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Assessing the Effect of People's Behaviour on Energy Consumption in Buildings

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Copyright Statement

Dedicated to my parents M.Salim and Ruksana Salim for their endless love, support and motivation. Your prayers and blessings helped me get through this arduos but fulfilling journey.

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Abstract

Energy consumption in the residential sector has become increasingly important. This is all the more significant considering the pandemic, when people spent more time at home. In order to achieve the zero-carbon target of the Paris Agreement of which the UK is a part, there is a drive to insulate buildings, on the assumption that the more insulated a building is, the more efficient it will perform. In this study, the author examines the effect of peoples' behaviour, particularly window opening, as a behavioural pattern of the occupants and examines impact of occupant behaviour on the energy consumption of residential buildings in the UK. To identify the key factors that influence occupant behaviour, thermal imaging of residential buildings across Nottingham was done, followed by survey with questions regarding window opening behaviour of the participants. This was followed by the analysis of energy usage in Social Housing. Temperature data collected for a period of 14 months, from 17 houses, were analysed and the energy demand was calculated. Findings show that energy efficiency of a building holds an explicate relationship with the behaviour of occupants in the buildings, regardless of the building insulation properties. A highly insulated building could consume as much energy as a badly insulated house, due to people's behaviour. There was empirical evidence that for a well-insulated house with window open, the heating time increases by a factor of 1.6 when compared to similar insulated house with window closed. Hence the assumption that the more the insulation, the more the energy efficiency, might not be true. Findings also show that people's behaviour could reduce the effect of insulation. So, what theoretically is a well-insulated building might behave like a badly insulated house in terms of energy efficiency, depending on the behaviour of occupants. Thermal imaging is a helpful tool in visualising the impact of window opening. and can be used to make occupants aware of the effect of their behaviour. ANN feed forward neural network model to predict the window opening behaviour based on the room

temperature, radiator temperature and outside ambient temperature was developed. Energy costs of highly insulated and window open house defers from that of badly insulated and window open house only by 2%, while there is a difference of 10% between highly insulated and window open house and highly insulated and window closed house, showing that a well-insulated house with window open behaves in a similar way to a poorly insulated house. ANN feed forward neural network model to predict the window opening behaviour based on the room temperature, radiator temperature and outside ambient temperature was developed. The model predicted window opening with 98.8% accuracy for well insulated window closed house and 92% accuracy for well insulated window open house. The findings suggest that people's behaviour could reduce the effect of insulation in residential buildings.

Publications

As a result of the research presented in this thesis, the following publications are already accomplished:

Conference Proceedings

Salim, S. and Al-Habaibeh, A. (2019) 'The Effect of Insulation on Energy Savings in Residential Buildings - Myth or Reality?'. In: Proceedings of The International Conference on Energy and Sustainable Futures (ICESF): Nottingham Trent University, Nottingham, 9 to 11 September 2019. Page: 101-106. Available at: http://irep.ntu.ac.uk/id/eprint/37982

Salim, S. and Al-Habaibeh, A. (2020) 'How often do you open your house windows when heating is ON? An investigation of the impact of occupants' behaviour on energy efficiency of residential buildings'. In: Proceedings of the 2nd International Conference on Energy and Sustainable Futures (ICESF): University of Hertfordshire, Hatfield,10-11 September 2020. Page: 233-240. Available at: https://irep.ntu.ac.uk/id/eprint/40903/

Journal Paper in progress

Salim, S. and Al-Habaibeh, A. (2022) 'Experimental Investigation and Modelling of the Effect of people's Behaviour on Energy Consumption in Buildings Using Artificial Intelligence'

Contents

Abbreviations

ACH	Air Changes per Hour
ANN	Artificial Neural Network
a_w	area of the window
a_{wo}	Area of window opening
A_y	Area of individual elements of the building fabric
BEMS	Building Energy Management Systems
C	Celcius
CCC	Committee on Climate Change
C_{ged}	Cost of gas based on energy demand
C_{grh}	Cost of gas based on radiator heating time
C_p	Specific heat capacity of air
EC	Energy Consumption
EE	Energy Efficiency
e_{ed}	Percentage of error between calculated energy demand and predicted energy demand
e_p	Percentage of error between actual window status and predicted window status
$e_{winstat}$	Error between actual window status and predicted window status
HI	Hingh Insulation
IAQ	Indoor Air Quality
IRT	Infrared Thermography
K	Heat loss coefficienct
kWh	Kilo Watt Hour
LI	Low Insulation
OB	Occupant Behaviour
PMV	Particle Measurement and Validation

Q_{ec} Energy consumption

Q_f Heat loss due to building fabric

Q_v Heat loss due to ventilation

T_{out} Outside Ambient Temperature

T_{rad} Radiator Temperature

$t_{radheating}$ Duration of heating of radiator

T_{room} Room Ambient Temperature

U_y U-value of individual elements of the building fabric

WC Window Closed

WO Window Open

WOB Window Opening Behaviour

WS Window Status

ρ density of air

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Chapter 1 | Introduction

1.1. Problem Definition

In 2008, the UK government committed to reduce 80% of its carbon footprint by the year 2050 (*Climate Change Act 2008*, 2008). Till 2017, the UK was working on track with the carbon reduction targets within the second and third budgets (2013-2022) and more challenging measures were required in addition to the existing progress, to reach the fourth budget target (2023-2027) (*How the UK is progressing - Committee on Climate Change*, 2017). In 2019, the target was increased to net zero carbon emission by the year 2050 (UK Statutory Instruments, 2019). This was officially adopted in June 2019, before the impact of the Covid 19 pandemic. The hiatus caused by the pandemic and the slowing of global economy has been one of the greatest challenges to meeting the net zero target, although there is progress on UK's clean energy policy. The UK energy sector has been hit hard due to the pandemic. Gas and electricity bill for a typical household in the UK is estimated to go up by 54% in April 2022 (*BBC News*, 2022). This is because the energy price cap, which is the maximum price suppliers can charge households, is being raised, because of increase in global gas prices. Although government has promised schemes like the warm Homes Discount Scheme wherein a household can get up to £140 off electricity bill for the winter of 2021-22, more households are expected to face fuel poverty due to this sudden spike in energy prices. An estimated 13.4% of households in England are in fuel poverty, according to 2019 statistics (Department for Business Energy & Industrial Strategy, 2021a). With today's increase in oil prices and the significant growth in energy demand, the issue of fuel poverty must be dealt with effectively. Energy savings in heating and cooling of buildings is becoming an important area to address to reduce energy consumption and thereby, energy bills. Although commercial buildings have the high energy consumption, it does not vary significantly due to changes in occupancy levels or room activities.

The domestic sector attributes to the highest share (40%) of end user Carbon dioxide (CO_2) emissions in the UK. Between 2019 and 2020, although the overall CO_2 emissions in the UK fell by 10.7%, the CO_2 emissions in the residential sector increased by 1.8% as people stayed more at home due to the pandemic(Department for Business Energy & Industrial Strategy, 2019, 2021d). With the domestic sector contributing to about 40% of the UK emissions (UK Statutory Instruments, 2019), this increase is an immense issue. The domestic sector also contributes significantly (32%) to the overall energy consumption in the UK. Although the total energy consumption across all sectors decreased by 11% in the UK in 2020 due to the impact of the pandemic on energy supply, the energy consumption in the domestic sector went up by 2.3% when compared to 2019 (Department for Business Energy & Industrial Strategy, 2021c).

These numbers make domestic energy use a salient target for greenhouse gas reduction. There has been a steady increase in the number of households in the UK, since 1991, contributed by factors such as net immigration rate and the long-term trend of single adult households. According to National Statistics, it has reached 27.8 million in 2020 and it is projected to reach 32.1 million by 2034 (UK Government, 2021). This means an expected increase in overall energy consumption in the domestic sector.

To improve energy efficiency in the domestic sector, the government introduced Green Homes Grant scheme to in August 2020, which provided households with vouchers to make energy efficient improvements to the house. The scheme had to be cancelled after reaching only 10% of the target since it did not perform as expected (Davies, 2021; Department for Business Energy & Industrial Strategy, 2021b). Other policies such as feed-in-tariffs (FIT) or renewable portfolio standards support the attainment of these tariffs have also been introduced (European Union, 2009). The effectiveness of this approach is questionable since they rely on the conventional building energy management systems (BEMS). It was found that smart BEMS produce better results when combined with policy measures than conventional BEMS (Rocha, Siddiqui and Stadler, 2015). However, UK requires to invest in a nationwide upgrade in energy efficiency of the UK housing stock in order to meet the country’s 2050 climate commitments (Timperley, 2018). Such a retrofit might increase the relative impact of the occupant’s behaviour on energy use, thereby defining success more and more as the way a building is being used by its occupants (Schweiker, 2017).

There has been an increase in the evaluation of energy use in buildings in the past 15 years, and it has been widely acclaimed that there is a considerable gap between the predicted and actual energy consumption in buildings. Extensive research has been done using energy simulation tools analysing climatic data and properties of buildings, but the impact of occupant behaviour in energy performance analysis has hugely been overlooked until the past few decades. In the past couple of decades, several studies have been undertaken to analyse post occupancy energy use (Hong *et al.*, 2015; Schakib-Ekbatan *et al.*, 2015; Zero Carbon Hub, 2015; Delzendeh *et al.*, 2017). However, occupant behaviour is one of the most overlooked parameters when considering factors that affect energy efficiency of buildings (Schakib-Ekbatan *et al.*, 2015).

1.2. Research Scope

Under the Paris Agreement, the UK government has committed to 'net-zero carbon emissions' by 2050. But steps need to be taken to reach this target (United Nations, 2015; BBC News, 2021). The Committee on Climate Change (CCC), an advisory board to the government of the UK suggests that although UK is progressing well, further steps to be taken at the earliest for this target to be met. The net zero strategy updated in October 2021 mentions insulation only once. The government also scrapped its Green Homes Grant scheme earlier this year. One reason for this might be because of the data from the latest English Housing Survey, according to which, in 2019, 7% of residents dwelling in residential homes reported that at least one part of their home got uncomfortably hot. Of these, 11% lived in homes built in 2003 or later, compared to homes built in 1990 or earlier (Ministry of Housing Communities & Local Government, 2020). This overheating invariably leads to window opening behaviour which in turn contributes to the stochastic nature of energy usage in buildings.

About one third of UK's energy is used in the domestic sector, which also produces about one third of all the CO_2 emissions. More than two thirds of the energy used in domestic sector, is used in heating, especially during winter. Managing the heating in houses can help reduce the nation's carbon footprint to a great extent. Heat pumps and other alternative forms of heating being considered, will potentially help in the longer run. However, about 75% of the UK housing stock have boilers for heating at present (Ministry of Housing Communities & Local Government, 2020). Therefore, helping the residents understand the effect of their actions on energy efficiency of the house, can provide a positive impact. This can be done only if there is information on the effect of occupant behaviour on energy efficiency. Analysing indoor temperatures with respect to the outside ambient temperature, taking into consideration the behaviour of occupants that may influence the energy demand, for different types of households, can provide statistical information that can help occupants understand in a simple way, the impact of their action on energy efficiency.

1.3. Aim

This research aims to study the impact of occupant behaviour on the energy consumption of residential buildings and to identify the key factors that influence occupant behaviour that affect the energy efficiency of the building, and to provide solutions and recommendations to improve energy efficiency in buildings using mathematical techniques and artificial intelligence.

1.4. Objectives

This research has the following objectives as a pathway to achieve the aims of the study:

- Identify the key factors that influence occupant behaviour that affect the energy efficiency
- Study the impact of occupant behaviour on the energy consumption of residential buildings.
- Further enhance the understanding of the energy efficiency of buildings and to validate the information regarding the building fabrics, and its relationship to occupant behaviour of window opening, by obtaining thermal images of buildings.
- Improve energy efficiency of residential buildings, using mathematical techniques

- Design and develop machine models using artificial neural network, that help predict window opening and closing behaviour of occupants, and energy demand.

1.5. Research Questions

1. Is there a relationship between the level of building insulation and the internal temperature of the building?
2. How much does the difference in people's behaviour influence the energy consumption, particularly the heating?
3. Why do people open windows in winter?
4. How important and how significant is thermal insulation to reduce energy consumption? Can we ignore people's behaviour?
5. How can we reduce the 'energy performance gap' in buildings? Can adding sensors in buildings over long time, allow us to identify the difference between people's behaviour and building characteristics?
6. Can control theory/ first order system modelling be used to characterise the performance of a building based on the opening and closing of windows? How helpful is T-constant in characterising building characteristics?
7. What characteristics of the people's behaviour needs to be addressed for better energy consumption in residential buildings? How can data be better represented?

1.6. Contribution to Knowledge

The research study was carried out considering the above aims, objectives and research questions, the following contributions to knowledge were obtained as a result:

- Energy efficiency of a building holds an explicate relationship with the behaviour of occupants in the buildings, regardless of the building insulation properties.
- A highly insulated building could consume as much energy as a badly insulated house, due to people's behaviour. Hence the assumption that the more the insulation, the more the energy efficiency, might not be true.
- People's behaviour could reduce the effect of insulation. So what theoretically is a well-insulated building might behave like a badly insulated house in terms of energy efficiency, depending on the behaviour of occupants
- Mathematical models can be used to characterise performance of a building based on opening and closing of windows using first order system modelling and to predict energy usage in a building.

1.7. Thesis Structure

The thesis consists of 9 chapters as explained below:

Chapter one provides a clear synthesis of the background of the research and defines the problem that is being addressed. This is followed by the aim of the research, its objectives, and the research questions.

Chapter two elaborates on the literature review that is sectioned into reviews about energy efficiency in buildings, occupant behaviour in residential buildings, thermal imaging of buildings, use and scope of machine modelling in building energy efficiency, existing artificial neural network models in the field of building energy consumption and their limitations.

Chapter three presents the methodology followed in carrying out the aims and objectives of the PhD. The methodology comprises of literature review, qualitative and quantitative methods of analysis and experimental work which are explained in the chapter.

Chapter four examines the results of the qualitative analyses performed to understand occupant behaviour of window opening in residential buildings. This includes thermal image analysis of residential buildings to understand heat-loss due to window opening, and the second part investigates reasons as to why people open windows in winter, with the help of a survey.

Chapter five presents the first stage of analysis of energy usage in social housing using data obtained from sensors fitted in Nottingham City Houses, with the aim of understanding the impact of occupant behaviour on energy efficiency of the dwelling.

Chapter six presents the second stage of analysis of energy usage in social housing using data obtained from sensors fitted in Nottingham City Houses, with aim of understanding the impact of occupant behaviour on energy consumption of the building. Here, energy consumption of four houses with specific patterns of occupant behaviour and building fabric properties, is compared.

Chapter seven includes the development of artificial neural network models with Nottingham city council houses data, to predict the energy consumption of house based on widow status and to predict the window status based on the energy consumption.

Chapter eight is the final chapter, with the results and discussion of the research, indicating how the research aim, objective and research questions are met. The chapter also includes the contribution to knowledge of the research undertaken, before adding limitations and recommendations for further study.

1.8. Summary

This chapter firstly describes the present situation in the UK regarding meeting net zero targets and the role of energy efficiency in buildings in meeting the net zero targets. The current situation of energy consumption in buildings and the discrepancy in actual and predicted value in energy consumption in buildings, is conferred. The role of occupant behaviour in energy consumption of buildings is looked into, and the scope for analysing occupant behaviour to understand its impact on energy efficiency of buildings is discussed. This is followed by addressing the aim of the research which is to assess the impact of people's behaviour on energy efficiency of buildings and to identify the key factors that influence occupant behaviour that affect the energy efficiency and to provide ideas for improving energy efficiency, by using mathematical techniques and artificial intelligence. The objectives and research questions are presented after the aim. Finally, the chapter wise structure of the thesis is briefly stated.

Chapter 2 | Literature Review

2.1. Introduction

The UK government aims to achieve net zero carbon emissions by 2050. In the housing sector the efforts to reduce energy usage has been focused on improving the insulation by retrofitting and other ways of improving building envelope performance. Several studies, presented in the previous section, show that this approach does not give a good outcome. In fact, in many cases, it has been proved to give a worse outcome than expected. This is because of the under-representation of role of occupant behaviour in energy efficiency of any building. Improving building insulation increases the internal temperature, even when the occupant demand is not higher temperature (Shipworth, 2011). This leads to the occupant trying to reduce the heat in the dwelling by resorting to methods like opening the window which impacts the energy usage to a great extent. This research aims to focus on the role of occupant behaviour in the energy efficiency of buildings.

Energy consumption depends highly on heating, and one way to reduce energy consumption is to improve energy efficiency in homes. To this end, the government installed cavity and loft insulation to achieve the new Building Regulations of reaching thermal efficiency standards. This was carried out such that between 2015 and 2020, 16.9 million homes out of 25.4 million homes were insulated. Moreover, smart meters were installed such that 42% of all meters in domestic households were smart(Department for Business Energy & Industrial Strategy, 2018a). However, the energy consumption still highly depended on the weather, since it rose by 2.7% in the third quarter of 2017, in colder weather but went down by 2.4% in the third quarter of 2019, reflecting the comparatively warmer weather(Department for Business Energy and Industrial Strategy, 2017, 2019).

Improving energy efficiency is a challenging multi objective optimisation problem and the measures employed must consider various factors like energy consumption, costs, environmental performance etc. (Diakaki *et al.*, 2010). Several policies have been brought forward by the government in the past decade to improve energy efficiency in the domestic sector. The green deal, The Energy Act 2011, incentives to improve insulation in houses (solid wall insulation and loft insulation) all concentrate on improving building performance by improving the fabrics of existing buildings (UK Public General Acts, 2011; UK Statutory Instruments, 2014; Davies, 2021). However, government statistics show that despite improvement to the buildings' fabric, houses do not meet the originally set energy targets. This has been inferred from a report after the analysis of data from a subset of 76 homes by the Innovate UK's Building Performance Evaluation Programme (BPE) (Innovate UK, 2016). In its strategies to achieve carbon budgets, it has been clearly stated that *'We can achieve a reduction in energy demand either by improving the energy efficiency of buildings, lighting and appliances, or by changing the way we behave so that we use energy more intelligently and reduce the amount we need.'*(Department of Energy and Climate Change, 2011).

Providing smart meters to every home and business by 2020 is another government commitment. According to the post installation survey was carried out to understand consumer experience, it was found that 62% of respondents felt that their energy use remained the same and 14% felt that it had increased. Of the latter group, 26% attributed the increase in energy use to having the heater on more (Department for Business Energy & Industrial Strategy, 2018b)

All these contribute to the idea that occupant behaviour (OB) plays a pivotal role in energy efficiency of residential buildings. Several studies have been performed, particularly in the past decade, to understand the effect of occupant behaviour in buildings, its impact on the energy efficiency and the energy gap. This chapter includes literature review about the studies, in a comprehensive manner.

2.2. Energy Efficiency in Buildings

Energy use in buildings is influenced by six parameters: climate, building envelope, building energy and services system, indoor design criteria, building operation and maintenance and occupants' behaviour (International Energy Agency, 2016; Balvedi, Ghisi and Lamberts, 2018). The performance of a building is the measure of how well it functions, based on criteria like physical, social, or environmental considerations. Although energy consumption in winter is accounted for mostly by space heating, in the UK, limited research has been done in this area (Sen and Al-Habaibeh, 2020). In the last couple of decades, energy efficient design strategies have been introduced with the help of more stringent energy codes with the aim of reducing the carbon footprint. Mallaburn and Eyre (2014) reviewed history of energy efficiency policies in the UK from 1973 to 2013 and shows that while the early policies focussed on technologies, the later ones started considering the demand side as well, i.e., people. These strategies would be successful depending on how occupants interact with the building, or rather, on the energy-related lifestyles they assume (Barthelmes *et al.*, 2017) . Dowson et.al (2012) conducted a detailed review of the thermal performance of the existing UK housing stock, to assess energy savings, financial payback etc and to review key outcomes of various fabric incentives. They concluded that although Green Deal, which aims to refurbish UK housing stock for better energy efficiency, is scheduled to be UK's main energy efficiency scheme, there is a risk that the payback period for these refurbishments will be very long. Marshall et.al carried out an investigation where low energy thermal comfort was delivered to three distinct household occupancy patterns. The results showed that energy consumption depended on appropriate matching between occupancy type and energy efficiency measures (Marshall *et al.*, 2016).

Sustainable energy economy can be improved greatly with the factor of energy efficiency in the built environment. The need for improving the efficiency of a building has been tried to be solved by incremental goals to improve the component efficiencies. Insulate Britain, an environmentalist group founded last year, who believe that retrofitting homes is fundamental to achieve UK's zero-carbon target. They initiated a series of protests, blocking motorways to meet their demand of the UK government agreeing to insulate all social housing in Britain by 2030 (Insulate Britain, 2021). This old approach must be replaced by the newer approach that focuses on the fact that energy use is influenced by a complex matrix of factors that include ambient temperature, building load, building controls, ventilation, and occupancy.

2.3. Impact of Occupant Behaviour of Window Opening on Energy Efficiency in Buildings

The effect of Occupant Behaviour (OB) on energy demand in residential buildings has been focussed on, only in the last couple of years. It is a complex process, depending on and varying based on the stochastic behaviour of occupants. Various factors contribute to it, some of which are natural ventilation or the window opening behaviour of occupants, space heating energy demand are two important factors that contribute to the varying energy demand, in addition to other factors like natural light, direction of the house with regarding to sun, etc.

One of the main aims of built environment is achieving deep building energy efficiency. Lack of knowledge about factors determining energy use is one of the most significant barriers to achieving energy efficiency. Extensive research has been carried out to analyse building energy efficiency using energy simulation tools, analysing climatic data and properties of buildings, but the impact of occupant behaviour in energy performance analysis has hugely been overlooked. The IEA project EBC Annex 53 (mentioned in Section 1.3) results showed the user related aspects and behaviour effects of energy use by the difference in energy usage in similar buildings and argued that better prediction of building and energy-related behaviour may result in benefits for energy savings, cost saving and better thermal comfort of occupants (Yoshino, Hong and Nord, 2017).

Dynamic building simulation has been used to predict the energy saving potential of common refurbishment methods, based on occupant behaviour. The study was conducted because of lack of evidence or clarity as to whether occupant behaviour should be included in building simulation models. The study was done in a public building and the results showed that there is significant impact on predicted energy saving potential of refurbishment measures; the experiment revealed that opening windows longer will reduce the impact of refurbishment drastically (Wei *et al.*, 2017). Balvedi et.al (2018) reviewed the current methods occupant behaviour in residential buildings. They found out that although occupant behaviour models applied in building performance simulations, a well-designed model including evaluation of accurate scenarios for human-building interactions would enhance building energy performance. Hong et.al reviewed literature and proposed a 'Drivers - Needs - Actions - Systems' framework to standardise the representation of energy-related occupant behaviour in buildings, based on needs, actions and drivers of behaviour of occupants, to act as supporting ontology to research aimed at standardising energy related occupant behaviour in buildings (Hong *et al.*, 2015).

The Zero Carbon Hub was established in 2008 (discontinued in 2016), to achieve the target of delivering zero carbon homes in the UK by 2016. It investigated the design and delivery of 24 flats, half of which were built in compliance with Code for Sustainable Homes and the other half built to achieve Fabric Efficiency Standards. The post occupancy evaluation of the project showed that the measured gas usage was higher than predicted for both sets of flats, higher for the latter ones. Breakdown of gas consumption confirmed that occupant behaviour had a string impact on consumption (Zero Carbon Hub, 2015). Many studies have been conducted, showing that occupant behaviour is one of the most overlooked parameters during energy efficiency design of buildings (Wilson, Bhamra and Lilley, 2010; Schakib-Ekbatan et al., 2015).

There has been an increase in studies related to OB analysis in building in the past decade. Pilkington *et al.,* (2011) analysed the effect of occupant's behaviour on energy efficiency of 6 similar passive solar dwelling with sun spaces and found that space heating demand varied between dwellings by a factor of 14, with evidence showing that it could vary up to a factor of 45. Esmaeilimoakher (2019) monitored indoor temperatures of households in Australia and found that OB significantly affected the thermal performance with respect to heating and cooling systems, thereby affecting the energy consumption. Jang and Kang studied individual apartments in a high rise building and developed a model integrating and implementing the unit specific consumption difference and found that the heating consumption varied with different locations from 96 to 171 $kWh/m^2/year$ (Jang and Kang, 2018). Van den Brom, Meijer and Visscher (2018) compared the average actual energy consumption with the theoretical values of 1.4 million social housing households in the Netherlands, one of their suggestions was that renovated buildings did not perform as well in reality, as expected. Da Yan et.al (2015) critically analysed literature regarding OB focussing on occupant monitoring and data collection, model development, evaluation, and implementation into simulation tools.

According to Steg and Vlek (2009)., three main factors influence domestic energy consumption; Occupants' knowledge about energy conservation and energy in general; the effect of individuals' energy usage in conservation of energy; and the readiness of occupant in engaging in energy conservation practices Darby (2008) proposed five categories of feedback for effective change in energy usage, which are direct feedback, indirect feedback, inadvertent feedback, utility-controlled feedback and energy audits. She argues that by allowing the user to analyse their own energy usage, the gap in action can be bridged better than by trying to generate a sense of social obligation. Wilson, Bhamra and Lilley (2010b) of Loughborough University examined the role of design in reducing domestic energy consumption. They suggest that providing feedback about energy consumption would promote energy conserving attitude in the occupants. They agree that the way the information is provided is vital for motivation. Design for Sustainable Behaviour is a branch of sustainable design theory that can be used by the designer to shape user perception, learning and interaction (Lilley, 2009; Tang, 2010). The aim was to bring about change in behaviour in the context of energy efficiency and to build upon the framework of DfSB to make it applicable in other contexts (Wilson, Lilley and Bhamra, 2013). The Carbon, Control and Comfort (CCC) is an interdisciplinary project aimed at reducing domestic energy usage by 20%, by exploring the relationship between fabric of houses, heating systems and occupant behaviour that work towards optimum comfort levels and the energy usage in the process. It explored the relationship between three 'components' of a domestic heating system occupants, heating systems, the fabric of houses - and how these three things interact to create comfortable environments - and the amount of energy being used during the process. The investigators of the project found it to be a complex problem and by trying to address it, realised that there is a lot of variability between and within households and over time. They found thermostat setting varied from as low as 15°C to as high as 30°C. Although energy costs were cited as a source of concern, the setting was found to be based on comfort rather than cost for most participants. They also found that the central heating was used in many ways; some of them adjusted the thermostat directly, some set timers, and some turned the whole heating system on and off as required (Wilson, Bhamra and Lilley, 2010b; Shipworth, 2012b, 2012a). Thermal performance of residential buildings is greatly affected by OB of natural ventilation, i.e., window opening behaviour. Sorgato and Melo (2016) conducted a study in Brazil to evaluate the relationship between window opening behaviour of resident and the building thermal mass, in the energy consumption related to HVAC system of the building. They used simulated models to predict difference in energy usage of HVAC systems, based on OB. Results of the study showed that OB played an important role in the performance of naturally ventilated buildings, but emphasises that generalising OB is not recommended, as it can be under or overestimated.

The study done by D.Yan et.al (2015) argues that energy performance of buildings a considerably influenced by OB and emphasises the representation of OB in building simulation models for more accurate results. Fabi et.al (2012) highlighted existing literature to identify and highlight the influence of window opening behaviour on energy performance of buildings. Behaviour of occupant in a residential building varies depending on factors like outdoor ambient temperature, indoor ambient temperature, indoor air quality, humidity etc. the past decade has seen an increase in the number of research papers focussing ion window opening behaviour of occupants in buildings and its impact of energy efficiency of a building. Several models have been tried, stochastic and dynamic ones, to include window opening behaviour so that the predicted value resembles the actual value to a good degree. These models are based on statistical algorithms to predict the probability of a specific condition or event, such as the window state or the window opening/closing action, given a set of environmental or other influential factors.

Occupant's action of window opening or closing has an important impact on building energy use and indoor environmental quality (IEQ)by changing the amount of fresh air to the building. Currently, there is no sufficient understanding of the relationship between occupant behaviour and how it can affect the energy efficiency (Hong *et al.*, 2016). According to ASHRAE standards, there are large discrepancies between measured energy consumption and actual energy consumption(Fulton and Bsme, 2004; Delzendeh et al., 2017). The inherent demand for an energy consumption model based on occupant behaviour arises. Delzendeh et.al (2017) did a review of the latest literatures published about the impact of occupants' behaviour on the efficiency of a building and one of their conclusions was that the inter-relationship between energy behaviour of occupants might have significant impact on the efficiency but has not been investigated enough. Actual energy consumption prediction by dynamic energy simulations tools is undermined by a weak representation of human behaviour in any model. D'Oca and Hong(2014) developed a conventional methodology by combining probabilistic user profiles for window opening and thermostat set-point adjustments into a dynamic building simulation tool (IDA ICE). Mean values of probabilistic distribution was compared against the results obtained by deterministic simulations. The findings indicated major discrepancies between models using standardised occupant behaviour profile in energy simulation and models based on in field measurement and probabilistic modelling of occupant behaviour, the latter proving to be much nearer to the actual values, thus proving the hypothesis that occupant behaviour is one of the key factors for the 'energy gap'.

Across the world, occupant behaviour is being identified as one the key drivers of managing energy efficiency in residential buildings. UNECE (United Nations Economic Commission for Europe) states: *Closing the energy performance gap between design intent (and regulatory requirement) and the actual performance is likely to become an important issue over the next decade if countries are to deliver the climate and environmental targets related to buildings* (United Nations Economic Commission for Europe, 2018). The World Business council for sustainable development recognises OB as having as much impact on energy efficiency as the effect of equipment in reducing energy efficiency (World Business Council for Sustainable Development, 2007). Measuring OB to understand its impact and implement in simulations has been realised to be one of the main drivers for a sustainable development'.

There has been an increasing evaluation of energy use in buildings in the past 15 years, and it has been widely acclaimed that there is a considerable gap between the predicted and actual energy consumption in buildings, one significant being lack of knowledge about the factors determining energy use, called the Energy Performance Gap (EPG).

Delzendeh *et al.,* (2017) reviewed literature based on evaluation of energy demand and its use in buildings and estimation, to identify gaps and found that there is an alarming EPG, ranging up to 300% difference. According to Yoshino et.al, *Building energy use is mainly influenced by six factors: climate, building envelope, building services and energy systems, building operation and maintenance, occupants' activities and behaviour, and indoor environmental quality* (International Energy Agency, 2016b). Although research was more focused on the former three factors, in the past, development in social and behavioural sciences showed that people were an important factor for energy efficiency in buildings (Mallaburn and Eyre, 2014) and more emphasis is being given to the latter three factors as well, at present. The International Energy Agency (IEA) employed 'Annex 53' to better understand energy use in buildings to improve energy use prediction in a more robust way to enable better energy saving measures, policies, and techniques. 100 researchers from 15 countries came together from January 2009 to March 2013 to focus on 4 subtasks for one taskforce, namely occupant behaviour. 13 offices and 12 residential buildings from 15 countries were studied and the key findings showed that simulation models depended on the chosen hypothesis and the output is result of assumed behaviour. The actual presented results depend very much on user behaviour being addressed, this being one of the most important findings of annex 53. The study showed that difference in patterns of heating induced huge differences in energy use results showing variation factor of 5 to 20 in case of heating (International Energy Agency, 2016b).

Past decade has seen an increase in the evaluation of energy use in buildings. This has brought to notice that there is there is significant discrepancy between the predicted and actual energy consumption in the investigated buildings(O'Kane, 2018; Salim and Al-Habaibeh, 2019). One reason for this is the lack of knowledge about the factors determining energy use (Yoshino, Hong and Nord, 2017). Studies about energy gap in the building sector are more recent. Cozza, Chambers and Patel (2020) analysed the existence and extend of energy gap in residential buildings in Switzerland and found that buildings with low energy ratings (Energy rating C to G) consumed less energy than expected, while buildings with high energy rating (A and B) consumed more energy than expected. This contrasted with the large drop in CO_2 emissions for the A and B labelled houses which is not matched by the energy consumption. Jones monitored six identical flats in the UK and compared the actual energy consumption with the design stage normative Standard Assessment Procedure calculations. Significant Energy performance gap (EPG) was identified between the calculated and the measured gas and electricity use (Jones, Fuertes and de Wilde, 2015).

Similar study was conducted by Bahadori-Jahromi et.al (2022) where actual and simulated energy consumption of 7 different single-family houses in the UK were studied. The results showed that the actual energy demand could be controlled by proper control of the heating set point and window opening schedules. By adjusting the heating set point, and window opening schedules by 10%, EPG was found to have reduced by 15%. Cozza et.al (2021) introduced the concept of 'optimal consumption' which they defined as the ideal energy consumption of the building, where the comfort of the occupants is guaranteed. They argued that EPG was a combination of the differences between theoretical consumption and optimal consumption, and that between actual and optimal consumption. Padey *et al.,* (2021) monitored energy use in high energy performance buildings in Switzerland, for a period of 4 years and compared the measured data to the calculated data. It was found that the calculated value under-estimated the actual heating demand by a factor of 2.

There has been a rise of advance in technologies to improve energy performance in buildings in the past few decades. There exist building simulation models but there are not many literatures on the effect of occupant behaviour and how it affects energy efficiency of buildings. Everyday human activities like opening and closing of windows, switching on and switching off lights and HVAC has been found to be the reason for the 'energy gap'. It has become a crucial aspect that this uncertainty be considered during the building of energy simulation models so that the impact of human behaviour and its impact can be incorporated into the model.

It has been established through research, presented in the previous chapter, that occupant behaviour plays a major role in the energy efficiency of buildings.

2.3.1. Factors Influencing Occupant Behaviour of Window Opening

Occupant behaviour influences energy use in office and residential buildings in various ways, which can be understood better by identification of relevant driving factors of energy related occupant behaviour, and quantitative approach to modelling it (Polinder *et al.*, 2013). Schweiker (2010a) defined occupant behaviour as *a human being's unconscious and conscious actions to control the physical parameters of the surrounding built environment based on the comparison of the perceived environment to the sum of past experiences.* It is more than just the action of opening or closing window and happens subconsciously, and depends on several parameters like thermal, visual, and auditory etc. The main factor that prompts a resident to behave in a certain way is their comfort or how comfortable they are. Thermal comfort plays a major role in determining the overall comfort level of a person. ASHRAE Standard 55 states *'Thermal comfort is essentially a subjective response, or state of mind, where a person expresses satisfaction with the thermal environment. While it may be partially influenced by a variety of contextual and cultural factors, a person's sense of thermal comfort is primarily a result of the body's heat exchange with the environment. This is influenced by four parameters that constitute the thermal environment (air temperature, radiant temperature, humidity and air speed), and two personal parameters (clothing and activity level, or metabolic rate).'* (ANSI/ASHRAE Standard 55-2004, 2004; Olesen and Brager, 2004). Shi *et al.,* studied occupant behaviour in two general wards in a hospital in China and found that Indoor air Quality (IEQ), particularly indoor air temperature and relative humidity played a major role in OB of window opening (Shi *et al.*, 2018). To ascertain comfort, occupants act in a certain way (Dear and Brager, 1998) or perform a set of specific adaptive actions, like wearing suitable clothing, dimming lights, controlling blinds, controlling thermostat etc. These actions are driven by various factors that can broadly be classified into environmental (temperature, humidity, odour, light intensity etc.), contextual factors like building insulation, type of heating system etc., individual factors that are unique to each person, like thermal comfort, indoor environmental quality etc., physiological factors like age, gender, and other demographic statistical factors. and social factors like household composition, community characteristics etc. The cumulative effect of these creates the difference in responses of people. The range of thermal comfort found acceptable at any one time is ±2ºC, which can increase if occupants are given the options to control it (Nicol and Humphreys, 2002). Occupants' well-being and productivity are impacted greatly by their thermal comfort. A strong link (84%) has been found to exist between physiological parameters like heart rate variation, body temperature etc. and human thermal comfort (Pigliautile *et al.*, 2020). Fernández-Agüera et.al (2019) argued that airtightness in buildings is not always a good element, when it comes to energy efficiency. In a recent study conducted in two houses in Spain, it was found that surface condensation as found to be more of a risk in the most airtight dwellings, prompting window opening and thereby more consumption in winter. Gupta et.al (2018) investigated the influence of building fabric, services, and occupant related factors on energy consumption in six low energy social housing in the UK. Difference between predicted and actual energy use was compared using data gathered by physical monitoring of indoor environment, window opening behaviour, building performance data and qualitative data from surveys. It was found that actual energy use was higher than the expected values, by a factor of three.

Collecting data regarding occupant behaviour that impacts energy consumption has been realised to be crucial, in the building sector. Various measuring techniques are implemented to study and collect data regarding different aspects of occupant behaviour like occupancy, interaction with building environment, use of control systems etc. to identify the correlation between observed conditions and energy performance.

2.4. Measuring Window Opening Behaviour

Creating ideal indoor environment has been preoccupation of people living in dwellings. In the UK, with the invention of window glazing, air infiltration was controlled to a high degree making houses airtight to a good extend. However, occupants became more aware of the need for ventilation. Ventilation systems in dwellings have three main functions: to improve indoor air quality, to remove odours and moisture due to condensation and pollutants in the air and for occupants' comfort 'for fresh air', as commonly said. Nevertheless, the level of ventilation and its impact on energy usage varies to a vast degree depending on how the ventilation is carried out by the occupants. Uncontrolled or excessive ventilation can cause more detrimental effect than benefits. For e.g., opening window when the heating is ON in winter can increase energy usage excessively.

Over the years many investigations had been carried out to understand the effect of ventilation on energy usage. One of the earliest studies regarding ventilation is one conducted in Princeton university in the US. The study measured energy usage in dwellings in the aim of making the occupants aware of their energy usage and encourage better practice by providing feedback. The results of the study indicated that energy use can vary up to a factor of two depending solely on how occupants operated their windows and doors (Harrje and Kempton, 1986).

Study of air flow through buildings and rooms are more recent. Generally, computer simulation modelling techniques are used for studying airflow: zonal modelling for airflow through single rooms and multizone modelling for airflow through-out the building. Zonal modelling (room air flow) and multizone modelling techniques are the two general types of computer simulation used for the studying of airflow and contaminant transport in buildings, with each one having their advantages and disadvantages. While multizone modelling looks at the air movement and indoor air quality by evaluating average pollutant concentrations, zonal modelling uses computational fluid dynamic program techniques to inspect detailed air flow fields in rooms (Fox, 2008). These calculations are more recent, being available in the past two decades. With software packages being more user friendly, the availability is more accessible and hence more popular.

The main aim of occupant behaviour modelling is to understand the reason/ driving force behind the behaviour, and to find the relationship between the energy demand and usage (Yoshino, Hong and Nord, 2017).

A post occupancy evaluation study was conducted in the UK in 'EcoHome' site in houses with excellent rating. Results showed that human factor account for 51% of variance in energy efficiency in high (energy) performance dwellings (Gill *et al.*, 2010). They suggested addressing human factors as a standard practice in low-energy design homes.

Occupant monitoring and data collection is further divided into observational studies wherein OB and indoor environment variables are passively monitored, possibly over many months, since OB changes according to seasons, and surveys (Rijal *et al.*, 2008; O'Brien, Kapsis and Athienitis, 2013). Schakib-Ekbatan *et al.*, (2015b) suggested simple logistic regression model to evaluate the interaction of occupants with building using a case study of an office building in Frankfurt Germany, the findings of which showed that behaviour profile of window usage gives useful information regarding the same. Cuerda *et al.,* (2019) tested the effect of using occupant profile in simulation models, instead of standard profiles, resulting in a difference of up to 15% based on whether actual or standard profiles were used. Haldi *et al.,* (2017) proposed a statistical model based on linear mixed models, by employing built-in probabilistic terms describing occupant diversity. This was done using collected data from three long term monitoring campaigns, but was not tested with other data, to find the reliability of the proposed model.

Fabi et.al (2012) proposed definitions to highlight OB related to building control systems, to develop a theoretical framework that can act help investigate drivers for the any certain OB. In their later work, Hong et.al (2017) reviewed approaches implementing occupant behaviour in building performance simulation (BPS) models, their strengths, and weaknesses and suggested standardising occupant behaviour to enable ease of use in BPS programs. A recent study (Dziedzic, Da and Novakovic, 2019) used depth registration camera to monitor occupant movement to understand the pattern of occupancy in real-time, providing new kind of data which is to help develop occupants transition model. Although it does not identify the person, it can be argued that it still interferes into the personal space and lifestyle of the participant.

OB monitoring varies in range from one day to years (Rea, 1984; Haldi and Robinson, 2009). To understand habitual behaviour of residents, at least one season or ideally, a year of continuous monitoring might be required. Sampling frequency also ranges from a minute to several times a day and depending on how long the data has been collected the discrepancies are likely to cancel out over a whole year data.

Accurate monitoring of window opening behaviour of occupants is a challenge because of the stochastic nature of occupants. Occupancy detection is done by motion detectors, carbon di oxide sensors, wearable sensors, cameras, security-based systems and diaries (Lam *et al.*, 2009; Attar *et al.*, 2011). Window opening behaviour is generally detected by contact sensors, while photographic approach has also been used in some cases (Haldi and Robinson, 2008; Rijal *et al.*, 2008).

Most studies focus on the window state as binary i.e., open, or close, since the most common type of monitoring device is the contact sensor. Fabi et.al (2013) proposed a probabilistic approach for modelling human behaviour related to control of indoor temperature. Model of occupant's window opening behaviour obtained by measurement, was implemented in building simulation programs. Results were presented as probabilistic distribution of energy consumption and the air quality inside, based on OB. It was found that the air change rate in bedroom of naturally ventilated house was 33.8% higher than mechanically ventilated house. Table 2.1 shows literature review of studies with mention of difference in energy usage due to occupant behaviour.

Another study, by D'Oca and Hong, (2014) suggested a methodology that combined simulated probabilistic values for window opening and thermostat set points and the values were implemented into a dynamic simulation tool. The study compared energy consumption values from obtained using probabilistic and deterministic simulations, arguing that deterministic standardised simulations were weak when compared to probabilistic models, in providing scenarios of OB in buildings. The results showed that houses in which occupants control the window opening and closing and heating set-points, had 61% higher energy consumption than when the system was controlled in a deterministic way. Results of this study established the proposition that OB played a key role in the incongruities between predicted and actual energy consumption in houses.

Zheng *et al.,* used MATLAB to develop an image recognition code and use it to detect open windows in the building elevation maps. Although the method identified open windows with an accuracy of 92%, and is non-intrusive, the accuracy is questionable as it can be highly affected by light reflection on windows, especially in the sun facing side of building (Zheng *et al.*, 2019).

Johnson and Long (2004) developed a linear regression model, where in a stepwise linear regression analysis helped identify factors that lead to opening of windows and doors. Andersen, Olesen and Toftum (2007) conducted a study to understand the effect of occupant behaviour by simulating a single room with a single occupant. The simulation allowed the occupant to control six factors, which included heating, adjusting clothing etc, with an aim to keep particle measurement and validation (PMV) value withing predefined limits. Results showed a difference of up to 300% between energy consuming and energy efficient models.

Table 2.2 shows review of studies with mention of difference in energy usage due to occupant behaviour. Although several studies have been conducted over the years to understand the effect of occupant behaviour on energy efficiency, but the findings were inconclusive due to varying lifestyles of the inhabitants and individual requirements. To understand the effect of window opening to a high accuracy, the air movement deliberations in the building needs to be considered which is not effectively accomplished in most existing studies. Some studies suggested intelligent systems should be developed to monitor indoor air quality (IAQ) and to automatically adjust the ventilation rate as required. Others suggested occupants prefer to control their own environment but require more information on how and when to run the installed system more effectively and efficiently.

2.4.1. Window Opening Behaviour Prediction

User behaviour was considered as early as 1990. Fritsch et.al. developed a stochastic model using Markov chains to generate time series of window opening angle, and then real and generated data were compared (Fritsch *et al.*, 1990). This model has later been used in further research.

Since last decade, building energy performance simulations models have been seen to consider occupant behaviour by including stochastic models of occupant behaviour in relation to energy efficiency of buildings. However, validation of these models has been sporadic. Developed models must be validated with similar but not same data, and the results analysed to understand the usability of a model.

Table 2.1: Literature review of studies with mention of difference in energy usage due to occupant behaviour

Authors	Case study	Short description	Energy Gap
(Bahadori-Jahromi *et al.*, 2022) (UK)	Simulation model of 7 single-family houses	Actual and simulated energy consumption depending on occupant behaviour	Energy performance gap reduced by 15% by adjusting heating set point and window opening schedules
(Andersen, Olesen and Toftum, 2007) (Denmark)	Simulation of single room with single occupant	Difference in energy usage between energy consuming and energy efficient simulated models	alarming EPG, ranging up to 300% difference
(Polinder *et al.*, 2013)' (International Energy Agency)	Simulation models based on 25 buildings from 15 countries	13 offices and 12 residential buildings from 15 countries were studied to understand difference in energy usage due to user beahaviour patterns	The actual presented results depend very much on user behaviour being addressed, this being one of the most important findings of annex 53. The study showed that difference in patterns of heating induced huge differences in energy use results showing variation factor of 5 to 20 in case of heating
(Andersen *et al.*, 2013) (Denmark)	15 dwellings	Modelling of user behaviour in the context of real energy use and applied to a case study	the air change rate in bedroom of naturally ventilated house was 33.8% higher than mechanically ventilated house
(Haldi and Robinson, 2011) (Switzerland)	Building simulation with identical design but different behavioural inputs		Occupants' behaviour has an impact that makes energy usage vary by a factor of two
(Harrje and Kempton, 1986) (US)	Multifamily building with airtight construction	Visual inspection of window opening, enhanced with infrared scanning in multifamily building	The results of the study indicated that energy use can vary up to a factor of two depending solely on how occupants operated their windows and doors
(Jones, Fuertes and de Wilde, 2015) (UK)	6 identical flats	Actual energy consumption compared with the design stage normative Standard Assessment Procedure calculations	1.5 to 1.7 times difference impact of design independent factors on the extent of the performance gap, such as occupant behaviour, variation in plug in equipment, etc.
(Padey *et al.*, 2021) (Switzerland)	High performance multifamily residential building	Measured to calculated heating demand	Measure was underestimated by calculated value a factor of 2. the active air flow and the shading factor were identified as the most influential parameters on the uncertainty of the heating demand
(Shipworth, 2012b) (UK)	Exploration of occupants practice to attain thermal comfort in dwellings for development of user centred systems for better house heating practices		Identical homes, with different occupants, can vary in energy use by a factor of two to three
(Gill *et al.*, 2010) (UK)	UK EcoHomes site with an excellent energy rating	Post evaluation study to distinguish energy efficient and energy consuming behaviour of residents in low energy homes	Occupants' behaviour account for 51% of variance in heat consumption in homes with excellent insulation rating

Anderson et.al compared simulated model values to actual values to get an estimate of the forecast realism (Andersen, Fabi and Corgnati, 2016). They proposed a new procedure called 'validation by simulating' wherein the combined predictive accuracy of two existing behavioural models of window opening and thermostat adjustments were estimated and compared to actual values taken in sensors fitted in apartments in Copenhagen, Denmark. Data was collected for two months and compared with data from a simulated model of the same building. Building energy performance simulations (BEPS) IDA ICE tool was used for simulation. It was found that although the predicted and actual values were in the same range, the model was unable to predict the actual indoor environmental conditions, which meant the model needed to be improved.

Zhang et.al. (Zhang, Wu and Calautit, 2022) reviewed recent studies employing machine learning methods to predict occupancy behaviour and patterns. Comparing literature from 2011 to 2021 it was seen that Neural Network based algorithms and decision tree based algorithms were being more frequently used since 2019. Review of literature in this study also showed that occupancy detection was of concern due to privacy issues and that window status detection could be recorded, as long as it was not affected by the room temperature or other sensors in the room.

