed in the parametric simulation to generate a dataset for the next stage. Because each room in the building is unique (e.g., location within the building, orientation and opening, materials and walls), it requires creating a dataset for each one. Hence, utilising the proposed approach will be a challenge. For example, in the first dwelling, three rooms were investigated. Each room requires the execution of 2100 simulation jobs divided into seven batches. Each batch includes 300 simulation jobs with three design parameters for temperature and 100 parameters for indoor humidity from (1-100%). Temperature and humidity were the only indoor environmental parameters used by energy tools to control indoor environment conditions. Moreover, the utilisation of humidity control assumed in the simulation, even there was no humidity control in the building, support the generation of a wide range of values from different indoor environmental factors that can provide a rich dataset for machine learning. Finally, the simulation time was estimated to be 16 minutes for 300 jobs, and output data were merged and saved as CSV for the next stage.

The AzureML cloud-based technology was used to develop the energy prediction model. The created dataset from the parametric energy simulation was used in the development of the ML model and to support the real-time energy prediction for indoor space heating. The platform is a cloud application and machine learning development environment that provide a server-side endpoint for real-time integration. The development of the energy prediction model was done using a regression algorithm. Five regression models were developed based on different regression algorithms, Bayesian Linear Regression, Boosted Decision Tree Regression, Decision Forest Regression, Linear Regression, and Neural Network Regression, before selecting Decision Forest Regression. A detailed discussion of scoring metrics and model evaluation is in chapter 6. In this study, nine prediction models were developed for every investigated room, three models for dwelling one, a lounge, a kitchen and a bedroom, and six models for dwelling two, a lounge, a kitchen, bedroom one, bedroom two, a studio, and a basement. The prediction models were cloud-based and integrated into the IoT system through an API. The ML cloud-based application required seven parameters to predict energy consumption, including three outdoor parameters, dry bulb temperature, relative humidity, and wind speed, and four indoor parameters, PMV, PPD, temperature, and humidity.

8.1.3 IoT prediction system

Objective 3. Produce a real-time system to assess thermal comfort conditions in the indoor environment.

The developed IoT system comprises environmental sensors, wireless technology and a microcontroller. The system captures environmental data and calculates thermal comfort using a fanger PMV/PPD index, used in most international standards to evaluate indoor thermal comfort. After that, the data is stored for visualisation and real-time analysis. The thermal comfort model was developed and evaluated against the CBE Thermal Comfort Tool (Tartarini et al., 2020), more detail in chapter 5. For real-time energy prediction, as explained earlier, seven parameters were used. These parameters were passed to the cloud-based prediction application through the IoT system. Then, the results from the prediction model are stored in the database. Evaluating the system for real-time prediction was made in the uncontrolled experiment for 37 days. The findings revealed no system errors in data capturer, PMV and PPD calculation and energy prediction, section 7.4.1.

8.2 Energy and thermal comfort performance evaluation

Uncontrolled and semi-controlled experiments were utilised to evaluate the performance of the built IoT system and identify issues in energy and thermal conditions. Before evaluating prediction accuracy, the system was examined to identify technical implementation faults.

8.2.1 Technical evaluation

Objective 4. Explore the developed integrated module and improve the validation approach for real-time implementation in the indoor environment when used for energy performance prediction.

The uncontrolled experiment was used to test the durability and applicability of the system to capture both outdoor and indoor environmental parameters, calculate PMV and PPD, and predict energy consumption accordingly. Generally, the findings in section 7.2 showed no technical error in the developed system. However, there were a few flaws in collecting outdoor data from the weather website Table 7.4, which were overcome in the semi-controlled studies using outdoor environmental sensors. The uncontrolled experiment diagnosed the system's technical performance, identified bugs, and fixed them for the following experiments. Sensors captured and stored data efficiently in eight experiments over 96 hours of operation in the semi-controlled experiment. In addition, thermal comfort equitation and energy prediction models were performed successfully with no technical faults.

8.2.2 Performance evaluation

Objective 5. Examine the finding from different experiments and validate the prediction results against the actual performance.