Zhou et.al (Zhou et al., 2021a) proposed an action-based Markov chain modelling approach for predicting window operating behaviour in office spaces, the validity of which was verified using data collected during summer of 2016 and 2018. The inspection standards proposed were opening rate, outdoor temperature, time distribution and on-off curve. The performance was compared with the more popular state-based Markov chain modelling approach to model occupant window operating behaviour. Results showed that state-based Markov chain modelling had better stability and accuracy in terms of opening rate, while action-based modelling approach showed good consistency in the measured data of on-off curves.

Another study by Zhou et.al (Zhou et al., 2021b) applied random forest (RF) method to predict window opening behaviour of occupants. Data from three open plan offices located in China was used. The weightage of each input element out of the eight input elements considered, were compared using random forest and was found to be consistent with the occupants subjective understanding as determined using a questionnaire. Results showed that RF with 4 inputs had the highest accuracy of 80%. The model also showed high accuracy and stability in predicting window opening behaviour for the same office over a period of time and for different offices as well. The models were also compared with two popular machine learning methods namely support vector machine (SVM) and XGBoost algorithms and it was found that the RF provided the highest accuracy out of the three.

Another study used Discrete-time Markov logistic regression models and decision tree models to predict thermostat use and window opening/closing instances and to identify the indoor conditions that trigger these actions, using data collected from two mixed-mode ventilation buildings in Ottawa, Canada (Liu *et al.*, 2021). The discrete time Markov logistic regression model was used to find the probability of increasing and decreasing thermostat setpoints. Both Markov chain and decision tree was used to understand window opening behaviour and it was found that occupants opened window when the indoor temperature was above 24^{o}C, relative humidity (RH) was above 30% and outdoor temperature was above 3^{o}C. However, useful information regarding window closing action could not be extracted, since they did not relate to the environmental factors in this study.

Park et.al compared six machine learning algorithms to understand the best model for predicting occupant's behaviour relating to manual control of windows. This was done using field data from 23 homes in Seoul, taken every 10 mins. The machine learning models compared were K-Nearest Neighbours (KNN), Random Forest (RF), Artificial Neural Network (ANN), Classification and Regression Trees (CART), Chi-Square Automatic Interaction Detector (CHAID) and Support Vector Machine (SVM). Linear regression model was also used, and results compared to the results obtained from the machine learning models. Results showed that the machine learning models could predict individuals' behaviour better than linear regression models. Out of the machine learning models, KNN had the best predictive performance. However, the larger the training data set, the more memory KNN requires to store the data set and the more complicated the calculations become, making KNN inefficient (Park *et al.*, 2021). Pan et.al. (2019) used Gauss distribution modelling approach to predict window opening behaviour of occupants in an office building located in Beijing, China, using indoor temperature outdoor temperature and a combination of both, as the variables. It also compared the results with logistic regression model approach. Results showed that Gauss distribution model 9.5% higher prediction accuracy. However, the field measurement in the study is not comprehensive, as the Gauss distribution model uses only the outdoor temperature is selected as the input, ignoring other important variables like CO_2 concentration etc. Also, only the window state is considered and not the window opening/closing action.

Mo et.al (Mo *et al.*, 2019) adopted XGBoost algorithm to model and predict occupant window opening behaviour and compared it with logistic regression model. XGBoost was found to have better prediction accuracy (80% vs. 60%). Parameters including indoor and outdoor temperature, RH, CO_2 concentration and outdoor $PM_{2.5}$ were considered. However, all the selected apartments had a similar layout thus limiting the results to one layout of apartments. A literature review carried out in 2020 (Dai, Liu and Zhang, 2020), reviewed the state-of-the-art application of machine learning models on prediction of occupancy and window-opening behaviour. It revealed the use of different machine learning models including logistic regression, ANN, random forest and SVM in prediction of occupancy and window opening behaviour, with satisfactory performances. Comparing different studies, it was found that for window opening behaviour, indoor temperature, outdoor temperature, and wind speed are the most common predictor variables. Logistic regression was found to be the most common model used in window opening behaviour modelling. However, it does not perform well for the 'cut-off' temperature. The literature review study also suggested to include building characteristics and occupant features to further improve prediction accuracy.

Table 2.2 compares different approaches to window opening behaviour prediction, discussed above.

2.4.2. Window Opening Occupant Behaviour Modelling

The impact of occupant behaviour on energy efficiency of a building is being increasingly addressed, as seen in the previous sections. Several research has been undertaken to implement human behaviour model into existing building simulations.

Machine learning is progressively being used in data analysis. Machine learning is the process wherein computational methods are used to create algorithms that help machines 'learn' information directly from data, without relying on a pre-determined equation or model. The algorithms find patterns in data to generate insights ('Machine Learning with MATLAB', 2020). Machine learning can widely be classified into unsupervised learning where grouping and interpretation is done based only on input data, and supervised learning where a predictive model is developed based on input and output data.

Table 2.2: Comparison of different approaches to window opening behaviour prediction

Reference	Details of Study	Approach to prediction of window opening behaviour	Results
(Zhang, Wu and Calautit, 2022)	A review on occupancy prediction through machine learning for enhancing energy efficiency, air quality and thermal comfort		Comparing literature from 2011 to 2021 it was seen that Neural Network based algorithms and decision tree-based algorithms were being more frequently used since 2019.
(Andersen, Fabi and Corgnati, 2016)	Verification of occupants' behaviour models in residential buildings	Compared simulated model values to actual values to get an estimate of the forecast realism.	Although the predicted and actual values were in the same range, the model was unable to predict the actual indoor environmental conditions
(Zhou et al., 2021a)	Window opening behaviour in an open plan office space was studied. The opening rate, outdoor temperature, time distribution, and on–off curve were proposed as four inspection standards.	An action-based Markov chain modelling approach for predicting window operating behaviour in office spaces was proposed. Also compared the performance of action-based Markov chain modelling approach to state-based Markov chain modelling approach.	State-based Markov chain modelling had better stability and accuracy in terms of opening rate, while action-based modelling approach showed good consistency in the measured data of on-off curves.
(Zhou et al., 2021b)	Predicting open - plan office window operating behaviour using the random forest algorithm. Data from three open plan offices located in China was used.	Random forest (RF) method to predict window opening behaviour of occupants.	RF with 4 inputs had the highest accuracy of 80%. The model also showed high accuracy and stability in predicting window opening behaviour for the same office over a period and for different offices as well. Also compared with SVM and XGBoost algorithms. RF provided the highest accuracy out of the three.
(Liu *et al.*, 2021)	Modelling window and thermostat use behaviour to inform sequences of operation in mixed-mode ventilation buildings.	Discrete-time Markov logistic regression models and decision tree models to predict thermostat use and window opening/closing instances and to identify the indoor conditions that trigger these actions.	Both Markov chain and decision tree was used to understand window opening behaviour and it was found that occupants opened window when the indoor temperature was above 24oC, relative humidity (RH) was above 30% and outdoor temperature was above 3oC. Useful information regarding window closing action could not be extracted, since they did not relate to the environmental factors in this study.

contd.

(Park *et al.*, 2021).	Machine learning algorithms for predicting occupants' behaviour in the manual control of windows for cross-ventilation in homes	Compared six machine learning algorithms to understand the best model for predicting occupant's behaviour relating to manual control of windows. K-Nearest Neighbours (KNN), Random forest (RF), Artificial Neural Network (ANN), Classification and Regression Trees (CART), Chi-Square Automatic Interaction Detector (CHAID) and Support Vector Machine (SVM). Linear regression model was also used.	Results showed that the machine learning models could predict individuals' behaviour better than linear regression models. Out of the machine learning models, KNN had the best predictive performance. However, the larger the training data set, the more memory KNN requires to store the data set and the more complicated the calculations become, making KNN inefficient
(Pan et.al. ,2019)	A model based on Gauss Distribution for predicting window opening behaviour of occupants in an office building located in Beijing, China	Gauss distribution modelling approach to predict window opening behaviour using indoor temperature outdoor temperature and a combination of both, as the variables. It also compared the results with logistic regression model approach.	Results showed that Gauss distribution model 9.5% higher prediction accuracy. However, the field measurement in the study is not comprehensive, as the Gauss distribution model uses only the outdoor temperature is selected as the input, ignoring other important variables like CO2 concentration etc. Also, only the window state is considered and not the window opening/closing action.
(Mo et al., 2019)	Developing window behaviour models for residential buildings using XGBoost algorithm	XGBoost algorithm to model and predict occupant window opening behaviour and compared it with logistic regression model.	XGBoost was found to have better prediction accuracy (80% vs. 60%). Parameters including indoor and outdoor temperature, RH, CO_2 concentration and outdoor $PM_{2.5}$ were considered. However, all the selected apartments had a similar layout thus limiting the results to one layout of apartments.
(Dai, Liu and Zhang, 2020)	A review of studies applying machine learning models to predict occupancy and window-opening behaviours in smart buildings	Compared use of different machine learning models including logistic regression, ANN, random forest and SVM in prediction of occupancy and window opening behaviour, with satisfactory performances.	Logistic regression was found to be the most common model used in window opening behaviour modelling. However, it does not perform well for the 'cut-off' temperature. The literature review study also suggested to include building characteristics and occupant features to further improve prediction accuracy.

Supervised learning aims to build a model taking a known set of input data and known set of output data and makes predictions to new data, based on evidence. Creating an algorithm and developing a model depends on several factors, including size and type of data, the expected outcome of the model and its application.

Literature shows that there are two fundamentally different approaches in modelling human behaviour in buildings: deterministic and probabilistic. Building simulation tools generally employ heat transfer and thermodynamic equations with human actions represented by predefined fixed schedules or rules, like the window being open after a certain indoor temperature, which may result in unrealistic results. On the other hand, the evolving empirical models are based on algorithms that predict the probability of occurrence of an event under certain conditions. These models have scope for including the stochastic nature of window opening behaviour, into the models, since they are based on statistical correlation between the window state and factors like external temperature, internal temperature, humidity etc. Clarke *et al.,* (Clarke et al. 2008) proposed a probabilistic model to indicate occupant discomfort and another probabilistic model to for the resulting action, which might cause the problem of ignoring reasons OB not related to comfort. Yun et. al developed an algorithm based on the Markov Chain and Mote Carlo methods to integrate probabilistic window opening OB model to dynamic energy simulation models, with the new algorithm predicted values showing good agreement to the actual values.

The total heat loss coefficient K and the heat capacity C of an empty low consumption building can be estimated by measuring transient states during heating and free cooling of empty low-consumption house (Mangematin, Pandraud and Roux, 2012). Naspi *et al.,* (2018) measured occupant behaviour in buildings to develop human-in-the-loop design o be applied to retrofit interventions. Measurements were done continuously for one year with a dedicated sensor network, with a time interval of 10 minutes, and enhanced with monthly survey of the occupants regarding thermal environment. Results showed better results than a standard approach, with a 26% reduction in discrepancy in window opening simulation and 58% in the case of light switching. Chen *et al.,* (2020) developed a Cox model using four environmental factors as indicators (indoor air temperature, CO_2 concentration, outdoor air temperature and $PM_{2.5}$ concentration) to detect window opening behaviour, which presented an accuracy of 78.9%. Nicol (2001) suggested the temperature change in buildings as a distribution rather than a discrete value; this according to him, would help model occupant behaviour as a stochastic process However, enough data or analysis has not been carried out on this hypothesis.

Identifying the factors that impact residential energy consumption is a key factor to be considered when designing models and in implementation of policies for energy efficiency. To analyse this both the contextual factors like the local climate, building characteristics etc and the behavioural factors like the user demography, their behavioural differences and energy usage pattern etc must be considered. Schweiker et.al (2012) analysed window opening behaviour data from two buildings in Switzerland and one building in Japan; the data included the choice of opening angles for axial openings. Although the Swiss data set provided a considerably reliable model to predict window usage, it was not further tested. Chen *et al.,* (2020) conducted a study in Tianjin in China, by measuring four environmental indicators that significantly influence window opening behaviour and analysed it using two models: Cox model for survival and logistic model. It was found that indoor air temperature, concentration of CO2, outdoor air temperature and concentration of particle matter (PM2.5) presented a significant influence on window opening behaviour. Window opening probability was the highest when indoor air temperature was between 15-21ºC and outdoor air temperature was less than 21ºC (Schweiker *et al.*, 2011). Fabi et.al. (2013) presented a probabilistic user behaviour model in the context of real energy usage and applied the same to a case study. Occupant behaviour was used to inferred from the case study and simulated. The results indicated the likelihood of open window under different circumstances like, occupancy during time of survey, number of occupants, time of year etc, represented as probability distributions of energy consumption and occupant behaviour.

Zhang and Barret (2012) conducted a field study of occupants' window opening behaviour for three months in a ventilated office building in Sheffield. Indoor and outdoor temperature, humidity, windspeed etc were observed and it was found that window opening behaviour depended strongly on-air temperature, season, time of day and occupancy pattern. A stochastic model was used to predict window opening depending on outdoor temperature. Haldi and Robinson (2009) verified three alternative approaches to modelling occupants' behaviour, based on probability distribution of state of window (open or close), on random processes based on transition probabilities or on distribution of time delays between actions. It was found that the model differed in predictive accuracy; while logistic models were better for predicting year-round probability of window opening, a model based on survival analysis was found to be more robust and more computationally efficient than Markov and logistic distribution models tested.

Barthelmes et.al. (2017) studied the potential applicability of Bayesian networks (BN) to capture the relationship between occupant behaviour, particularly window opening behaviour and its influence on energy efficiency, with the help of a case study. The aim of the study was to bridge the gap between outcome of simulations, and reality, using Bayesian Network (BN) framework. Data was collected from a residential apartment located in Copenhagen, Denmark and Data collected in 10 min intervals continuously for 3 months. The study demonstrated the potential benefits of using Bayesian Network Framework for stochastic modelling of window opening behaviour in residential buildings. Results indicated that stochastic nature of window opening behaviour can be well captured by BN, provided the initial set up and variable selection is correctly set up.

Jones *et al.,* (2017) developed a stochastic model of main bedroom window operation, based on data collected from 10 houses in the UK over a period of one year. Multivariate logistic regression is used to predict window status depending on environmental and time factors. Although the model showed the influence of environmental factors on window status, the accuracy of the model is questionable. The current challenge is integrating these systems and to make them work together to provide a truly integrated system in which different Building Management Systems (BMS) could communicate, based on continuous monitoring, provide improved performance to have optimum energy efficiency along with optimum comfort to its occupants. To achieve this, new and innovative technologies must be introduced or rather added to the existing systems, to gather valuable data. By doing this, the behaviour patterns of the occupants and various other information can be collected and used to analyse and deliver the required information, to enable them to take the necessary actions for better performance.

One of the most effective ways to bridge the difference between predicted and actual energy consumption in residential buildings is by analysing occupant behaviour and its relationship with the energy efficiency of the building. However, effective statistical and data mining approaches resulting in meaningful correlation is largely undiscussed. Last few decades have seen a change, giving way to more probabilistic models, wherein a correlation is established between the recorded environmental conditions and observed factor of human-building interaction (Hong *et al.*, 2017). The output of such models is the probability of the occupant factor like window opening occurring, due to various changes in the environmental factors. As discussed in Chapter 2, multivariate analysis is more common, with OB models selecting different variables as the influencing factor. As a result, a standardised method for representing OB in BPs is lacking.

2.5. Investigating Effect of Window Opening Behaviour on Energy Efficiency of Buildings and Reasons for Window Opening Behaviour of Occupants

2.5.1. Thermal Imaging

Infrared thermography is the process of observing the heat transfer due to electromagnetic radiation emitted by the object. The applications of infrared thermography (IRT) in the commercial and industrial sector have increased in the past 50 years. In the building sector, initially, IRT was used for quick periodic inspections and preventive maintenance of buildings (Lucchi, 2018). Later, with the introduction of single IR camera, the scope of its applications widened to include building diagnosis focussed on characterisation of structures, materials, surface defects etc.(Milne and Reynolds, 1985; Moropoulou *et al.*, 2013). Youcef *et al.,* (2020) used passive IRT to analyse energy performance of buildings with based on insulation level of walls. According to Steffan-Boltzmann law, the net heat transfer due to radiation is partly a function of the temperature of the object. Al-Habaibeh et. al. conducted a case study of deep retrofitted to bring it closer to Passivhaus standard. Artificial intelligence was used to predict the energy savings due to retrofitting and this was compared with the actual values. The thermal performance of the building after retrofitting, was evaluated using infrared thermography (Al-Habaibeh, Sen and Chilton, 2021). Goodhew et.al (2015) conducted two studies with 43 and 87 houses in each study, to understand the effect of thermal imaging on energy conservation households. Participant households were provided with thermal image of their houses, to show heat escaping from or cold air entering the house. A post evaluation study of the first study, showed that householders who saw the thermal image reduced their energy use and householders who were provided carbon footprint audit and non-intervention control did not show any change in energy usage. The second study showed that occupants were five times more likely to install draught proofing measures after seeing thermal image. The explicit descriptive nature of thermal imaging can be used to study otherwise unnoticed loss of heat in buildings. The same can be used to understand the amount of heat loss due to window opening behaviour of occupants in dwellings.

2.5.2. Survey

Pattern of occupancy is determined by various factors including lifestyle, preferences, personal comfort perception, general characteristics of the household etc. It has been understood with many previous studies that personal factors play an important role in the way people use heating systems (Andersen *et al.*, 2009; Schweiker, 2010; Valentina, Andersen and Corgnati, 2012; Esmaeilimoakher *et al.*, 2016; Hamilton, 2018; Salim and Al-Habaibeh, 2020). Therefore, it is an advantage to understand the perception of occupants as preliminary part of a research. Several OB studies use surveys to understand actual perception of occupants. Nevius and Pigg (2000) conducted a study to understand space heating and thermostat usage pattern in households. It was found that there was not much difference in energy use between houses with programmable thermostat and manual thermostat since many occupants use programmable thermostat as an on-off switch. Esmaeilimoakher (2016) conducted a survey which collected information about several building and occupant related factors, including floor area, household size, household income in Perth, West Australia. Perth is warm throughout the year with temperatures ranging in between 15°C to 30°C any time of the year. The survey showed that floor area, household size, income were significant factors affecting energy consumption, rather than window opening behaviour. This might be because the survey did not include any temperature data or window opening behaviour data, and because it is a warm country where heating was not a factor contributing to high energy consumption. Shipworth *et al.,* (2009) conducted national survey on central heating demands and temperatures and found that thermostat setting was found to be based on comfort rather than cost for most participants. Energy consumption in residential buildings can be better understood with a better idea of OB patterns, which will help understand the effect of OB in energy use. A standard behavioural pattern can be understood form the results from statistical analyses of surveys (Andersen *et al.*, 2009). This can be used on calculation of OB factor in energy consumption of building in building simulation models. Goodhew et.al (2017) interviewed 25 participants to explore their understanding of how heating systems in dwellings worked. Participants were asked their notion of various factors regarding home heating, like how thermostat worked, how heat flows around the house, how insulation works etc. A variety of ideas and impressions could be seen in the participants. It was evident that most occupants had their own idea of how a heating system worked and behaved accordingly. For example, one of the assumptions was that the higher the thermostat setting, the faster the house gets warm.

Occupant behaviour in dwellings is unpredictable, making it difficult to model. Understanding peoples' perception of energy usage and their reasons for different actions to attain thermal comfort in homes, will contribute extensively to understand the patterns in occupant behaviour that impact energy efficiency in dwellings.

2.6. Summary

This chapter provided a comprehensive summary of review of literature done during this doctoral research. With the upcoming increase in energy tariffs in the UK, managing energy efficiency of buildings is of primary concern. Review has shown that there is a gap in the predicted and actual energy usage in buildings and that occupant behaviour has a considerable impact on energy efficiency of buildings. Various methods have been implemented by different studies shown in literature, to understand, measure and include the stochastic behaviour of occupants in buildings. Window opening behaviour in particular, has been found to have a strong impact on the energy efficiency of a building. Studies involving window opening behaviour and its effect on energy efficiency in buildings are new. It is evident from review of literature that there is still a gap in knowledge to understand the effect of people's behaviour on energy for different type of houses. Most studies focus on single buildings or single buildings with multiple occupants. The effect of window opening on energy efficiency has not been explored much on an urban scale. Understanding the effect of window opening in social housing will provide a valuable insight and contribution to this research area. Although several studies have been carried out employing various qualitative and quantitative methods, providing distinct acuities on energy consumption in buildings, the adaptation and incorporation of these insights into building simulation models are still a challenging area of research, and substantial developments in predicting occupant behaviour in buildings are yet to be obtained. Also, there is still a gap in knowledge regarding studies comparing the impact of occupant behaviour on energy efficiency of different types of buildings.

Although machine models have been used to model occupant behaviour of window opening, most of the studies use a deterministic model wherein occupant behaviour is assumed based on few instances. Few studies have been done to predict occupant behaviour and relate it to the energy efficiency based on the pattern of window opening.

Understanding the reasons behind window opening behaviour of occupants is a vital factor to be considered when studying the impact of occupant behaviour on energy efficiency of buildings. The pattern of window opening needs to be analysed in detail to quantify the effect of occupant behaviour on energy consumption. Therefore, a mixed methods approach is required for a comprehensible understanding of the effect of occupant behaviour in energy efficiency of residential buildings.

Chapter 3 | Methodology

3.1. Introduction

This chapter explains the methodology followed to achieve the aims and objectives of the research. The different stages of the research are presented, and the methods implemented to complete them are presented.

This research follows a mixed method. In mixed method of research, qualitative and quantitative data are systematically integrated in order to answer research questions (Tashakkori & Newman, 2010). Mixed method research starts with the researcher gathering evidence based on the nature of the research aim and research questions. Qualitative methods are inductive methods to help the researcher understand the 'why' or 'how' of an occurrence and their effects. The quantitative methods are employed for the deductive reasoning and for inference of causality (Pasick et al., 2009). Mixed methods involve collection of both qualitative data (e.g., surveys with open ended questions, observations, interviews etc.) and quantitative data (e.g., surveys, data collection like temperature data etc.) and integrating the assets of both the data to answer the research questions (Greene, 2006). A mixed method is employed in this research to develop a complete understanding of the research problem. The quantitative outcomes are enhanced and better comprehended using the qualitative outcomes.

3.2. Overview

The research is split into three phases. The first phase is literature review which gathers insights about background and scope of the research, which is followed by the qualitative analysis. This includes thermal imaging of residential buildings and survey which includes open ended questions, to understand occupant behaviour. This is followed by quantitative analysis, wherein data collected form social housing is analysed to understand occupant behaviour, which is done in two stages. The first stage involves a macro level investigation into the energy usage and temperature characteristics in social housing. The second stage involves a more detailed analysis of four houses shortlisted form the first stage of analysis. Figure 3.1 shows the stages followed during this research.

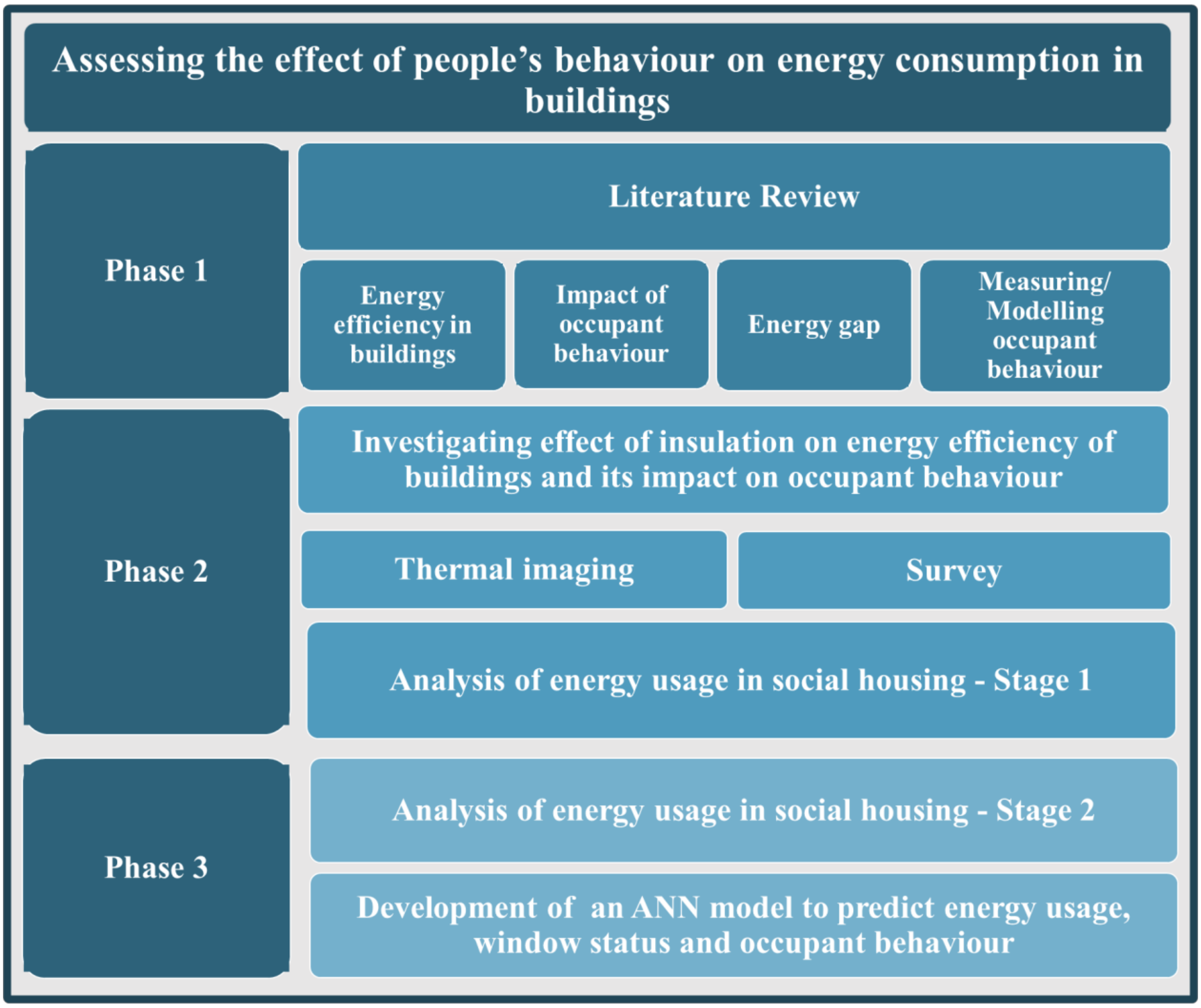


Figure 3.1: Overview of stages of this research study

3.3. Literature Review

Literature review is the initial phase of the research and continues through the research. Energy consumption in buildings is reviewed initially and the role of heating in increasing energy consumption is explored. This gives an insight into the impact of human behaviour in increasing energy use in residential buildings. This is further reviewed, to understand the existence of 'energy gap' and factors leading to it. Literature on different approaches of measuring occupant behaviour is investigated, and the advantages and limitations of various methods are studied. Occupant behaviour models using ANN and other algorithms, are reviewed. The stochastic nature of occupant behaviour has been model in a deterministic manner, with a few studies using a probabilistic model. It is evident from literature review that there is a considerable discrepancy between actual and predicted energy usage in residential buildings and window opening behaviour is one of the main reasons contributing to this discrepancy. This led to the next stage of the research where thermal images and survey helped enhance knowledge about impact of OB on energy usage in dwellings.

3.4. Investigating Effect of Window Opening Behaviour on Energy Efficiency of Buildings and Reasons for Window Opening Behaviour of Occupants

The initial stage phase of the research included qualitative analysis, which comprised of thermal imaging and survey collection to understand the impact of window opening on the heat energy demand of a dwelling. Occupants in dwellings perform various actions for their thermal comfort. One main action is window opening, the reason being its speed of reaction: when room is hotter than the occupants comfort level, opening a window reduces the temperature of the room quickly, bringing it back to occupant's comfort level.

Here, the factor of energy usage is disregarded to give more importance to occupants' comfort level. There may be other reasons for opening a window, like the indoor air quality, odour removal etc. An inductive study to understand occupants' thought process, their reasons for opening windows, their comfort temperature etc. gives a solid understanding of occupant behaviour and the drivers leading to window opening.

3.4.1. Thermal Imaging

The impact of occupant behaviour on energy efficiency is complex and depends on various factors. Visualising the thermal characteristics of buildings brings to light areas of heat loss in the building that are otherwise not observed. To understand impact of window opening behaviour on energy usage in dwellings, thermal images of residential buildings in Nottingham, were collected on two cold winter nights. Heat transfer in object occur by means of conduction, convection, and radiation. Transfer of heat from one solid to another is conduction and convection is transfer of heat through fluids. Radiation is the heat transferred due to electromagnetic radiations from the object. Although heat transfer is not visible to human eye, infrared radiation which is one of the electromagnetic waves emitted by the object, can be detected by an infrared camera. Infrared thermography is the process of using infrared camera to capture infrared image to understand thermal patterns, by calibrating the emissive power of surface at various temperature range (Balaras and Argiriou, 2002)The neat heat energy (q) emitted by the surface of an object is:

$$q = \mathcal{E}\sigma T^4 \tag{3.1}$$

$where$ Ɛ is the emissivity of the surface ($0 < \mathcal{E} < 1$), σ is the Stephan Boltzmann's constant (5.67 x 10-8 W/m^2K^4) and T is the absolute surface temperature (K) of the object.

By using infrared technology, areas of heat-loss in the buildings can be identified. Random sampling technique was used, to understand window opening pattern in different types of housing across Nottingham. Thermal images of buildings were taken on two cold winter nights and were studied based on their temperature range and the building features. The images collected were of buildings built in different decades, with different types of insulations. The images helped understand the amount of heat lost by leaving window open. The insulation properties of houses were also visible in the thermal images, making it comparable to the heat lost through open window. The thermal images were captured using FLIR T640 thermal imaging camera (FLIR, 2013) and FLIR software was used to analyse the temperature readings.

3.4.2. Survey

People are shaped by everyday behaviours and when these behaviours are performed repeatedly over time, a habit is formed (Orbell and Verplanken, 2010). Households affect the energy performance of buildings directly and indirectly (Estiri, 2015; Belaïd, 2017). Incorporating household energy use and the impact of behaviour of occupant on energy consumption in the choice processes is drawing attention (Kelly, 2011). The extend to which occupant behaviour affects energy use depends on various factors, including climatic conditions, personal preferences, building thermal properties etc. (Guerra-Santin and Itard, 2010; Wei, Jones and de Wilde, 2014). This study focusses on occupant behaviour, in particular window opening behaviour of occupants, in residential buildings. Occupant behaviour in general has been evaluated since 1951, however, the significance and number of studies noticeably increased since 2001 (Yan *et al.*, 2017). Studies show difference in energy performance between households of similar size and type, based on behaviour of occupants (Yun, Tuohy and Steemers, 2009).

The high complexity and unpredictability of occupant behaviour is known to be the main cause for the discrepancy between actual and predicted energy consumption in buildings (Fabi et al., 2013). Adjusting window position is one of the most common adaptive actions, particularly in naturally ventilated buildings (Yun, Tuohy and Steemers, 2009). A complex combination of physical, comfort, and behavioural models influences occupants' window opening behaviour (Markovic et al. 2018). The above reviews emphasise the importance of understanding occupant perception and occupant behaviour, with respect to energy efficiency of a residential building. The survey was designed, to understand perception of occupants on their own window opening behaviour, and to understand their knowledge about how it affects energy efficiency of the building. Ethnography is the study of social interactions, behaviours, and perceptions that exist within groups, organisations, or communities, providing rich and holistic insight into peoples' perceptions and behaviours (Reeves et al., 2008). The survey can be considered to be an ethnographic study, since it includes detailed qualitative observations of the participants, regarding the considered criteria, which is window opening behaviour in this case. As mentioned in section 3.1, this research follows a mixed method of research, wherein qualitative and quantitative data are systematically integrated in order to answer research questions. Based on review of literature and to further understand research question 'Why do people open windows in winter', the survey was developed. It also aimed to understand why people open windows even in winter and if opening window when the heating is turned on, is s common practice across the UK.

To explore the impact of occupants' behaviour on energy efficiency of a building and enhance understanding of energy usage by understanding people's perceptions, with the focus on opening of windows, a survey was carried out. The survey was aimed at people (over the age of 18) residing in the UK. Random sampling is sampling technique in which participants are selected depending on availability and willingness to respond (Gravetter & Forzano, 2006). The survey was structured in such a way to include questions with answers in accordance with a Likert scale with options for open-ended answers where the participants were welcome to express their own opinions if they chose to. The questions in the survey were intended at examining the windows-opening behaviour of people and its consequent effect on the energy efficiency of buildings. The objective close ended Likert scale and objective answer questions contributed to the quantitative data while the answers to open ended questions provided valuable data toward qualitative analysis of the reasons for window opening and the conditions that came together for an occupant in a house to open windows in winter when heating is ON.

A survey link, containing a brief information on the aim of the research and purpose of the survey, was sent through emails and social media groups to a collective of people across the UK. A survey collecting website called prolific was also utilised to collect survey from a representative sample of the UK.

3.4.2.1. Ethical Considerations

An ethical approval process was followed during this research work to make sure that the study complied with all ethical clearance requirement of the university,namely the Joint Inter-College Ethics Committee (JICEC). This included ensuring that privacy and confidentiality of the participants was satisfied. The survey was kept short and could be answered within 5 mins so that participants did not feel constrained.

3.4.2.2. Sample Size

To make reliable inference about a population, with an empirical study, like a survey, choosing the right sample size is important. Confidence interval (CI) is the quantitative representation of uncertainty associated with the collected data, calculated from the data statistics. The most common CI employed is 95%. The margin of error is the percentage of random sampling error that can occur. A reasonable margin of error of 5.5-6% is chosen for this study. With the above values, the sample size is calculated using normal distribution and z-score values, to be between 267-318.

The survey results with objective answers were analysed and the open-ended questions were qualitatively analysed and the observations from the results that revealed information relevant to the research, were reported.

3.5. Analysis of Energy Usage in Social Housing

Preliminary qualitative analysis was followed by the nest phase of the research. This included the quantitative analysis of data obtained. Nottingham Trent University (NTU), in partnership with Nottingham City Homes (NCH), conducted a study to better understand energy efficiency in social housing. The project focussed on 40 homes based in Nottingham with a diverse construction design, constructed over a period ranging from 1902 to 2012. The experiment was conducted over a period of 51 weeks from Feb 2013 to March 2014 and data was collected. The data obtained, from the above-mentioned experiment, was analysed using MATLAB, with a goal to capture patterns of energy usage and its relationship to occupant behaviour, based on outside ambient temperature.

The analysis aims to look at some hypothesis regarding relationship between:

1. External ambient temperature and radiator usage
2. External ambient temperature and room ambient temperature
3. Room ambient temperature and room radiator temperature
4. Room ambient temperature and status of window in the room(open/close)
5. Window usage and outside ambient temperature
6. Window usage and radiator usage

The analysis has been carried out for data collected from houses with different architecture, insulation and built year. While this helps to have a wider range for analysis, it should be noted that these houses may not be typical of all such houses. The data included in this study are from houses that have successful data collection from all the sensors installed and does not include houses that have faulty sensor readings are from houses that do not have missing sensor readings for the specific period mentioned in the forthcoming analysis. They will reflect the energy usage characteristics of occupants based on various factors, particularly based on the opening of windows in the bedroom and lounge.

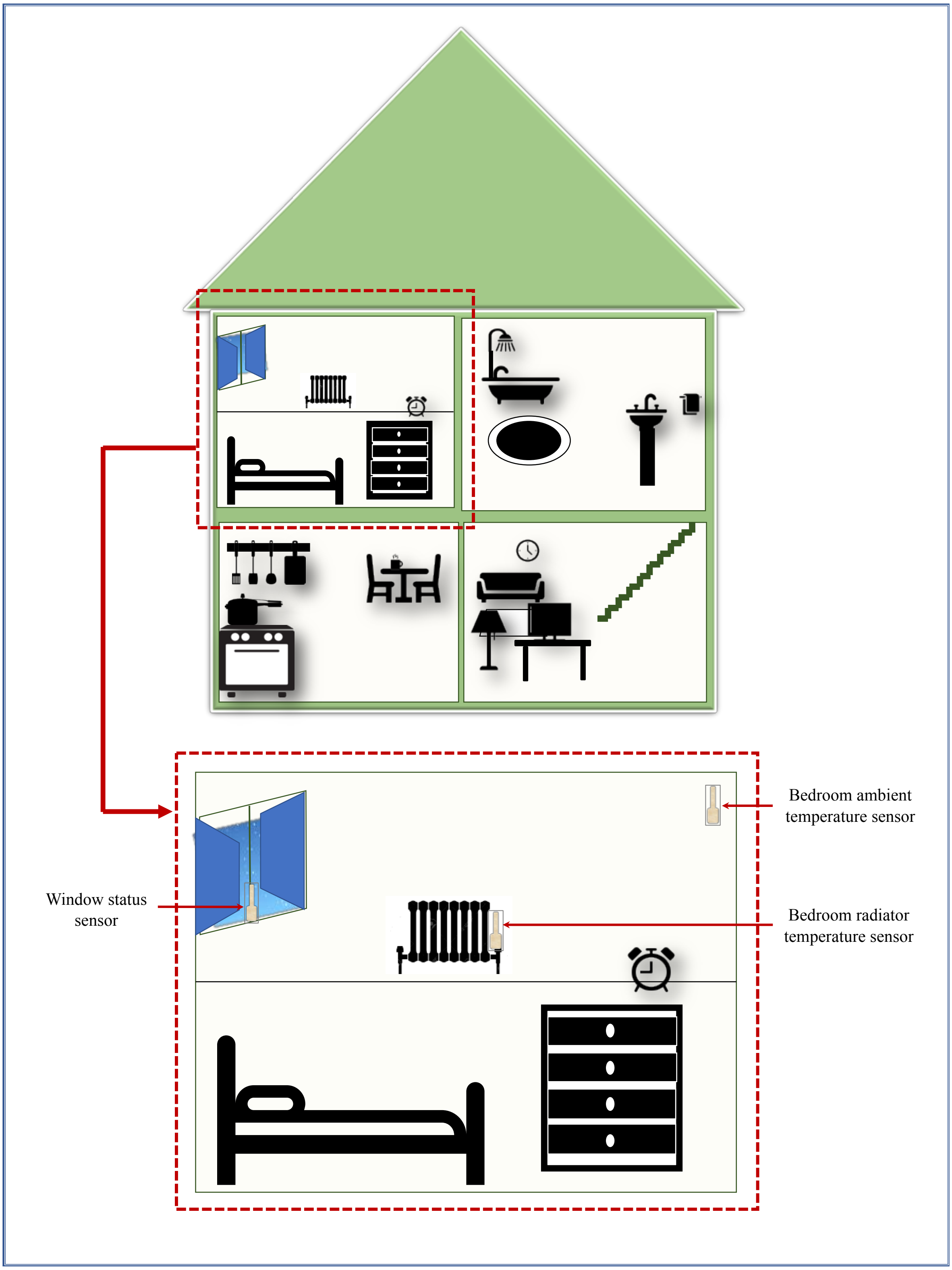


Figure 3.2: Location of sensors in the house

3.5.1. Sensor set-up

Houses were equipped with Wireless Sensor networks (WSN) to record the utility readings, ambient temperature of rooms, radiator temperatures and to monitor the opening and closing of doors and windows.

Figure 3.2 shows the representation of the location of the sensors in the bedroom of the house. The bedroom considered in this analysis is the master bedroom, and the variables considered are, bedroom ambient temperature, bedroom radiator temperature, bedroom window status and the outside ambient temperature. The temperature is sensed using sensor LoRa RF PT100 from Invisible systems.

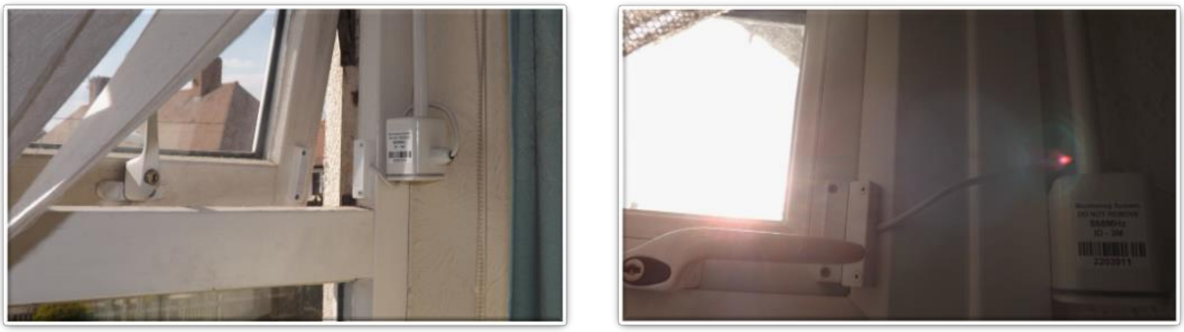
Figure 3.3: Sensors measuring room temperature

Figure 3.4: Sensors measuring radiator temperature

To detect the ambient temperature of room, the sensor is installed high on the wall, near the ceiling, away from doors, windows, and radiators, to capture the average temperature without compromising the value, as shown in Figure 3.3. The radiator temperature is detected by installing a temperature sensor right next to the radiator. Temperature sensors installed near radiator, for two houses are shown in Figure 3.4.

Window status is sensed using Invisible systems status transmitter, shown in Figure 3.5. The status transmitter is a wireless transmitter that captures the status of the required equipment, normally via open/closed contact. The sensor used comes with a magnetic switch to report the status. The switch has two parts that must be installed to report change in status with respect to contact/ no-contact with the other part of the switch. In the experiment conducted, one part of the switch was connected to the frame of the door/ window and the other part was attached to door itself, in such a way that when the door was closed the two parts were in contact with each other and signal would be send out, as 1, representing a closed circuit, as shown in Figure 3.6(a).

Figure 3.5: Sensor measuring window status



(a) Window Open (b) Window Closed

Figure 3.6: Working of the window status sensor

When the window was open the circuit remained open and the value transmitted, would be zero as shown in Figure 3.6(b). In short, ‘1’ indicated a closed window and ‘0’ indicated an open window. However, the measure of opening of the window cannot be identified, using this system. The system would remain in ‘0’, regardless of the window being fully open or partially open. Each sensor in each house was identified using the unique serial number marked on the side of the sensor, together with the barcode, to identify the values form different houses, after data collection.

3.5.2. Data Cleansing

Data was collected from forty houses over a period of 51 weeks. The quality and usability of any data set depends on several factors. Any shortcoming in the quality of the data may impact the performance of the decisive process (Islam et al., 2014). Therefore, it is crucial that the data is cleaned before analysis. The data cleansing process followed in this study is concisely given below:

1. A copy of the obtained raw data was made.
2. The raw data was checked for corrupt values.
3. Outliers were identified and removed.
4. The data was then checked for missing values and imputed, using interpolation or extrapolation depending on the location of missing data in the whole data set.

5. Since the data was collected using wireless sensors, the time stamp of the 12 different sensors varied. The data from all the sensors were synchronised, using interpolation wherever required.

6. The whole process was performed using MATLAB, which is an ideal software for iterative analysis and design processes.

There were sensors that did not work for major part of the data collection and sensors that were faulty. After consolidation and for clarity of analysis, 17 houses that had data from all the sensors and had negligible missing data, were chosen for this analysis.

The cleansed data was saved in two different data sets: first one based on house data (17 data sets with data from 12 sensors) and the second one based on sensor data (12 sensors each having data from 17 houses). All data was dealt with in such a way as not to lose any valuable data during analysis. Data, starting form raw data obtained from the houses was categorised, coded, and documented to make sure it was safe.

3.5.3. Heat Energy Demand Calculation

The increase in temperature of a room depends on several factors. Human body temperature is around 37.4°C, which is less than room temperature. Therefore, there is transfer of heat form human body to room. Sunlight accounts for increase in heat of a room, the intensity of which depends on the season and weather. Electrical appliances and human activities like cooking also contribute to the increase in heat. But the major increase in room temperature is attributed to the heating system. The energy used for maintaining temperature of comfort in the room, depends on the outside ambient temperature. The lower the temperature outside, the more energy required to maintain ambient temperature inside. The amount of heat required to maintain a temperature comfortable to the occupant also varies depending on several factors as discussed earlier.

Calculating energy demand in residential buildings is an intricate process since it involves energy loss due to building fabric, energy loss due to ventilation, energy loss due to infiltration and other factors. Each of these in turn depend on various factors. Energy loss through 'cold bridges', such as pipes inside walls and metal coves, and cracks in walls are not considered.

Heat loss through building fabric is constant for a building depending on factors like construction, built year, insulation type etc. Hence, while calculating energy demand, heat loss in a house, due to building fabric does not change over time. On the other hand, heat loss due to ventilation is highly fluctuating since it depends on the behaviour of the occupant of the building. Opening and closing of windows is the most common way of controlling room temperature in dwelling. However, in winter, the action of opening window leads to increase in energy usage. This is because when window is opened, the warm air form inside the room leaves the room through the open window, to be replaced by cold arti form outside. The heating system must then provide heat energy to warm the air again to the required thermal comfort temperature. This energy used to heat the cold air is called heat loss due to ventilation. Quantifying heat loss due to ventilation is a complex process due to the number of factors involved. The rate, time and degree of window opening depends on the occupants and is highly stochastic.

However, ventilation varies depending on the type of ventilation: automated, where in it depends on the set time of ventilation; or manual wherein it is unpredictable since occupants tend to open windows or increase thermostat temperature base on their thermal comfort. The total energy demand in a room can be calculated as the sum of energy loss through building fabric and energy loss through ventilation.

Energy consumption Q_{ec} is given by

$$Q_{ec} = Q_f + Q_v \tag{3.2}$$

where Q_f is the heat loss due to building fabric and Q_v is the heat loss due to ventilation

3.5.3.1. Heat-loss due to Building Fabric

$$Q_f = \left(\sum U_y \, A_y\right) \times \Delta T \qquad (3.3)$$

where U_y is the U value of individual elements of the building fabric, Ay is the area of individual elements of the building fabric and ΔT is the difference in temperature between the considered room and outside. From (3.3), the contribution of heat loss due to building fabric to overall heat-loss is

$$\frac{Q_f}{\Delta T} = \sum U_y \, A_y \qquad (3.4)$$

$$\frac{Q_f}{\Delta T} = U_1 A_1 + U_2 A_2 + U_3 A_3 \qquad (3.5)$$

Table 3.1: U-values of different fabrics with different insulation types

Wall Types	U-value (W/m2K)	
Solid wall in very old buildings	2.3	~ 2
Solid wall in old buildings	1.7	~ 2
Unfilled cavity wall	1.5	~ 2
Solid wall with 100mm thick external insulation	0.32	~ 0.3
Filled Cavity wall with 100 mm thick external insulation	0.25	~ 0.3
Double Glazed windows	2.8	
Insulated Roof	0.15	
Uninsulated Roof	2.5	

Heat energy can be lost through the walls facing the external atmosphere, through the window frames and glass and through the roof. The rate of heat loss can be calculated by knowing the U value of each element mentioned. The heat loss through the fabric is the U-value multiplied by the total area of the fabric, as given in (3.4) and expanded in (3.5). Hence, the contribution of heat loss due to fabric elements is given by

$$\frac{Q_f}{\Delta T} = U_1 A_1 + U_2 A_2 + U_3 A_3 \qquad (3.5)$$

where U_1A_1 is U value and area of wall with one side facing outside atmosphere, U_2A_2 is U-value and area of window fabric and U_3A_3 is U-value and area of roof. The U-values of different materials in a building fabric, are given in Table 3.1.

3.5.3.2. Heat loss due to Ventilation

As given in (3.2) the total heat-loss Q_{ec} of a house is the sum of the heat-loss due through building fabric (Q_f) and heat-loss through ventilation (Q_v). Majority of dwellings in the UK are naturally ventilated. Heat loss due to ventilation, Q_v is most commonly due to the opening and closing of windows. When windows are opened in winter, cold air from the outside replaces the existing warm air. The cold air has in turn to be heated to the required temperature set by the occupant. The amount of heat energy required to maintain thermal comfort in a room or the energy consumption due to ventilation, can be calculated considering heat capacity of the room, as

$$Q_v = m \times C_p \times ACH \times \Delta T \tag{3.6}$$

where m - mass of air in kg, C_p - specific heat of air (under constant pressure) which is 1 kJ/kgK at 300K (26.85°C), ΔT - rate of change of temperature and ACH – Air Change Rate per hour.

Mass of air (m) is given by

$$M = \rho v \tag{3.7}$$

where ρ is density of air which is 1.225kg/cubic metre and v is the volume of air in the room (l x b x h cubic metre). Therefore, Energy demand Eh is

$$Q_v = \rho \times v \times Cp \times ACH \times \Delta T \tag{3.8}$$

$$Q_v = 1.3 \times b_{vol} \times 1 \times ACH \times (T_{room} - T_{out}) \tag{3.9}$$

where T_{room} is the ambient temperature of the room and T_{out} is the ambient temperature outside. The unit is derived as (*kg* x *m* x *m* x *m* x *(kJ/kgK)* x *K)* which simplifies to kJ or kiloJoules or (kJ/3600) Watts. The contribution to total heat-loss due to ventilation is given by

$$\frac{Q_v}{\Delta T} = \frac{1.2\ x\ bvol\ x\ ACH}{3600} \tag{3.10}$$

From (3.5) and (3.10), the total energy consumption Q_{ec} is

$$Q_{ec} = \left(U_1A_1 + U_2A_2 + U_3A_3) + (\frac{1.2\ x\ bvol\ x\ ACH}{3600})\right) \Delta T\ Watts$$

(3.11)

Energy demand is usually expressed in kWh. Therefore expressing (3.11) in kWh

$$Q_{ec} = \frac{(Q_f + Q_v)\Delta T}{1000}\ kWh \quad (3.12)$$

Air Changes per hour

There are standard regulations given for air tightness for different types of ventilated buildings. Calculating the air changes per hour of a naturally ventilated building is a complex process, since there are many factors to be considered in the process, including dimension of window, area of window that is open, height of window from ground outside, height of window from floor inside, height from ceiling to window, speed and direction of wind, outside ambient temperature etc. The speed of wind and the outside ambient temperature for the considered time frame, has been obtained from MET office data (Weather Observation Website, n.d.). For this study, the ACH for window open and window closed houses, has been calculated using a calculator(*Air Change Rate Calculator | Estimate Air Change | WindowMaster*, n.d.).

3.5.4. Analysis - Stage I

The analysis has been carried out for data collected from houses with different architecture, insulation and built year. While this helps to have a wider range for analysis, it should be noted that these houses may not be typical of all such houses. The data included in this study are from houses that have successful data collection from all the sensors installed and does not include houses that have faulty sensor readings are from houses that do not have missing sensor readings for the specific period mentioned in the forthcoming analysis. They will reflect the energy usage characteristics of occupants based on various factors, particularly based on the opening of windows in the bedroom.

In the first stage of analysis of energy usage in social housing, the construction type, built year, and insulation type of houses are explored. The window opening pattern in the houses are also studied. This study focusses on the window status of the main bedroom window. Several previous studies show that the main bedroom is most often used for ventilation in domestic buildings (Brundrett, 1977; Centre, 1986; Dubrul, 1988; Fox, 2008; Jack et al., 2015; Jones et al., 2015; Pretlove, 2000). Installation notes indicate that the bedroom chosen for the study in the houses was the master bedroom and hence the bedroom for all the houses is the master bedroom throughout the analysis. Since energy consumption variation is more evident in winter, data from the winter months were chosen for analysis. Houses are categorised based on their insulation type and window opening behaviour. A detailed description of the analysis is given in Chapter 6.

3.5.5. Analysis - Stage II

In the previous section, the methodology followed in the first stage of analysis of energy usage in social housing is explained. Following the analysis of all the houses, a more detailed analysis of four houses is done, to further understand and quantify the effect of energy efficiency and to compare values between high insulation and low insulation houses. Four houses are selected based on their insulation property and window opening frequency: high insulation window open house, high insulation window closed house, low insulation window open house and low insulation window closed house. By comparing the energy usage in these four houses, a robust representation of difference in energy usage in window open and closed houses and its relationship to insulation property of the house, can be understood.

3.6. Development of ANN Model to predict energy usage and window opening behaviour in residential buildings

Occupant behaviour (OB) is a major factor influencing energy efficiency of a building, but not represented enough in building performance simulation (BPS) models. In most BPS until the past few decades, OB is represented by predetermined 'deterministic' schedules or fixed settings, which, when incorporated into BPS, provides a homogenous model which does not consider the stochastic nature of OB. Past few decades have seen an increase in probabilistic models of OB representation, which are derived from data collected, including the temperature details of indoor and outdoor environments, other physical parameters and the factors that change due to occupant behaviour. Different studies use different combination of these variables and therefore a standardised model is lacking.

This study follows a stochastic model of representing OB, with measured temperature data and indoor and outdoor environmental conditions, window opening frequency and the building fabric properties. Artificial neural network is used to develop models to predict energy usage in buildings based on indoor room temperature, radiator temperature, outside ambient temperature, and window status of the house. The thermal characteristics of the room and its relationship to occupant behaviour of window opening is investigated. By analysing the collected data, the temperature patterns that lead to an occupant opening window is extracted, to develop Artificial Neural Network model to predict window opening behaviour and energy consumption based on window opening behaviour of occupants. Deciding on an algorithm and developing a model depends on various factors in a multi-variate analysis. There will be some trade-off between model speed, accuracy, and complexity. A systematic workflow is required to choose the right model.

Multivariate statistic modelling poses an inherent difficulty of visualising data with many variables and to find the relationship between variables, their relevance and correlation. It is important to find out the driving force that governs the behaviour of the system (MathWorks, 2021). A key question in predicting window opening behaviour and stochastic modelling is the identification of the key variable/variables responsible for window opening behaviour. It is important to figure out the main factor that triggers the behaviour for ideal modelling of residential buildings to include the predictability of window opening. In this study, supervised learning is used, since both input and output characteristics are being observed to find optimum conditions of window opening behaviour of occupants, for better energy efficiency. The overall algorithm of the whole process is given in Figure 3.7.

MATLAB Neural Network is used to create models. To understand and predict window opening behaviour, different models are tried.

3.6.1. Steps to Development of Model

Selecting a model involves considering all factors to be considered, and a trade-off between specific characteristics of the algorithm like speed, memory usage, transparency etc. The study aims to understand the window opening behaviour of occupants; to find the conditions under which window is opened.

Measurements of window opening and room temperature, radiator temperature, time of day and outside ambient temperature are taken. Window opening temperature is the 'input' and the other variables are the 'targets'. This makes supervised learning technique more apt for the development of a model. Supervised learning can in turn broadly be one of the two types, namely, classification or regression. The optimum model is chosen by trial and error. Different algorithms are tried and the best performing one is chosen.

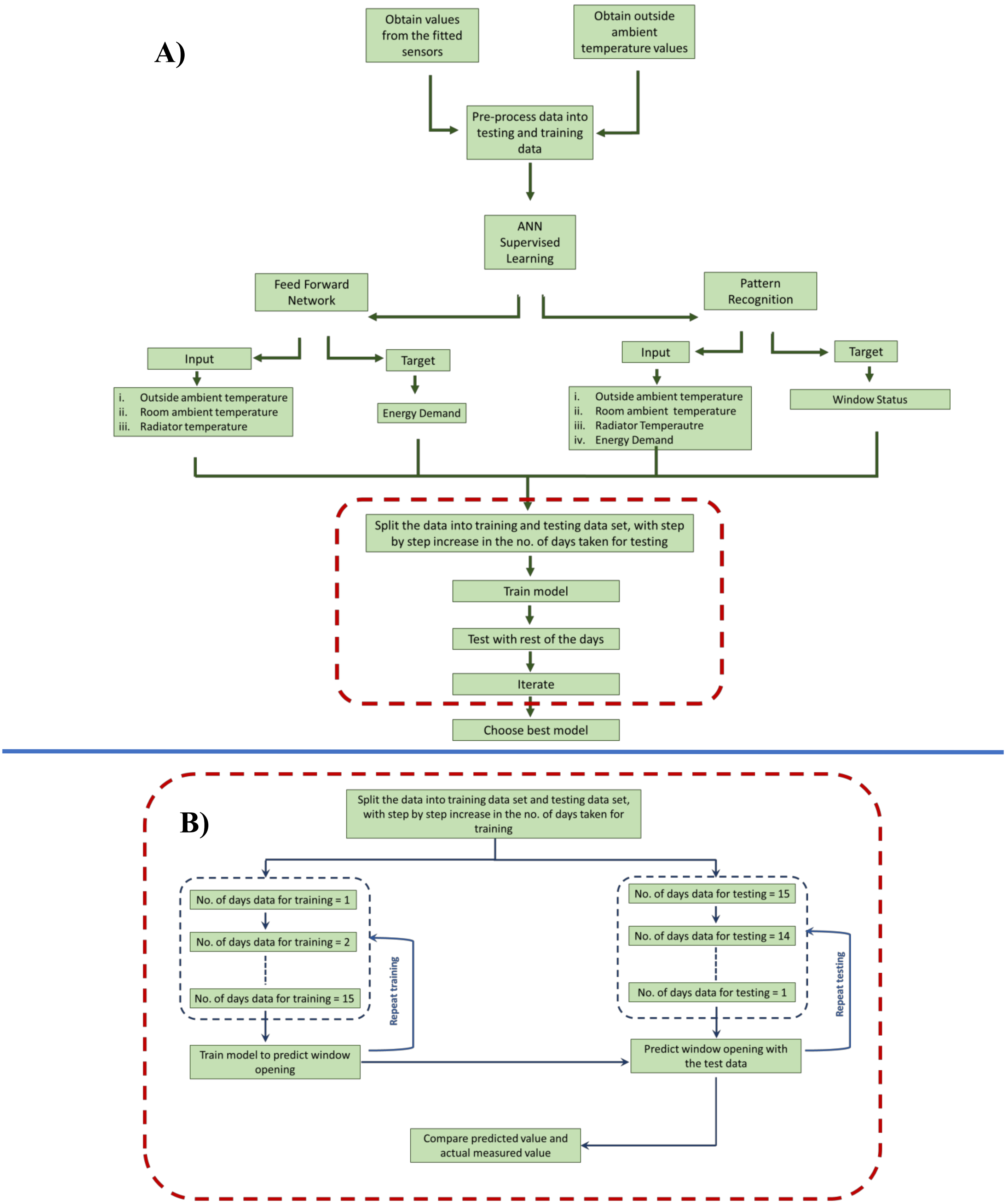


Figure 3.7: A) Block Diagram explaining process followed; B) further details of the process

Only features with the most predictive power are chosen, to create a model that generalises well to any data set of the same type.

3.6.1.1. Data Pre-processing - Feature Extraction

The obtained data has pre-processed to suit stochastic modelling for prediction of window opening behaviour. The variables in question are all different data types, requiring different pre-processing techniques. The sensor values are numerical. The room temperature and radiator temperature are continuous values while the window temperature is made discrete by considering it as two states (open or close).

3.6.1.2. Variable Selection

The focus of study of this research is the relationship between window opening and its impact on energy efficiency (EE). Hence House A (High Insulation -Window Open) and House B (High Insulation, Window Closed) are the houses chosen for development of neural network models. The variable considered for Model development are the room temperature, radiator temperature, window status and calculated energy demand. Each house data is grouped into days, with 83 samples in each day. This helps predict energy demand and window open status per day. The data is split into winter 1 and winter 2 data with 29 days data in winter 1 and 13 days data in winter 2.

3.6.1.1. Correlation between variables

Development of statistical stochastic models depend to a great extend to the correlation between variables being considered. Only then can the effect of individual variables on window opening behaviour be identified. The analysis of correlation between the variables are given in detail in the previous chapters.

3.6.1.2. Develop Models

The data is split into training and testing data. The training data is used to develop a machine learning model. The testing data is used to validate the developed model. This is done by testing the data with the developed model and comparing the result with the actual measured value. The percentage error of the model is calculated.

The input in this study is binary - window open or closed which is expressed as a logical array (1 - open, 0 - closed). The total error is the number of times the window status (open or closed) is predicted wrong.

Therefore, the error is the sum of inequality between the two logical arrays, as shown in equation. The percentage error is the total error over the total number of observations. In this study, data is collected every minute giving observations of 1440 per day.

$$Error_{energydemand} = \frac{ED_{predicted} - ED_{actual}}{ED_{actual}} \; x\, 100 \tag{3.13}$$

$$Error_{winstat} = (winstat_{\ predicted} \sim= winstat_{measured}) \tag{3.14}$$

$$Percentage\ error = \frac{\sum_{i=0}^{n} E_{winstat}}{n} \times 100 \tag{3.15}$$

where n = 83.

The training and prediction process is repeated 15 times, each time increasing in step, the number of days taken for training, to see the overall performance of the machine learning model with different data sets.

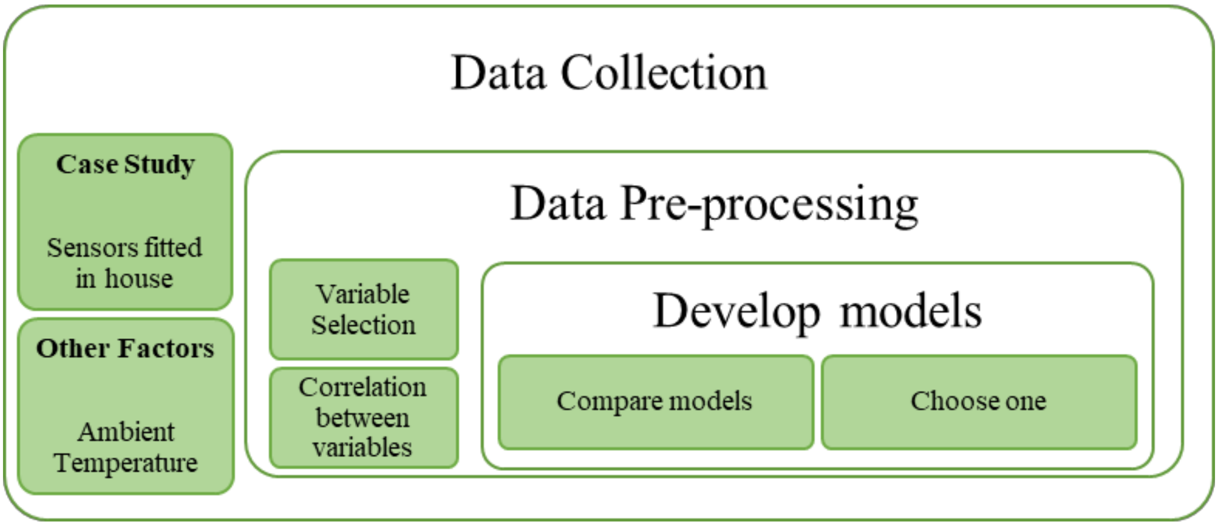


Figure 3.8: Block Diagram of Methodology of development ANN models

3.6.1.3. Compare Models

Once the models are developed, they are compared to check for accuracy and repeatability, while making sure over fitting is not done.

The best model is chosen, based on various conditions and it is chosen to be used as a base for testing on data form House B and House C and for further development. The block diagram of methodology is shown in Figure 8.

3.6.1.4. Testing and validation

Window status is considered as the input. The targets are radiator temperature, room temperature, timeofday and outside ambient temperature. The data is divided into three subsets. The first subset is used for gradient computation and weight adjustments. The second subset is used to validate the first set. The third subset is used to test the model and see the error. In this study, the data is divided randomly into three subsets, with 70% of the data in subset 1, 15% of the data in subset 2 and 15% in subset 3.

The input class is binary, window open or window closed. Initially, one day data is taken for training and model is created. The model is used to test the other days data of winter 1. The predicted data is compared with actual data and the percentage error is calculated. Model is modified to have 2 days data as training data and the other 14 days are tested. The process is repeated with up to 15 days data. The created models are tested with the rest of the data. The model with the least average percentage error is chosen as the best model.

3.7. Summary

The aim of this research is to assess the effect of window opening behaviour of occupants on energy efficiency of buildings. Based on this aim, the objectives were set out and consequently, the research questions were formulated. A methodology was followed to achieve the aim and objectives, with guidance of the research questions. The methodology followed for this research study is elaborated in this chapter. Mixed method of analysis was followed for the research, which included qualitative analysis with data from thermal images and survey, and quantitative analysis with data from social housing. The methodology was carried out in three stages. The first stage being literature review which continued throughout the course of the study, the second stage being the preliminary analysis of thermal images and survey and the second stage being analysis of energy use in social housing, to understand the impact of window opening on energy usage. This was followed by development of artificial neural network models to predict energy usage and window opening behaviour of occupants.

Chapter 4 | Investigating the Effect of and Reasons for Window Opening Behaviour of Occupants

4.1. Introduction

Literature review emphasised the role of occupant behaviour, particularly, window opening behaviour of occupants, in energy efficiency of a building. To investigate this further, two courses of action were undertaken:

1. To get a visual understanding, thermal images of residential buildings across Nottingham were collected. Infrared thermography was used to identify areas of heat-loss in buildings.
2. A survey was carried out, to understand why people open windows in residential buildings and the key ‘drivers’ to window opening behaviour in occupants.

This chapter discusses both the above, which contribute to the qualitative analysis of the study.

4.2. Thermal imaging

Heat transfer in object occur by means of conduction, convection, and radiation. Transfer of heat from one solid to another is conduction and convection is transfer of heat through fluids. Radiation is the heat transferred due to electromagnetic radiations from the object.

The net heat energy due to Infrared (IR) radiations is given in Chapter 3, equation (3.1). While IR radiation ranges between 0.7µm and 100µm atmospheric IR transmission is between 3 µm to 13µm (FLIR, n.d.). Different IR thermal imaging cameras capture different ranges of IR, depending on the application. IR thermography can be valuable tool to identify heat loss in buildings in a non-destructive way. Several studies have been done in the past fifty years, where IR thermography has been used to understand heat characteristics of buildings, which have been reviewed in Section 2.5.2.

Several studies use thermography has been used in non-destructive analysis of cultural architecture and building defect diagnostics (Al-Habaibeh et al., 2021; Al-Habaibeh & Siena, 2012; Costanzo et al., 2015; Daffara et al., n.d.; Fokaides & Kalogirou, 2011; Glavaš et al., n.d.; Grinzato, n.d.; Lo & Choi, n.d.). However, the 'ease of understanding' aspect of IR thermography has not been utilised to it full extent. Goodhew et. al investigated behavioural changes in occupants, by providing them with thermal image of heat loss in their homes. IR images of the building interior and exterior were provided to occupants. Results showed that residents who received thermal images were more prone to reduce their energy usage (Goodhew et al., 2015). The impact of occupant behaviour of window opening can be better understood using thermal imaging.

4.2.1. Data Collection

To better understand and evaluate occupant behaviour with respect to thermal comfort, a survey was done on two cold nights in February 2019, in different areas of Nottingham, United Kingdom, as given in Table 4.1.

Table 4.1: Specifics of data collection

Location	Date	Time	Outside Ambient Temperature (°C)
City Centre, NG1	11/02/2019	17.30 to 19.30	3
Sneinton, NG2	12/02/2019	19:15:00	5
Forest Field, NG7	12/02/2019	19:30:00	5
Broxtowe, NG8	12/02/2019	19:45:00	5
Lenton, NG7	12/02/2019	20:15:00	5
Calverton, NG14	12/02/2019	21:00:00	5

By using infrared technology, areas of heat-loss in the building can be specified. Thermal images of buildings were taken on two cold winter nights and were studied based on their temperature range and the building features. The images collected were of buildings built in different decades, with different types of insulations. A selection of the images is presented in this chapter.

4.2.2. Analysis and Discussion

As discussed in literature review chapter, residential buildings play an important part in increase in energy consumption and thereby emissions, in the UK. Renovating old buildings and construction of new buildings with good insulation formed an important part of the government's plan to reduce energy consumption and improve energy consumption practices in the domestic sector, However, in the past few decades, the importance of occupant behaviour in energy consumption is being realised. There are studies documenting the benefits of environmentally responsible behaviour (ERB) of occupants (Hamilton, 2018). This section focusses on thermal images taken from outside student halls. Studies shows that there is a lack of student awareness of energy conservation strategies (Collins, 2010). Thermal images make it possible to observe heat dissipation which is otherwise invisible to the human eye. IR radiation from the surface of the building emits heat, which is visible in the thermal imager camera. This can be compared with the environmental temperature. In winter, the difference between the indoor and outdoor temperature is high. Therefore, the thermal image depicts a clear idea of where heat energy is lost, in the building. This helps capture the stochastic behaviour of occupants in a dynamic manner. Thermal images make it possible to observe heat dissipation which is otherwise invisible to human eye. IR radiation from the surface of the building emits heat, which is visible in the thermal imager camera. This can be compared with the environmental temperature. In winter, the difference between the indoor and outdoor temperature is high. Therefore, the thermal image depicts a clear idea of where heat energy is lost, in the building. This helps capture the stochastic behaviour of occupants in a dynamic manner.

Images were captured from Nottingham Trent University campus student accommodations, on a cold winter night. The outside ambient temperature was 3°C. Nottingham Trent University campus buildings are post 2000 built high insulation buildings. Figure 4.1 shows images of windows left open in the student halls. One of the windows is wide open, regardless of the temperature outside (3°C). The same trend is seen in other buildings across the area. There is a lack of student awareness of energy conservation strategies (Collins, 2010). Several studies have been undertaken to understand the energy awareness of students living in residence halls (Amin et al., 2016; Dixon & Parker, 2021; Emeakaroha et al., 2014; Jami et al., 2021; Laurent et al., n.d.; Wisecup et al., 2017). Energy use in student halls vary to a great extent depending on the characteristics of energy use in the actual house of the students (Amin et al., 2016). This is evident from the collected thermal images. Airflow Q through window is given by the equation

$$Q = A_c v_c \tag{4.1}$$

where A_c (m^2) is the minimum cross section area of air flow through the opening and v_c (m/s) is the velocity of air through this area. A_c can be determined by

$$A_c = C_c A \tag{4.2}$$

where C_c is contraction co-efficient, and A (m^2) is the area of the opening.

It is clear from (4.3) that the degree of window opening affects how much air flow occurs. The higher the value of A, the higher the quantity of cold air form outside entering the building. This in turn makes the room cold, prompting the occupant to increase heating. Figure 4.2 show thermal images were captured from Nottingham City Centre buildings and nearby areas.

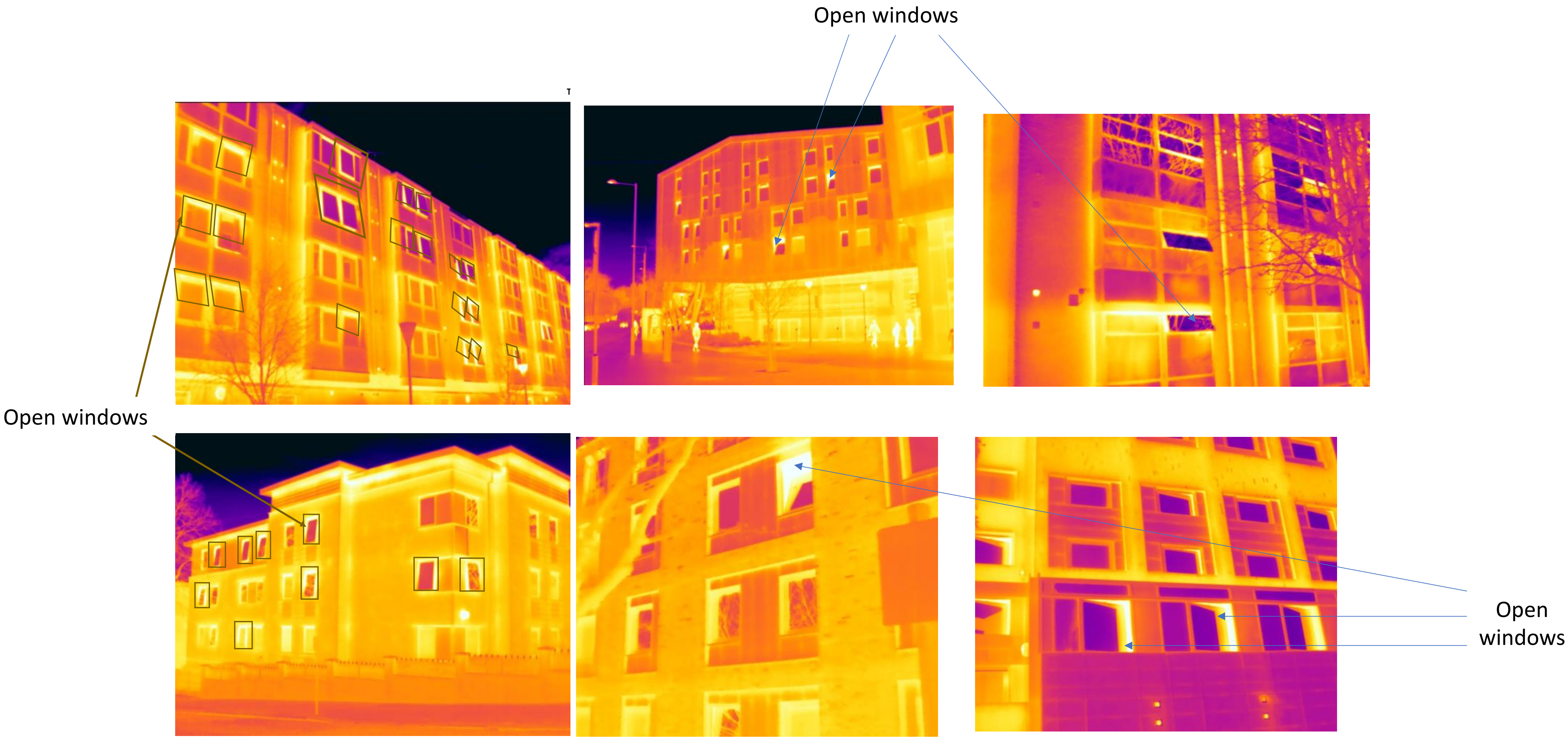


Figure 4.1: Thermal image of NTU Student Halls

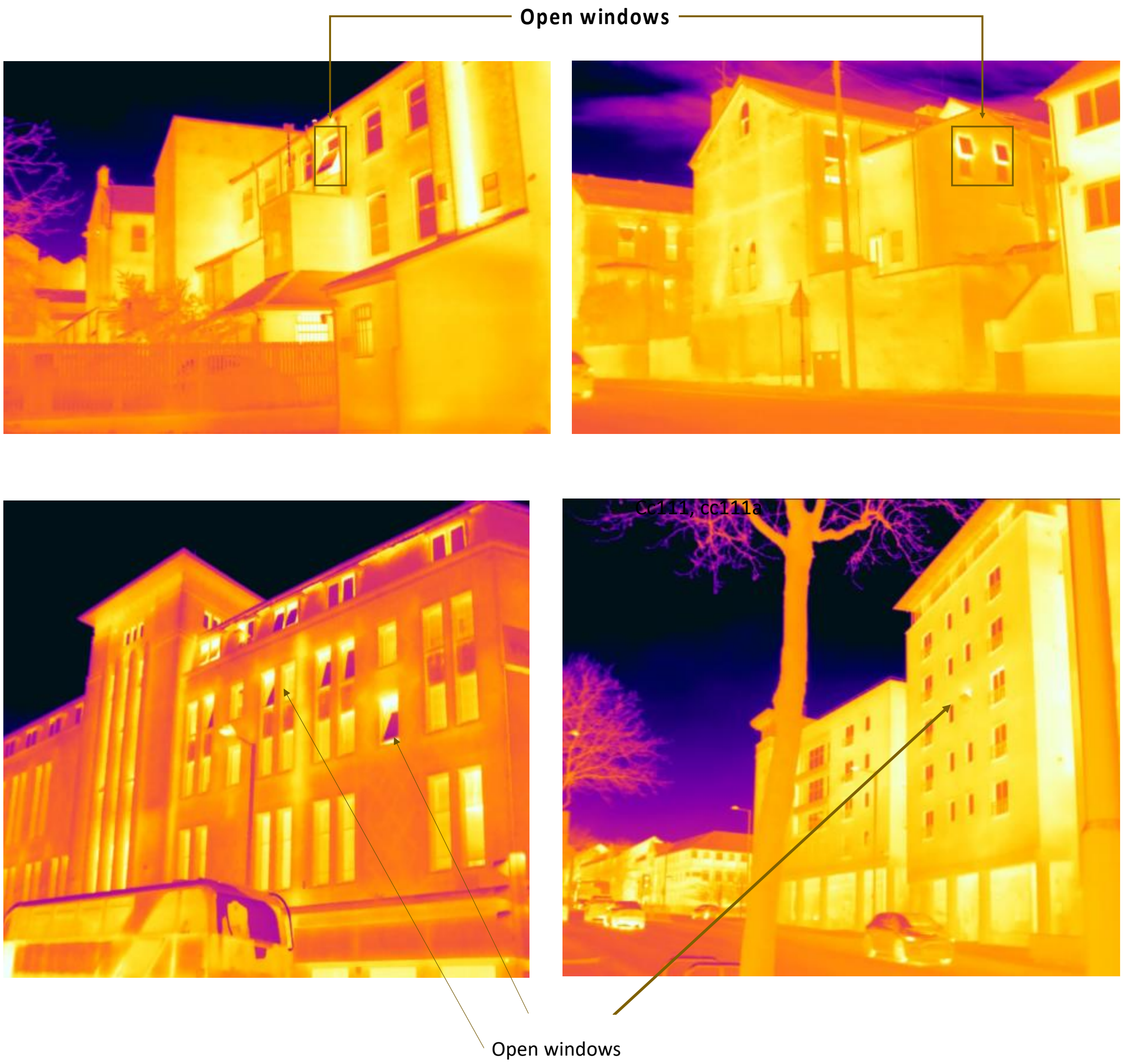


Figure 4.2: Thermal image of buildings in Nottingham City

To further understand the characteristics of occupant behaviour, thermal image collection was continued the next day. The outside ambient temperature at the time of data collection was 5°C. Other areas of Nottingham, with different age houses, were covered. This was done to understand the impact of insulation in window opening behaviour. Figure 4.3 shows semi-detached social housing and an early 19th century-built terrace houses, both having windows open when outside ambient temperature is 5°C.

It aims to identify the key factors that influence occupants' behaviour, like lifestyle, perception of comfort and household characteristics (Andersen et al., 2009; Schweiker & Shukuya, 2009). Several studies that explain variation in energy efficiency in residential buildings have been discussed in Chapter 2. Understanding behaviour patterns and trends in energy usage in homes, will help reduce energy consumption.

Figure 4.3: a) Semidetached house and b) a terrace house with window open when outside ambient temperature is 5°C

From the thermal images people tend to open windows even on cold winter nights and there is loss of heat through the open window. This understanding strengthened the basis for the analysis on the collected data and would help in recognising patterns of window opening amongst the participants in various instances of the data.

4.3. Survey

Thermal imaging illustrated the effect of occupant behaviour of window opening and how it can potentially affect the energy efficiency of a building. To understand why people open window in winter, a survey was conducted. Chapter 3 explains the relevance of the survey and how the survey questions were developed.

4.3.1. Data Collection

To explore the impact of occupants' behaviour on energy efficiency of a building and enhance understanding of energy usage by understanding people's perceptions, with the focus on opening of windows, a survey was carried out. The survey was aimed at people (over the age of 18) residing in the UK. The survey was structured in such a way to include questions with answers in accordance with a Likert scale with options for open-ended answers where the participants were welcome to express their own opinions if they chose to. The questions in the survey were intended at examining the windows-opening behaviour of people and its consequent effect on the energy efficiency of buildings. The objective close ended Likert scale and objective answer questions contributed to the quantitative data while the answers to open ended questions provided valuable data toward qualitative analysis of the reasons for window opening and the conditions that came together for an occupant in a house to open windows in winter when heating is ON.

A survey link, containing a brief information on the aim of the research and purpose of the survey, was sent through emails and social media groups to a collective of people across the UK. A survey collecting website called prolific was also utilised to collect survey from a representative sample of the UK.

4.3.2. Sample sizing

To make reliable inference about a population, with an empirical study, like a survey, choosing the right sample size is important. Confidence interval (CI) is the quantitative representation of uncertainty associated with the collected data, calculated from the data statistics. The most common CI employed is 95%. The margin of error is the percentage of random sampling error that can occur. A reasonable margin of error of 5.5-6% is chosen for this study. With the above values, the sample size is calculated using normal distribution and z-score values, to be between 267-318.

Overall, 300 responses were collected for the survey which is analysed in the following sections.

Survey characteristics

The survey took account of household characteristics that were regarded to have an impact on energy efficiency of the building. Demographics like size of household, age, main occupation, building ownership status (rented/ shared/ own house etc.) were collected. There is an assumption that there is a relationship between age of the occupant and energy usage; hence age of the occupants and of other household members were considered. This also helped indicate the presence of child/senior citizen. The entire questionnaire can be seen in Appendix.

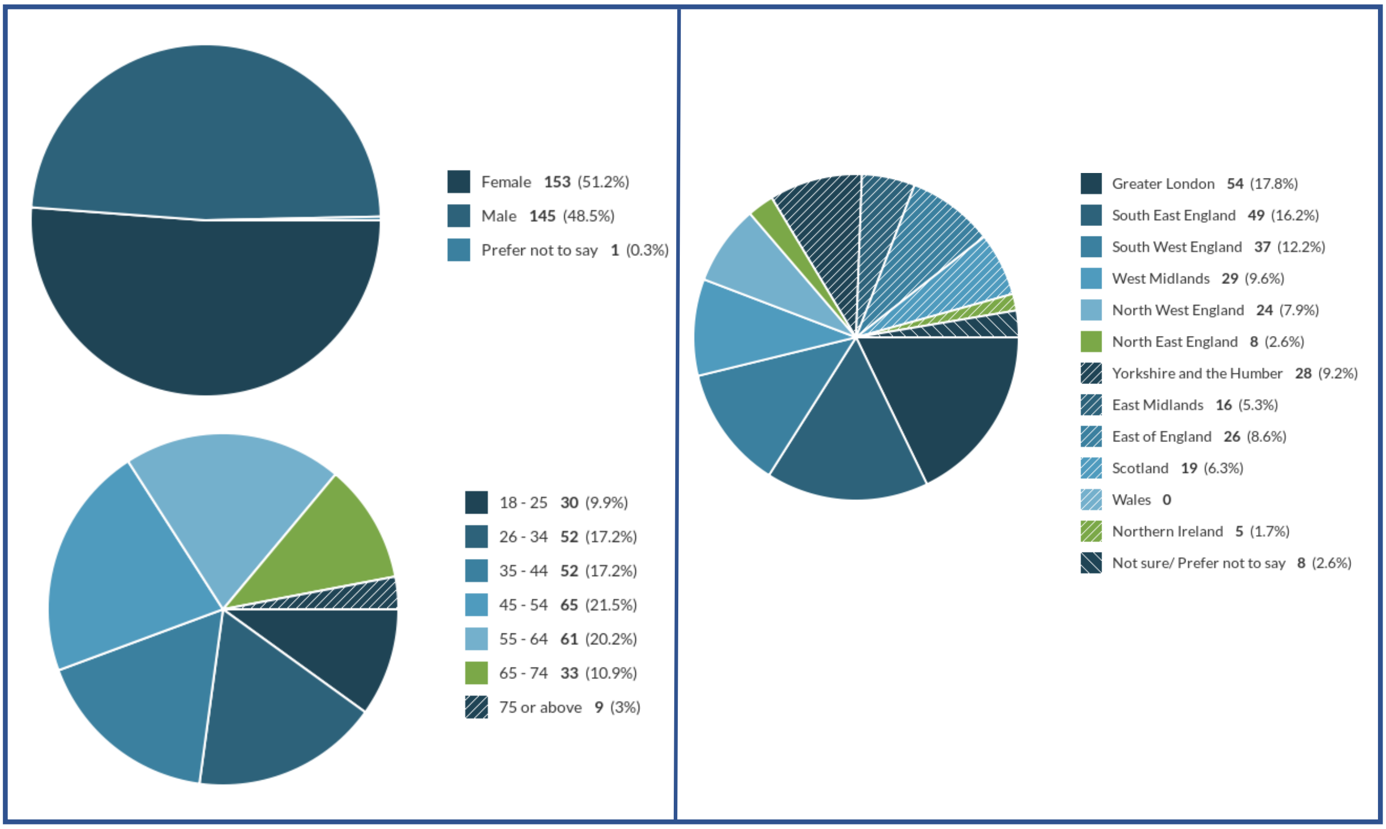


Figure 4.4: Survey demographic details

Building and other associated particulars

Participants were asked about the type of accommodation they live (Detached/Semi-detached/Flat/Bungalow/Terraced), type of ownership (Own/Rented/Shared/council House/Other), type of insulation (External Wall/Internal Wall/Cavity Wall/Loft/Other/Not Sure), type of heating (Electric/Gas/Both/Other/Not Sure), preferred ambient temperature, type of heating control (Programmable/Manual etc).

Occupant behaviour

The questionnaire focussed on questions that would help understand the factor that prompted window opening, like '*How often do you open your windows in winter'*, '*How long do you leave them open*', '*are windows open when heating is ON'*, '*What time of the day are you most likely to open windows*' etc. Option was provided for detailed answer for some of the questions, for qualitative analysis.

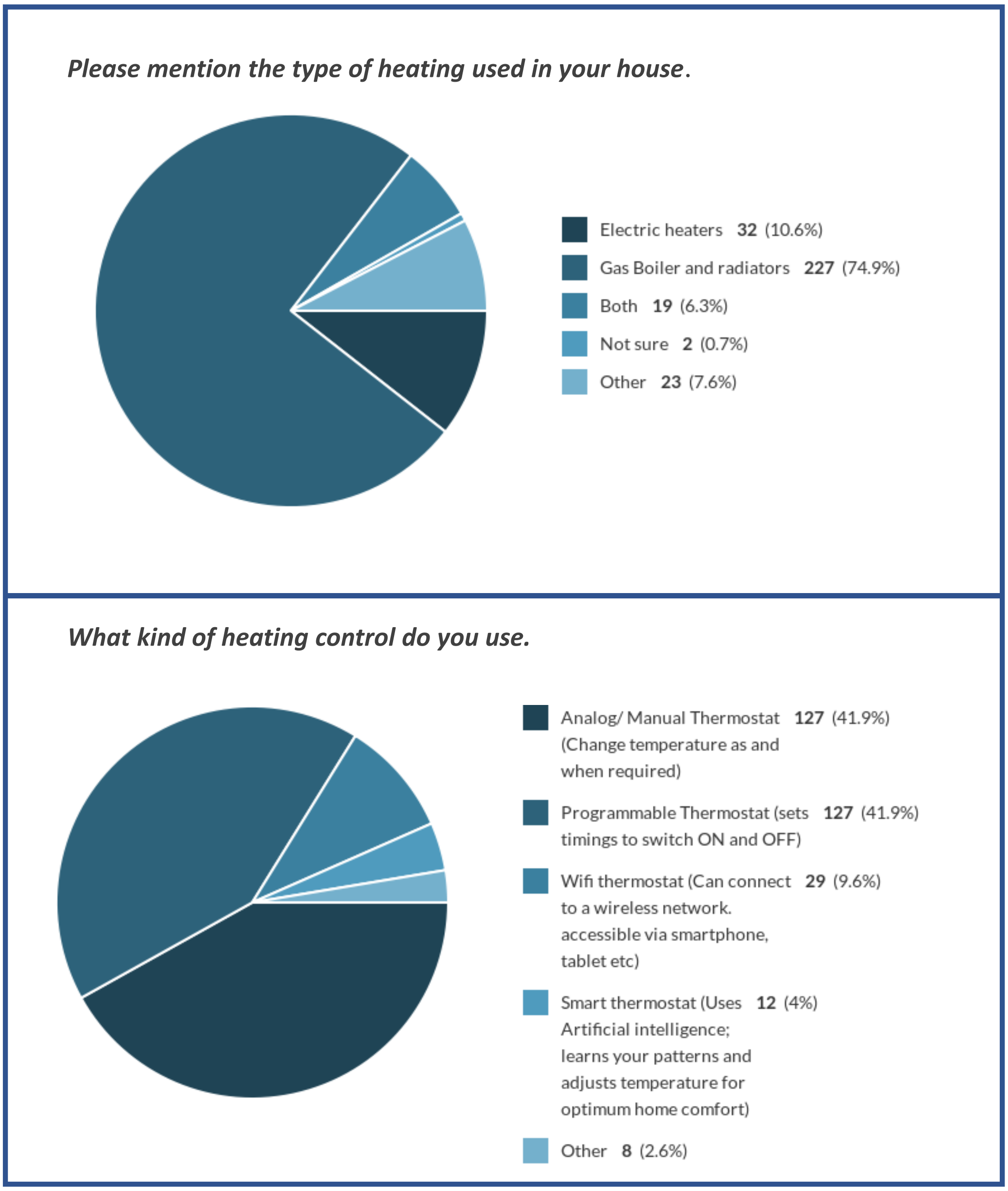


Figure 4.5: Type of heating and heating control

4.4. Analysis of Survey Results

Figure 4.4shows the demography of the participants, which is seen to be representative of the UK population. 75% of the participants used gas boilers to heat their houses and 84% of the participants had manual or programmable thermostats to control the temperature (Figure 4.5).

4.4.1. Frequency of Window Opening

Participants were asked how often they open windows of their house, in winter. Figure 4.6 shows the frequency of window opening in winter. 35.3% of participants open their window once every day. Only 5.6% of the participants never open the window. One out of the 300 respondents answered, *'Whenever central heating isn't on and feel the need to do so (usually in the afternoons)'*.

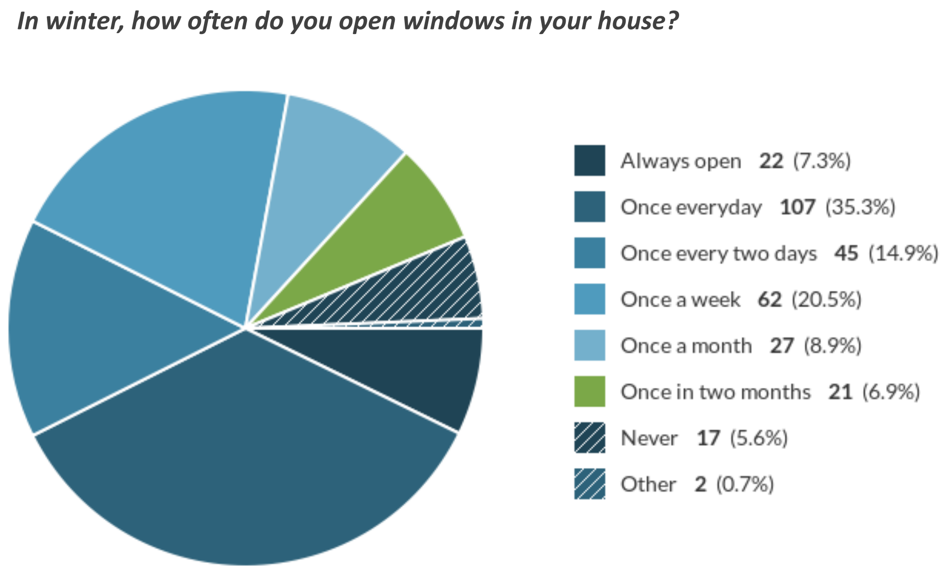


Figure 4.6: Frequency of window opening

Although this does not derive any conclusions, it can be seen that energy efficiency factor of making sure the heating is off before opening the window was considered mandatory by only one participant. It is to be noted that of the 22 participants who left their windows always, 18 were adults and 2 were senior citizens; 3 of the households had adults and children in them; none of them had babies in their household. Further studies need to be done to understand whether age of household occupants is a relevant factor that leads to window opening behaviour.

4.4.2. Duration of Window Opening

Participants were asked regarding the duration of window opening. Figure 4.7 shows the response for this question. The duration varied, with 80% of the participants opening their window for a duration ranging from 5 minutes to 5 hours. 34.7% of the respondents opened their window 2 hours or more, with 5.9% leaving window open all through the day. 23.8% left their window open 30 mins to an hour a day. While one of the respondents answered, *all day and night'*, another left 2 windows open throughout the day and another one during cooking (*'Usually 2 windows 24/7 for ventilation. Another one during cooking.'*).

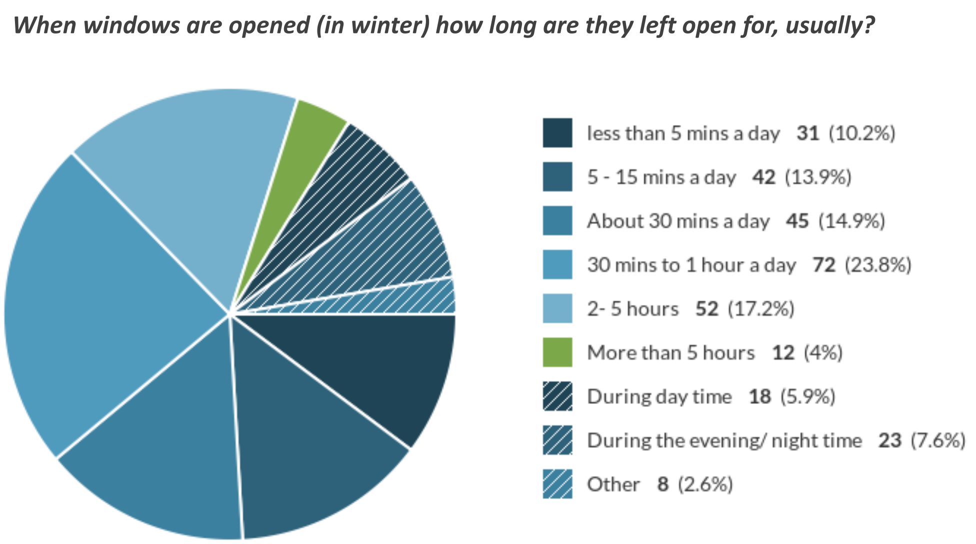


Figure 4.7: Duration of window opening

Concern about viral spread was another one of the reasons mentioned. While some were attempting to act in an energy efficient manner to an extent ('*Kitchen windows are open during cooking as heat from oven and hob counter act the heat loss. Bedroom windows open for 2 mins per day to allow circulation'*, '*I leave the bathroom window open (roughly a centimetre) on a latch all the time and fully open after a bath or shower, the bedroom window is always open (roughly a handspan) and the living room one is shut in winter and kitchen open when cooking*'), others considered air quality ('*I have my bedroom window open all night during the Winter. The heating is turned off at night. I open all our windows for an hour on Sundays as it's the only day I can safely air out the house due to* *lower traffic levels. Opening windows is also important to reduce viral spread*', '*Usually when cleaning to get ventilation*', '*just to let fresh air in and take condensate out*').

The stochastic nature of occupant behaviour was understood evidently through some of the responses:

'*I open some windows more than others. The window in the kitchen gets open all the time as the cat goes in and out and I need to let out the smoke as I burn the food a lot (I am quite distracted person). The bedroom gets window open as my husband does not feel cold and that window stays open sometimes a day or two. The windows in the children's rooms get opened hardly ever. Maybe once a week a bit. The living room....not often as it is noisy and quite a bit of pollution.*'

'*Windows are open for a few hours to all day in the bedroom to air out the bed. Rest of the house we tend to open windows in the bathroom for an hour or so after getting ready. Open windows in all other rooms when needs, e.g. when airing out laundry, get rid of smells, while cooking etc.*'

'*I'm opening my windows everyday, few times a day for 10 min.*'

4.4.3. Window Opening Time of Day

Participants were asked the time of the day they were most likely to open windows in winter. There was a mixed response with 32.3% of participants most likely to open windows early in the morning. The pie chart of all the responses for this question is given in Figure 4.8. The responses were very stochastic, some of them given below (Full response data is given in Appendix A):

'*Bedroom windows in morning and kitchen during evening dinner'*

'Only when it snow'

'Only open if needed e.g. steam in bathroom, cooking in kitchen, this is random.'