Analysing the findings from the experiments (Whole-building, Zone-based) in both dwellings provides an opportunity for robust assessment of the energy prediction performance and quantifying thermal conditions to the amount of energy consumption. The accuracy of the prediction results was determined by comparing them to actual energy use. Graph 7.12 the findings from the uncontrolled experiment investigating whole-building performance showed three different results, where (A) near the radiator and (B) far from the radiator:

- The average energy prediction of (A) and (B) was 36%
- Energy prediction in (A) was 29%
- Energy prediction in (B) was 43%

It is worth mentioning, in the uncontrolled experiment, two rooms with radiators in operation were unable to collect their data due to sensor shortages.

Figure 7.17 The findings from the semi-controlled experiments revealed similar results:

- The Average energy prediction was (20% to 28) in two experiments, 35% to 39% in 3 experiments, 61% to 75% in 3 experiments.
- Energy prediction in (A) was less than 10% in 6 experiments, 24% in 1 experiment, and 44% in 1 experiment. The 44% performance gap in experiment 5 was discussed in section 7.4.2. Furthermore, this experiment was the only experiment that overpredicted energy consumption.

The average energy prediction reflects the position of the IoT system. For example, prediction results are affected by placing the sensor in a poor thermal location. A good energy performance gap was achieved when the sensor was close to the radiator. To this end, the accuracy of the prediction system depends on its location in relation to the radiator in the room. However, a good performance gap does not mean the temperature is evenly distributed in the room.

The portable room thermostat was used to control thermal performance in the zone-based experiments. It was observed in some experiments that thermal reading and prediction results beyond portable PRT were lower than the rest of the room, such as experiments 8, 4, 3. So it is clear there were temperature distribution issues that affected thermal performance.

Temperature variations are investigated by analysing room layout, size, air volume, and sensor placement, resulting in an unpleasant indoor environment. The findings revealed that the position of the PRT is essential to ensure a better temperature distribution across rooms.

- Generally, IoT systems in point (A) recorded a higher temperature than the setpoint.
- Even though the PRT was set to 23°C, The radiator was operating to heat the room until the ambient temperature reached the desired temperature, at which the PRT was placed.
- The IoTs near the PRT recorded the lowest temperate differences, such as experiments 3, 4, 7 and 8
- The temperature dropped lower than the heating setpoint when the PRT was near the radiator.
- The radiator could not heat the room beyond the TRV setpoint even if the PRT setpoint were not reached.
- The results exposed that the position of the PRT, the layout, and the room's size is essential factor that affects thermal condition in the indoor environment.
- Temperature variation across the room indicates that one radiator is insufficient to distribute the temperature evenly.

Furthermore, several performance issues related to the central heating system were identified

- Apart from the system's efficiency, its operational method does not equally distribute temperature across the room; in small rooms, experiments 1 and 8.
- If the room thermostat reaches the setpoint, it will prevent other rooms from reaching the same setpoint. Therefore, the location of the PRT has a significant impact on the thermal condition and temperature distribution. For example, In experiment 8, the PRT reached the setpoint sooner because it was close to the radiator; in experiments 6 and 7, the PRT could not reach the setpoint because the TRV had already reached its own setpoint.
- The PRT controls the central heating system that is responsible for gas consumption.

The findings of high and low-temperature differences in Table 7.6 revealed performance issues in thermal conditions and energy consumption. For example, suppose the gap between high and low temperatures is significant; in that case, there is an issue with the thermal condition in the room, which might lead to higher energy consumption or occupant dissatisfaction. The relationship between PRT and radiation is illustrated in Figure 8.2