4.4.1. Window Opening when Heating is ON

Participants were asked frequency of window opening when heating was ON. Although 52.5% of the participants never or rarely opened their windows, 47% of them opened their windows at least occasionally, if not always or frequently open. Of this 47%, 18.9% left their window open always or frequently.

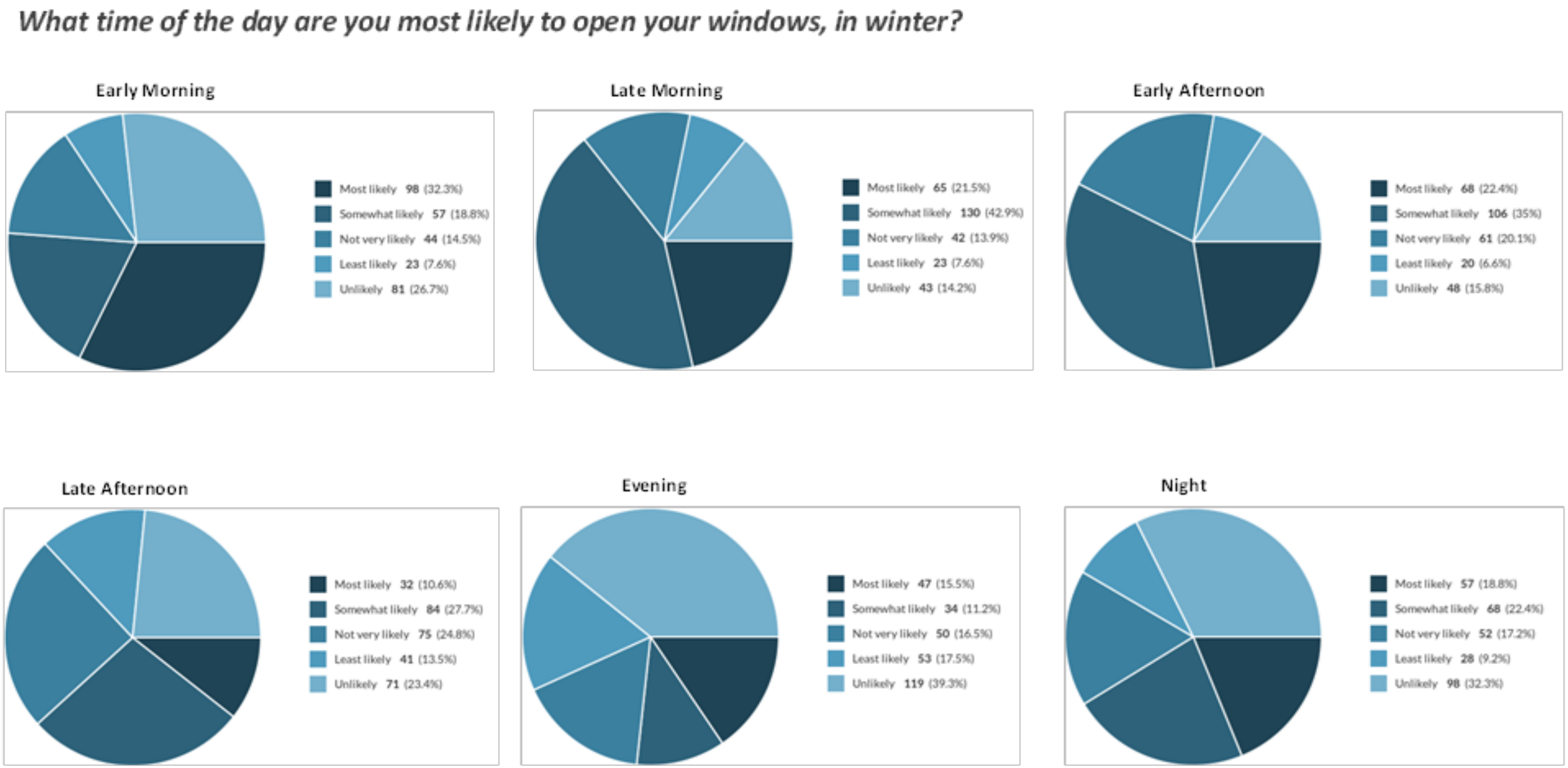


Figure 4.8: Time of day when window is opened

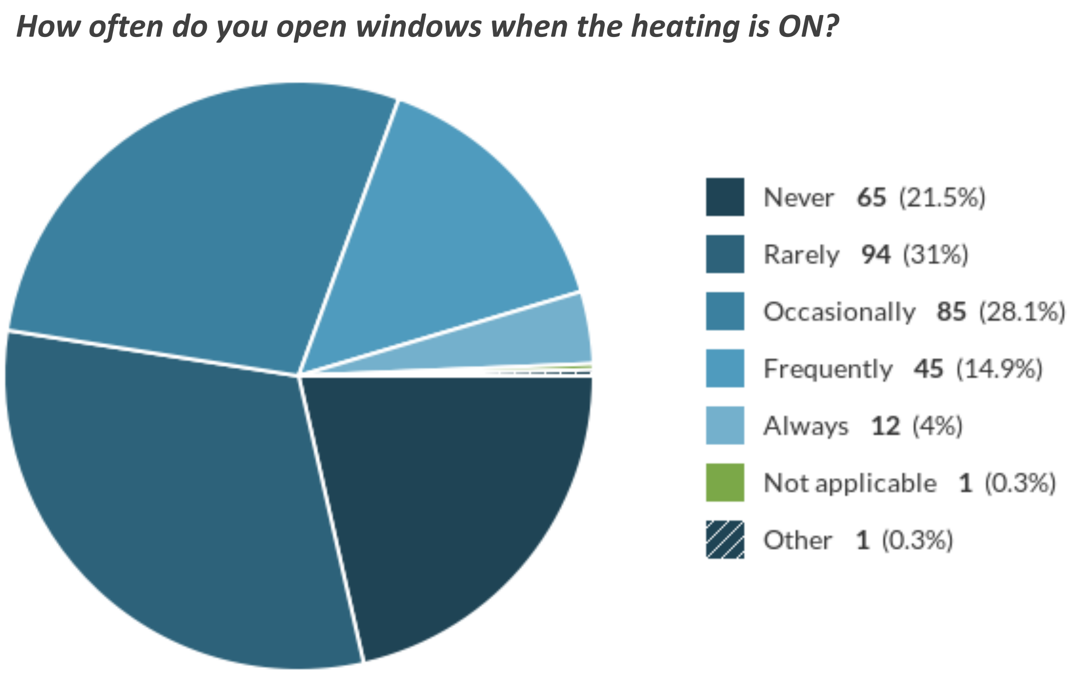


Figure 4.9: Frequency of window opening when heating is ON

To understand if the type of insulation of the house affected the frequency of window opening when window is open, this set of 57 respondents were investigated further to find any corelation between house insulation and window opening when heating ON.

Table 4.2: Response analysis - 'Window open always or frequently, when heating is ON'

Row Labels	No. of responses
A.Internal Wall Insulation	**2**
B.External Wall Insulation	**2**
C.Cavity Wall Insulation	**4**
D.Loft Insulation	**7**
Group1	**26**
E1.Cavity Wall Insulation, Loft Insulation	18
E2.External Wall Insulation, Internal Wall Insulation	1
E3.External Wall Insulation, Loft Insulation	1
E4.Internal Wall Insulation, Loft Insulation	2
E5.Internal Wall Insulation, Cavity Wall Insulation, Loft Insulation	2
E6.External Wall Insulation, Internal Wall Insulation, Cavity Wall Insulation, Loft Insulation	2
Total	**41**

15 out of 57 were not sure of the insulation type of their house and one response was not complete. This brought the number of respondents who left their window open always or frequently, to 41.

The insulation type of the dwelling of the 41 respondents were investigated, as shown in Figure 4.10. 18 respondents out of the 41 (44%) had cavity wall and loft insulation in their houses. 26 (63.4%) of them had more than one type of insulation in their house.

Table 4.2 shows the insulation type of the dwelling of the 41 respondents. This is indicative of the effect of insulation on the window opening behaviour of occupants. It can be argued from these results that well insulated houses can behave as bad as a poorly insulated house, in terms of energy usage.

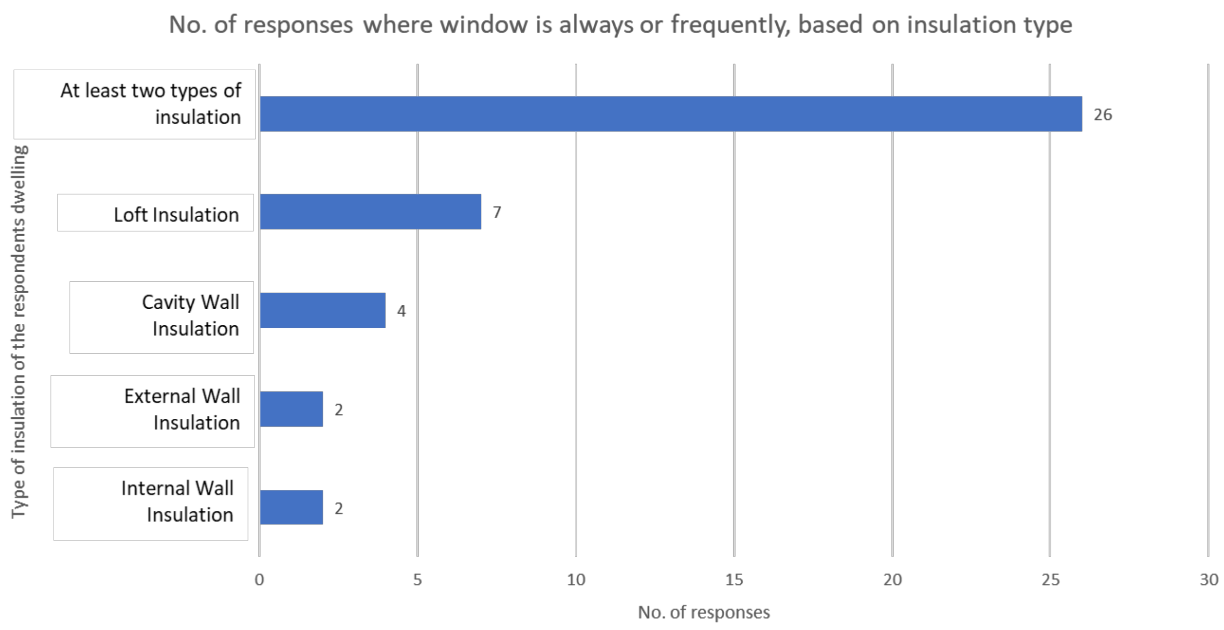


Figure 4.10: Number of responses where participant leave window always/frequently open when heating is ON

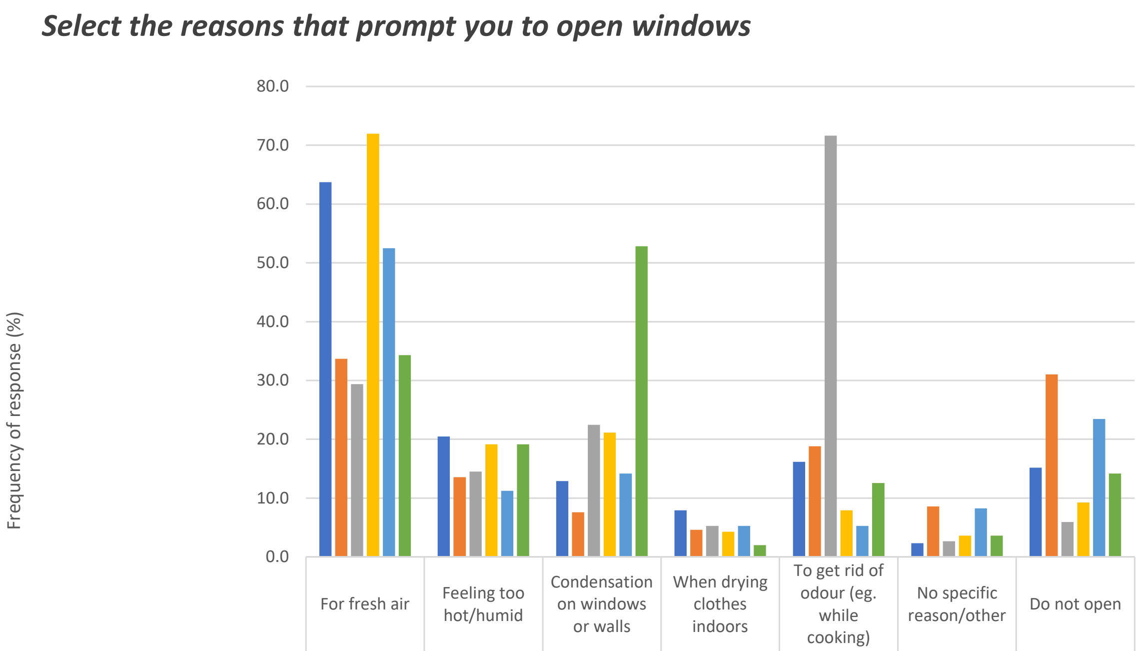
Depending on the comfort perception of the occupant, people living in well insulated houses may feel ‘too warm’ and open the window even when heating is ON. This contradicts the actual purpose of insulating the house, which is energy efficiency. Some of the reasons for window opening (when heating is ON), relevant to this research, are given below:

'My son sometimes decides his room is too warm and opens the window while heating is on.'

'As mentioned our bathroom windows & office windows are open mostly even when heating is on.'

'I'll open the windows if it gets too hot but only for a short time to keep the warmth.'

'Thermostatic control mean the heating doesn't have a regular on/off cycle. So heating can come on while windows are open.'



	For fresh air	Feeling too hot/humid	Condensation on windows or walls	When drying clothes indoors	To get rid of odour (eg. while cooking)	No specific reason/other	Do not open
Living room/ open plan living room	63.7	20.5	12.9	7.9	16.2	2.3	15.2
Dining Room	33.7	13.5	7.6	4.6	18.8	8.6	31.0
Kitchen	29.4	14.5	22.4	5.3	71.6	2.6	5.9
Main Bedroom	71.9	19.1	21.1	4.3	7.9	3.6	9.2
Other Bedrooms	52.5	11.2	14.2	5.3	5.3	8.3	23.4
Bathrooms	34.3	19.1	52.8	2.0	12.5	3.6	14.2

Figure 4.11: Reasons for opening window in different rooms in the house

Occupants were asked to select the various reasons that prompt them to open windows in different rooms. Figure 4.11 shows the frequency of response for reasons for window opening. 72% of the occupants open their main bedroom widnwo for fresh air, while 63.7% participant opened living room window for the same reason. Another rmain reason for window oepning was to remove odour from rooms, especially kitchen, where 71.6% of participants open window. 52.8% of participants open bathroom window to reduce condensation.

4.4.2. Reason for Opening Window

It can be inferred that one of the main rooms where occuants open window is the main bedroom (72% of participants) while kitchen is the next common room where window isopened (71% of participants).

What is the preferred ambient temperature of your house.

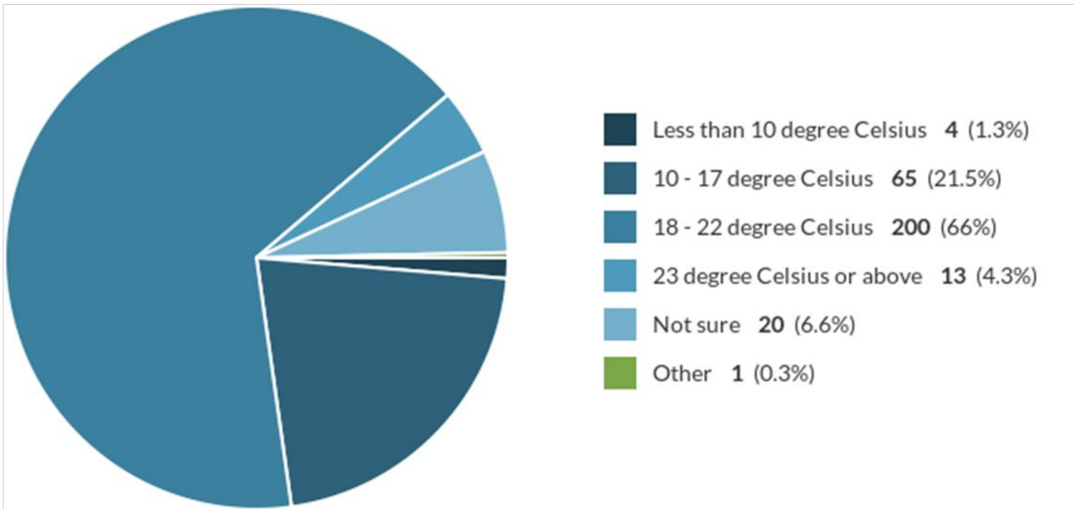


Figure 4.12: Preferred ambient temperature of house

4.4.3. Ambient Temperature of House

Participants were asked the ambient temperature preference in their dwelling (Figure 4.12). 66% of participants have a preferred ambient room temperature between 18 - 22ºC, while 21.5% had a preference of T_{room} to be between 10 - 17ºC.

Responses from participants show awareness to energy efficiency to an extent. One participant responded *'our incentive for reducing heating is financial to save money'* indicating fuel poverty, while another response showed how window opening action of a dwelling affected another: *I'm rarely able to achieve my desired temps as the windows in the flat above are open all winter, I'm lucky if I can* *manage to get any part of my flat as high as 16c in the winter despite using a fan heater to supplement the central heating.'*

4.5. Summary

'Energy gap' is a major concern in building model simulations, as seen in Chapter 2. The thermal images demonstrate that window opening behaviour of residents vary, regardless of the temperature outside. Including occupant behaviour in simulation models is critical to overcome major discrepancies between the designed and real energy usage in buildings.

Thermal imaging was done with the aim of studying the impact of occupant's behaviour on energy consumption of residential buildings. The findings suggest that occupants' behaviour could have a great influence on the energy efficiency of buildings.

Survey was done with the aim of studying the impact of occupant's behaviour on energy consumption of residential buildings and to identify the key factors that influence occupants' behaviour; thus, providing ideas for improving energy efficiency by suggesting enhanced policies, approaches, and techniques. 93.7% of the survey participants open windows in winter, with 47% of them opening windows when heating is ON. The duration of window opening varied, with 80% of survey participants opening their windows for a duration within the range of 5 minutes to 5 hours. The most opened window was that of the main bedroom, with 72% of the participants opening their main bedroom window for fresh air, while 19% opened because they were feeling too hot or humid. It is evident from the survey results that people do open windows in cold weather and when heating is ON. The open-ended answers to the survey questions showed the range of reasons for window opening, varying from person to person.

Thermal imaging illustrated the occupant behaviour of window opening across Nottingham, even on two cold winter nights, in different type of buildings. The results of the survey showed similar findings, where people across UK had similar practice of opening window in winter even when the heating was ON. To quantify the effect of this occupant behaviour of window opening in the energy efficiency of a building the next stage of research was carried out.

Chapter 5 | Analysis of Energy Usage in Social Housing Stage I

5.1. Introduction

Literature review and the three consecutive chapters brought to light the impact of occupant behaviour on energy consumption. However, the unpredictability and the wide variability of window opening behaviour (WOB) between houses makes it difficult to incorporate the pattern into energy consumption models. The capability to estimate energy usage in residential buildings to a good standard depends on the first-hand knowledge of a home's window usage. The performance of a building depends on several variables including human, environmental, and physical and each of these need to be studied concomitantly post occupancy. The qualitative analysis carried out by the capturing thermal images of buildings in winter showed that regardless of the outside ambient temperature, people tend to open windows, even when outside ambient temperature is 3°C to 5°C. The various reasons for opening windows, even in winter, by the occupants were further understand with the help of survey responses, which has been discussed in detail in the previous chapter. The next two chapters help quantify these findings with data collected from social housing. The following two chapters explains the quantitative analysis part of this research. Along with investigation into occupant behaviour with the help of survey explained in chapter 5, this chapter focusses on the analysis of the environmental factor of energy performance in conjunction with occupant behaviour of window opening.

5.2. Methodology

Energy performance depends on the building fabric properties as well. Hence the veracity of the building characteristics, like insulation properties, ventilation rates etc are also considered. This is because dwellings of different physical properties are considered in the study. To have a precise understand of the impact of occupant behaviour of window opening it must be analysed considering the physical properties as well.

To understand and quantify the effect of window opening behaviour (WOB), an investigation was carried out on window opening behaviour in 40 houses in Nottingham. The project focussed in 40 homes based in Nottingham with a diverse construction design, constructed over a period ranging from 1902 to 2012. The experiment was conducted from over a period of 51 weeks from Feb 2012 to March 2014 and data was collected. Each house was fitted with twelve sensors. The sensors were fitted in different areas of the house, as shown in and their names are shown. The experiment was conducted over a period of fourteen months in forty houses. The data obtained from the above-mentioned experiment, forms the basis of investigative study of this research. The data was analysed using MATLAB, with a goal to capture patterns of energy usage and its relationship to occupant behaviour, based on outside ambient temperature.

To understand the impact of occupant behaviour on energy efficiency, several studies have been carried out in the past few decades, as elaborated in chapter 2. Occupant behaviour is predominantly subjective and difficult to measure and interpret, since it depends on several variables that might include physical, emotional, contextual, habitual characteristics of occupants. These factors come together to give inimitable results of usage if tangible factors like heating, electricity, and water consumption. Due to its highly stochastic nature, outcomes of such studies are simplified to a certain degree based on the relevance and importance of each factor.

The overall methodology, sensor set-up, data cleansing and heat energy demand calculation are given in Chapter 3 (Section 3.5). As mentioned in Chapter 3, 17 houses are considered for the analysis, after data cleansing and scrutiny. Table 5.1 shows the category, building construction and built year of the 17 considered houses. Each house is fitted with sensors to log various factors including room temperature, radiator temperature and window opening. Each sensor in each house can be identified using the unique serial number marked on the side of the sensor, together with the barcode, to identify the values form different houses, after data collection.

Table 5.1: Archetype and built date of the considered houses

House Identification Number	Category	Building Construction	Built Year
1	Radburn	Concrete	1960 - 1980
2	Semi-detached Cavity Wall	Traditional Cavity	1930-1940
3	Concrete	Concrete	1940-1960
4	Concrete	Concrete	1960 - 1980
5	Concrete	Concrete	1940-1960
6	Concrete	Concrete	1940-1960
7	BSIF	BSIF	1940-1960
8	Semi-detached Solid Brick	Traditional solid brick semi terrace	1920-1930
9	Semi-detached Solid Brick	Traditional solid brick semi terrace	1920-1930
10	Semi-detached Solid Brick	Traditional solid brick semi terrace	1920-1930
11	Semi-detached Solid Brick	Traditional solid brick semi terrace	1920-1930
12	Sheltered Housing	Traditional Cavity	1960-1980
13	Sheltered Housing	Traditional Cavity	1960-1980
14	New Built	Traditional Cavity	2000+ (2012)
15	New Built	Traditional Cavity	2000+
16	Solid brick terrace	Traditional solid-brick terrace	1901-1919
17	Solid brick terrace	Traditional solid -brick terrace	1901-1919

The houses also have different insulation properties. The houses are categorised based on the insulation properties. In the UK, the most common constructions are solid brick and cavity wall buildings. The insulation properties considered in each house are:

i. Roof insulation
ii. Internal Wall Insulation
iii. External Wall insulation
iv. Cavity Wall Filling

According to the Energy Saving Trust of UK, 45% of heat in a house is lost through uninsulated solid walls, 33% is lost through uninsulated cavity walls, 25% of heat is lost through the loft (*National Insulation Association*, n.d.). Uninsulated solid walls can be insulated either externally or internally. External Wall insulation is the addition of insulation boards to the outside wall of the property. Even a 10cm PIR board helps increase the R-value to a great extent. It also helps the house to withstand the elements of nature. Internal wall insulation increases energy savings significantly at comparatively less installation costs, but at the loss of internal space of the property. Based on the above given assumptions a weightage is given to each type of insulation property of each house, indicated as House Insulation Property value (HIP value). Table 5.2 gives the HIP values for each type of insulation property of a house and different combination of insulation properties.

Table 5.2: House insulation property weightage

Roof Insulation	Solid Wall		Cavity Wall	Roof + Internal	Roof + external	Roof + cavity	Roof + internal + external
	Internal Wall Insulation	External Wall Insulation	Cavity Wall Filling				
0.25	0.45	0.45	0.33	0.7	0.7	0.6	1.15

Table 5.3: House Insulation Property (HIP) value range

House Insulation Property Value (Maximum 1.15)	Percentage	House Insulation Type
0 to 0.4	0 to 25%	Low Insulation (LI)
0.41 to 0.58	25 to 50%	Medium Insulation (MI)
0.6 and above	50% and above	High Insulation (HI)

Table 5.4 shows the insulation property of the 17 houses and their house insulation property (HIP) calculation. The HIP values of the houses based on this calculation, can be seen in Table 5.5.

Table 5.4: Insulation property of the house and their HIP value

House number	Roof Insulation		Solid Wall				Cavity Wall		Total	Out of	%
	YES(1) / NO(2)	Weightage	Wall Internal insulation		Wall External insulation		Cavity fill				
1	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
2	1	0.25	2	0	2	0	1	0.33	0.58	1.15	50.43
3	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
4	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
5	1	0.25	2	0	2	0	2	0	0.25	1.15	21.74
6	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
7	1	0.25	2	0	2	0	2	0	0.25	1.15	21.74
8	1	0.25	1	0.45	2	0	2	0	0.7	1.15	60.87
9	1	0.25	1	0.45	2	0	2	0	0.7	1.15	60.87
10	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
11	1	0.25	2	0	1	0.45	2	0	0.7	1.15	60.87
12	1	0.25	2	0	2	0	1	0.33	0.58	1.15	50.43
13	2	0	2	0	2	0	1	0.33	0.33	1.15	28.70
14	1	0.25	2	0	2	0	1	0.33	0.58	1.15	50.43
15	1	0.25	2	0	2	0	1	0.33	0.58	1.15	50.43
16	1	0.25	2	0	2	0	2	0	0.25	1.15	21.74
17	1	0.25	1	0.45	2	0	2	0	0.7	1.15	60.87

5.3. Analysis

As mentioned earlier, the houses were initially categorised based on the architecture, in to 9 categories. The 17 houses considered have different built and insulation properties and built year. The houses are of one of five different building construction types (Concrete, traditional cavity, BSIF, traditional solid brick terrace and traditional cavity). Based on built year the houses can be divided into five (1901-1919, 1920-1940, 1940-1960, 1960-1980, 2000^+). As the first stage, the window opening characteristics of the house, during winter, is explored.

Table 5.5: House Insulation Property

Sl.No	House Numbers	House Insulation Property (HIP)	Insulation
1	h1	1.1	HI
2	h2	0.58	HI
3	h3	0.7	HI
4	h4	0.7	HI
5	h5	0.25	LI
6	h6	0.7	HI
7	h7	0.25	LI
8	h8	0.65	HI
9	h9	0.65	HI
10	h10	0.7	HI
11	h11	0.7	HI
12	h12	0.58	HI
13	h13	0.33	MI
14	h14	0.58	HI
15	h15	0.58	HI
16	h16	0.25	LI
17	h17	0.65	HI

Figure 5.1 shows the thermal image of bedroom window status for all houses from Feb 2013 to March 2014. It was identified that there was no linear relationship between the age of the house and heating pattern and hence the energy consumption of the house, which questioned the hypothesis that the older the house, the more the energy consumption.

h3, h11 are all high insulation houses as seen Table 5.5. However, the frequency of window opening is quite high in these houses. In the past, natural ventilation in residential buildings was not considered to be of importance when considering the energy efficiency of a building. However, with building construction improving air tightness of buildings, occupants tend to open windows more as can be seen from Figure 5.1. To understand the extent of the effect of window opening on energy usage, the window opening frequency of the houses on a cold winter day when temperature was below 5°C is considered, as shown in Figure 5.2. House

11, which is a high insulation house, has the highest frequency of window opening on a cold winter day. The occupants of the house leave window open for more than 59% of the time.

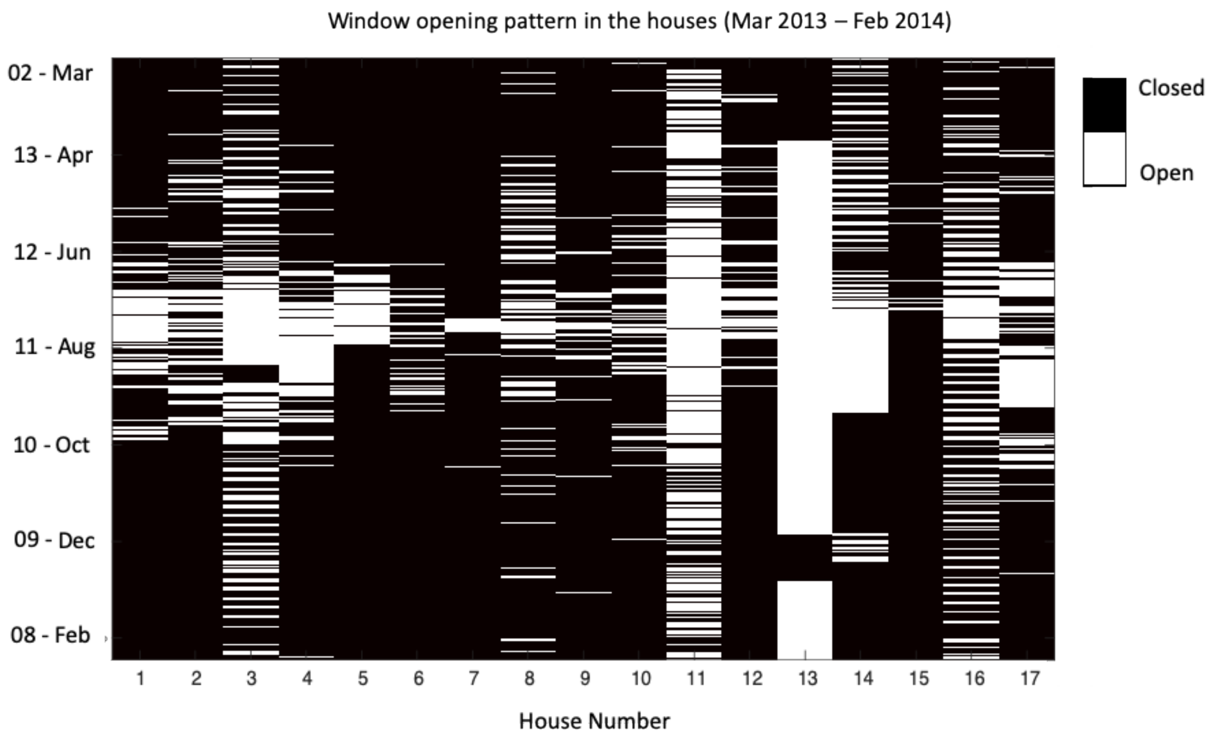


Figure 5.1: Bedroom Window Status

Figure 5.2 shows that 70% of the houses open their windows at least once even when the outside ambient temperature is less than or equal to 5^{o}C. Even at a temperature of 5^{o}C or below, 43% of the houses keep the windows open more than 5% of the time, of which 29% keep it open more than 30% of the time. The impact of window opening on energy usage can be inferred.

To maintain the desired temperature in a room the heating must be turned on and off, depending on the prevailing ambient temperature of the room. This is done either manually, using a manually operated thermostat, or automatically, where the thermostat is set such that it turns on when the room temperature falls below the set temperature. The frequency of heating on/off cycle varies depending on the occupant's perception of thermal comfort. Houses are insulated in the expectation that the heat is retained, and the radiator heating cycle can be reduced consequently reducing the energy usage. Considering one day in winter, the frequency of the radiator cycle was checked, to verify the hypothesis that better insulation leads to better energy usage.

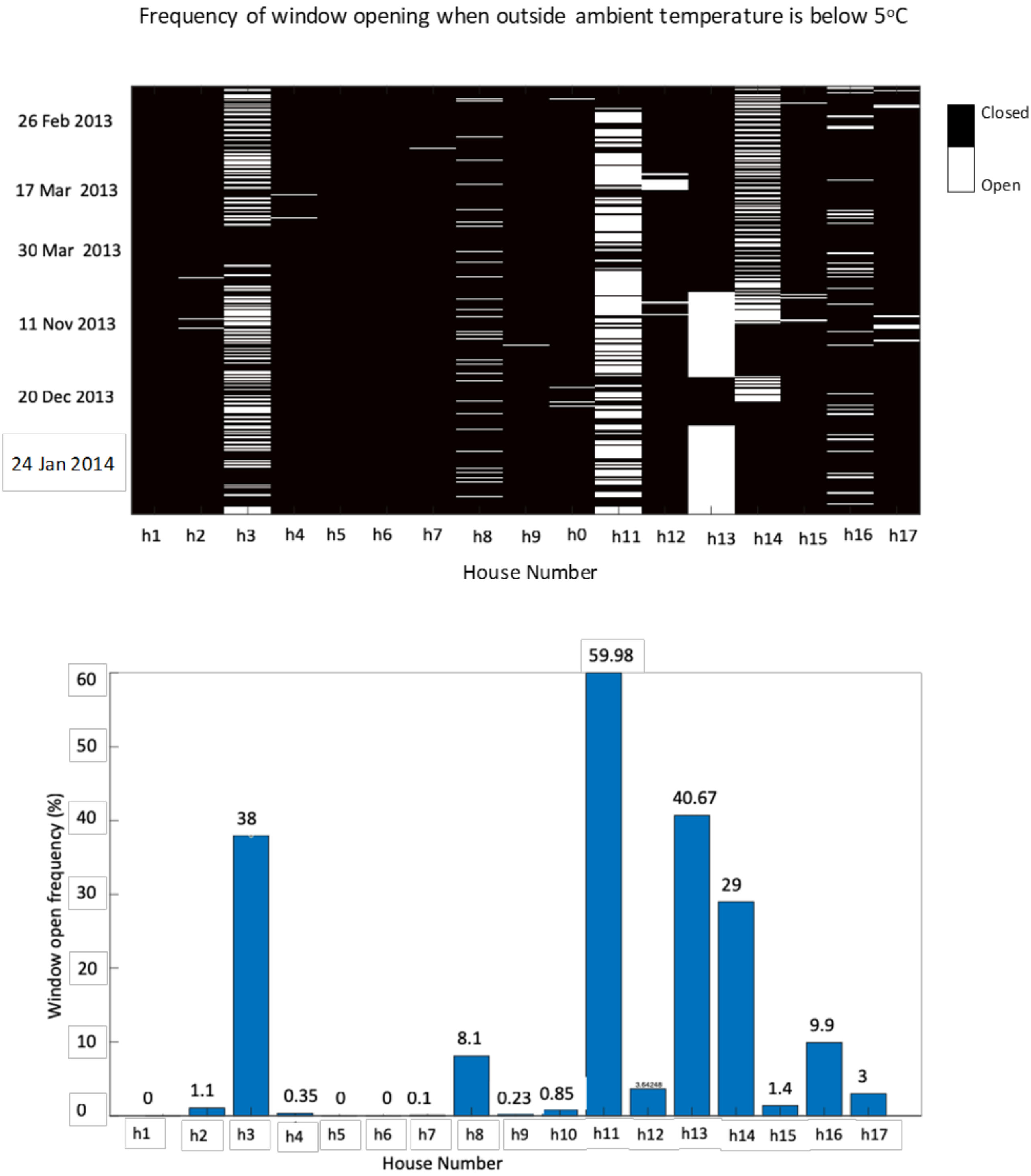


Figure 5.2: Bedroom window opening frequency ($T_{out} \leq 5^{o}C$)

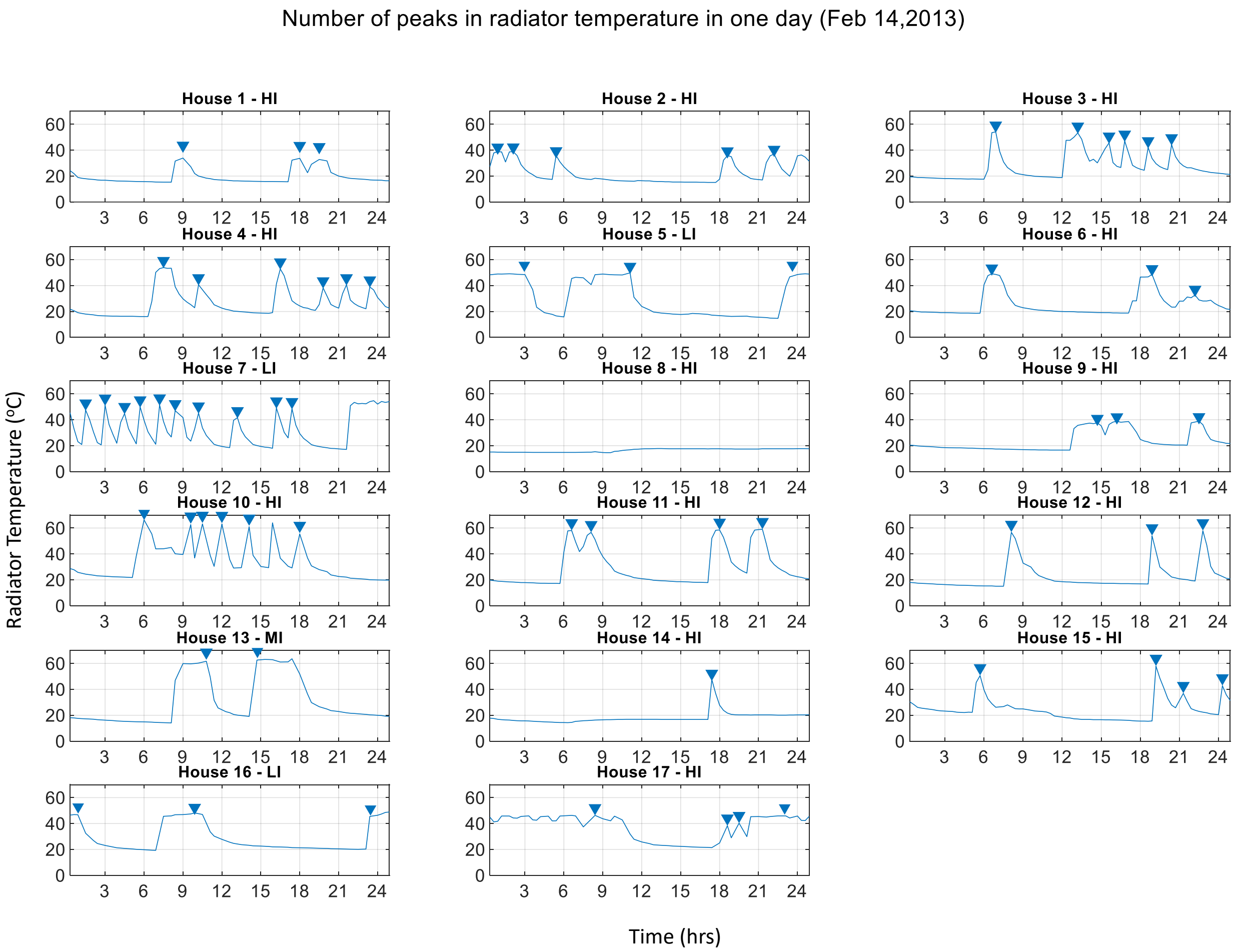


Figure 5.3: Frequency of radiator on/off cycle

As seen in Figure 5.3, there was no linear relationship between the frequency of radiator cycle and the insulation property of the house. To further understand the window opening frequency, the percentage of window opening for in winter is considered. The collected data consist of data from two winters:

i. Winter 1 - Feb 2013 to March 2013
ii. Winter 2 - Nov 2013 to Feb 2014

The percentage of time window is open in winter 1 and winter 2, for the 17 houses, is shown in Table 5.6. Based on the percentage of time the window is open the houses are categorised into two as shown in Table 5.7. Therefore, based on the house insulation property and window opening percentage the houses are categorised as shown in Table 5.8.

Table 5.6: Percentage of time window is open in Winter 1 and Winter 2 for the 17 houses

House No.	Upstairs Bedroom Window Status			
	Winter 1		Winter 2	
	12 Feb 2013 to 31 March 2013		1 Dec 2013 to 21 Feb 2014	
	%	Window open status	%	Window open status
1	0	Closed	0	Closed all the time
2	1.87	Open rarely	0.06	Open rarely
3	25.87	Open sometimes	29.2	Open sometimes
4	2.4	Open rarely	0.55	Open rarely
5	0	Closed	0	Closed
6	0	Closed	0	Closed
7	0.5	Open rarely	0.015	Open rarely
8	9.2	Open rarely	9.81	Open rarely
9	0.83	Open rarely	0.57	Open rarely
10	1.99	Open rarely	1.51	Open rarely
11	53.1	Open frequently	49.57	Open frequently
12	5.88	Open rarely	0.07	Open rarely
13	0	Closed	64.6	Open frequently
14	32.4	Open sometimes	10.83	Open rarely
15	0.76	Open rarely	0.25	Open rarely
16	15.73	Open sometimes	27.85	Open sometimes
17	2.8	Open rarely	0.57	Open rarely

Table 5.7: Window open percentage range for categorisation

Window open percentage	House category based on window status
0 to 15%	Window closed (WC)
15% and above	Window Open (WO)

Table 5.8: House Categories based on house insulation and window opening frequency

Sl.No	House Numbers	Insulation	Window Open Status (WOS)	Category
1	**h1**	HI	WC	HI-WC
2	**h2**	HI	WC	HI-WC
3	**h3**	HI	WO	HI-WO
4	**h4**	HI	WC	HI-WC
5	**h5**	LI	WO	LI-WO
6	**h6**	HI	WC	HI-WC
7	**h7**	LI	WC	LI-WC
8	**h8**	HI	WC	HI-WC
9	**h9**	HI	WC	HI-WC
10	**h10**	HI	WC	HI-WC
11	**h11**	HI	WO	HI-WO
12	**h12**	HI	WC	HI-WC
13	**h13**	MI	WO	MI-WO
14	**h14**	HI	WO	HI-WO
15	**h15**	HI	WC	HI-WC
16	**h16**	LI	WC	LI-WC
17	**h17**	HI	WC	HI-WC

5.4. Heat Energy Demand Calculation

Domestic sector accounts for 42% of total energy consumption in the UK ((Department for Business, 2021) and almost 30% of the CO_2 emissions (BEIS, 2021). To meet the net zero target, residential sector, the entire elimination of emissions from the residential sector will be necessary. Studies show that importance of behaviour of people in influencing energy use of a building, is at least as imperative as that of the building's properties. Studies also show that CO_2 in houses are most sensitive to change in the ambient temperature inside the house, which depends highly on the occupants (Energy efficiency and human behaviour | University of Cambridge, 2013). Analysis of actual measured data provides a good understanding of OB and provides possibilities of improving the energy efficiency (EE) of buildings.

5.4.1. Heat loss due to Building Fabric

The insulation properties of the building contribute to the heat loss of the building, hence must be considered to understand the heat loss due to ventilation to good standardisation. The heat loss due to building fabric is calculated for the houses, based on the construction year and U-values of the building construction materials. The calculation of the contribution to heat loss of each material of the building and consequently their sum, is the total heat loss due to building fabric, denoted by Q_f Watts. The equations for the calculation of Q_f are given in the methodology chapter (Chapter 3, Section 3.5.3). Equation (3.4) gives the contribution of heat loss due to building fabric to overall heat-loss. Based on the U-values of different materials (given in Table 3.4, Chapter 3), Q_f for the houses are calculated and tabulated, as seen in Table 5.9. The dimensions of the main bedroom which is the considered room for the analysis as mentioned in methodology, is shown in Table 5.10. For standardised value, the average dimension of the 17 houses is considered for the analysis. The standard window dimension in the UK is considered and the window is awning window, which is the most common type of window in the UK. 69% of dwellings int eh UK have double glazing (Department for Communities and Local government, 2010). As given in (3.3), heat loss due to fabric is the sum of heat loss of different elements of the building wall facing the external environment, multiplied by the difference in temperature between the inside and outside environments. Since the main bedroom is the room of interest, heat loss in main bedroom is considered. Figure 5.4 visualised heat loss through building fabric and heat loss through ventilation, for the main bedroom in a house. Considering the main bedroom, which is most commonly on the first floor of the house, there will be heat loss through the roof, heat loss through wall facing external environment (assuming all rooms in the house will have the same temperature) and heat loss through windows. The area of wall facing outside is the total area of the wall minus the area of the window.

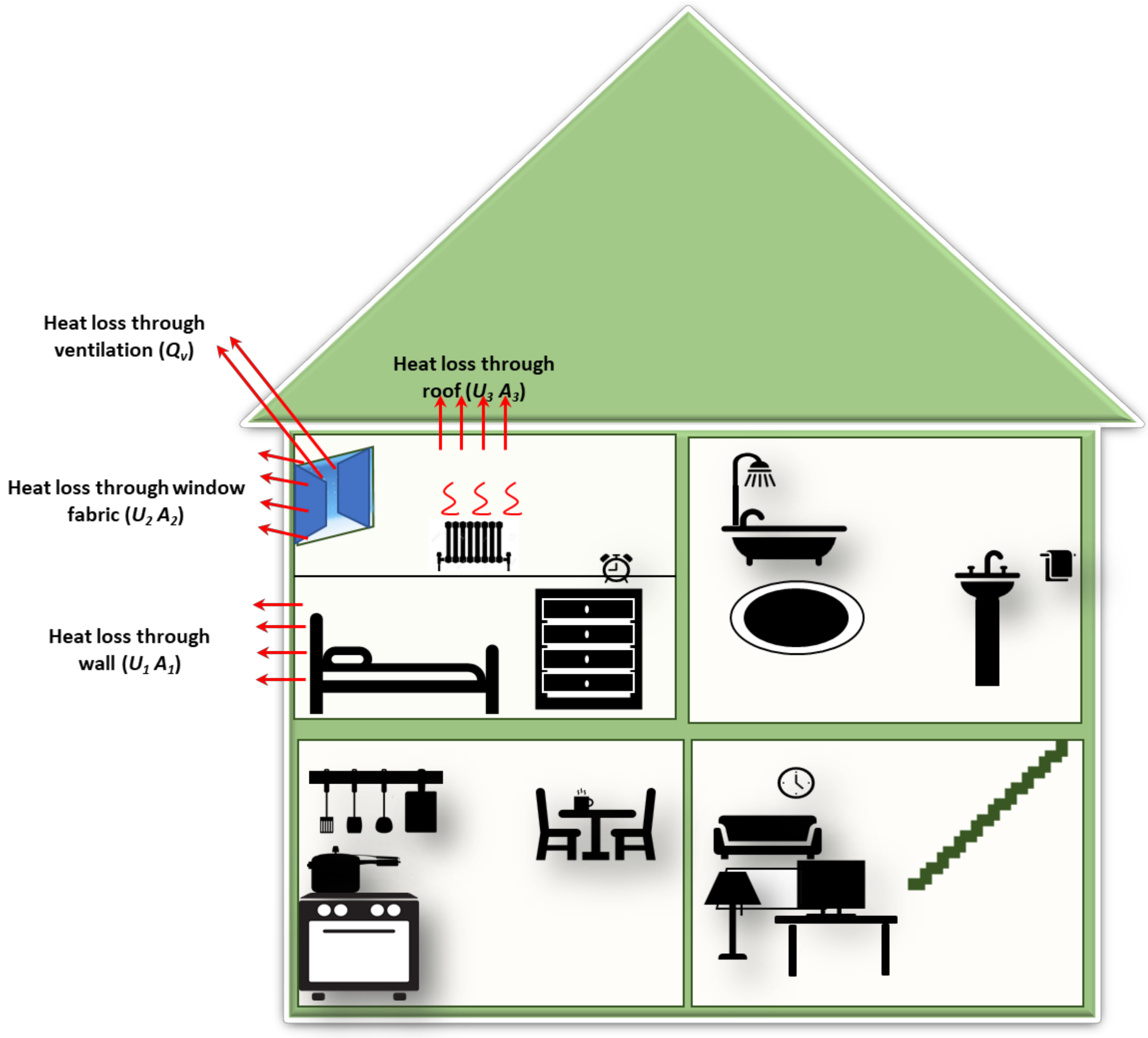


Figure 5.4: Heat-loss in main bedroom through building fabric and ventilation

Table 5.9: Actual Wall area (after taking away window area) for calculation of U-value

House No.	Room dimensions					Window Dimensions			Actual wall Area = Wall Area - Window Area (m2)
	Length (m)	Width(m)	Height(m)	Area(m^2)	Volume(m^3)	Length (m)	Width(m)	Area(m^2)	
1	3.79	3.49	2.8	13.23	37.04	0.89	0.64	0.57	12.66
2	3.16	3.54	3.2	11.19	35.80	0.89	0.64	0.57	10.62
3	3.2	3.175	3	10.16	30.48	0.89	0.64	0.57	9.59
4	4.3	2.5	2.8	10.75	30.10	0.89	0.64	0.57	10.18
5	3.81	3.84	3	14.63	43.89	0.89	0.64	0.57	14.07
6	3.91	3.56	3	13.92	41.76	0.89	0.64	0.57	13.35
7	3.56	3.4	3	12.10	36.31	0.89	0.64	0.57	11.54
8	4.17	3.43	2.6	14.30	37.19	0.89	0.64	0.57	13.74
9	3.16	3.54	2.6	11.19	29.08	0.89	0.64	0.57	10.62
10	3.61	3.35	2.6	12.09	31.44	0.89	0.64	0.57	11.53
11	4	2.7	3.3	10.80	35.64	0.89	0.64	0.57	10.23
12	3.78	3.45	2.8	13.04	36.51	0.89	0.64	0.57	12.48
13	3.8	2.66	2.8	10.11	28.30	0.89	0.64	0.57	9.54
14	2.95	3.6	2.5	10.62	26.55	0.89	0.64	0.57	10.05
15	3.18	4.47	2.5	14.21	35.54	0.89	0.64	0.57	13.65
16	3.2	3.89	3.5	12.45	43.57	0.89	0.64	0.57	11.88
17	4.49	3.58	3.5	16.07	56.26	0.89	0.64	0.57	15.51
Average	**3.65**	**3.42**	**2.91**	**12.40**	**36.20**	**0.89**	**0.64**	**0.57**	**11.84**

Table 5.10: Calculation of co-efficient of heat loss due to building fabric

House No.	Building Construction	Insulation		Built Year	U-Value (W/m2K)			Fabric Heat Loss (Qf)(W/K)			Total Q_f
					Wall	Window	Roof	Wall	Window	Roof	
1	Concrete	Roof Insulation and External Wall insulation	H	1960 - 1980	0.30	2.80	0.15	3.23	1.58	1.84	6.67
2	Traditional Cavity	Roof Insulation and Cavity Wall insulation	M/H	1930-1940	0.30	2.80	0.15	3.23	1.58	1.84	6.67
3	Concrete	Roof Insulation and External Wall insulation	H	1940-1960	0.30	2.80	0.15	3.23	1.58	1.84	6.67
4	Concrete	Roof Insulation and External Wall insulation	H	1960 - 1980	0.30	2.80	0.15	3.23	1.58	1.84	6.67
5	Concrete	Roof Insulation Only	L	1940-1960	2.00	2.80	0.15	21.55	1.58	1.84	24.97
6	Concrete	Roof Insulation and External Wall insulation	H	1940-1960	0.30	2.80	0.15	3.23	1.58	1.84	6.67
7	BSIF	Roof Insulation Only	L	1940-1960	2.00	2.80	0.15	21.55	1.58	1.84	24.97
8	Traditional solid brick semi terrace	Roof Insulation and Internal Wall insulation	H	1920-1930	0.30	2.80	0.15	3.23	1.58	1.84	6.67
9	Traditional solid brick semi terrace	Roof Insulation and Internal Wall insulation	M/H	1920-1930	0.30	2.80	0.15	3.23	1.58	1.84	6.67
10	Traditional solid brick semi terrace	Roof Insulation and External Wall insulation	H	1920-1930	0.30	2.80	0.15	3.23	1.58	1.84	6.67
11	Traditional solid brick semi terrace	Roof Insulation and External Wall insulation	H	1920-1930	0.30	2.80	0.15	3.23	1.58	1.84	6.67
12	Traditional Cavity	Roof Insulation and Cavity Wall insulation	M/H	1960-1980	0.30	2.80	0.15	3.23	1.58	1.84	6.67
13	Traditional Cavity	Cavity Wall Insulation Only	M	1960-1980	0.30	2.80	2.50	3.23	1.58	19.19	24
14	Traditional Cavity	Roof Insulation and Cavity Wall insulation	H	2000+ (2012)	0.30	2.80	0.15	3.23	1.58	1.84	6.67
15	Traditional Cavity	Roof Insulation and Cavity Wall insulation	H	2000+	0.30	2.80	0.15	3.23	1.58	1.84	6.67
16	Traditional solid brick terrace	Roof Insulation Only	L	1901-1919	2.00	2.80	0.15	21.55	1.58	1.84	24.97
17	Traditional solid brick terrace	Roof Insulation and Cavity Wall insulation	M/H	1901-1919	0.30	2.80	0.15	3.23	1.58	1.84	6.67

Table 5.11: Dimensions of the 17 houses and average dimensions

House No.	Length (m)	Width(m)	Height(m)	Area(m^2)	Volume(m^3)
1	3.79	3.49	2.8	13.23	37.04
2	3.16	3.54	3.2	11.19	35.80
3	3.2	3.175	3	10.16	30.48
4	4.3	2.5	2.8	10.75	30.10
5	3.81	3.84	3	14.63	43.89
6	3.91	3.56	3	13.92	41.76
7	3.56	3.4	3	12.10	36.31
8	4.17	3.43	2.6	14.30	37.19
9	3.16	3.54	2.6	11.19	29.08
10	3.61	3.35	2.6	12.09	31.44
11	4	2.7	3.3	10.80	35.64
12	3.78	3.45	2.8	13.04	36.51
13	3.8	2.66	2.8	10.11	28.30
14	2.95	3.6	2.5	10.62	26.55
15	3.18	4.47	2.5	14.21	35.54
16	3.2	3.89	3.5	12.45	43.57
17	4.49	3.58	3.5	16.07	56.26
Average	**3.65**	**3.42**	**2.91**	**12.40**	**35.57**

Table 5.12: Heat-loss through building fabric

House No.	Fabric Heat Loss (Qf)(W/K)			Total Q_f (W/K)	House Insulation Type
	Wall	Window	Roof		
1	3.23	1.58	1.84	6.67	HI
2	3.23	1.58	1.84	6.67	HI
3	3.23	1.58	1.84	6.67	HI
4	3.23	1.58	1.84	6.67	HI
5	21.55	1.58	1.84	24.97	LI
6	3.23	1.58	1.84	6.67	HI
7	21.55	1.58	1.84	24.97	LI
8	3.23	1.58	1.84	6.67	HI
9	3.23	1.58	1.84	6.67	HI
10	3.23	1.58	1.84	6.67	HI
11	3.23	1.58	1.84	6.67	HI
12	3.23	1.58	1.84	6.67	HI
13	3.23	1.58	19.19	24.97	LI
14	3.23	1.58	1.84	6.67	HI
15	3.23	1.58	1.84	6.67	HI
16	21.55	1.58	1.84	24.97	LI
17	3.23	1.58	1.84	6.67	HI

The U-Values of each material is given in Chapter 3 (Table 3.4). the calculation of actual area of wall for the 17 houses is given in Table 5.9. From the room dimensions, the area of roof is calculated and from the area of the wall, window and roof, and their U-values, the contribution to heat loss of each element is calculated, with Equation (3.5) and the values are given in Table 5.10. It can be seen from Table 5.12, there is a vast difference in coefficient heat loss due to building fabric (Q_f) between insulated and uninsulated houses, with insulated house having a Q_f coefficient of 6.67 and uninsulated house having a Q_f of 24.97. Table 5.11 gives the length, breadth, height, area and volume of the upstairs bedroom of the 17 houses. It also gives the average values of the above, for the 17 houses.

5.4.2. Heat loss Due to Ventilation

Heat loss due to ventilation in winter effects the energy usage of the house. To understand the level of impact of window opening, the heat loss due to ventilation needs to be considered when calculating the energy demand of a house. Heat loss due to ventilation due to open window, can be calculated as the amount of heat energy required to heat the cold air coming in through the open window, replacing the already existing warm air.

This heat energy demand is given by Equation (3.6) in Chapter 3. The equation considers the specific heat capacity of the volume of air in the room multiplied by the difference in temperature between inside and outside, multiplied by the air changes per hour.

Few studies include heat loss due to ventilation with respect to window opening. Window opening is a very stochastic characteristic, which is complex to predict and include in calculations. For this study, they type of window considered is awning window, as seen in most UK houses. The volume of air through entering a room due to opening of awning window (example shown in Figure 5.5) is 70% (Breezeway, 2012)The values and graph of the calculations are given in Appendix.

Figure 5.5: Awning window

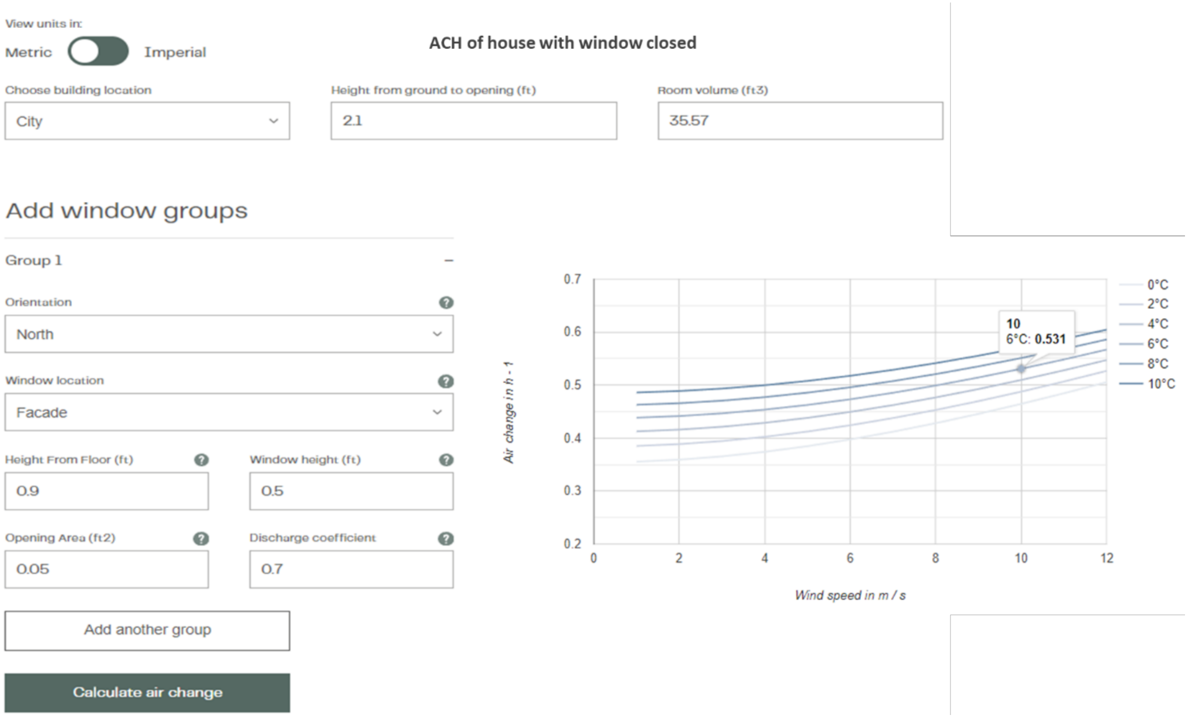


Figure 5.6: ACH of main bedroom when window is closed

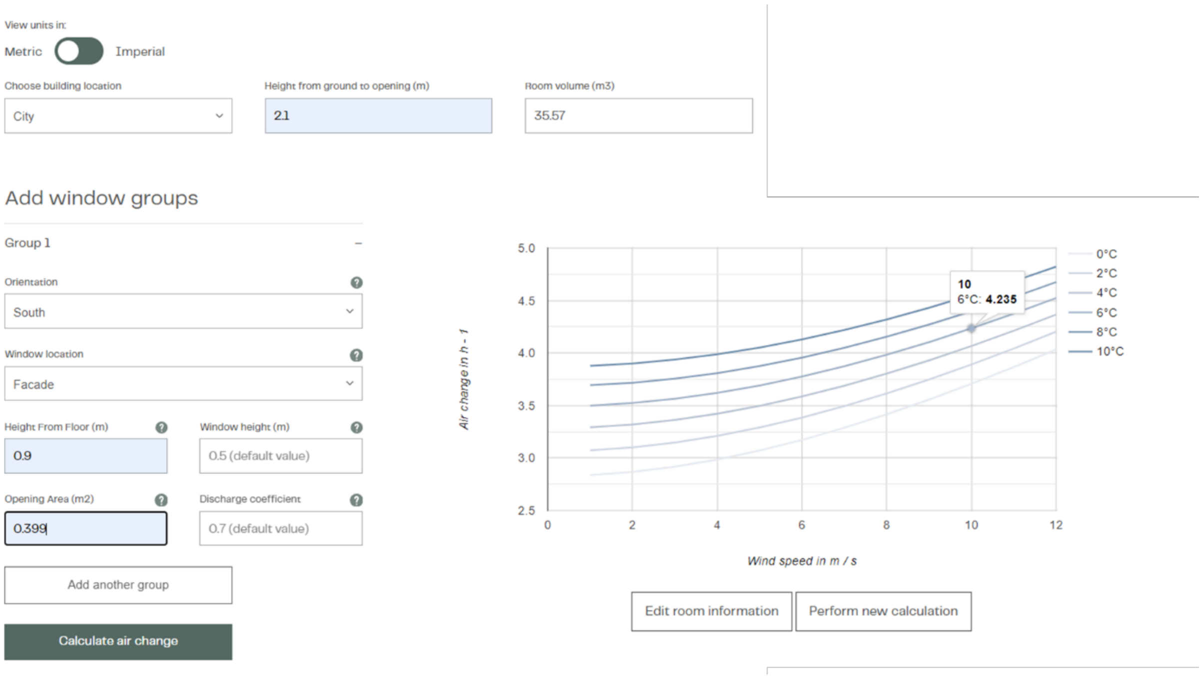


Figure 5.7: ACH of main bedroom when window is open

Table 5.13: Heat-loss due to ventilation

House No.	Window Open Status		Ventilation Heat Loss (Qv)		
	wos	%	**Air Changes per Hour n (ACH)	Average Volume (m3)	Qv = 0.33*n*V (W/K)
1	Closed	0	0.50	35.57	5.87
2	Open rarely	0.06	0.50	35.57	5.87
3	Open	29.2	4.00	35.57	46.95
4	Open rarely	0.55	0.50	35.57	5.87
5	Closed	0	0.50	35.57	5.87
6	Closed	0	0.50	35.57	5.87
7	Open rarely	0.015	0.50	35.57	5.87
8	Open rarely	9.81	0.50	35.57	5.87
9	Open rarely	0.57	0.50	35.57	5.87
10	Open rarely	1.51	0.50	35.57	5.87
11	Open frequently	49.57	4.00	35.57	46.95
12	Open rarely	0.07	0.50	35.57	5.87
13	Closed	0	0.50	35.57	5.87
14	Open	10.83	4.00	35.57	46.95
15	Open rarely	0.25	0.50	35.57	5.87
16	Open sometimes	27.85	4.00	35.57	46.95
17	Open rarely	0.57	0.50	35.57	5.87

The air changes per hour for the main bedroom when window is open and window is closed, is a complex process and is calculated, as mentioned in Chapter 3, using an online calculator. The area of opening when window is open is 70% of the whole area.

$$a_{wo} = a_w \times \frac{70}{100} = 0.57 \times \frac{70}{100} = 0.399 \tag{6.1}$$

The area of opening when window is closed is considered to be 0.05. The speed of wind and the outside ambient temperature for the considered time frame, has been obtained from MET office data (Weather Observation Website, n.d.). Plugging in the values in the software, the air changes per hour of the room when window is open and when window is closed, is calculated. Screenshots of the calculation is shown in Figure 5.6 and Figure 5.7.

Table 5.14: Fabric heat-loss + Ventilation heat-loss

House No.	Building Construction	Insulation		Window Open Status		Qf+Qv
				wos	%	
1	Concrete	Roof and External Wall insulation	HI	WC	0	12.54
2	Traditional Cavity	Roof and Cavity Wall insulation	HI	WC	0.06	12.54
3	Concrete	Roof and External Wall insulation	HI	WO	29.2	53.62
4	Concrete	Roof and External Wall insulation	HI	WC	0.55	12.54
5	Concrete	Roof Insulation Only	LI	WC	0	30.84
6	Concrete	Roof and External Wall insulation	HI	WC	0	12.54
7	BSIF	Roof Insulation Only	LI	WC	0.015	30.84
8	solid brick semi terrace	Roof and Internal Wall insulation	HI	WC	9.81	12.54
9	solid brick semi terrace	Roof and Internal Wall insulation	HI	WC	0.57	12.54
10	solid brick semi terrace	Roof and External Wall insulation	HI	WC	1.51	12.54
11	solid brick semi terrace	Roof and External Wall insulation	HI	WO	49.57	53.62
12	Traditional Cavity	Roof and Cavity Wall insulation	HI	WC	0.07	12.54
13	Traditional Cavity	Cavity Wall Insulation Only	MI	WC	0	29.87
14	Traditional Cavity	Roof and Cavity Wall insulation	HI	WO	10.83	53.62
15	Traditional Cavity	Roof and Cavity Wall insulation	HI	WC	0.25	12.54
16	Traditional solid brick terrace	Roof Insulation Only	LI	WO	27.85	71.92
17	Traditional solid brick terrace	Roof and Cavity Wall insulation	HI	WC	0.57	12.54

5.4.1. Total Coefficient of Heat loss due to Fabric and Ventilation

Combing the values form Table 5.12 and Table 5.13, the total coefficient of heat loss due to building fabric and ventilation can be calculated, as shown in Table 5.14. The energy consumption in the house will be heat loss coefficient times the inside outside temperature difference ($T_{room} - T_{out}$).

5.5. Discussion

Inference 1

With the values calcualted in the previsou sections of this chapter, the energy consumption for the 17 hosues is calculated. Figure 5.8 shows the energy consumption in the 17 houses for Winter 1 (Feb 14 – March 14, 2013), with the insulation property and window status of the houses specified in the graph. In ideal situation where windows are closed, and the insulation property of the hosue is high, the energy demand of the house is lower than the average energy demand of the 17 houses.

In high insualiton and window open houses (h3, h11, h14), the energy demand is higher htan the average nergy demand. In case of low insualtion houses, energy demand is similar when window is open or closed. While houses with high insulation and window closed have low energy consumption, the energy consumption can be seen to be more than double houses with high insulation, but windows open. Under typical circumstances, thermal insultion can reduce heat loss through conduction of building fabric , to a good extend. However, if the occupants leave windows open frequently, the heatloss due to ventilation becomes excessive, thereby negating the effect of insulation to an extend.

Inference 2

Inference 1 showed that EC relied more on other ‘drivers’, than the insulation property of the dwelling. To understand the impact of window opening, two houses with similar frequency of window opening are compared. The window opening frequency and ED from Feb 12 to Feb 28, 2013, is considered.

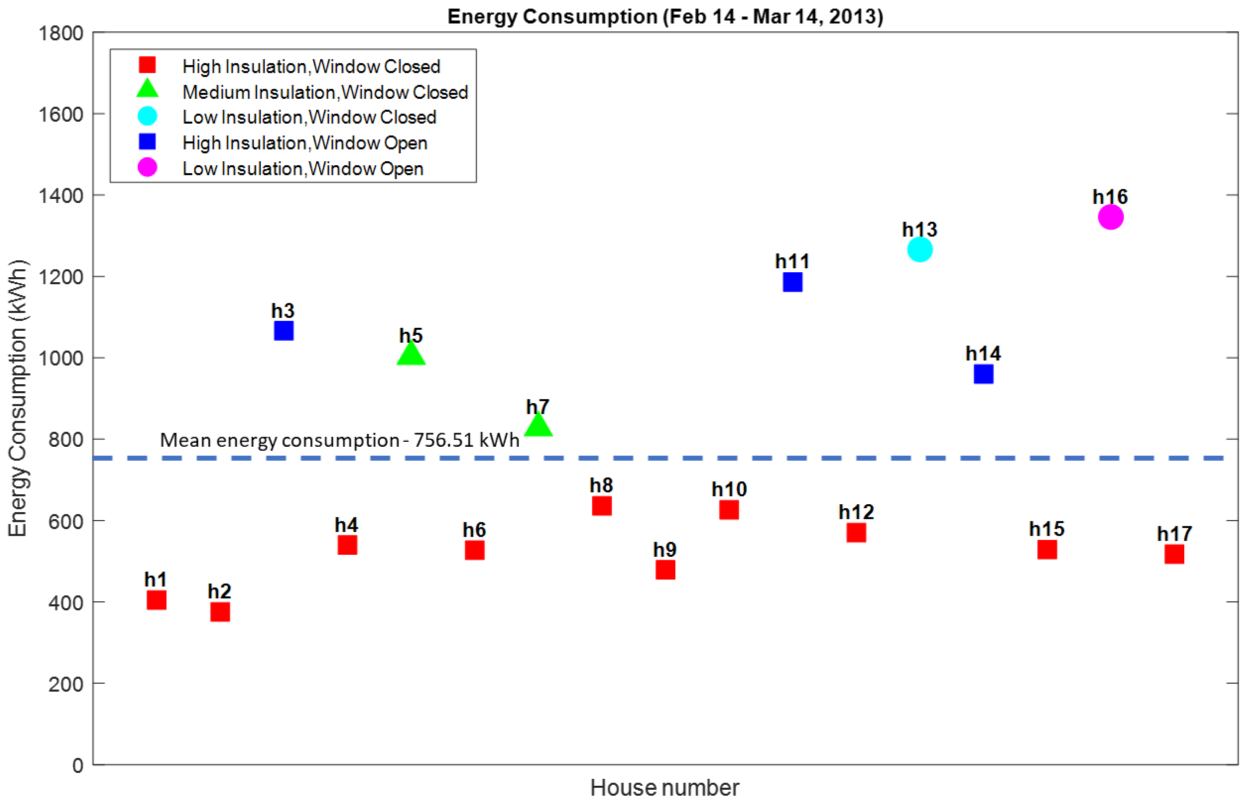


Figure 5.8:Energy Consumption in main bedroom of the houses (Feb-March 2013)

While h12 has EC of 230.8 kWh, h11 has an EC of 509.5 kWh which is more than double the EC of house 12. The correlation between the radiator temperature (T_{rad}), room temperature (T_{room}) and the window opening frequency for h11 and h12 can be seen in Figure 5.9. From the figure it is evident that the occupants of h11 open windows when radiator is on; this might be a contributing factor to the fact that although the radiator is heating up to 60°C, the average room temperature of the house is 17.9°C. In the case of house 12 the radiator heats up to 60°C occasionally and the average room temperature is 18.9°C, which is higher than that of House 11.

House 11 and House 12 are two similar houses with high insulation property and similar built construction but different window opening frequencies, as shown in Figure 5.9. the occupants of h11 open windows very frequently while those of h12 do not open windows. Figure 5.10 shows the scatter plot of radiator temperature, ambient room temperature and window status of house 11 and house 12 for two weeks in February 2013. The calculated energy consumption (EC) of the two houses is also displayed in the figure.

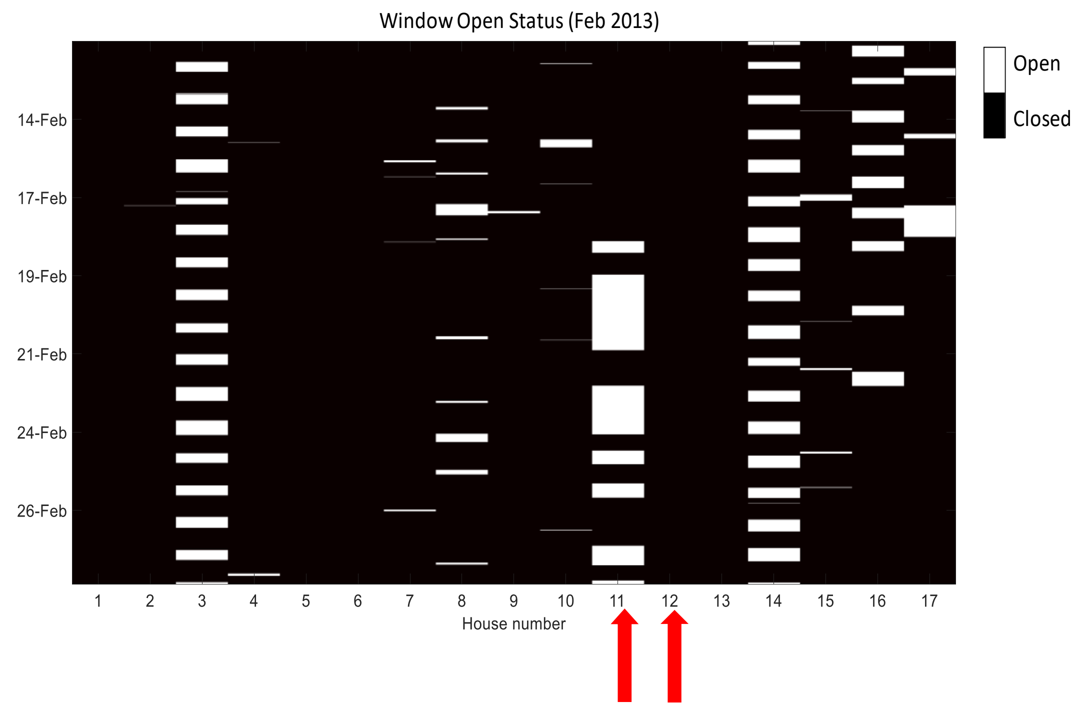


Figure 5.9: Window opening frequency of main bedroom for one month in Winter

Looking at the bedroom radiator temperature, comparing it to the window open pattern. It can be seen that the occupants of h11 open windows when the radiator temperature frequently, regardless of the heating status, resulting in heat loss and more energy consumption. When a house is well insulated, the occupants tend to open the window due to increase in the ambient temperature of the room. Occupants in less insulated houses also tend to open windows, since they have the radiator temperature at high, most of the time and the room gets too hot. In both cases, the thermal comfort of the occupant depends on the ventilation in the room. The energy consumption depends highly on the occupant behaviour of opening windows.

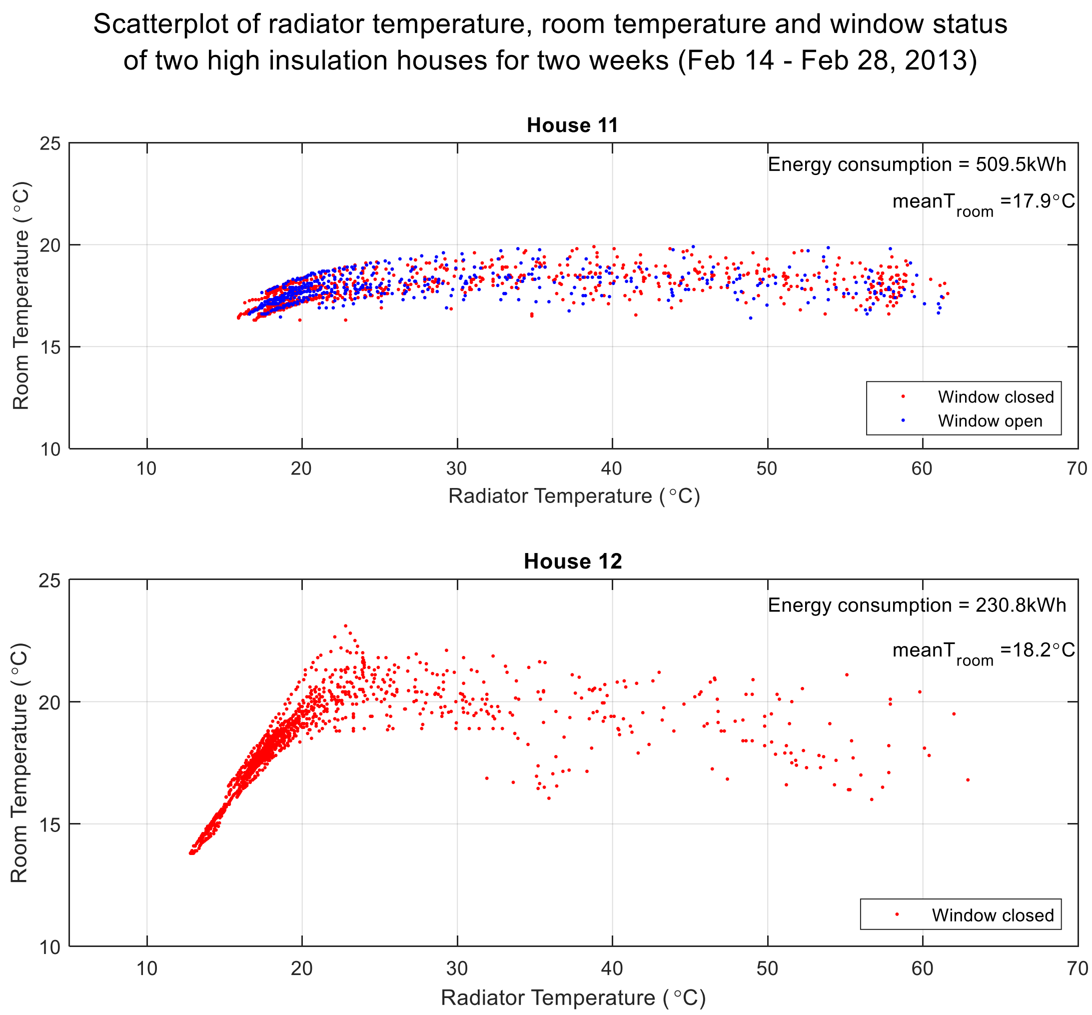


Figure 5.10: Comparison between two high insulated houses (scatter plot)

Figure 5.11 shows the correlation between the radiator temperature (T_{rad}), room temperature (T_{room}) and window status (WS) of the 17 houses. The correlation coefficient given in the figure is that of window open percentage and radiator temperature (T_{rad}). In this case, a positive correlation means higher window open percentage (WOP), higher T_{rad}.

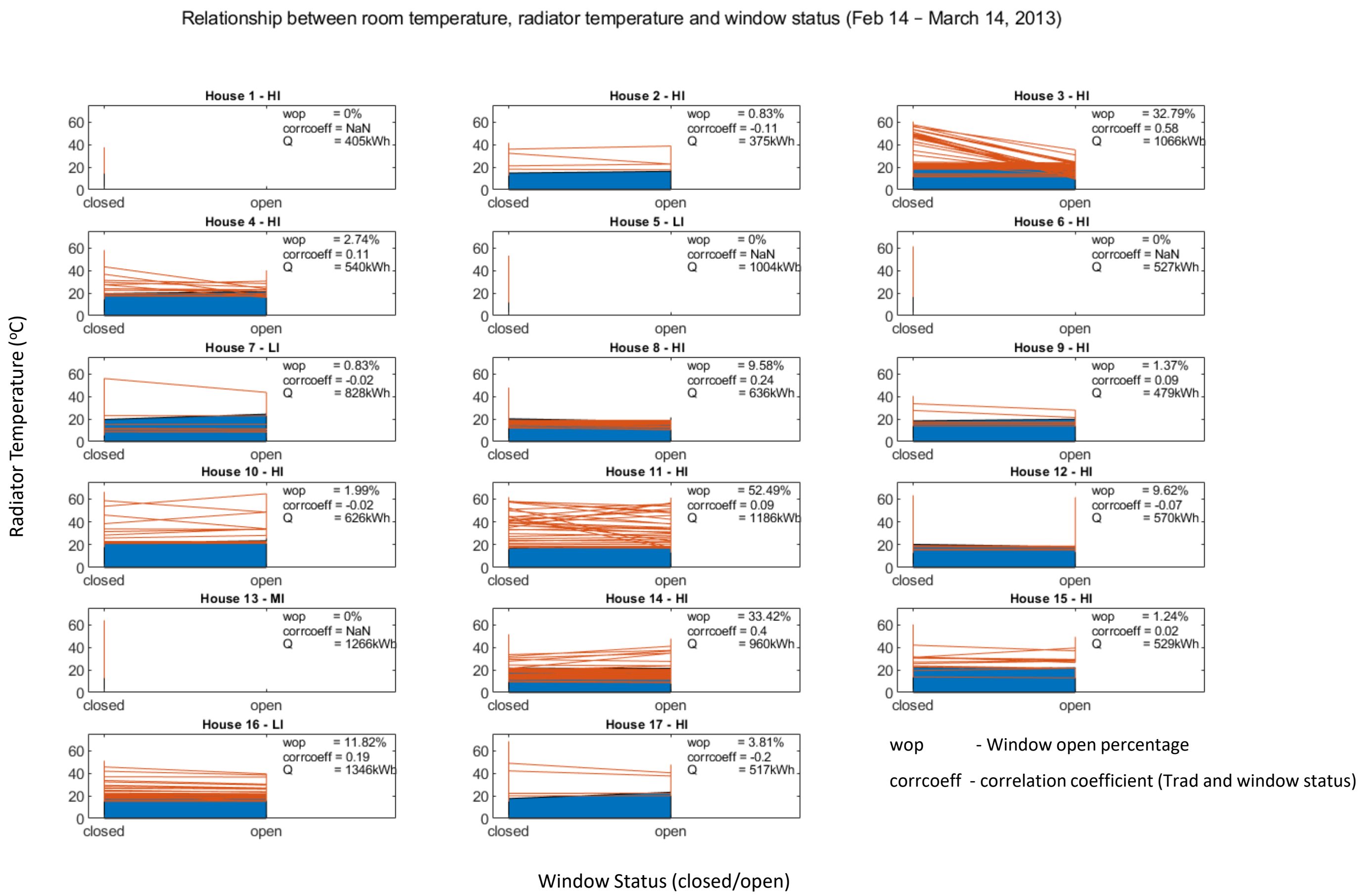


Figure 5.11: Relationship between T_{room}, T_{rad} and window status

From Figure 5.11, it can be seen that a positive correlation exists between Trad and WOP when WOP is higher than 10%, as seen in houses 3,8,11 and 14. Energy consumption is seen to be high for houses where Trad fluctuated (Houses 3,4 ,11,14). These houses have a positive correlation between Trad and WOP (specified in Figure 5.11). There are exceptions to this hypothesis, as seen in house 5, where ED is still high although the WOP is not high. This may be again due to occupant behaviour, where in the thermal comfort of the occupant is satisfied only when room temperature is maintained high. To investigate this further, the scatter plot of T_{rad}, T_{room} and WS for all the houses is plotted.

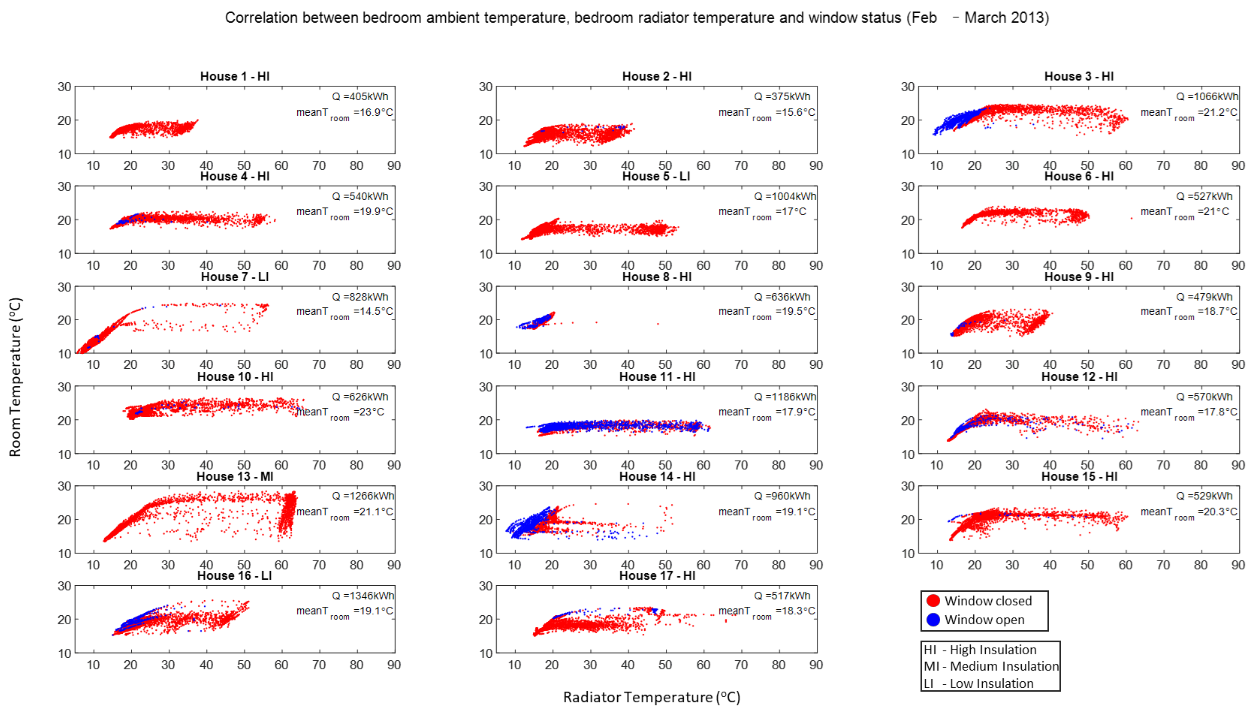


Figure 5.12: Correlation between T_{room}, T_{rad} and window status (Scatterplot)

Figure 5.12 shows the scatterplot of Troom, Trad and WS of the hosues, with the energy demand and mean Troom displayed. It can be seen that ED is high then the avewarge room teemprature is high. ED is also high when window opening percentage in the house is high. This implies that window opening percentage plays a major role in the enregy consumption of a dwelling. The need for thermal comfort of the occupant is a principal factor that plays an important role in deciding the enregy consumption of a building.

The first stage of analysis indicated that there is a higher correlation between energy use and window opening frequency, than the building insulation property. This can be better understood considering houses under four scenarios/ conditions:

1. House A - High insulation house with frequently open windows (HI and WO)
2. House B - High insulation house with rarely open windows (HI and WC)
3. House C - Low insulation house with frequently open windows (LI and WO)
4. House D - Low insulation house with rarely open windows (LI and WC)

5.6. Summary

This chapter elaborates on the first stage in the survey of data obtained from sensors set up in Nottingham City Council houses. The project focussed in 40 homes based in Nottingham with diverse construction design and built date. Houses were equipped with Wireless Sensor networks (WSN) to record the utility readings, ambient temperature of rooms, radiator temperatures and to monitor the opening and closing of doors and windows. The experiment was conducted from over a period of 51 weeks and data was collected. The first stage of analysis of the data is explained in this chapter, involves data cleaning, explanation of the sensor set up and preliminary analysis of data. The findings show that WOB plays a crucial role in the energy consumption of a residential building.

The action of window opening is the most common and technique impulsive used by people, to obtain the required thermal comfort in a room. Regardless of the type of housing or building construction, occupants open windows purely based on their comfort levels, thereby making it difficult to standardise the element in building simulation model energy consumption calculations.

Chapter 6 | Analysis of Energy Usage in Social Housing Stage II

6.1. Introduction

Chapter 7 implied that opening a window in winter will increase heat loss and consequently, the energy consumption of a building. However, taking into consideration the unpredictability of WOB, incorporating it into building simulation models for better energy prediction, is complex. This chapter attempts to quantify the impact of WOB on energy consumption of a building. Energy consumption of four types of houses is compared and the results are analysed. There is no definitive answer to the question how big the sample size should be for a study. Studies shows that as long as there is reasonable amount of data collected from each sample, based on nature and design of the study and quality of the data, so as to unfold rich understanding of the factor being studied, then a few participants are sufficient (Morse,2000). In this study, considering the scope of the study, 4 houses were considered for the further analysis as a pilot study, to be used as a benchmark for future studies which can include larger number of samples.

6.2. Analysis

The first stage of analysis indicated that there is a higher correlation between energy use and window opening frequency, than the building insulation property. This can be better understood considering houses under four scenarios/conditions:

1. House A - High insulation house with frequently open windows (HI and WO)
2. House B - High insulation house with rarely open windows (HI and WC)
3. House C - Low insulation house with frequently open windows (LI and WO)
4. House D - Low insulation house with rarely open windows (LI and WC)

Table 6.1: Insulation and WOS of the 17 dwellings

House No.	Main Bedroom Window Status				Insulation		
	Winter 1		Winter 2				
	12 Feb 2013 to 31 March 2013		1 Dec 2013 to 21 Feb 2014		Properties	Type	
	%	Window open status	%	Window open status			
1	0	WC	0	WC	Roof Insulation and External Wall insulation	HI	
2	1.9	WC	0.1	WC	Roof Insulation and Cavity Wall insulation	HI	HI-WC
3	26	WO	29	WO	Roof Insulation and External Wall insulation	HI	
4	2.4	WC	0.6	WC	Roof Insulation and External Wall insulation	HI	
5	0	WC	0	WC	Roof Insulation Only	LI	LI-WC
6	0	WC	0	WC	Roof Insulation and External Wall insulation	HI	
7	0.5	WC	0	WC	Roof Insulation Only	LI	
8	9.2	WC	9.8	WC	Roof Insulation and Internal Wall insulation	HI	
9	0.8	WC	0.6	WC	Roof Insulation and Internal Wall insulation	HI	
10	2	WC	1.5	WC	Roof Insulation and External Wall insulation	HI	
11	53	WO	50	WO	Roof Insulation and External Wall insulation	HI	HI-WO
12	5.9	WC	0.1	WC	Roof Insulation and Cavity Wall insulation	HI	
13	0	WC	65	WO	Cavity Wall Insulation Only	MI	
14	32	WO	11	WO	Roof Insulation and Cavity Wall insulation	HI	
15	0.8	WC	0.3	WC	Roof Insulation and Cavity Wall insulation	HI	
16	16	WO	28	WO	Roof Insulation Only	LI	LI-WO
17	2.8	WC	0.6	WC	Roof Insulation and Cavity Wall insulation	HI	

Table 6.1 shows the houses with the window open frequency and the insulation properties. Considering the four conditions, as described in the previous chapter (Chapter 6), 4 houses are chosen. The houses chosen are shown in Table 6.2. Data from Feb-March 2013 is considered as Winter 1 and Nov 2013 - Feb 2014 is considered as Winter 2. It is to be noted

that the instances chosen are when the window is open in WO houses (and closed in WC houses).

Table 6.2: Houses chosen for analysis

House	House number	Type	No. of Bedrooms	Boiler Type	Property	Type
House A	11	Semi detached	3	Combi	High Insulation Window Open	HI-WO
House B	2	Semi detached	3	Combi	High Insulation Window Closed	HI-WC
House C	16	Mid terrace	3	Combi	Low Insulation Window Open	LI-WO
House D	5	Semi detached	3	Combi	Low Insulation Window Closed	LI-WC

Figure 6.1: The four houses considered for analysis

The English Housing Survey, one of the oldest government polls in the UK, is a comprehensive study of housing circumstances, conditions, energy efficiency in England.

The first section of the report focusses on households, covers tenure, demographic, and economic characteristics of people who live in different tenures. The second sections give a general overview of the housing stock in England, including the age, size and kind of homes as well as their energy efficiency, decentness, dampness, mould problems and smoke alarms. According to the English housing survey, about 75% of the UK housing stock use combination boilers (*English Housing Survey*, 2020).

Figure 6.1 shows the image of the four houses considered for further analysis. The four houses are seen to have combination boiler for heating. Energy consumption due to heating depends on the heating cycle of boilers. A diagnostics study of 221 boilers revealed that half 50% of them had an average of 50 starts per day (Bennett, Elwell and Oreszczyn, 2019). The efficiency standards are not met due to this detrimental performance. Cycling contradicts assumptions in efficiency testing standards, which assume steady state operation, weighted by full and part power measurements. To understand energy consumption due to heating, a micro level investigation of the heating cycle is beneficial. This is described in the following sections.

6.3. Heat Energy Demand Analysis

Thermal comfort and indoor air quality of a room are the factors that occupants in a room are concerned of most commonly. Any person in a room in their house, would prefer to be in a thermal environment in which they are comfortable. To attain the degree of comfort they envision, they easiest way is to open window of the room they are in, to let 'fresh air' in and reduce the temperature in the room, in case of over-heating. This behaviour of occupants, of window opening, has a significant effect on energy consumption. Studies show that the main bedroom is one of the most common rooms where window is left open in residential buildings, as mentioned in Section 7.3 (Chapter 7). Therefore, the main bedroom is focussed on this study. The volume of bedroom for the four houses are given in Table 6.3. b_{vol} is the average value of the volume of the main bedroom for the four houses. By considering the average value, the energy demand to heat the same volume of room for different house conditions, can be compared. To analyse the relationship between house insulation property, WOS and the enregy demand of the house, energy demand in the four houses are calculated, using measured values b_{vol},T_{room} and T_{out} and compared. Energy consumption in the houses are calculated using the formulas given in Equation (3.12) in Chapter 3.

Table 6.3: Volume of main bedroom

House	Length	Breadth	Height	Volume (m3)
A	4	2.7	3.3	35.64
B	3.16	3.54	3.2	35.80
C	3.2	3.89	3.5	43.57
D	3.81	3.84	3	43.89
Average volume of main bedroom (b_{vol})				39.72

To have a comprehensive understanding of changes in the indoor environment, the regulating mechanisms that contrbute to the changes, need to be studied. With this objective, the field measurment data collected form social housing and tapered down to four houses, is explored. The energy consumption is calculated for all of Winter 1 and Winter 2 with the temeprature data collected. By comparing energy usage of high insulation and windowopen and higjh insualtion window clsoed hosues, the imapct of energy usage can potentially be quantified. For anlaysis purposes, some instances from winter 1 and winter 2 are considered, to analyse the realtionship between window opening and the temperature environment of the room. 7 instances from winter 1 and 11 instances from winter 2 are analysed. Each instance was a 24 hour duration. The instances selected are given below:

Winter 1 Instances

1. Inst1 = [18-Feb-2013 00:00:00 ; 18-Feb-2013 23:59:00]
2. Inst2 = [19-Feb-2013 22:00:00 ; 20-Feb-2013 22:00:00]
3. Inst3 = [22-Feb-2013 09:00:00 ; 23-Feb-2013 09:00:00]
4. Inst4 = [02-Mar-2013 00:00:00 ; 02-Mar-2013 23:59:00]

5. Inst5 = [03-Mar-2013 00:00:00 ; 03-Mar-2013 23:59:00]
6. Inst6 = [04-Mar-2013 15:00:00 ; 05-Mar-2013 15:00:00]
7. Inst7 = [09-Mar-2013 00:00:00 ; 09-Mar-2013 23:59:00]

Winter 2 Instances

1. Inst1 = [20-Nov-2013 00:00 ; 20-Nov-2013 23:59]
2. Inst2 = [21-Nov-2013 00:00 ; 21-Nov-2013 23:59]
3. Inst3 = [22-Nov-2013 00:00 ; 22-Nov-2013 23:59]
4. Inst4 = [23-Nov-2013 18:00 ; 24-Nov-2013 18:00]
5. Inst5 = [24-Nov-2013 18:00 ; 25-Nov-2013 18:00]
6. Inst6 = [25-Nov-2013 18:00 ; 26-Nov-2013 18:00]
7. Inst7 = [26-Nov-2013 18:00 ; 27-Nov-2013 18:00]
8. Inst8 = [27-Nov-2013 18:00 ; 28-Nov-2013 18:00]
9. Inst9 = [28-Nov-2013 18:00 ; 29-Nov-2013 18:00]
10. Inst10 = [30-Nov-2013 00:00 ; 30-Nov-2013 23:59]
11. Inst11 = [01-Dec-2013 20:00 ; 02-Dec-2013 20:00]

Window opening behaviour in buildings are best studied with field measurements due to its stochastic nature. Previous study results show that there are large discrepancies in household energy consumption even of similar layout (Bahaj & James, 2007; Ouyang & Hokao, 2009). The radiator heating time (in minutes) for the four houses for the considered instance is charted, shown in Figure 6.2(a). This is calculated by adding the time when the radiator is heating during the 24 hours considered.