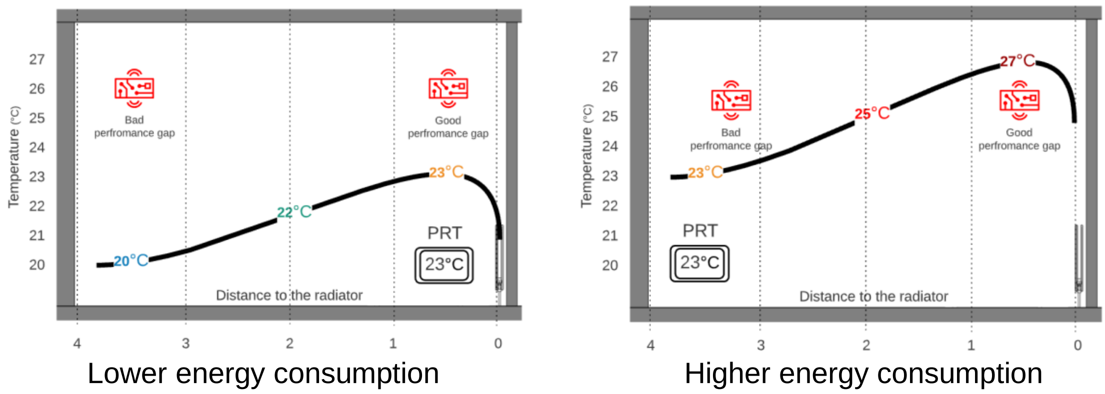


Figure 8.2 an illustration of the relationship between PRT and radiator

8.2.3 Final framework

Following the findings from both experimental stages (whole building experiment and zone-based experiments), the final framework of this study is developed. The final framework provides a guideline for predicting in real-time space heating energy consumption in domestic buildings by evaluating thermal comfort conditions. As the study focused on computer simulation, the framework offers an approach to extend building performance simulation to the operational stage. In addition, the framework involves the utilisation and integration of sensor technologies through the internet of things, machine learning approach, and building energy analysis tools. Finally, the analysis and lessons from implementing the initial proposed framework support the formulation of this final framework.