House A, which is a high insulation window open house (HI-WO) has a radiator heating time of 200 mins which is double that of House B, high insulation window closed house (HI-WC). While defining radiator heating time, it is important to look at the average room temperature to get a valid representation. Figure 6.2 (b) shows the ratio of radiator heating to the average room temperature during the instance. The following inferences can be made:

- In House A, radiator takes 11 mins to increase room temperature by 1°C, while in House B it takes 5.75 mins for the same which is almost half that of House A.
- The percentage of time the radiator is also longer for House A (14%) when compared to House B (7%).

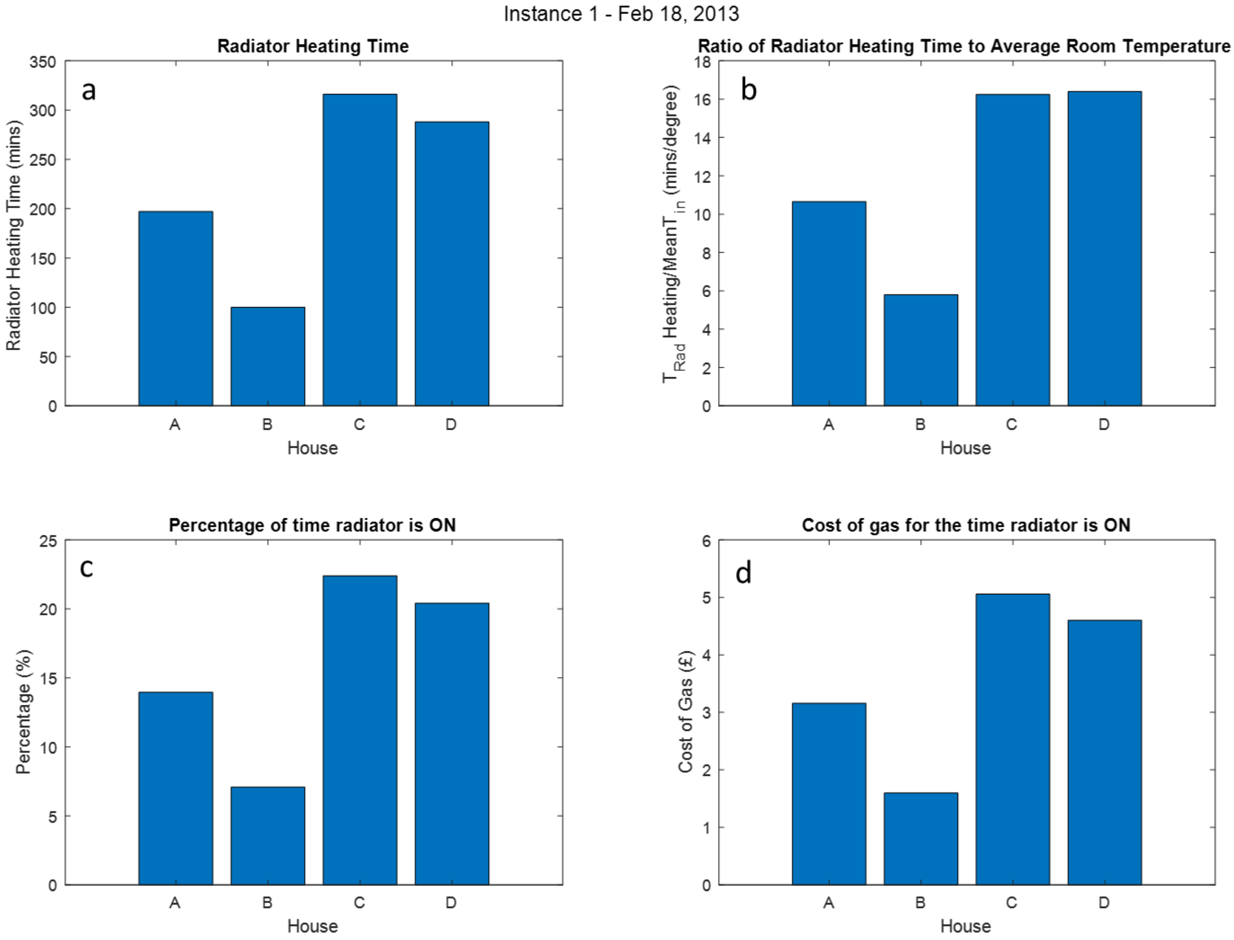


Figure 6.2: Comparison of the houses based on radiator heating time – Winter 1, Instance 1

- The four houses have combi boiler and 5-8 radiators. The cost of gas in UK currently is £0.04 per kWh which will increase to £0.07 after 1 April 2022 *(Check If the Energy Price Cap Affects You* | Ofgem, 2022). Assuming they have a 24kW boiler, which is the ideal size required for the given numbers, the cost of gas for the percentage of time the radiator is ON can be calculated as

$$Cost\ of\ gas\ based\ on\ radiator\ heating\ time\ C_{grh} = 0.04 \text{ x } 24 \text{ x } t_{radheating} \quad (7.1)$$

The cost of gas House A can be seen to be almost twice that of House B (Figure 6.2d).

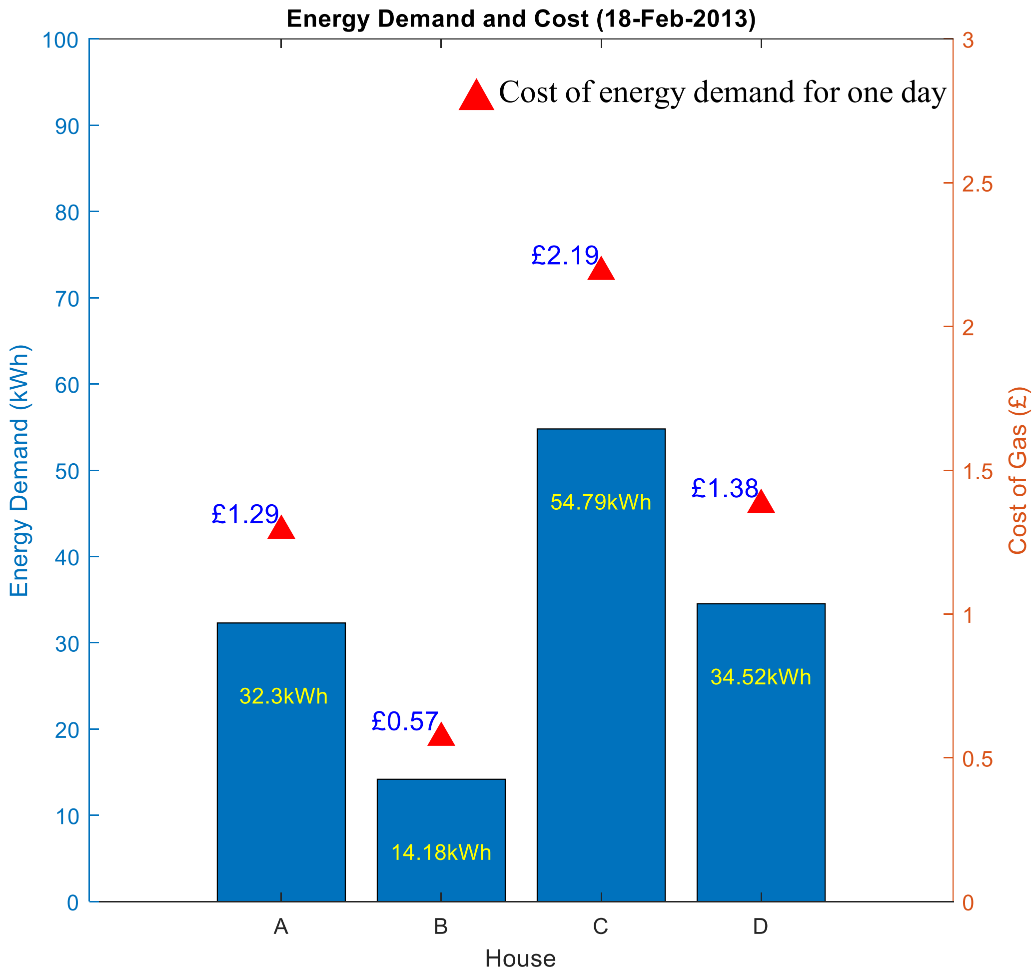


Figure 6.3: Energy Demand and Cost – Winter 1, Instance 1

Figure 6.3 shows the energy demand in the main bedroom, for Instance 1, calculated using Equation (3.12) from Chapter 3. The energy demand can be seen to be in par with the radiator heating rime of the houses discussed in Figure 6.2. for the first instance of 24 hours, the energy demand for House A is 32.3 kWh and that of House B is 14.18 kWh. The corresponding gas price is £1.29 and £0.57 respectively.

Figure 6.4 shows the radiator heating time and corresponding variates for the second instance in Winter 1. Here, the radiator heating time for House A is 200 mins and the radiator heating time for House B is 40 mins. The energy demand and cost for Instance 2 is shown in Figure 6.5. The energy demand for House A is 73.81 kWh and that for House B is 14.48 kWh.

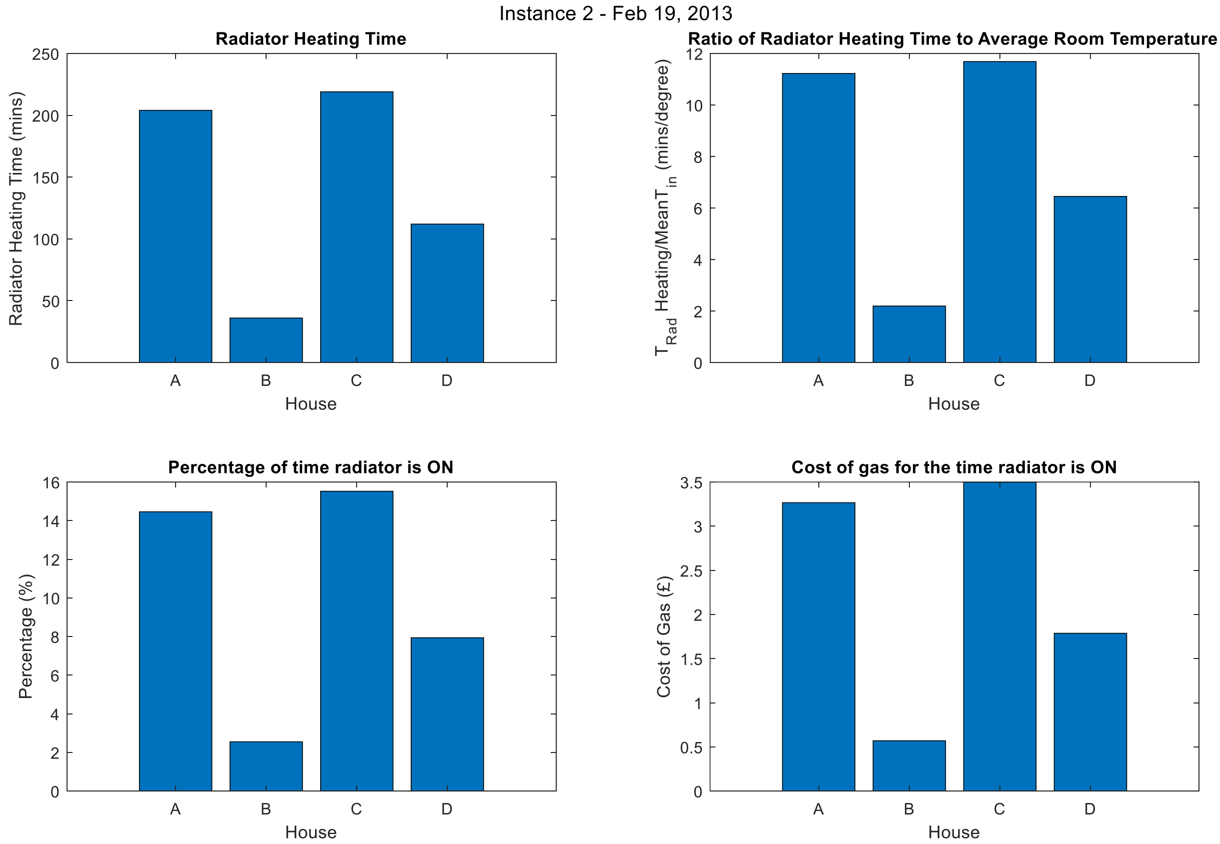


Figure 6.4: Comparison of the houses based on radiator heating time – Winter 1 Instance 2

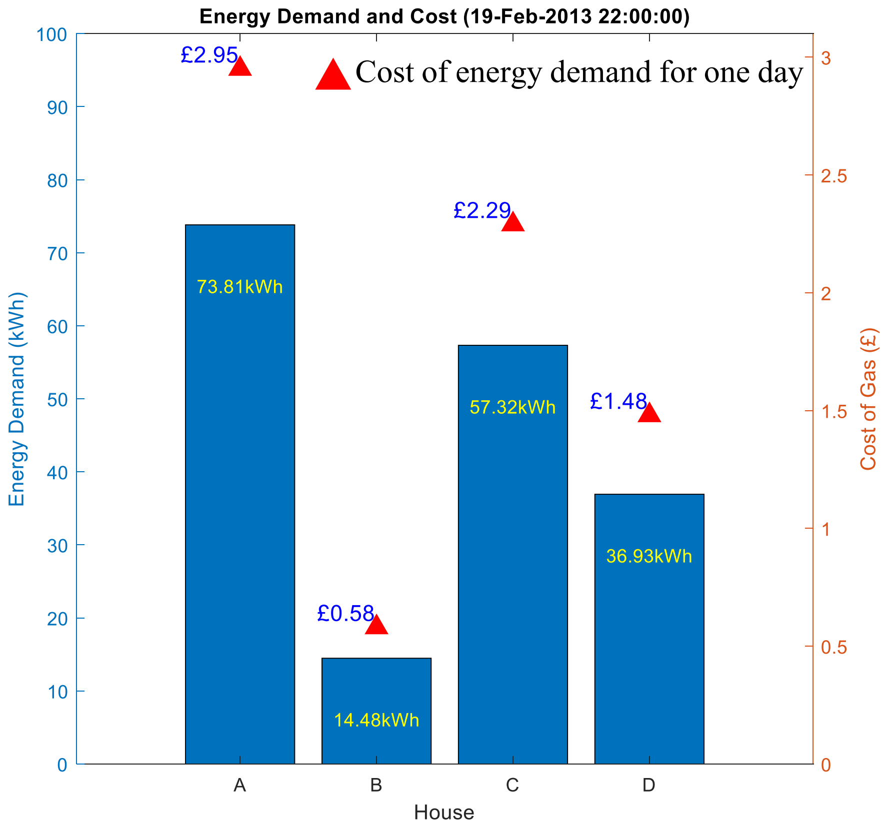


Figure 6.5: Energy Demand and Cost - Winter 1, Instance 2

The energy demand for House C (low insulation window open, LI-WO) and House D (low insulation and window closed, LI-WC) is higher than that of House A in Instance 1 and lower than that of House A in Winter 2.Similar pattern is in instance 1 of winter 2, as show in Figure 6.6 and Figure 6.7. the radiator heating time is higher for House A in November (250 mins) than February. With the percentage of time the heater is on increasing to 19%, it takes 16 mins to raise the room temperature by 1^{o}C for winter 1, instance 1.

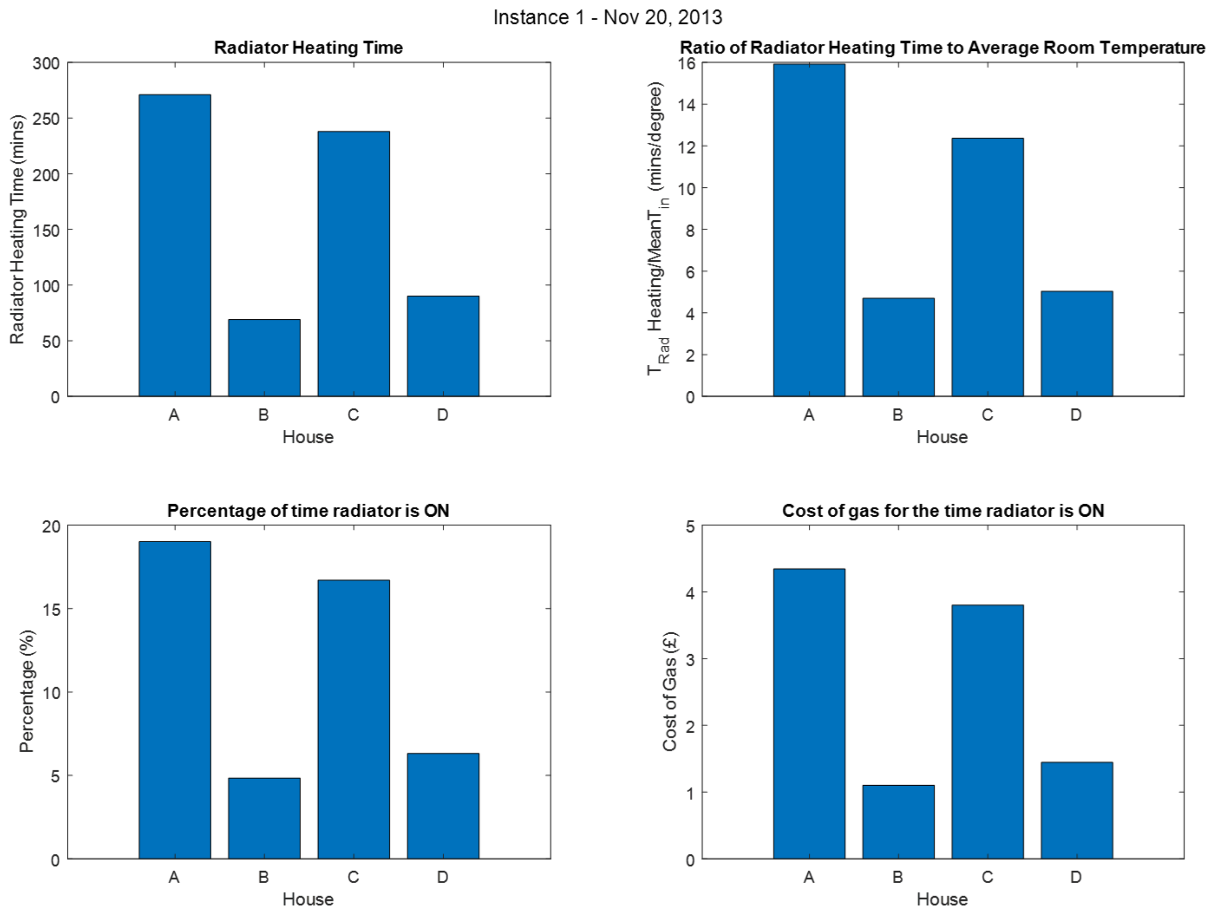


Figure 6.6: Comparison of the houses based on radiator heating time - Winter 2, Instance 1

The energy consumption of House A is also considerable higher for Winter 2, instance 1 (57.79 kWh), when compared to that of House B (11.77 kwh). The average energy demand and cost and total energy demand and cost is calculated for all of winter 1 (Figure 6.8) and winter 2. The graphs for all instances for winter 1 and winter 2 and the average and total energy demand and cost for winter 1 and winter 2 are given in Appendix B.

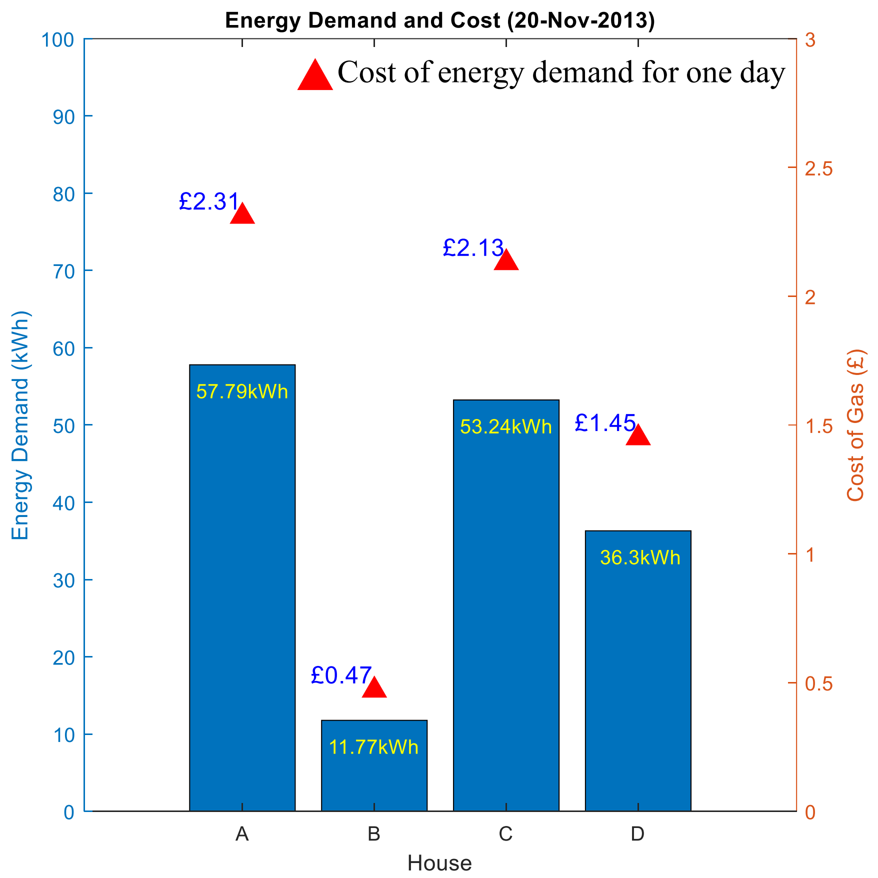


Figure 6.7: Energy Demand and Cost - Winter 2, Instance 1

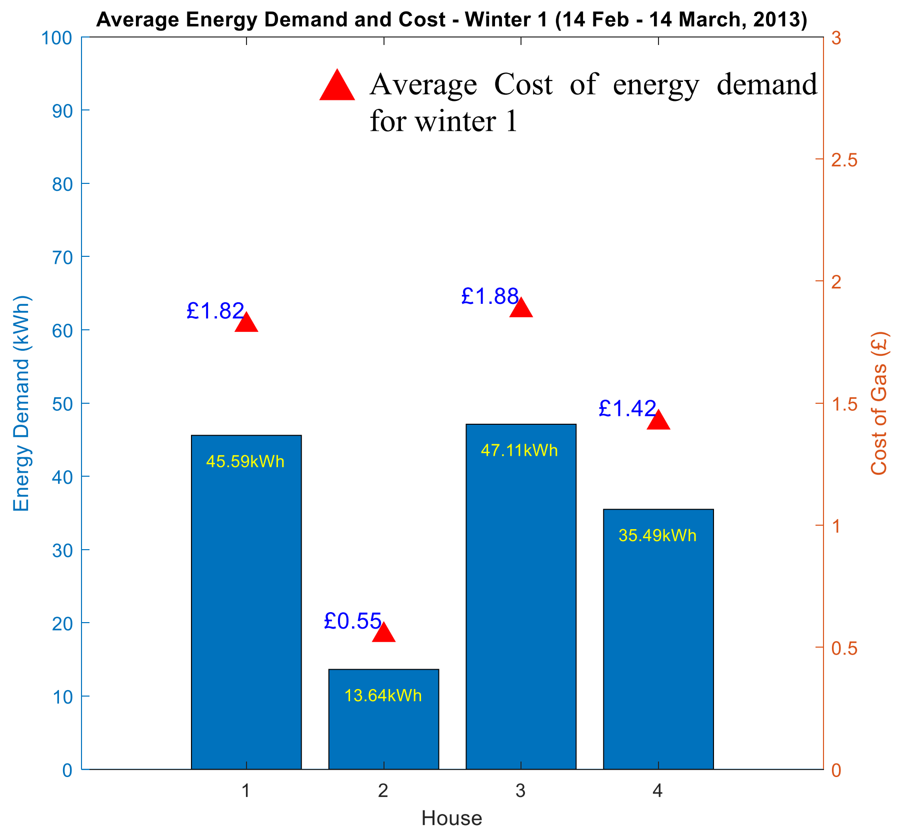


Figure 6.8: Average Energy Demand and Cost - Winter 1

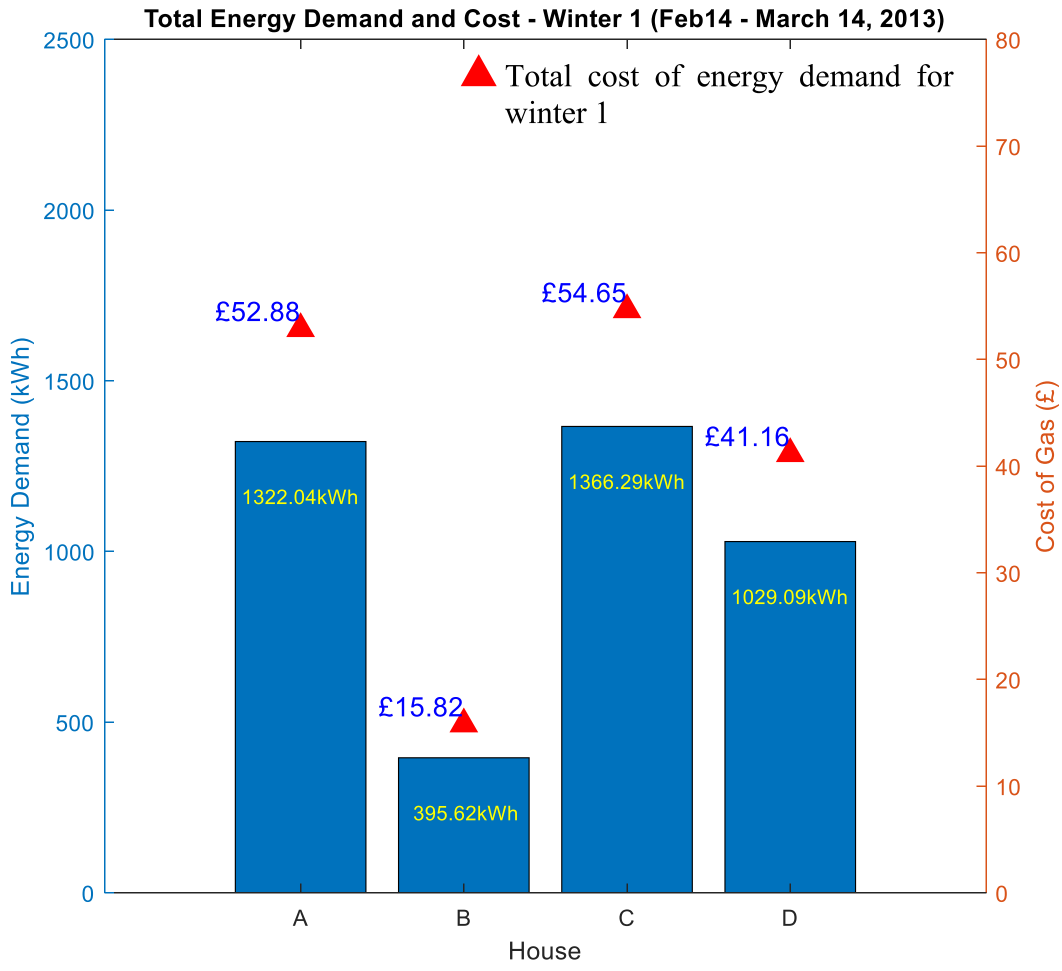


Figure 6.9: Total Energy Demand and Cost - Winter 1

The behaviour of occupants in dwellings, that involves interaction with the building parameters like heating, lighting, opening of windows is one of the main reasons for discrepancy between actual and predicted indoor environmental conditions and as a consequence, the energy performance of the dwelling (Bruce-Konuah et al., 2019).

Comparing energy consumption of houses with similar insulation properties but different window opening behaviour indicated the difference in energy usage due to window opening behaviour of the occupants. Figure 6.9 shows the total energy demand and the corresponding cost for energy, for all the instances in winter 1. It can be seen that well insulated and window closed house, House B, has much lower energy demand than the other houses. House A, which is a well insulated house with window open has energy demand similar to house C, which is a poorly insulated and window closed house.

6.3.1. Comparison of Average Energy Demand and Cost

The energy demand of winter 1 and winter 2 are calculated. From the calculations, average energy demand for one month and the same for one day is calculated. The cost of gas in UK currently is £0.04 per kWh (which will increase to £0.07 after 1 April 2022).

$$\textit{Cost of gas based on energy demand} \quad C_{ed} = 0.04 \times ED_{month} \tag{7.2}$$

$$\textit{New Cost of gas based on energy demand} \quad C_{ednew} = 0.07 \times ED_{month} \tag{7.3}$$

Figure 6.10 and Figure 6.11 show the average energy demand and cost for one day and one month respectively, for the 4 houses. The results show that in high insulation houses, the energy demand of one room can increase by £1 per day by leaving windows open.

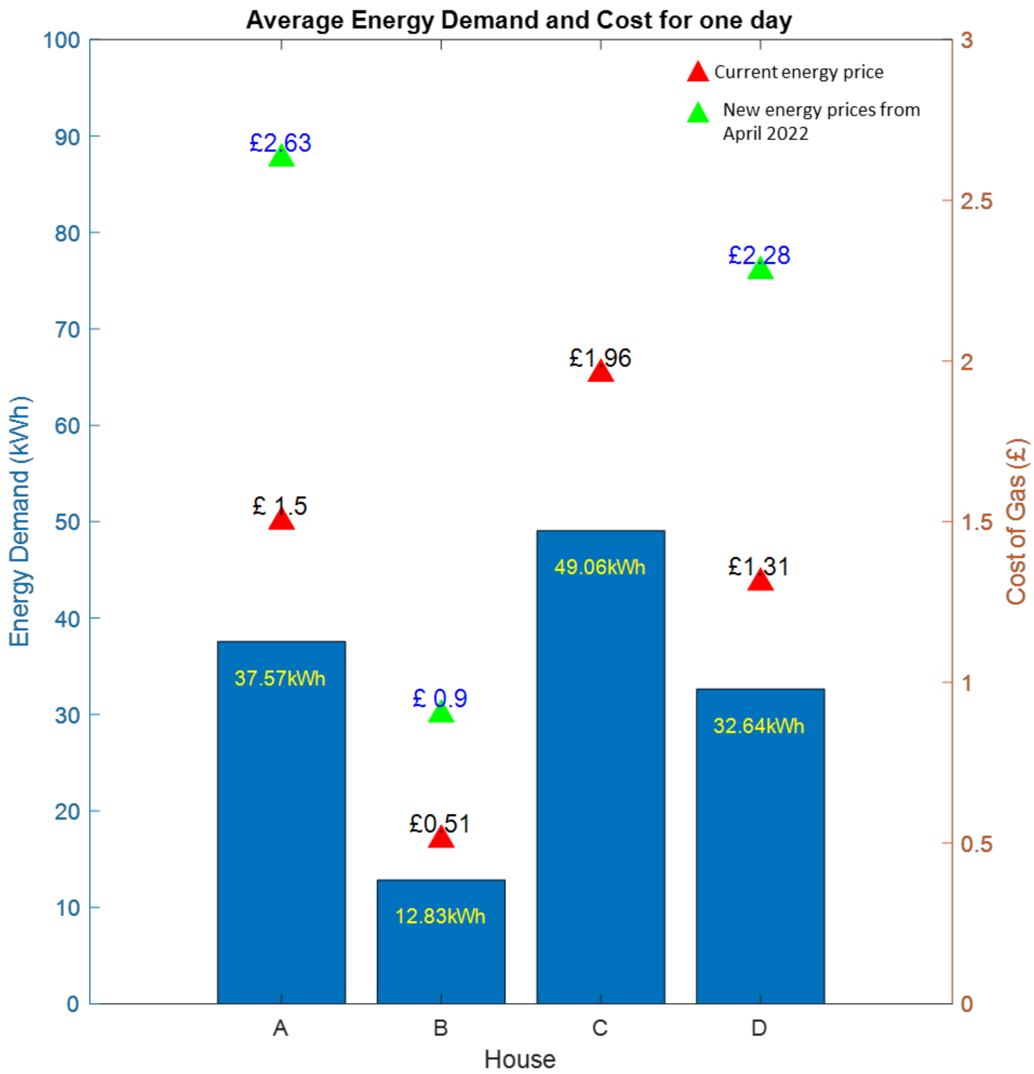


Figure 6.10: Average energy demand and cost for one day

In case of low insulation houses, energy demand increase of £0.65 in a window open house (House C), when compared to window closed house (House D). The energy consumption of high insulation window open house (House A) is seen to be comparable to the energy consumption of low insulation houses (House C and House D).

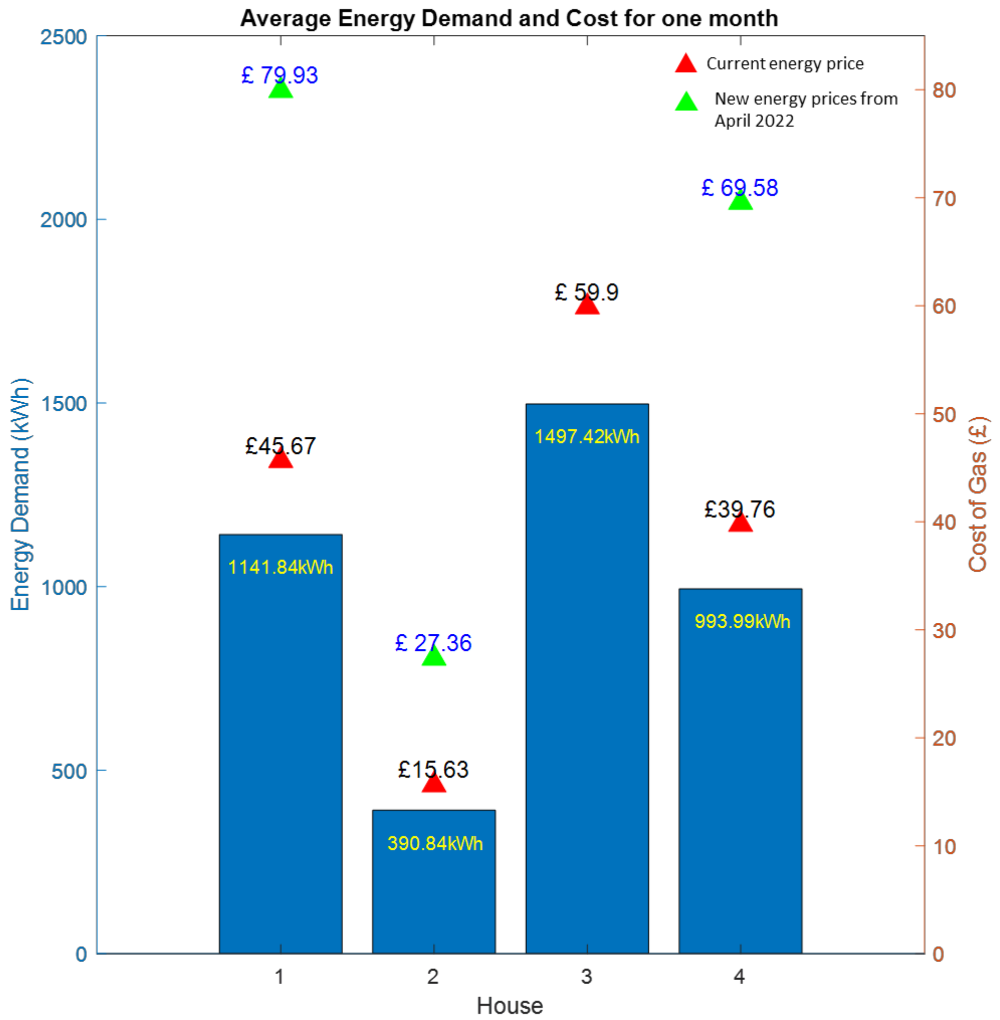


Figure 6.11: Average energy demand and cost for one month

The difference in energy demand is better represented in percentage or as change factor, for comparison. The percentage increase in cost of gas, in house where window is open, when compared to house of similar insulation, with windows closed, is calculated as

$$Percentage\ increase = \frac{C_{gwo} - C_{gwc}}{C_{gwc}} \times 100 \tag{7.4}$$

Where C_{gwo} is cost of gas in house with window open and C_{gwc} is cost of gas in house with windows closed. The change factor is calculated as

$$Change\ factor = \frac{Percentage\ value \times 100}{100} \qquad (7.5)$$

6.3.2. Inference

The energy demand of high insulation window open house (HI-WO, House A), high insulation window closed house (HI-WC, House B), low insulation window open house (LI-WO, House C) and low insulation window closed house (LI-WC, House D) were compared. The following inferences were made from the conducted study

- In high insulation houses, the energy demand of one room increases by a factor of 2.9, when comparing a window open and window closed house.
- Consequently, the energy cost increases by £1 for one room per day, between two high insulation houses with window open and window closed.
- In poorly insulated houses, energy demand of one room increases by a factor of 1.5, in winter months, in a house with windows open, causing an increase of £0.65 for one day.
- Considering the average energy demand of one month, in high insulation houses, there is a difference of £30 in energy costs between a high insulation window open house and high insulation window closed house, for one room in a month.
- There is only a difference of 13% in energy demand of a high insulation window open house and a low insulation window closed house.
- As of April 2022, the gas prices will increase from £0.04 to £0.07. Based on this, the energy cost in a high insulation and window open house will increase by £1.73 for one day when compared toa high insulation and window closed house, which will account for an increase of £52.57 for one month.

6.4. Home Heating System as a First Order Control System

Home heating system is a simple control system, that regulates the temperature of a room. The radiator temperature is the controlled input, and the room temperature is the output that acts as feedback and helps in directing the input to the required value, which can be done manually or automatically. Figure 6.12 represents the block diagram for a basic home heating system, with feedback control, wherein feedback is the returning of the controlled variable (ambient temperature of the room) to the controller to further influence the controlled variable for optimum thermal comfort of occupant.

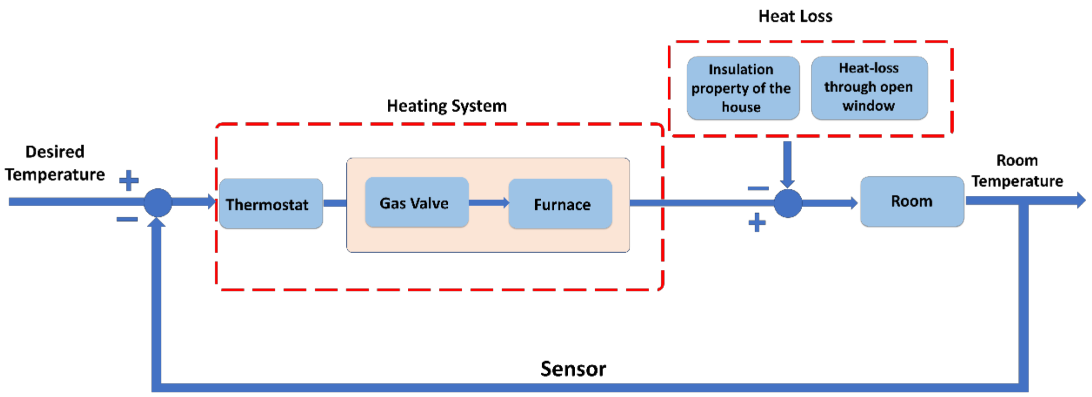


Figure 6.12: Home heating(control) system

The control system above can be represented as differential equations, using transfer functions. A transfer function G(s) can be defined as

$$G(s) = \frac{Y(s)}{U(s)} \tag{7.6}$$

where Y(s) is the output and U(s) is the input of the system.

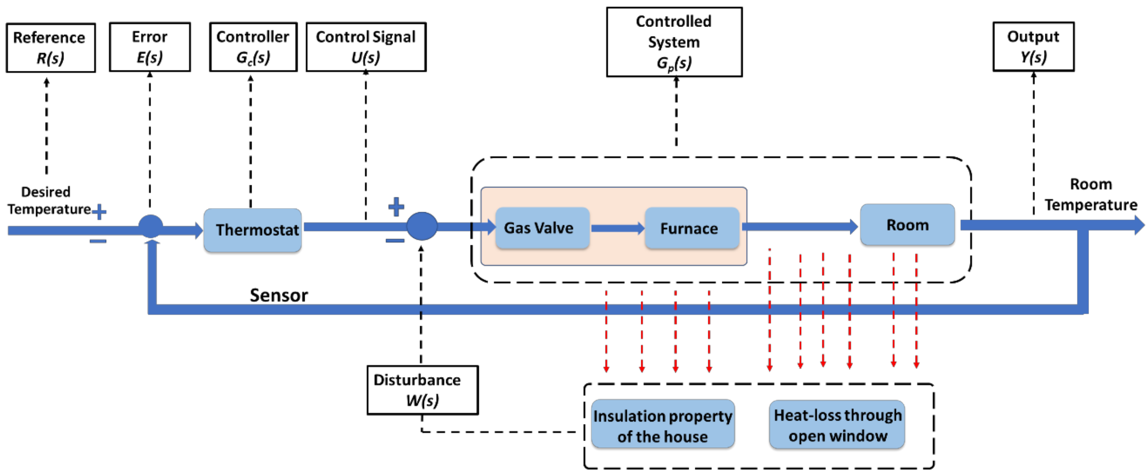


Figure 6.13: Block diagram of home heating control system

Laplace transform can be used to obtain the dynamic response of a system. It also helps in understanding the qualitative behaviour of a system and the change in dynamic response of a system due to change in parameters. The values can be changed in a trial-and-error method, till a desired response is obtained; then it can be verified by solving for the time response of the system. This in turn can be used to find the response of an ideal system, for comparison. The control system in Figure 6.13 can be represented as block diagram of transfer functions in Laplace domain as shown in Figure 6.14, where, the desired temperature is the reference signal R(s); the difference in temperature between the actual room temperature and the desired temperature is the error signal E(s); the thermostat is the controller with transfer function Gc(s); the signal from the thermostat, is the control signal; heat loss is the disturbance W(s); the heating system and the room is the plat, with transfer function Gp(s); the room temperature is the output Y(s).

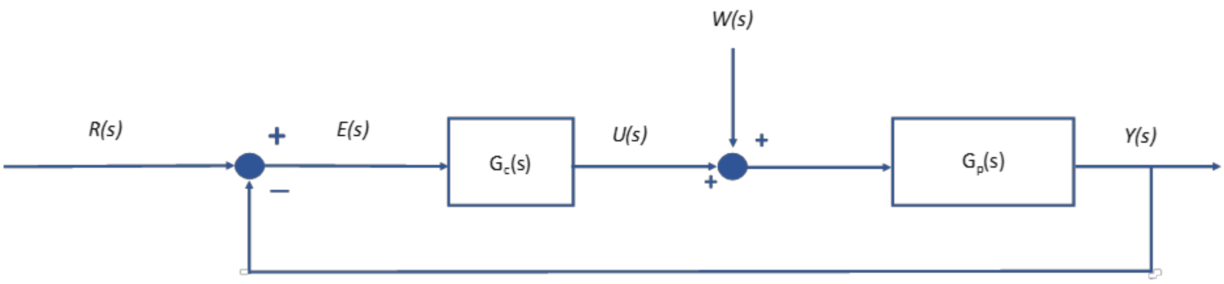


Figure 6.14: Block diagram of home heating system as transfer functions

The output of one component is the input of the next. This representation is useful in obtaining the equations of a system, including the effects of the controller and to study its behaviour. Figure 6.13 can be represented as block diagram of transfer functions as shown in Figure 6.14.

In the Laplace domain, input signal multiplied by the transfer function gives the output signal. Figure 6.14 can be represented into three separate systems with output of one acting as input to the next, as shown in Figure 6.15, where block (a) represents the controller block, (b) represents the plant block and (c) represents the error signal.

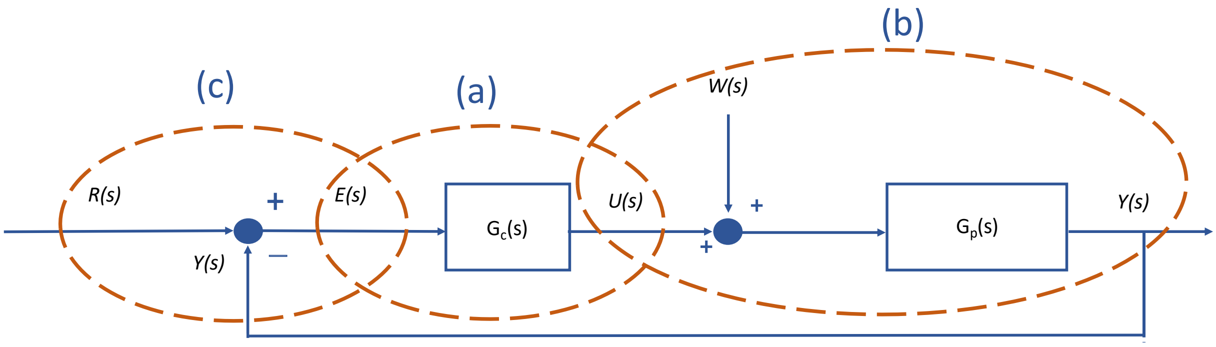


Figure 6.15: Transfer function blocks

Block (a) in Figure 6.15 is equivalent to the equation $G_c(s)$

$$E(s).G_c(s) = U(s) \tag{7.7}$$

Similarly block (b) in Figure 6.15 is equivalent to the equation

$$[U(s) + W(s)].G_p(s) = Y(s) \tag{7.8}$$

Block (c) can be
written as

$$R(s) - Y(s) = E(s) \tag{7.9}$$

which can be combined as

$$[E(s).G_c(s) + W(s)].G_p(s) = Y(s) \tag{7.10}$$

(7.9) and (7.10) can be combined as

$$\big[[R(s) - Y(s)].G_c(s) + W(s)\big].G_p(s) = Y(s) \tag{7.11}$$

Which can be rewritten as

$$R(s).G_c(s).G_p(s) + W(s).G_p(s) = Y(s).\big[1 + G_c(s).G_p(s)\big] \tag{7.12}$$

$$Y(s) = R(s).\left[\frac{G_c(s).G_{p(s)}}{1+G_c(s).G_{p(s)}}\right] + W(s).\left[\frac{G_{p(s)}}{1+G_c(s).G_p(s)}\right] \tag{7.13}$$

Considering the ideal condition where there is no disturbance (W(s) = 0),

$$Y(s) = R(s).\left[\frac{G_c(s).G_{p(s)}}{1+G_c(s).G_{p(s)}}\right] \tag{7.14}$$

(7.14) can be represented as system diagram as shown in Figure 6.16

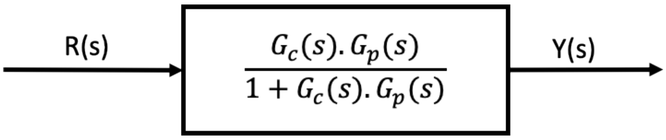


Figure 6.16: System diagram

$$\frac{G_c(s).G_{p(s)}}{1+G_c(s).G_{p(s)}} \tag{7.15}$$

(7.15) is called the closed loop transfer function since it includes the effect of feedback in the loop. It can be concluded that if $G_c(s)$ and $G_p(s)$ are known, then the output of the system can be obtained by multiplying the reference input to the closed loop transfer function of the system.