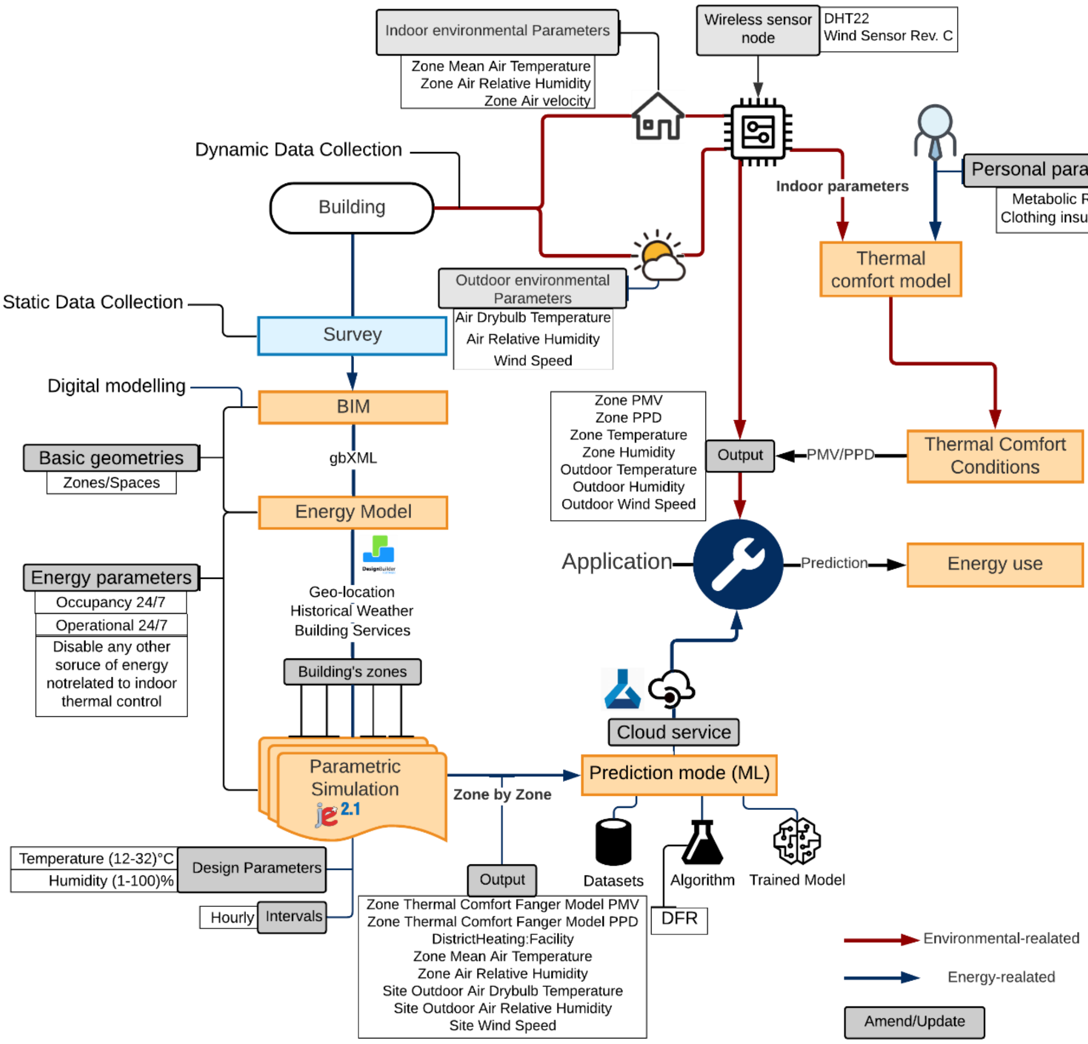


Figure 8.3 Final framework

8.3 Summary

This chapter discusses research findings and the development of the final framework. The initial framework was implemented in two-stage experiments (uncontrolled and semi-controlled), with several processes discussed. The findings from the uncontrolled experiment examined the durability and applicability of the implemented work. Meanwhile, the semi-controlled experiments provide an in-depth analysis of the accuracy of the prediction. Moreover, the finding provides an insight into the performance of space heating systems in domestic buildings. Finally, findings from individual experiments establish some similarities and differences that can draw an initial understanding of the performance issues in thermal comfort conditions and energy use.

Chapter 9

Conclusion

The overall global energy consumption in the construction industry accounted for 35%, and domestic buildings are responsible for 22% of it. Providing a healthy, productive environment in domestic buildings raised energy demand by about 80% in building operation, with thermal comfort accounting for about half. Moreover, it is evidenced that building energy consumption can be 5 to 10 times higher than energy predictions made during the design phase. The work presented in this research, the detailed analysis of thermal comfort conditions and energy performance on multiple indoor environments in domestic buildings, provide insight into the performance issues for indoor space heating. In addition, identifying and verifying performance issues using the developed technical implementation framework increases the possibility of determining operational issues in real-time. The developed framework extends the use of the energy model to the operational stage by predicting thermal and energy performance following indoor and outdoor environmental parameters. Moreover, using a parametric energy simulation and machine learning approach connected to an IoT sensor system enable users to identify thermal comfort conditions in the indoor environment and the amount of energy consumed for space heating.

The research identified several lessons that can potentially inform and improve the existing domestic buildings, especially for winter space heating. The outcome of the performance issues, thermal and energy efficacy, are likely unique to the studied dwellings. However, the significance of finding the balance in the operating of thermal heating for better energy performance and indoor environmental quality applies to the construction industry as a whole.

9.1 Key findings

The work presented in this study is a technical implementation framework for examining the energy consumption of indoor space heating in real-time, focusing on energy-related thermal comfort conditions at the zone level. Buildings with good IEQ are objectively assessed using simulation tools. However, The IEQ, especially thermal comfort, is experienced subjectively, making the building energy and thermal performance evaluation task challenging. In order to address this, A framework developed was based on two fundamental modules, thermal comfort and energy prediction. To this end, the key finding has been categorised into the thermal comfort module, energy prediction module, and experiments.

9.1.1 Finding from the thermal comfort module

The framework of the thermal comfort module is shown in Figure 9.1**.** The following are the finding from the development of the thermal comfort module:

- The thermal comfort model used for the indoor environment is PMV/PPD index developed by Fanger. PMV/PPD calculation depends on environmental and personal factors; calculating thermal comfort conditions in real-time requires capturing these parameters. The environmental parameters can be captured from the indoor environment using IoT-based environmental sensors, including temperature, humidity, and air velocity. The personal factors, metabolic rate and clothing insulation, can be pre-defined for real-time application. The metabolic rate can be defined based on the general activity in the indoor environment and clothing insulation based on the season.

- Following the proposed initial framework, a prototype IoT-based system was developed to accommodate environmental sensors for real-time application, recording and storing air temperature, relative humidity, and air velocity. In addition, the ability to communicate with cloud-service applications. The system was divided into three layers: the physical layer, including data acquisition using environmental sensors; the back-end, including data storage and processing; the front-end layer, for data visualisation.

- Wireless and cloud technology reduces the processing power of capturing and storing data from sensors and calculating PMV/PPD.

- Real-time monitoring for outdoor weather is essential for the prediction system to identify the difference between indoor and outdoor environmental conditions.

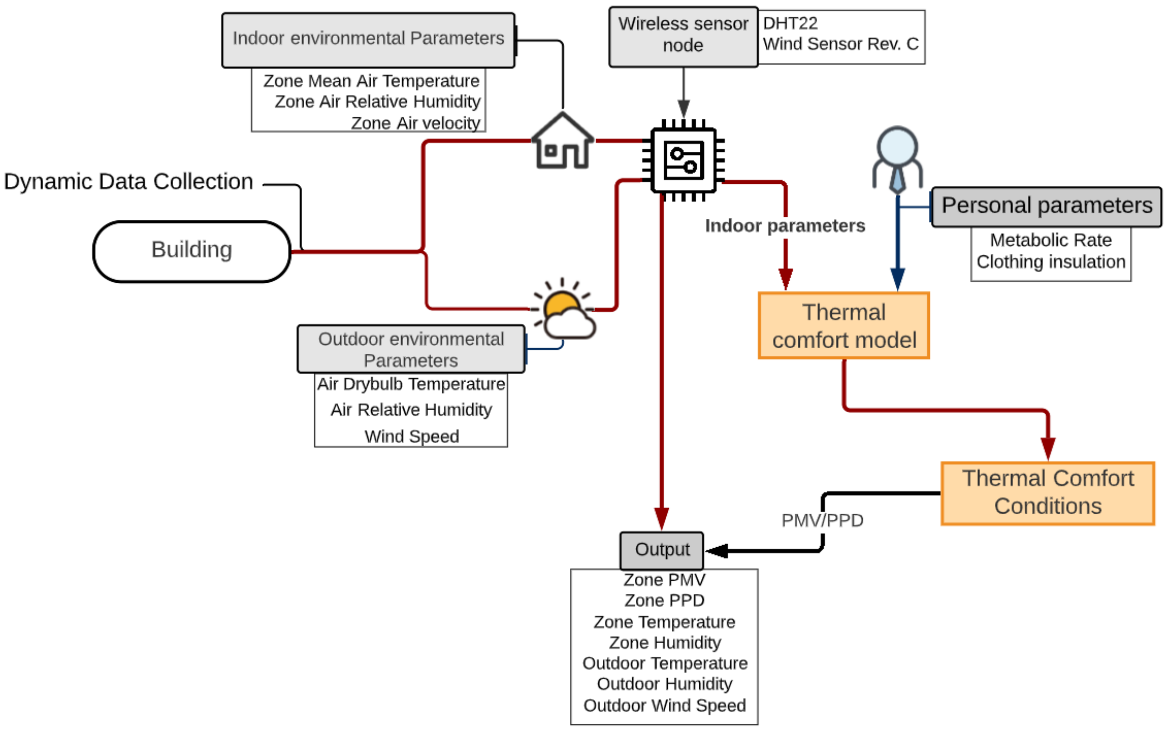


Figure 9.1 The processes of thermal comfort module

9.1.2 Finding from the energy prediction module

The energy prediction module predicts energy consumption based on the indoor environment parameters captured and processed from the thermal comfort module. Figure 9.2 illustrates the process of the energy prediction module. The finding from the energy prediction module are as follows:

- Computer simulation is the most convenient approach to analysing the energy use of a specific indoor environment over different weather conditions. Using parametric energy simulation tools can generate a synthetic dataset of energy consumption that is case-specific for a building.