Step Response of a first order system

The first order system with controlled variable y(t), input u(t) can be written as

$$y(t) + a.y(\dot{t}) = K.a.u(t) \tag{7.16}$$

where K and a are constants. In Laplace domain, the equation can be represented by considering Figure 6.16 and (7.15) as

$$\frac{Y(s)}{R(s)} = \frac{G(s)}{1+G(s)} \tag{7.17}$$

Substituting $G(s) = \frac{1}{sT}$, we get

$$Y(s) = \left(\frac{1}{sT+1}\right) R(s) \tag{7.18}$$

where Y(s) is the Laplace Transform of the output signal *y(t),* R(s) is the Laplace Transform of the input signal *r(t)* and T is the time constant

The step response is important to determine how quickly a system response to changing inputs. For unit step signal *r(t) = u(t).* Applying Laplace Transform, we get

$$R(s) = \frac{1}{s} \tag{7.19}$$

Combining (7.18) and (7.19) and applying inverse Laplace Transform, we get

$$c(t) = \left(1 - e^{-\left(\frac{t}{T}\right)}\right) u(t) \tag{7.20}$$

The time constant can be calculated using the above formula. The response of a system can be analysed using the time constant of the system. (7.20) can be represented as shown in Figure 6.17. It is the time taken for the response to reach 63.2% (36.8% for a falling curve) of its final value. Smaller value of T corresponds to faster systems. The performance of a system can be understood by studying the T response of a system.

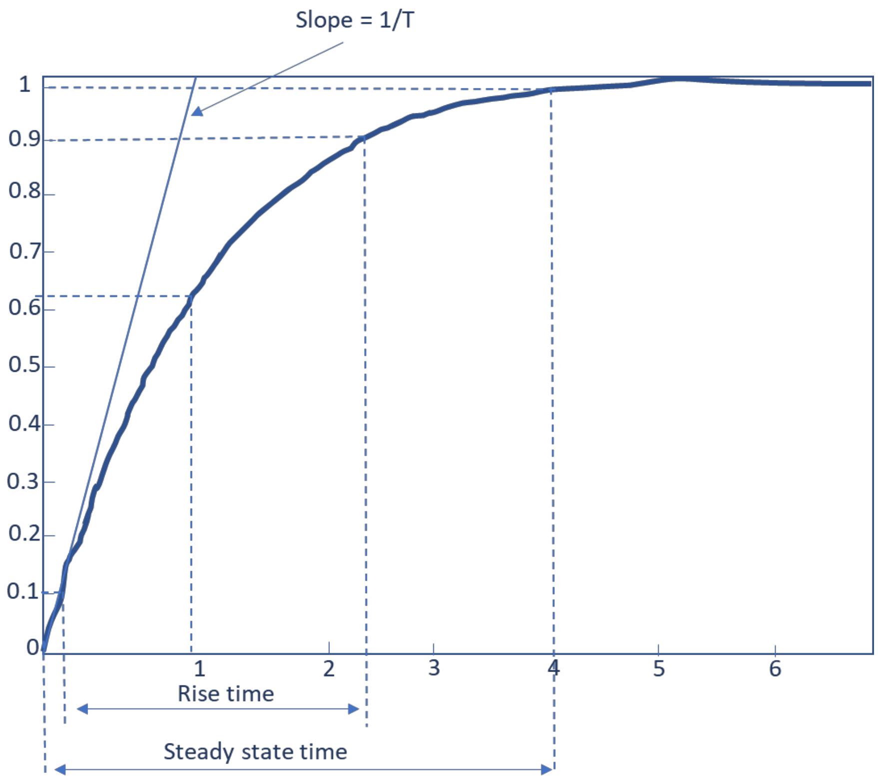


Figure 6.17: Step response of a first order system

6.4.1. Comparison of Time constant T

Time constant T denotes the speed of response of the system or the response rate of the process variable to changes in the output of the system. In terms of the home heating system, it is the change in radiator temperature with change in room temperature. Comparing the time constant of the 4 houses will help in quantifying the difference in energy consumption. Hence the time constant T of the four houses is compared.

T_{rising} and $T_{falling}$

The heating cycle consists of the heating curve and the cooling curve. The T constant of the rise time is denoted as T_{rising} and that of the falling curve is $T_{falling}$. Figure 6.18 shows one heating cycle of House A which is HIWO, for one instance considered (Feb 18, 7:00am to 1:00pm, 2013). The time taken for the radiator to reach 63.8% of the maximum value, i.e. the T_{rising} value, is 32.24mins. When the heating is turned off, the time taken for the temperature to fall to 36.8% of its end value, i.e. the $T_{falling}$ value, is 48.78 mins.

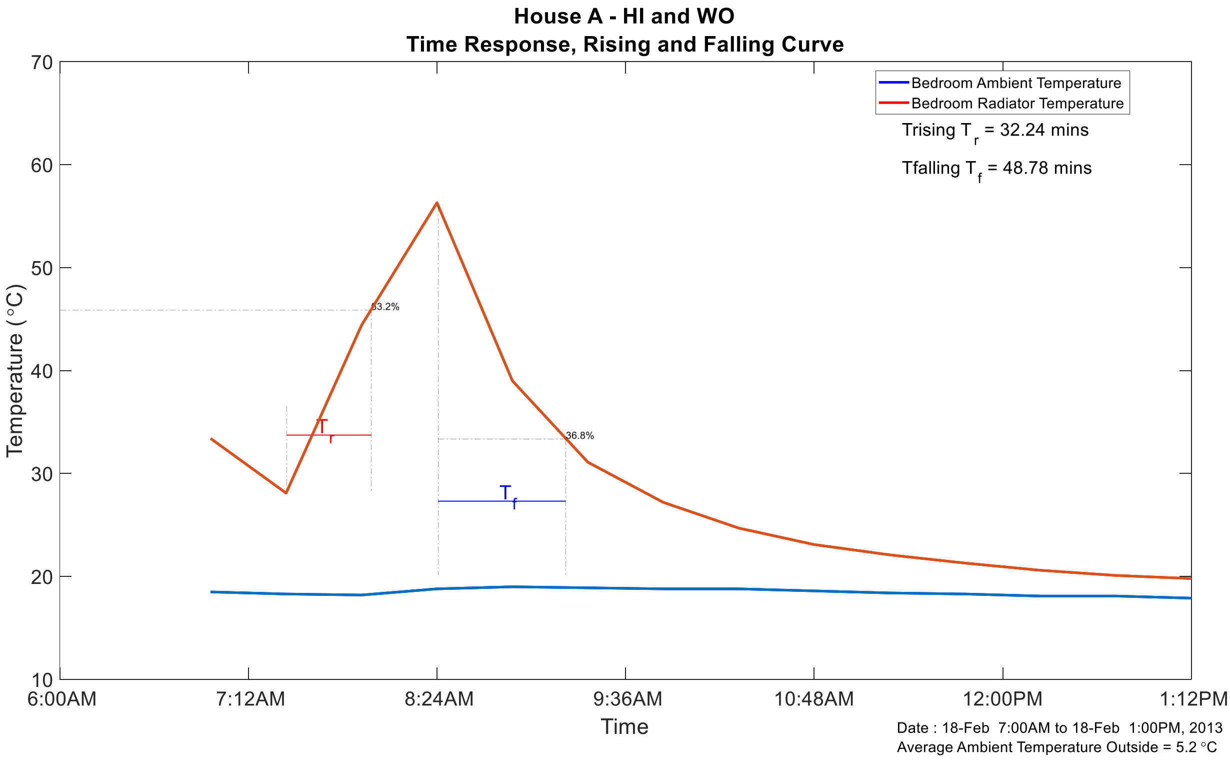


Figure 6.18: House A-T_{rising} and $T_{falling}$ values for one heating cycle

Figure 6.19 shows the T_{rising} and $T_{falling}$ values of House B (HIWC), for the same instance. The T_{rising} is 27mins, meaning the radiator heats faster than HIWO house. $T_{falling}$ is 91 mins which is almost twice that of HIWO house.

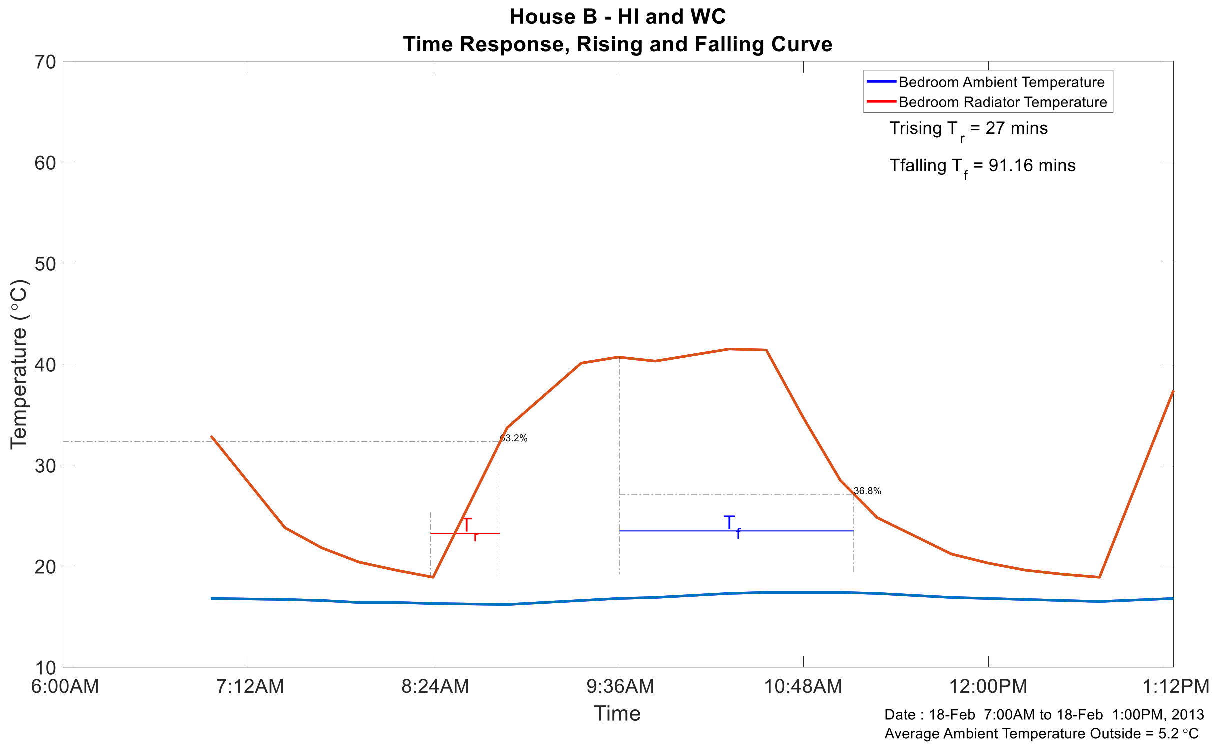


Figure 6.19: House B-T_{rising} and $T_{falling}$ values for one heating cycle

The T_{rising} and $T_{falling}$ values for the four houses for the above-mentioned instance, is shown in Figure 6.20.

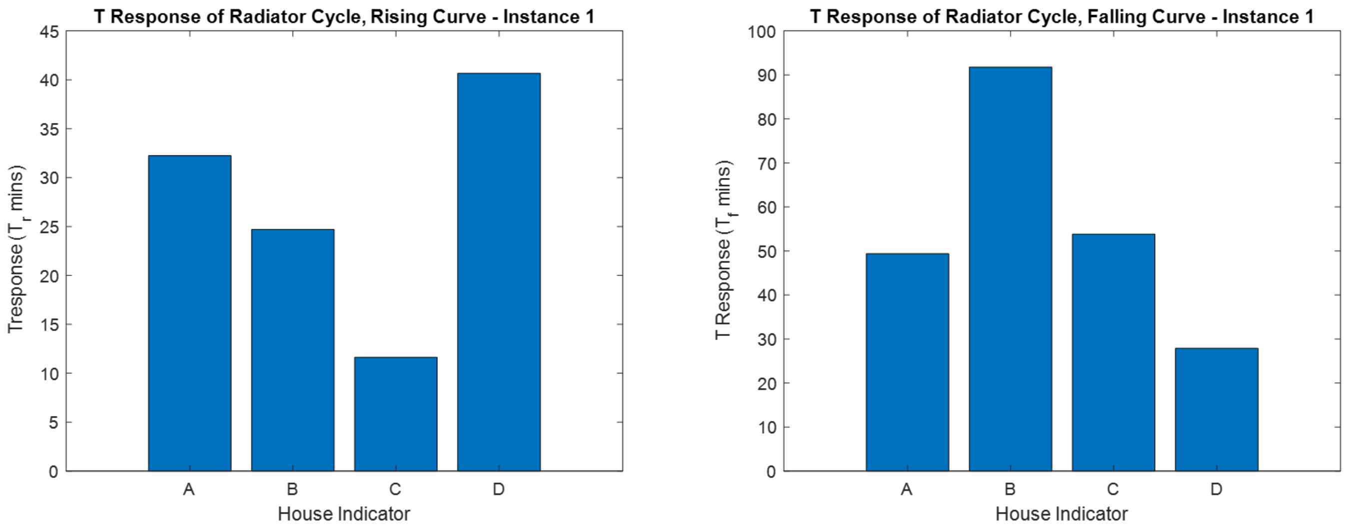


Figure 6.20: T-response of the four houses for one instance

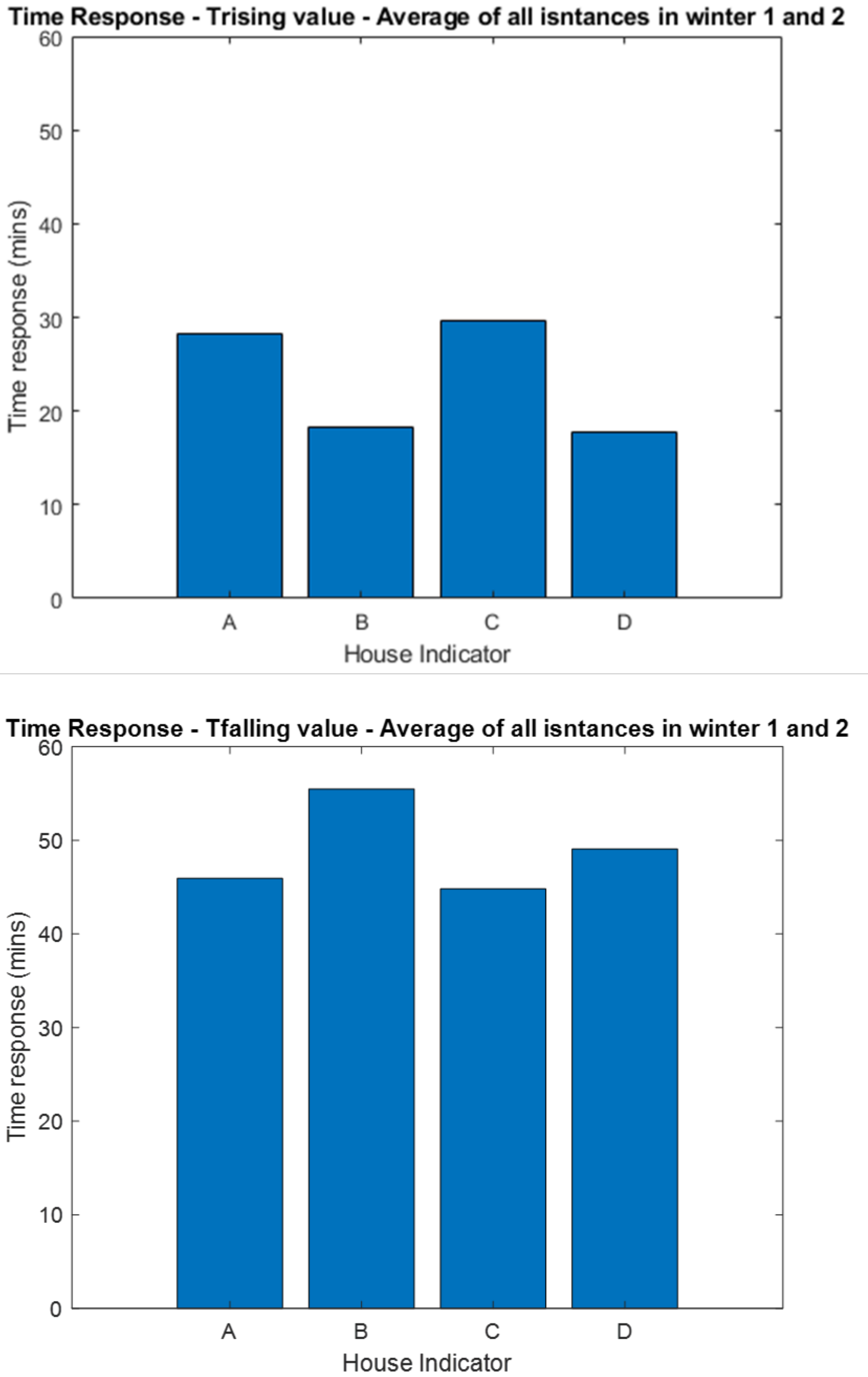


Figure 6.21: T response - Average of all instances

Seven such instances across winter 1 (Feb 2013 – March 2013) and 11 instances from Winter 2 (Nov 2013 to Feb 2014) are considered, shown below:

Winter 1 Instances:

1. TRInst1 = [18-Feb-2013 04:40:00 ;18-Feb-2013 13:00:00]
2. TRInst2 = [20-Feb-2013 05:00:00 ;20-Feb-2013 12:00:00]

3. TRInst3 = [22-Feb-2013 16:00:00 ;23-Feb-2013 01:50:00]
4. TRInst4 = [02-Mar-2013 14:00:00 ;03-Mar-2013 01:59:00]
5. TRInst5 = [03-Mar-2013 05:00:00 ;03-Mar-2013 11:59:00]
6. TRInst6 = [05-Mar-2013 04:00:00 ;05-Mar-2013 11:59:00]
7. TRInst7 = [09-Mar-2013 04:30:00 ;09-Mar-2013 14:59:00]

Winter 2 Instances:

1. TRInst1 = [20-Nov-2013 04:30:0020-Nov-2013 09:59:00]
2. TRInst2 = [21-Nov-2013 05:00:0021-Nov-2013 10:30:00]
3. TRInst3 = [21-Nov-2013 10:50:0022-Nov-2013 09:59:00]
4. TRInst4 = [23-Nov-2013 04:30:0023-Nov-2013 12:30:00]
5. TRInst5 = [25-Nov-2013 05:30:0025-Nov-2013 10:00:00]
6. TRInst6 = [26-Nov-2013 06:00:0026-Nov-2013 19:00:00]
7. TRInst7 = [27-Nov-2013 06:00:0027-Nov-2013 14:00:00]
8. TRInst8 = [28-Nov-2013 05:30:0028-Nov-2013 09:30:00]
9. TRInst9 = [29-Nov-2013 04:30:0029-Nov-2013 10:00:00]
10. TRInst10 = [30-Nov-2013 04:30:0030-Nov-2013 10:59:00]
11. TRInst11 = [02-Dec-2013 05:00:0002-Dec-2013 09:30:00]

The T_{rising} and $T_{falling}$ values of the 4 houses for all the instances are in Appendix C. The average T_{rising} and $T_{falling}$ all 18 instances in winter 1 and winter 2 is shown in Figure 6.21.

6.4.2. Inference

The abbreviations used here are

HI - High insulation
WO - Window open
LI - Low insulation
WC - Window closed

The following inferences are obtained from the investigation

- In HI houses, by leaving window open, the heating time increases by a factor of 1.6.
- The heating time of a HI-WO house differs from that of HI-WC house by 43% while there is only 12 % difference in heating time between HI-WO and LI-WC house.
- In HI houses, by leaving window open, the heat retaining time reduces by a factor of 1.2.
- The behaviour of HI-WO house resembles that of LI-WC house more than HI-WC house.

6.5. Summary

Occupant behaviour plays a critical role the energy demand of a residential building. The energy demand of four houses selected based on their insulation and window opening properties, was compared in this Chapter. The first part explains analysis done considering home heating system as a first order control system. The response time of the heating system of the 4 houses was compared to find that a HI-WO house takes higher response time than HI-WC house. The second part of the chapter explains energy demand analysis. It has been found that occupant behaviour of window opening is a major driving factor in controlling the energy demand in a dwelling. It can be summarised that a HI-WO house most resembles LI-WC house, than a HI-WC house.

Chapter 7 | Development of ANN Model to Predict Energy Usage and Window Opening Behaviour in Residential Buildings

7.1. Introduction

The residential sector contributes significantly to the overall energy consumption in the UK. Occupant behaviour is major factor that is being overlooked when considering energy efficiency of a building. Although building simulations plays a major role in the design of energy efficient buildings, a lot of discrepancies have been seen between the actual and predicted energy values in simulation models, one reason being under representation of the effect of occupant behaviour. Innovate UK conducted a building Performance Evaluation Programme the aim of which was to make design match reality. Their results included the following statistics (Innovate UK, 2016): *'Nearly ten times as much energy was used in the highest energy-consuming home as the lowest.' ; 'Average total carbon emissions were 2.6 times higher than the average design estimate. None of the 'zero-carbon' design estimates were achieved in practice.'*

They recommended that the simplest controls be specified for heating, lighting, and renewable energy systems, since majority of households were not willing to spend time in learning complex systems. ANN models have been used in studies to predict energy demand and window status, some of which are reviewed in Chapter 2. However, there is limited research on prediction and comparison of energy demand based on the relationship between the window status and radiator temperature. By including radiator temperature as one of the predictors, the correlation between energy consumption and window opening behaviour can be clearly understood. In the previous chapter, the difference in energy consumption between high insulation window open house, high insulation window closed house, low insulation window open house and low insulation window closed house were analysed. Results showed a difference in energy consumption between window open and window closed houses. In this chapter, the development of artificial neural network (ANN) models to predict energy demand and window status, is presented. Three models are discussed: Model A, to predict energy demand (in kWh), based on radiator temperature (T_{rad}), ambient room temperature (T_{room}), outside ambient temperature (T_{out}) and window status; Model B, to predict window status (open/closed) based on T_{rad}, T_{room}, T_{out} and energy demand; Model C, to predict the characteristic of the house (good practice/bad practice) based on T_{rad}, T_{room}, T_{out} and window status. In the following study two houses are considered for model development and prediction: House A which is high insulation and window open house, and House B which is high insulation and window closed house.

7.2. Development of Models

Neural networks are a network of simple elements working in parallel to provide a complex reasoning capability, the performance of which is largely determined by the connections between the elements. These connections are termed weightages. The general block diagram of ANN model is given in Figure 7.1. ANN generally consists of three layers: input layer, hidden layer, and output layer, which are connected through a collection of nodes. Depending on the type of neural network model, the weightage assignment varies. The weights and biases in the hidden layer are optimised during the training process so that the network gives an output as close to the actual target, as possible. To get a suitable model the ANN architecture and optimisation algorithm must be chosen carefully. This study follows a stochastic model of representing occupant behaviour (OB), with measured temperature data and indoor and outdoor environmental conditions, window opening frequency and the building fabric properties.

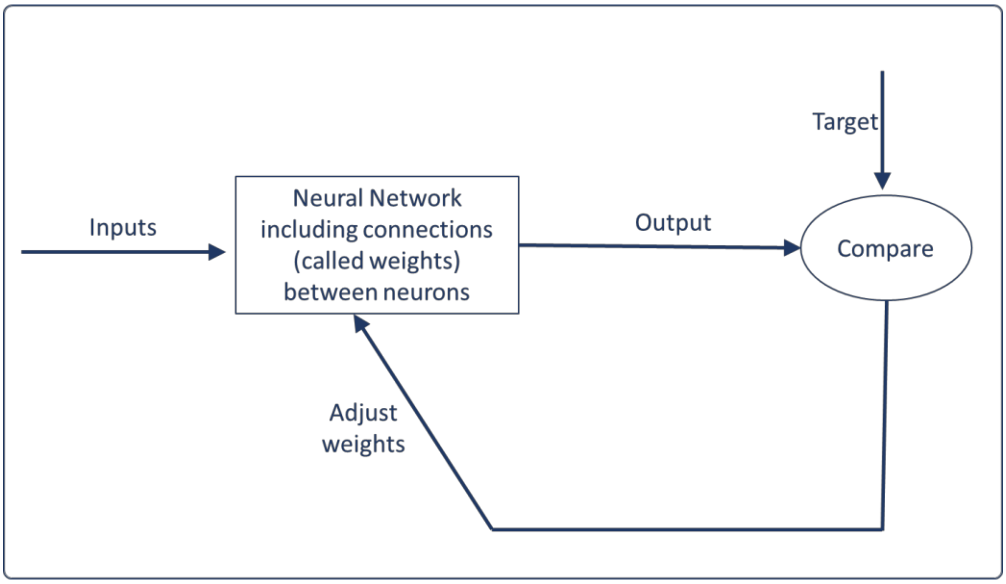


Figure 7.1: General block diagram of ANN model with feedback

The thermal characteristics of the room and its relationship to occupant behaviour of window opening is investigated. By analysing the collected data, the temperature patterns that lead to an occupant opening window is extracted, to develop Artificial Neural Network model to predict window opening behaviour and energy consumption based on window opening behaviour of occupants. Deciding on an algorithm and developing a model depends on various factors in a multi-variate analysis. There will be some trade-off between model speed, accuracy, and complexity. A systematic workflow is required to choose the right model, depending on the input variables and the output target. The models developed in this study has one target variable and 4 input variables. The methodology followed for development of ANN model is given in chapter 3 (Section 3.6.1).

Heat energy demand calculation

In this study, the energy consumption in the main bedroom in residential buildings is calculated, using the values obtained by recording the internal temperature of the house and the outside ambient temperature. The total energy consumption in a room is the sum of heat-loss through building fabric and heat-loss through ventilation. The calculation of heat energy consumption is shown in detail in chapter 3 (section 3.5.3). Equation (3.12) is used to calculate the total energy consumption in kWh. Using equation (3.12) the energy consumption is calculated for all of winter 1 and winter 2 of the collected data from the houses. the considered data set consists of the indoor and out temperature variables of main bedroom of House A and House B, with the calculated energy demand in kWh. The data set is divided into days, with each day having 83 samples. The total energy demand for the day is the sum of the energy demands of the 83 instances in the day. The energy demand for the winter 1 and winter 2 is the sum of energy demand of days considered in winter 1 and winter 2 respectively. For the development of ANN model, 29 days from winter 1 (Feb 14, 2013, to March 14, 2013) and 13 days from winter 2 (Nov 20, 2013 to Dec 02, 2013) is considered, corresponding to the instances considered for analysis explained in chapters 6 and 7. The predicted target is compared with the output and the weights are adjusted till the network output matches the target. The error of an ANN model is the difference between the ANN predicted value of the target and the actual value of the target. The target is energy demand in case of Model A, and window status in case of Model B. In case of Model C, the house is house following good practice, if the windows are open less than 10% of the time, and bad practice, if windows are open more than 10% of the considered time. The percentage error is calculated using equation (3.13) for Models A and equation (3.15) for Model B. The models are developed with different number of days data taken for training, to find the model with the lowest percentage of error between the actual and predicted values of the target. The dataset is trained with different algorithms to find the best performing model.

7.3. Model A - Feed Forward Neural Network to Predict Energy Demand

To attain the required thermal comfort in a room, occupants perform adaptive behaviours, some of which lead to notable changes in the energy consumption of the dwellings. One of the key adaptive behaviours carried out by occupants, due to which the energy consumption is affected, is window opening and closing. However, the rate of effect of occupant behaviour varies widely, due to differences in each occupants' perception of thermal comfort and consequently, behaviour. For the same reason, modelling occupant behaviour is a tedious task, and the design of the model impacts the model performance significantly. Choosing the right set of parameters is an important factor that impacts the prediction accuracy of an ANN models. To predict energy demand in main bedroom of the house, the predictors are room ambient temperature (T_{room}), radiator temperature (T_{rad}), outside ambient temperature (T_{out}) and window status (0 for window closed and 1 for window open). The target variable is calculated energy demand in kWh.

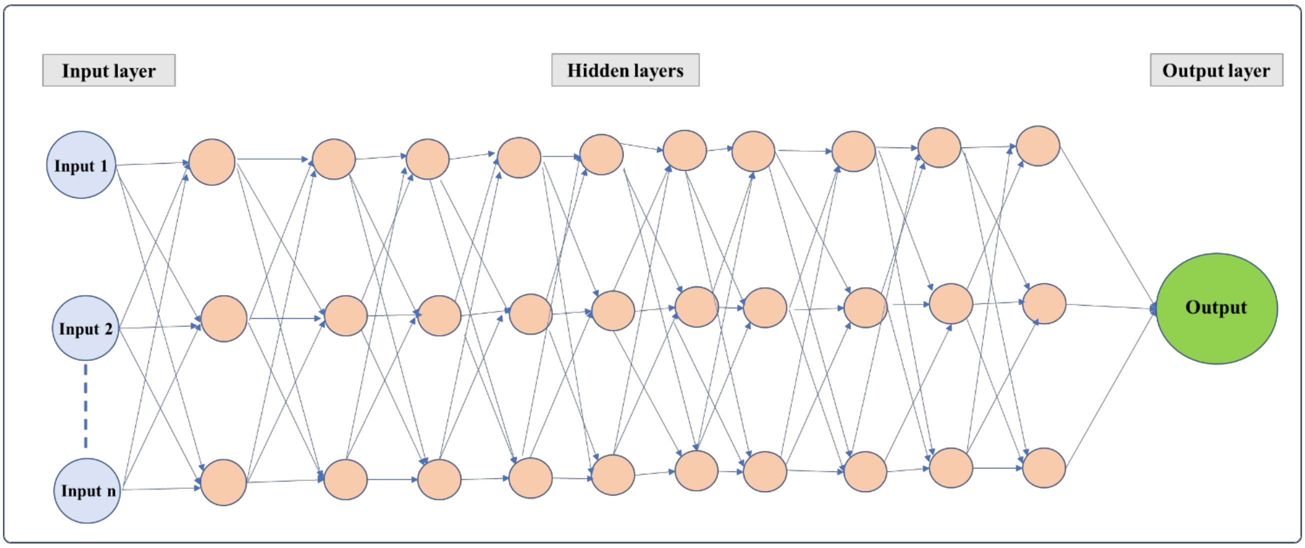


Figure 7.2: Feed forward neural network model

There are different ANN architectures that can be used to develop a model, feed forward neural network, pattern recognition neural network, clustering, fitting being some of the architectures, based on the algorithm used. In this study, feed forward network is considered first, for the development of ANN model (Model A) for prediction of energy demand. Feed forward neural network consists of single or multiple layers of computational units. In feed forward neural network, the connections between the nodes of input layer, hidden layer and output layer, do not form a loop. No feedback is given from the output back to the input. The hidden layer is between the input and output layers and consists of a set of weighted inputs and produce an output through an activation function. The general representation of feed forward neural network is shown in Figure 7.2. Energy consumption in a room depends on the room temperature, the radiator temperature, the outside ambient temperature during the considered time.

From chapter 6 and 7 it can be seen that energy demand depends to a great extend to the window status of the room as well. Hence, the inputs considered for Model A is the room temperature, radiator temperature and window status of main bedroom, and the recorded outside ambient temperature for the considered time. The block diagram of the feed forward neural network of Model A, with the inputs and target is shown in Figure 7.3.

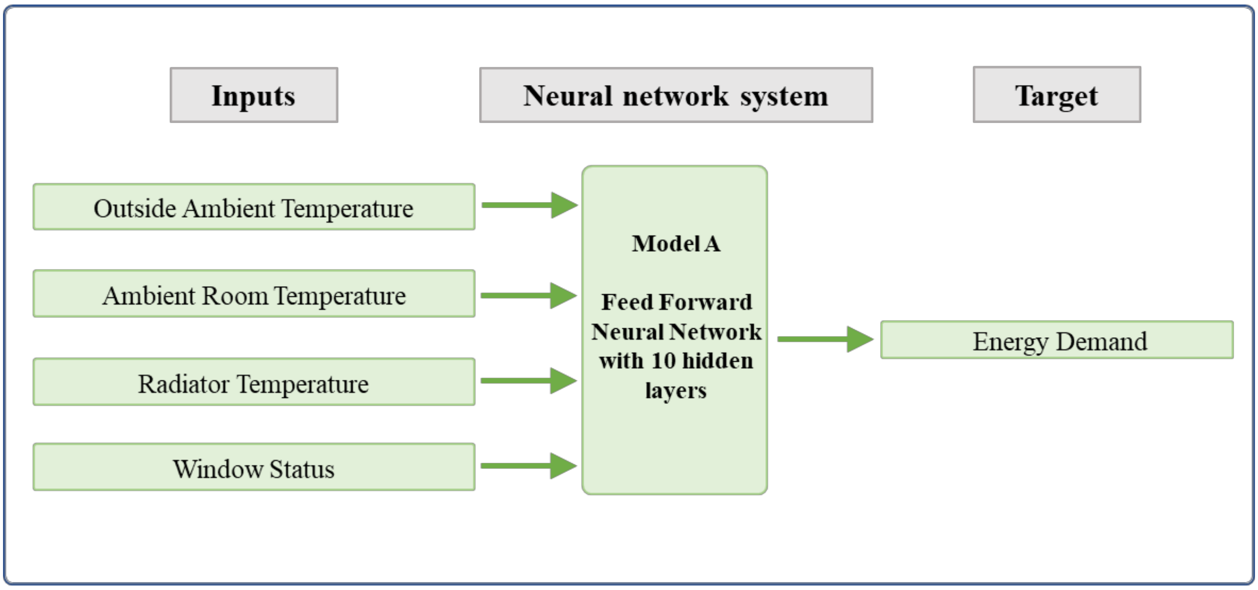


Figure 7.3: Block diagram of feed forward neural network to predict energy demand

The neural network architecture (generated using MATLAB) for pattern recognition model to predict window opening behaviour (Model A) is shown in Figure 7.4, where w stands for weights and b stands for biases. These 'hidden layers' are chosen depending on the accuracy of the model. Different number of hidden layers are trialled, to choose one. The error percentage for 1 to 10 hidden layers with different number of days data taken for training are found and the best performing model is chosen.

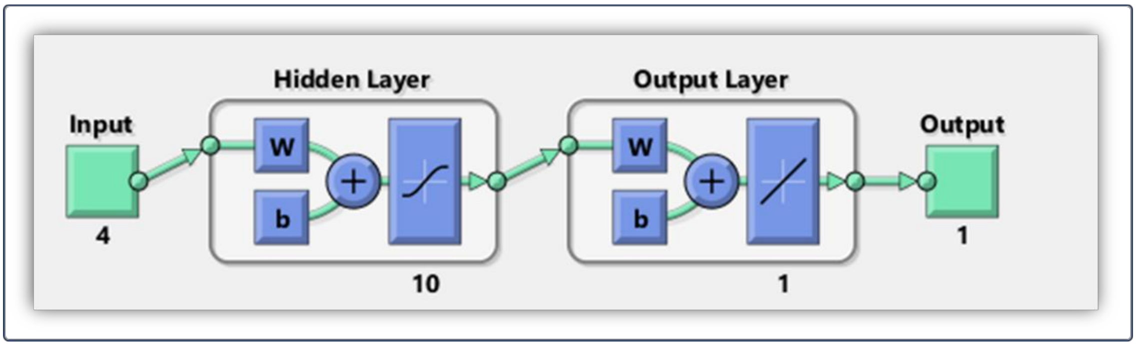


Figure 7.4: Network diagram of Model A neural network [Source: generated using MATLAB software]

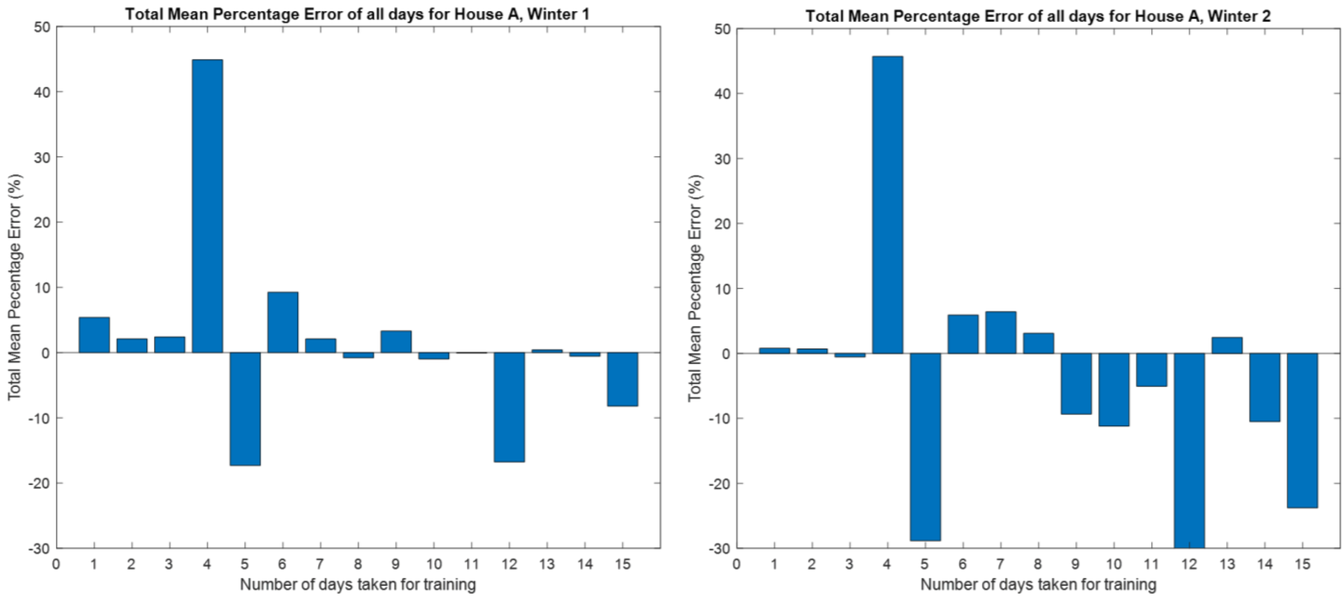


Figure 7.5: Total mean percentage error of feed forward neural network with 10 hidden layers, for House A, with 1-15 days data taken for training

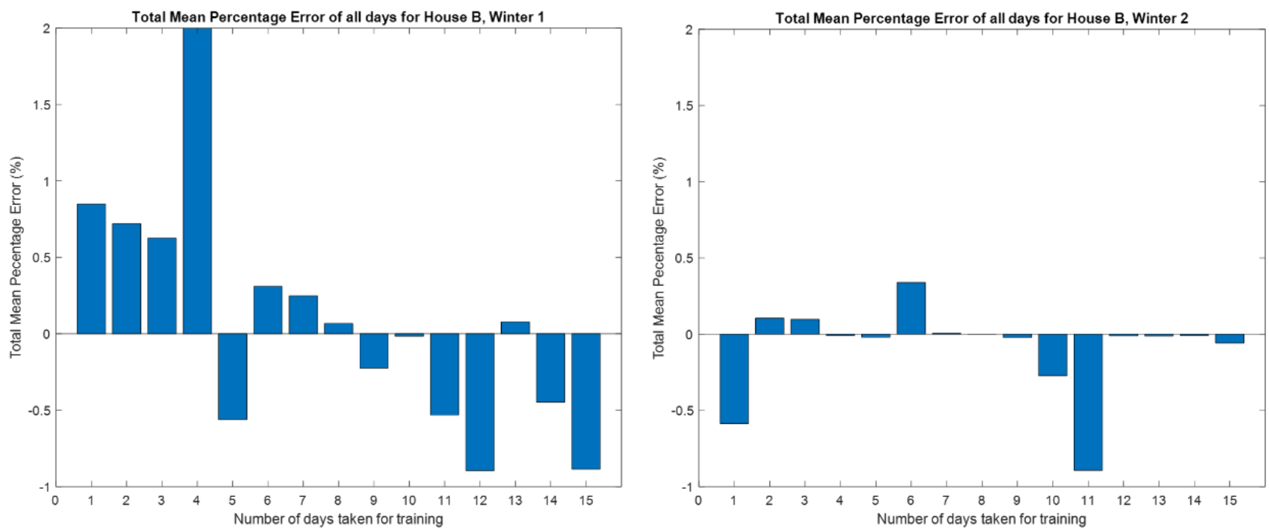


Figure 7.6: Total mean percentage error of Model A (feed forward neural network with 10 hidden layers), for House B, with 1-15 days data taken for training

ANN models are developed with different number of hidden layers and different number of days data taken for training. Models are tried with 1 to 10 hidden layers. Training data was selected as follows: for House A, first model was tried with winter 1, day1 data for training and tested with the other 28 days and 13 days of winter 2 data. The second model was tried with winter one, day 1 and day 2 data and tested with the other 27 days and 13 days of winter 2. The process is repeated, and 15 different models are tried with up to fifteen days data taken for training and tested with the rest of data form Winter 1 and 13 days data from Winter 2.

For house B the same process is repeated with the data from House B. The percentage of error for House A and house B for all days in winter 1 and winter 2, when considering 1 to 15 days data for training, can be seen in Appendix D. Comparing the models, the feed forward neural network with 6 days data taken for training, and 10 hidden layers was found to perform considerably well for House A and House B. The percentage of error of the predicted energy demand when compared to the calculated energy demand, for the different models, are compared.

Figure 7.5 shows the total mean percentage error between the ANN predicted energy demand and calculated energy demand for House A in Winter 1 and Winter 2. Figure 7.6 shows the same for House B. Comparing, the model using 6 days data for training is found to have an average percentage error of 7.6% for House A and 0.25% for House B. Hence the model using 6 days data for training for each house is chosen as Model A.

Figure 7.7 shows the ANN predicted energy demand and the calculated energy demand for House A, from day 7 to day 29 (the first 6 days are taken for training). Figure 7.9 shows the same for House B. Figure 7.8 shows the ANN predicted energy demand and the calculated energy demand for House A for 13 days in Winter 2.