- Interoperability is a critical issue between BIM and energy modelling tools. It was found that the optimal approach for data exchange over the gbXML format was basic modelling techniques with simple geometries focusing on zones/spaces.
- Parametric simulation for energy analysis requires an energy model, weather information, and defining design parameters. Accordingly, the thermal-energy-related design parameters in the energy model were connected to the HVAC system and indoor environmental control.
- The energy modelling accuracy depends on the model's level of detail. However, creating datasets for energy prediction is not the same as creating realistic energy analysis. Thus, the ambiguously and limitations addressed by previous research on modelling occupancy and operational schedules are not a limitation of this study.
- The parametric simulation generates massive data, and defining the output parameters is essential. In addition, it is the basis for creating the dataset for energy prediction development.
- A regression model was employed to predict energy consumption. Each regression models use a distinct regression algorithm. Five regression algorithms, BLR, BDTR, DFR, LR, and NNR, were evaluated based on MAE, RMSE, RAE, RSE, and CoD. The outcome showed DFR model has the best fit for this research.

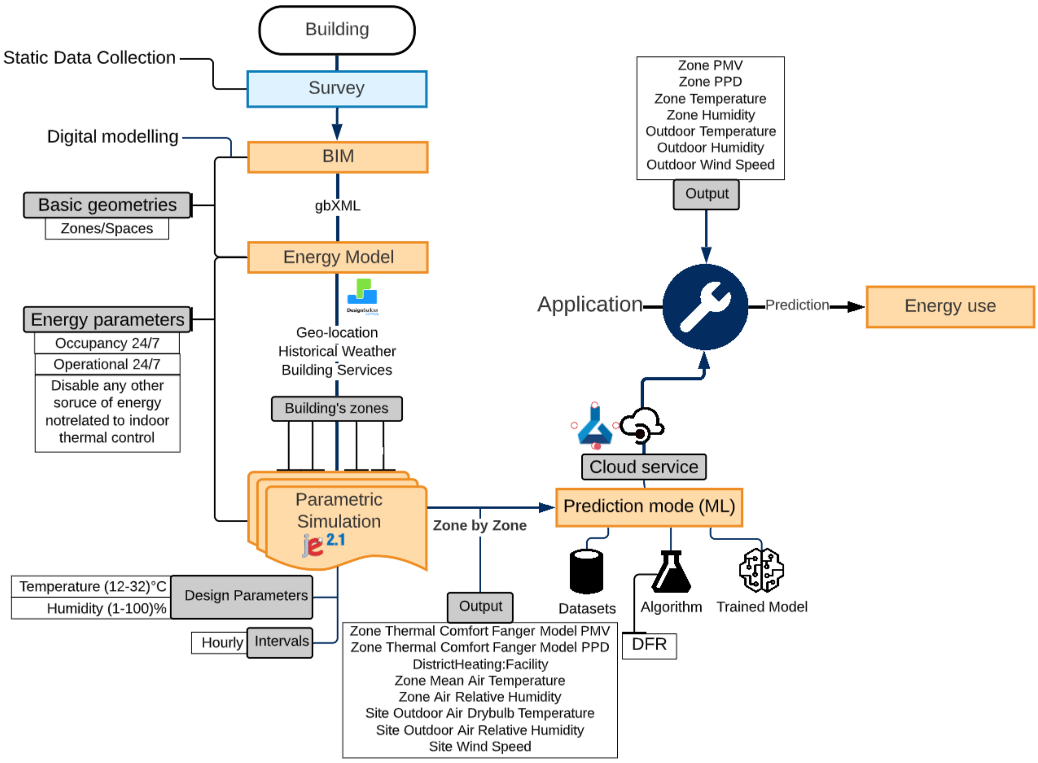


Figure 9.2 The processes of the energy prediction module

9.1.3 Finding from the experiments

A prototype IoT prediction system was developed following the technical implementation framework. Two dwellings and nine experiments were conducted to evaluate building performance and validate the framework. The uncontrolled experiment evaluated the whole building for both energy use and thermal comfort conditions. The following are the key findings from the uncontrolled experiment:

- The recorded energy performance gap was 29% from the sensors close to the heating source and 43% from other sensors.
- The uncontrolled experiment identified minor errors in the approach used to collect weather information, fixed for the semi-controlled experiments.
- Any failure in the real-time data capture produces wrong predictions.
- Thermal comfort condition was not stable, especially in large rooms. Temperature variation was recorded between both sensors.

In eight semi-controlled experiments, individual rooms were analysed. The following are the key findings:

- The IoT system near PRT has an accurate reading that matches the room's thermostat.
- The IoT prediction system near the radiator has a better energy performance gap.
- In experiment 8, the IoT system was placed near PRT and the radiator. The results showed accurate energy and thermal prediction.
- The energy performance gap from IoT near the heat source was less than 10% in 6 experiments, 24% in 1 experiment, and 44% in 1 experiment.
- Experiment 5 was the only experiment that overpredicted energy performance by 44% because the IoT system was placed 10 cm away and height of 30 cm from the radiator.
- The location of PRT is critical to both energy use and thermal conditions.

9.2 Scope of research and limitations

The scope of this research is extending the use of the BPS model to the operational stage of the building life cycle, focusing on the real-time energy prediction of individual zones for space heating in domestic buildings. Studying building zones can provide a better insight into the energy performance during building operation, which can further be used to understand building energy and thermal performance. The research looks at the parameters used in the BPS model related to energy consumption for space heating in individual zones. Classify the static and dynamic data in the BPS, finding out the necessary parameters that can be captured from the indoor environment for real-time energy prediction. In addition, the research attempts to connect thermal comfort conditions in the BSP calculation and the amount of energy end-use for space heating by applying the developed model in a real-world setting, comparing the actual energy end-use to the expected.

The research delivers a technical implementation framework for real-time energy performance prediction for space heating based on the BPS prediction model and capturing the outdoor and indoor environmental conditions. The framework will allow users and researchers to understand better the implication of outdoor conditions on the indoor environment and the amount of energy used for space heating to achieve a specific thermal comfort condition in domestic buildings.

Achieving optimum thermal comfort conditions is out of the scope of this work. The thermal comfort calculation requires two sets of factors, environmental and personal. Therefore, the study did not consider occupants' behaviour nor conduct a thermal comfort assessment. Instead, only environmental factors were captured for a real-time thermal-energy performance prediction; personal factors were set to fixed values based on the function of the studied zones and the season of the year.

The proposed framework was implemented in an innovative IoT sensing device. The device was tested and evaluated through an experimental approach. On-site measurement was undertaken for model creating, including five different zones in a total of two dwellings in the UK. Due to time, Covid-19 restrictions, and equipment constraints, the data were collected simultaneously. The study was also limited to the number of domestic buildings available to conduct field measurements and site experiments.

9.3 Future work

The findings of this study can be enhanced by further investigations in the following research areas:

- Investigate more domestic buildings to identify similarities and differences to the findings of this research, including studying the cause and effect of different thermal conditions.
- The framework can be further developed to include real-time data collecting for personal factors. This can improve the thermal comfort predictions module. For example, findings from previous studies demonstrated the possibility of collecting personal data using personal sensors, such as skin temperature and wearable sensors.
- Research focuses on thermal comfort and energy performance, taking the proposed framework forward. Follow-up research can look at the importance of other parameters to investigate.
- The research was implemented to investigate space heating using the most common heating system in the UK. Further investigation can occur on other types of HVAC systems, including energy consumption for space cooling.

- Smart houses and building automation systems can also benefit from the framework, which can be further developed to optimise and control strategies.

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