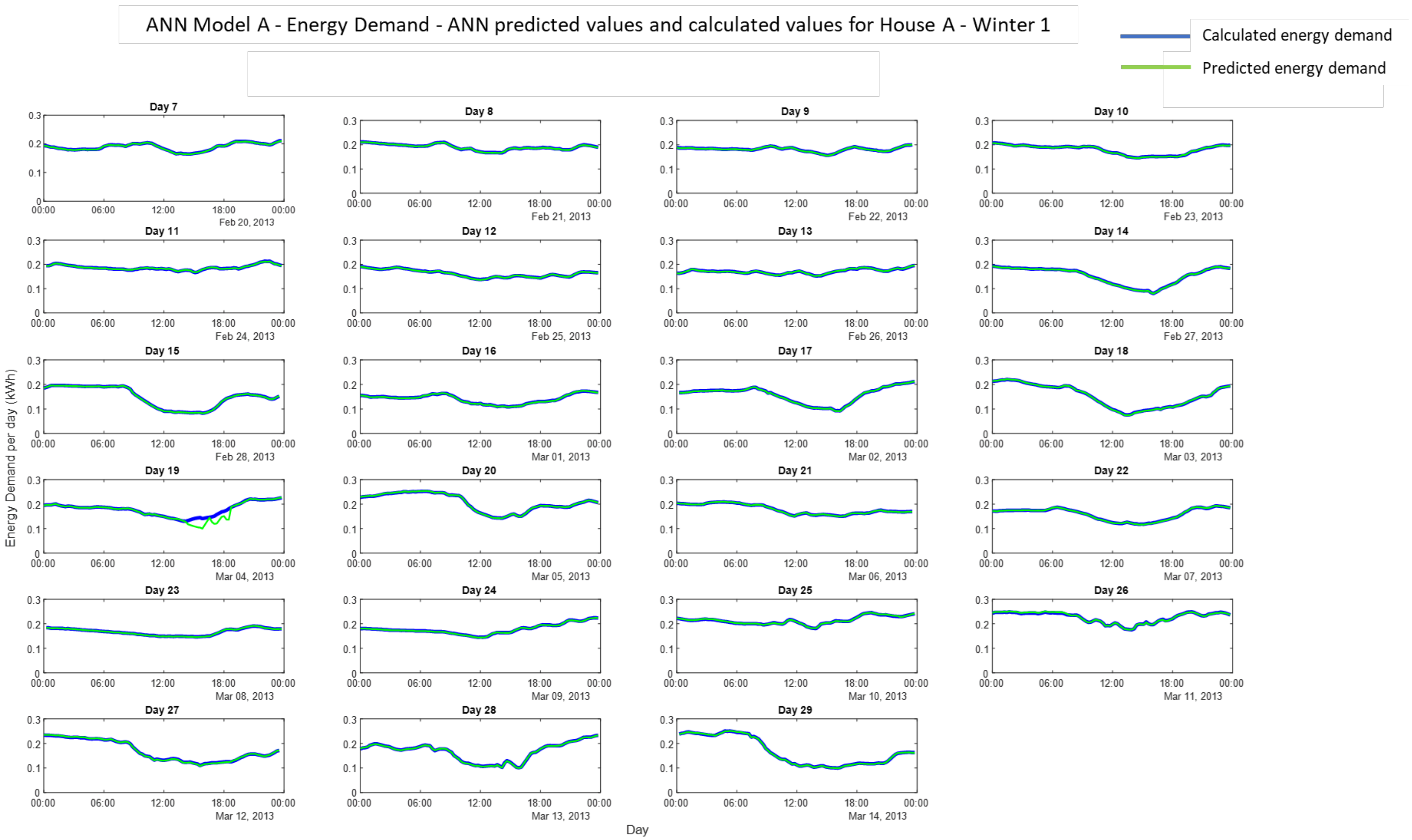


Figure 7.7: ANN Model A Results - House A - Winter 1

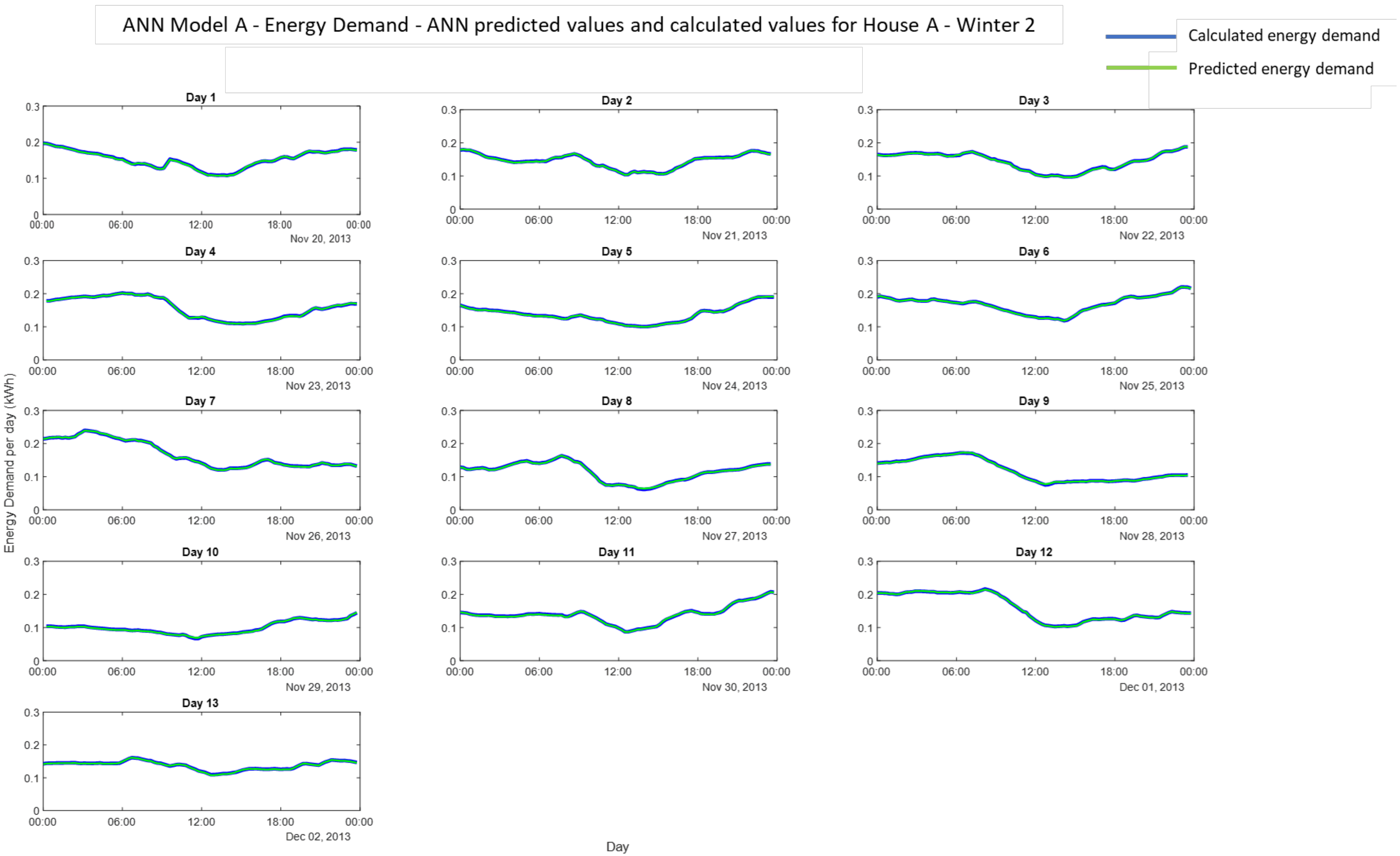


Figure 7.8: ANN Model A Results - House A - Winter 2

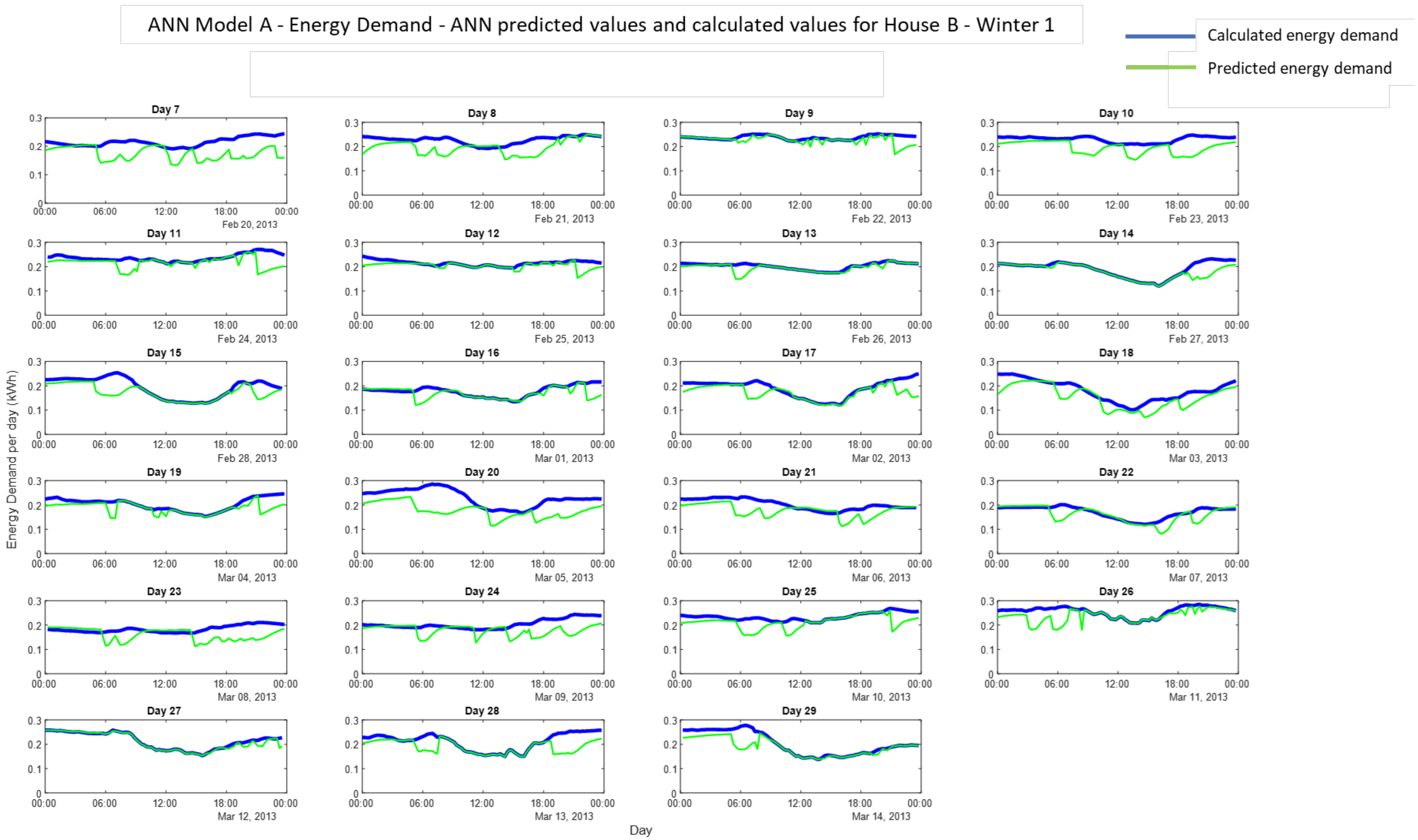


Figure 7.9: ANN Model A Results - House B - Winter 1

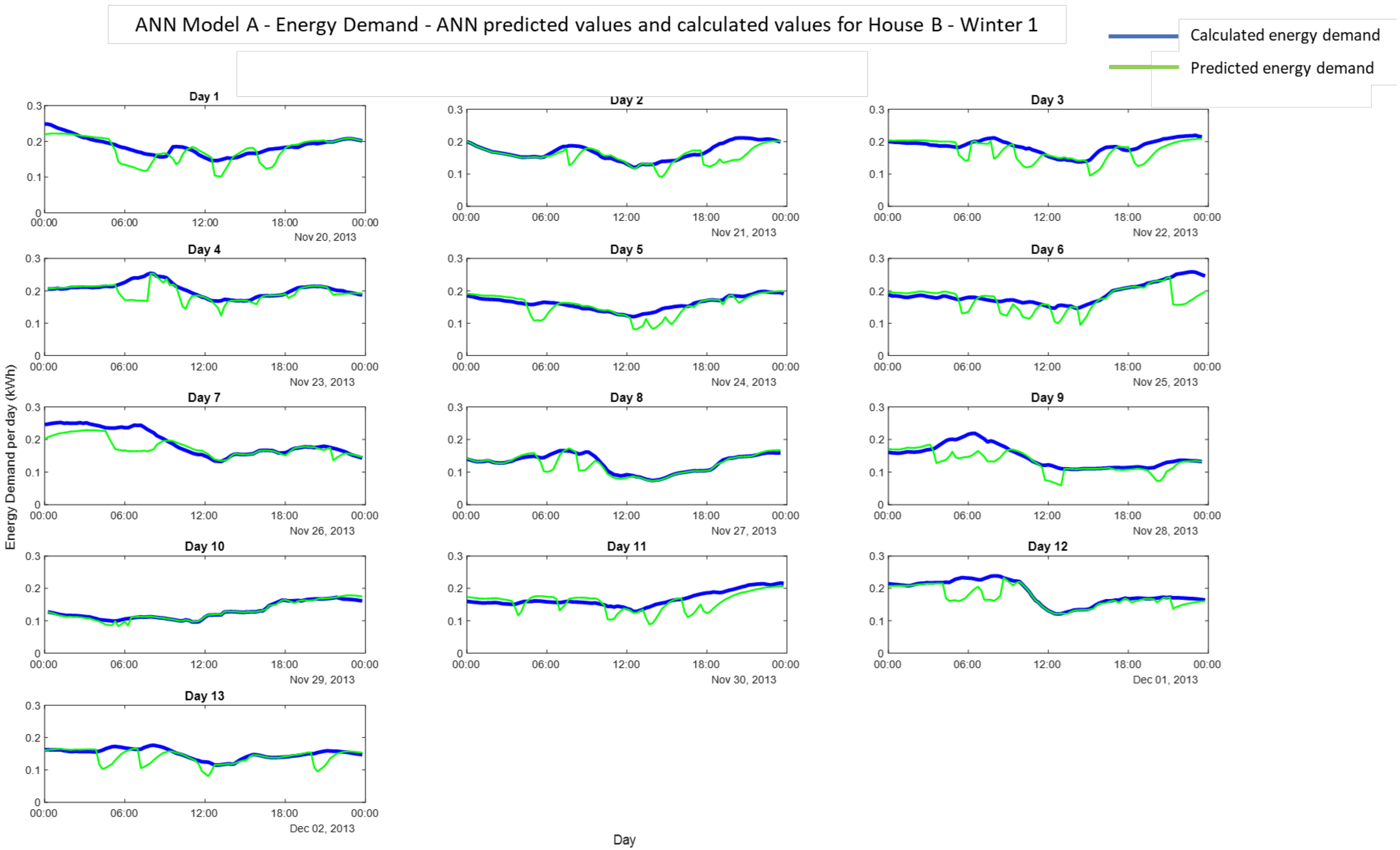


Figure 7.10: ANN Model A Results - House B – Winter 2

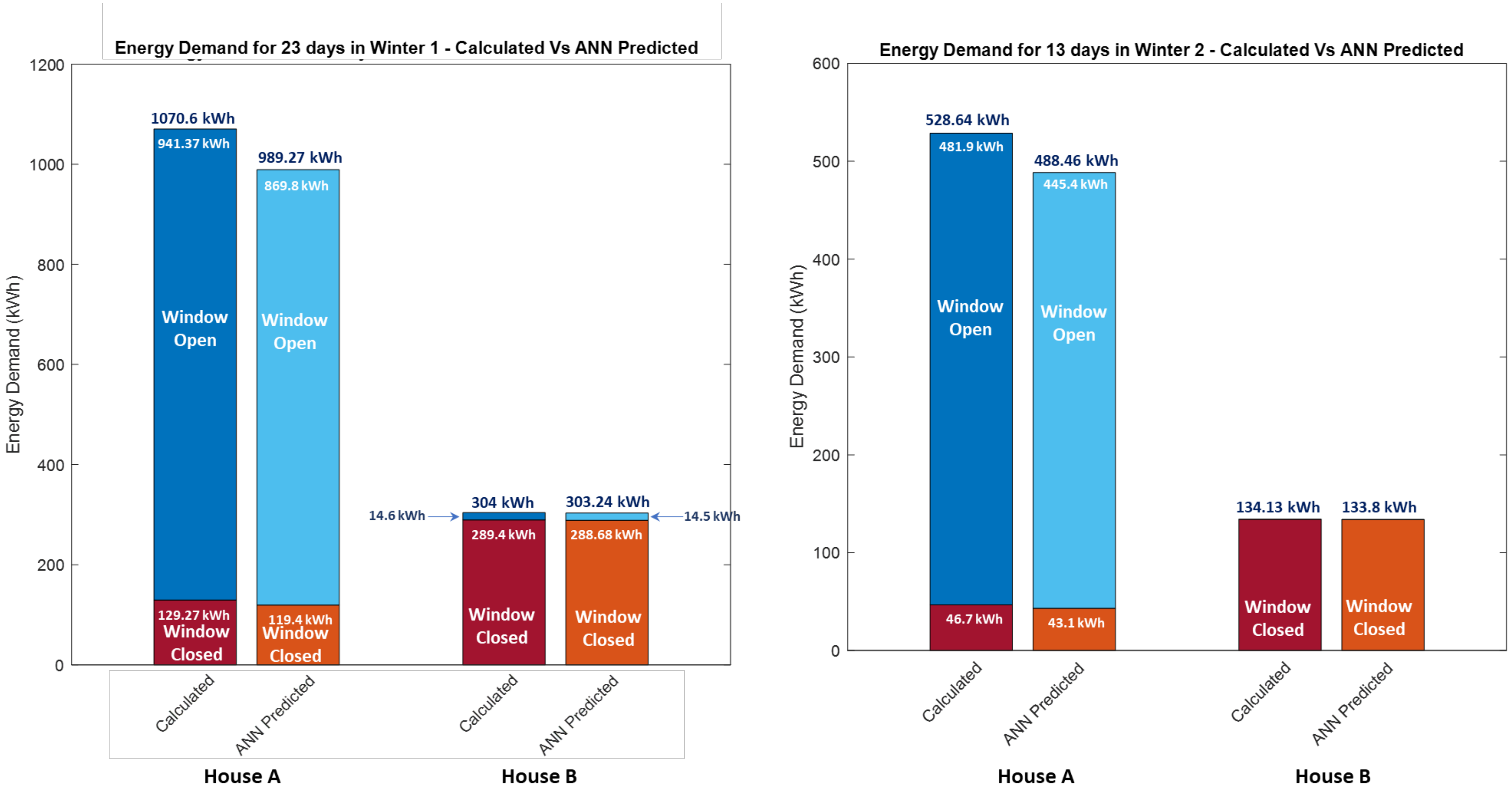


Figure 7.11: Comparison of calculated and ANN predicted energy demands of Winter 1 and Winter

Figure 7.10 shows the same for House B. Model A feed forward neural network thus satisfactorily predicts the energy with the inputs provided. By including the window status of the room as one of the inputs, the difference in energy demand due to window opening, can be understood. This information can potentially be used in understanding and modelling occupant behaviour in building simulation models. Figure 7.11 shows the comparison between actual and ANN predicted energy demand for House A and House B for Winter 1 and Winter 2. The figure shows the effect of window opening on energy demand in winter, in two high insulation houses, one with window open and one with window closed. It can be seen that in House A, which is a high insulation window open house, the calculated energy consumption when window is open accounts for 89.5% of the total energy consumption, when considering the average energy demand for Winter 1 and winter 2. Also, the actual energy demand has been predicted to a good degree of precision by the ANN model developed. It can be seen for Model A, that:

- The developed feed forward neural network model predicts energy demand for House A, a high insulation, window open (HI-WO) house (winter 1 and 2) with 92.4% accuracy (7.6% error).
- The proposed feed forward neural network model predicts energy demand for House B, high insulation window closed (HI-WC) house (winter 1 and 2) with 99.8% accuracy (0.2% error).

7.4. Model B - Pattern Recognition Neural Network to Predict Window Status

Analysing the window opening behaviour (WOB) to understand patterns in it will help find solutions to reduce WOB without compromising on thermal comfort. As initial step towards this, Model B is developed to predict window status based on the temperature variables and energy demand of the main bedroom of House A and House B.

Literature showed that logistic regression is the most common machine learning model used for prediction of window opening behaviour. Few studies have used artificial neural networks (ANN) to predict window opening behaviour. However, the predictors (inputs) used for study do not include the radiator temperature. As seen earlier and in previous chapters, the window opening behaviour impacts energy efficiency of a building. By including radiator temperature as one of the predictors, the direct correlation between window opening behaviour and energy efficiency of the building can be identified. This study proposes the development of ANN model to predict window opening behaviour based on room temperature, radiator temperature, outside ambient temperature, and energy demand.

Occupant behaviour of window opening is very stochastic in nature and varies from household to household. Each household has their own characteristics and reasons for opening windows, thereby having a unique pattern of window opening. To identify and predict the pattern of window opening, the pattern recognition architecture of artificial neural network, is chosen.

Artificial Neural Network models use pattern recognition algorithm to recognise patterns in data, using neural networks. Data is trained to automatically discover regularities in data, which is used to classify the data into categories.

The general block diagram of pattern recognition neural network is shown in Figure 7.12. The pattern is identified from the training data and the data is classified based on the recognised pattern.

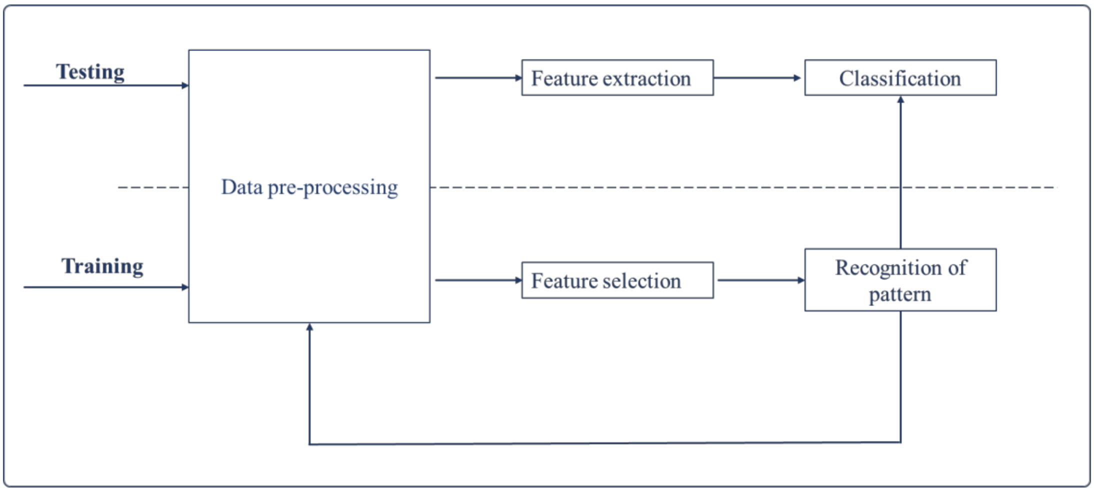


Figure 7.12: Block diagram of pattern recognition model

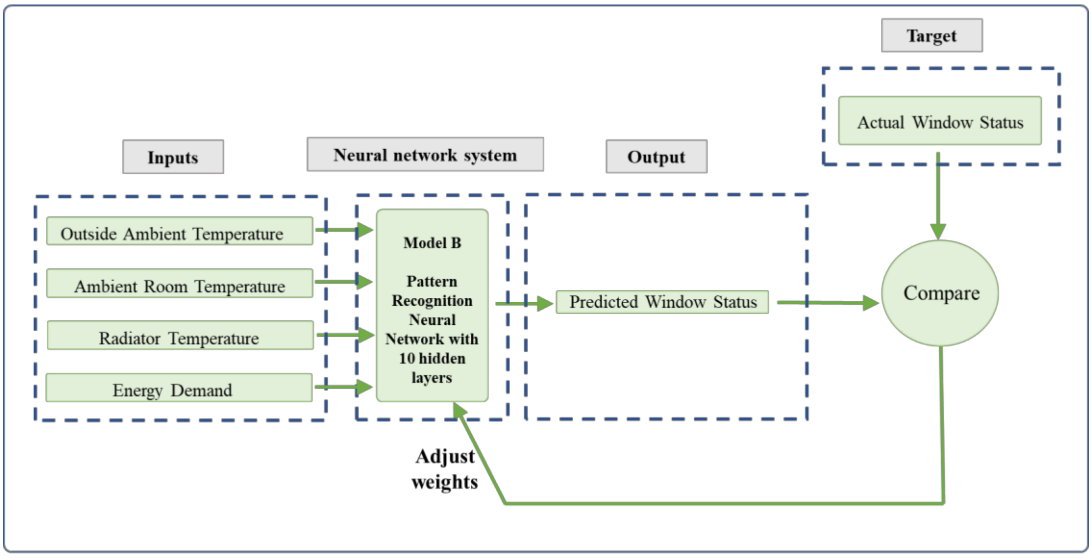


Figure 7.13: Model B Neural network to predict window status

The block diagram of the proposed pattern recognition neural network model (model A) is shown in Figure 7.13. For the proposed pattern recognition model (Model B), the input variables are outside ambient temperature (T_{out}), ambient room temperature (T_{room}), radiator temperature (T_{rad}) and the calculated energy demand of the room (in kWh). Each variable is data collected from the main bedroom in one day, with 83 samples per day. The target is the observed and recorded window status, with window closed represented by 0 and window open represented by 1.

The predicted variable is window status. This is compared to the observed window status and the process is repeated till error is minimum (see Chapter 3, Figure 3.4). The trained model then uses the recognised pattern to identify similar pattern in the variables being tested.

Figure 7.14 shows the neural network architecture (generated using MATLAB) for pattern recognition model to predict window opening behaviour. The model is trained with different number of hidden layers and the error is seen to remain the same regardless of the number of hidden layers (Appendix D). Therefore, the number of hidden layers chosen is 10 and the training data is divided randomly such that 70% of the data is used for training, 15% for testing and 15% for validation.

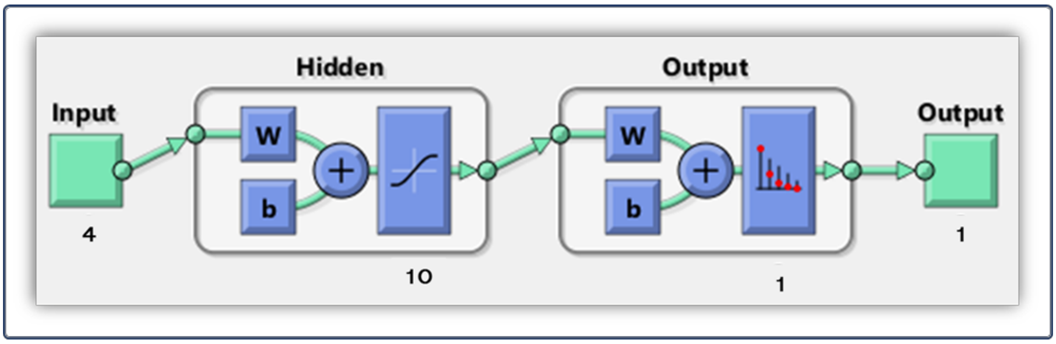


Figure 7.14: Network diagram of ANN Model B

[Source: generated using MATLAB software]

Choosing the training data is crucial to get optimum results. The objective of the proposed model is to identify the window status, based on room temperature, radiator temperature, energy demand of the room, and outside ambient temperature. For the initial trials, training data was chosen as follows: training data 1 was a combined matrix of Winter 1 day 1 data of House A and Winter 1 day 1 data of House B; training data 2 was Winter 1 day 2 data of House A and Winter 1 day 2 data of House B, and so on to training data 6 which was Winter 1 day 6 data of House A and Winter 1 day 6 data of House B. However, the average percentage error between the predicted window status and actual window status was exceedingly high. This is since in House A, the main bedroom window is open more than 50% of the time, on some days the windows remain closed more than 50% of the time when considering the day, making modelling more complex. Hence for simplification, training data is chosen such that window is fully closed for House B and fully open for House A. Based on the window opening percentage (WOP), training days are chosen as shown in Table 7.1. For House A, windows are open 100% of the time on day 7 and day 10 in winter 1, and day 10 and day 11 in Winter 2. For House B, windows are closed 100% of the time for most of the days, including day 1 and day 2 of Winter 1 and Winter 2.

Table 7.1: Selection of training data for Model B neural network

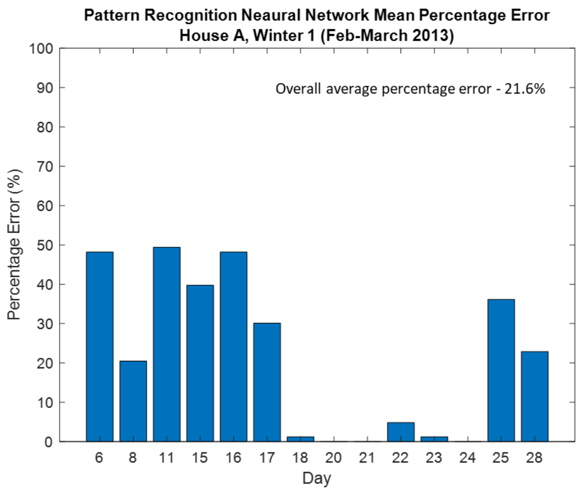
Winter 1	Training data	Training data is matrix containing		
			House A (days with window open percentage 100%)	House B
1	1		day 7 data	day 1 data
	2	Training data 1	day 10 data	day 2 data
2	1		day 10 data	day 1 data
	2	Training data 1	day 11 data	day 2 data

The target class for this model, which is the window status, is binary, with 0 for window closed and 1 for window open, represented as a logical array. The total error for each day is the number of times the window status is predicted wrong. The percentage error is calculated using the formula shown in Chapter 3, equation (3.14) and (3.15) shown:

$$e_{winstat} = (\text{winstat}_{predicted} \sim= \text{winstat}_{measured}) \tag{3.14}$$

$$e_p = \frac{\sum_{i=0}^{n} E_{winstat}}{n} \times 100 \tag{3.15}$$

where n= 83, $e_{winstat}$ is error in window status prediction for one day, and winstat is window status. The average percentage error for each day is calculated. It was seen that for House A, for days when window was open more than 50% of the time, the error was considerably high. Hence the testing days for House A was chosen such that the window is open more than 50% of the time on the day. For House B, the average percentage error for days when window is open more than 50% of the time, is considered for testing.



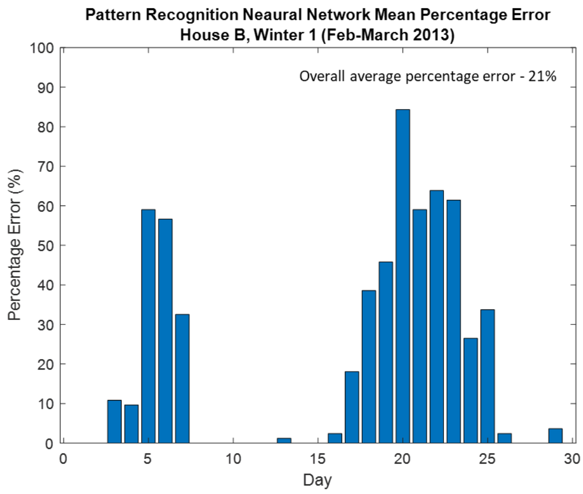
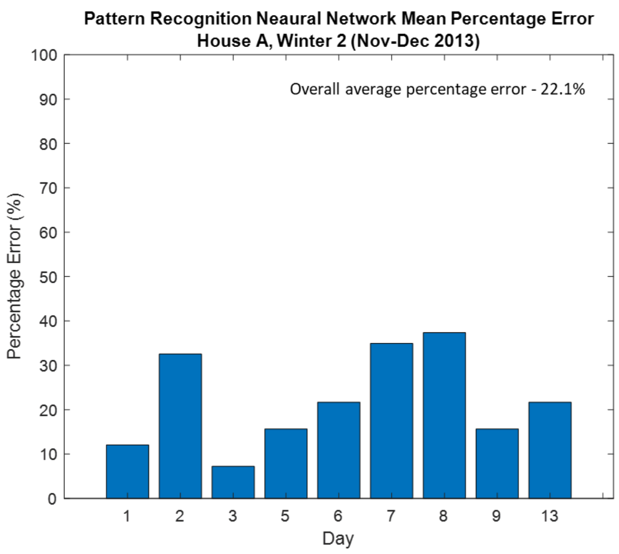


Figure 7.15: Average percentage error for House A and B for Winter 1 with training data 2



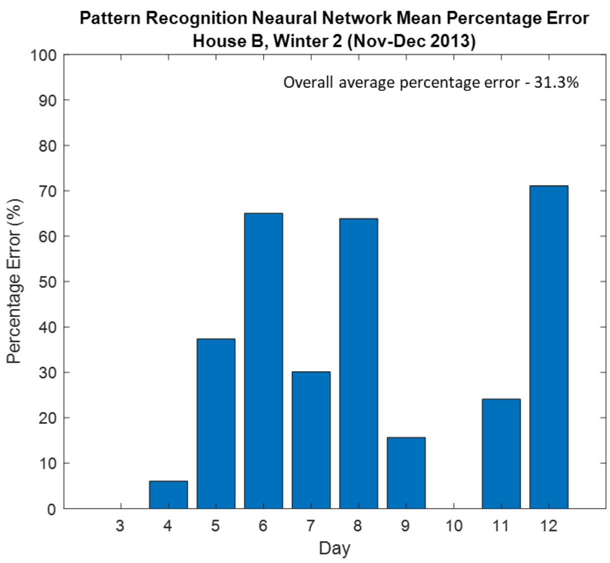


Figure 7.16: Average percentage error for House A and B for Winter 2 with training data 2

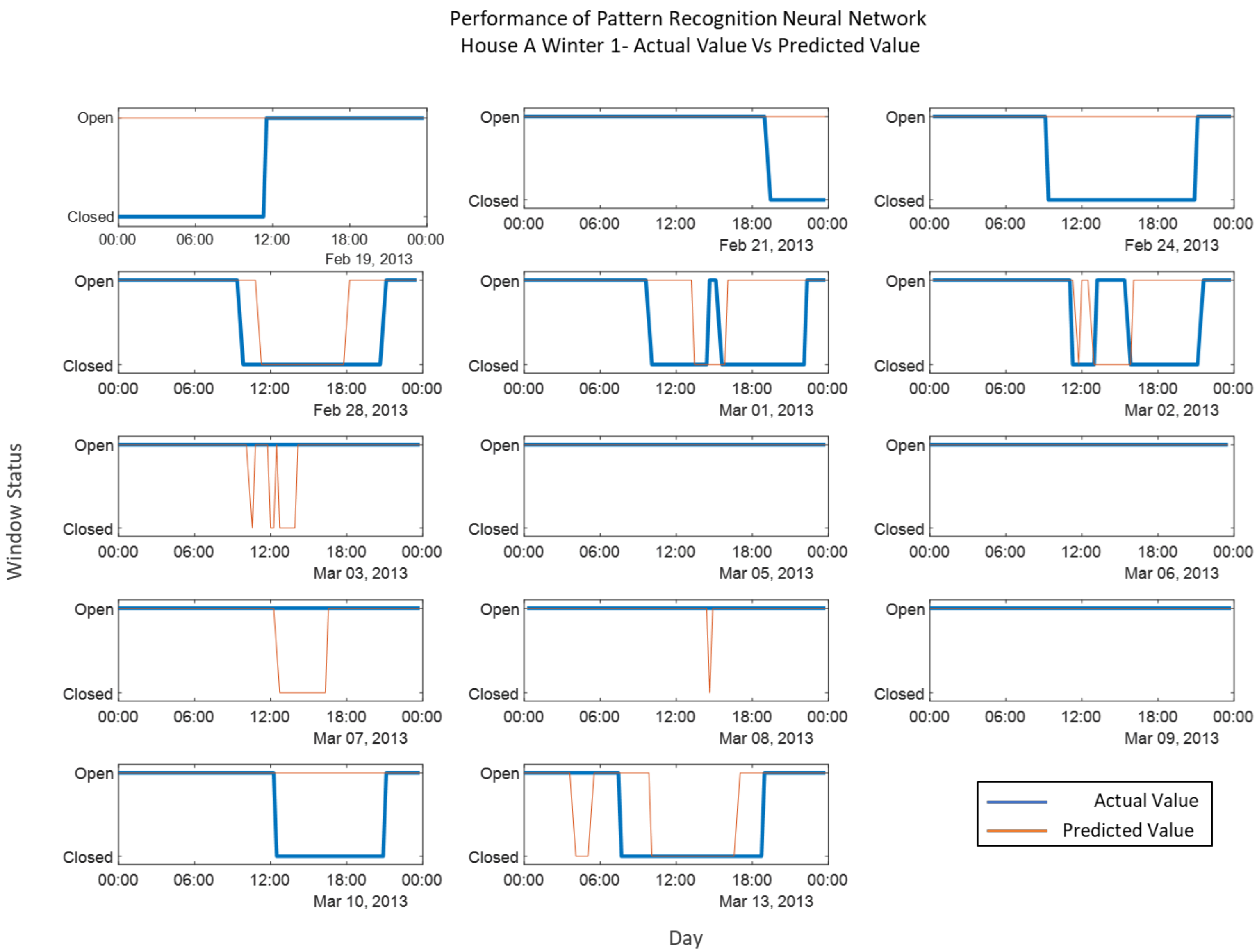


Figure 7.17: Performance of Model B neural network for House A Winter 1

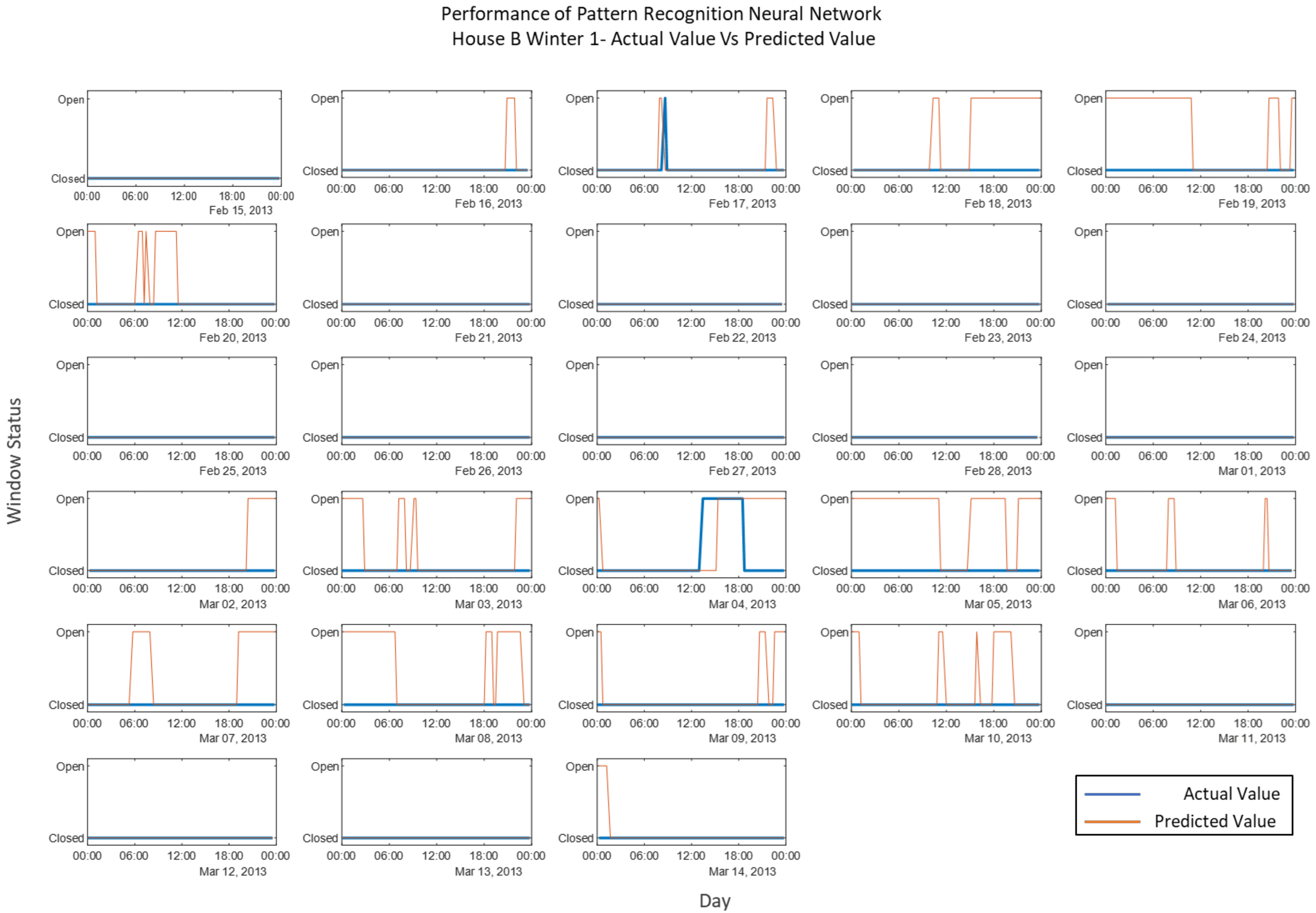


Figure 7.18: Performance of Model B neural network for House B Winter 1

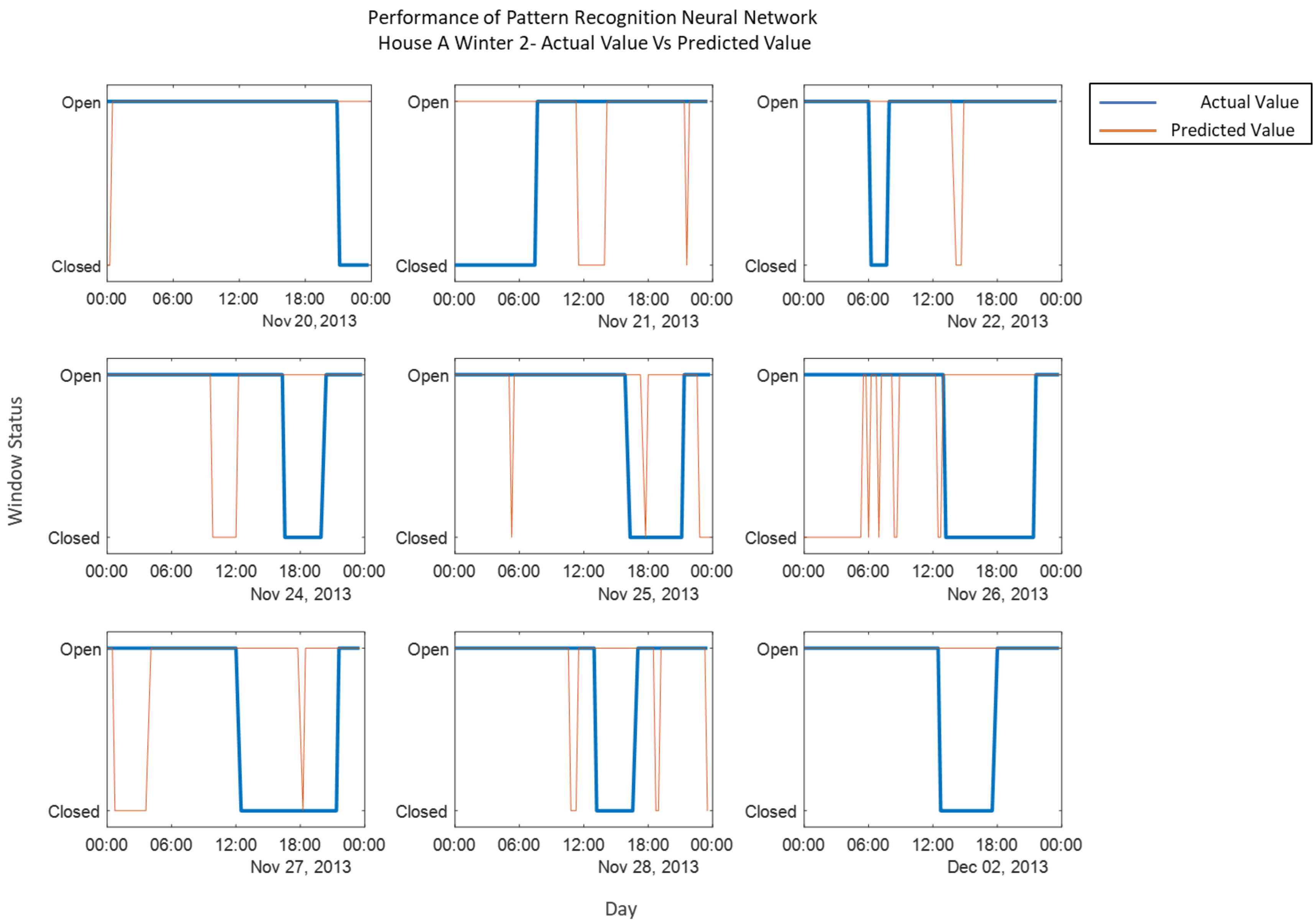


Figure 7.19: Performance of Model B neural network for House A Winter 2

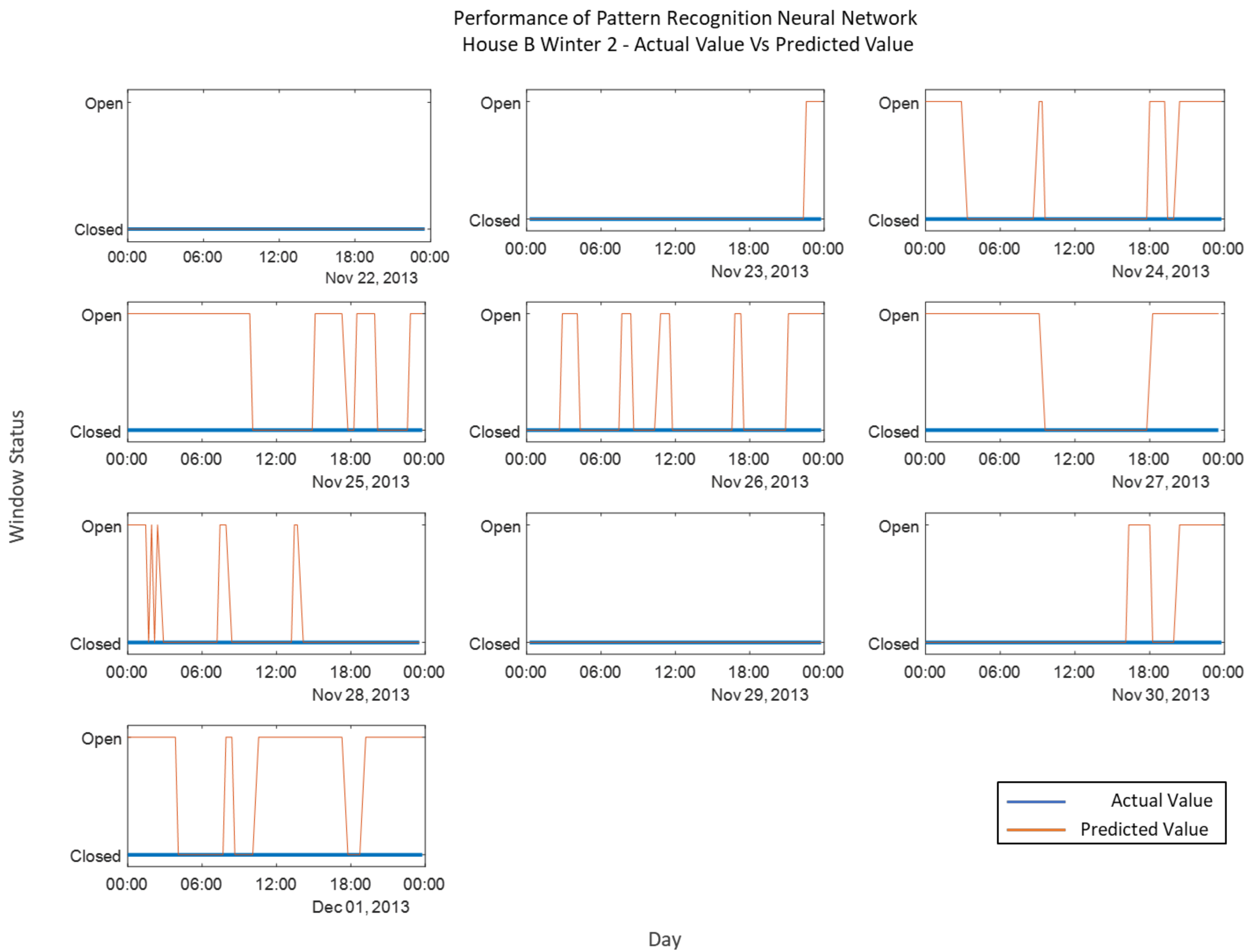


Figure 7.20: Performance of Model B neural network for House B Winter 2

The model with training data 2 was found to have slightly higher performance for both houses and for Winter 1 and Winter 2. The average percentage error for the tested days for House A and House B, for winter 1, with training data 2, is shown in Figure 7.15 and the same for winter 2 for House A and house B, are shown in Figure 7.16. the average percentage error for both houses for both winters, when trialled with training data 1, is shown in Appendix D.

Figure 7.17 to Figure 7.20 show performance of Model B pattern recognition neural network for House A and House B for Winter 1 and winter 2. For House A, only days where window is open more than 50% of the time is tested. The overall average percentage error for House A, considering both Winter 1 and winter 2, is 21.8% and for House B is 26.1%.

7.5. Model C - Pattern Recognition Neural Network to Predict Occupant Behaviour (Good Practice/Bad Practice)

In Model B, although the overall percentage error for both House A and house B was less than 30%, the average percentage error for some days were considerably high. For House A, the error went up to 90% while for House B it went up to 50%. This is because when the window open status is considered as the target, the actual occupant behaviour is difficult to predict due to the stochastic nature of window opening. Therefore, instead of predicting the window status for each day, the house is categorised based on window status behaviour, radiator temperature, room temperature and outside ambient temperature and based on these predictors, the days are categorised into good practice day or bad practice house.

Pattern recognition algorithm is chosen for Model C as well, since the purpose of the Model is to recognise pattern and categorise the data. Based on pattern recognition algorithm, another model is developed, to predict occupant behaviour.

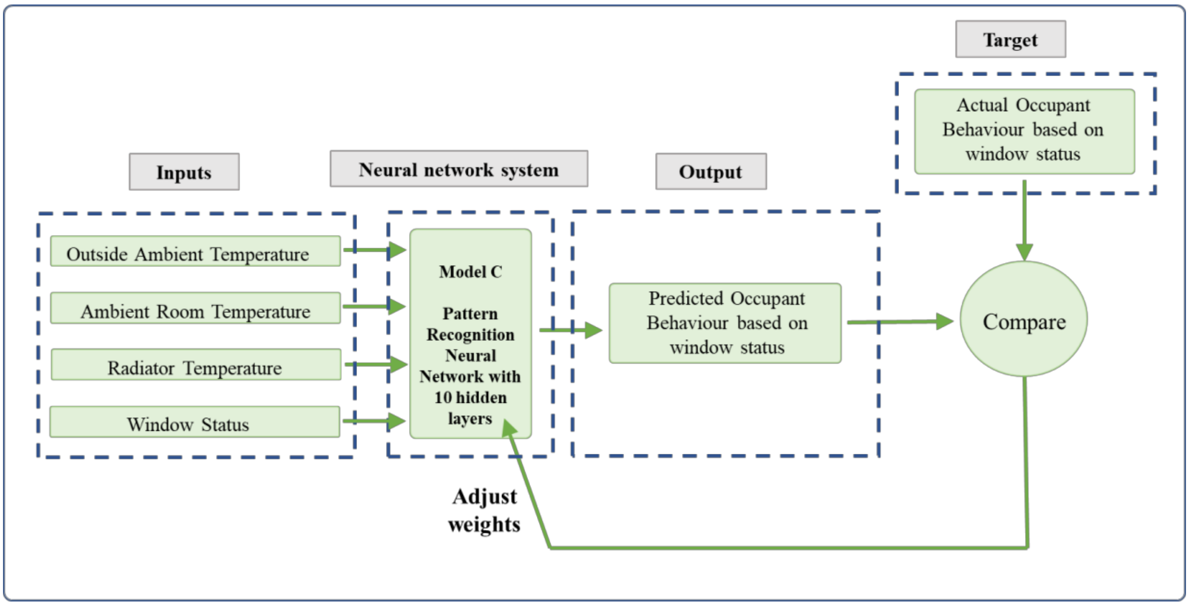


Figure 7.21: Block diagram of ANN Model C

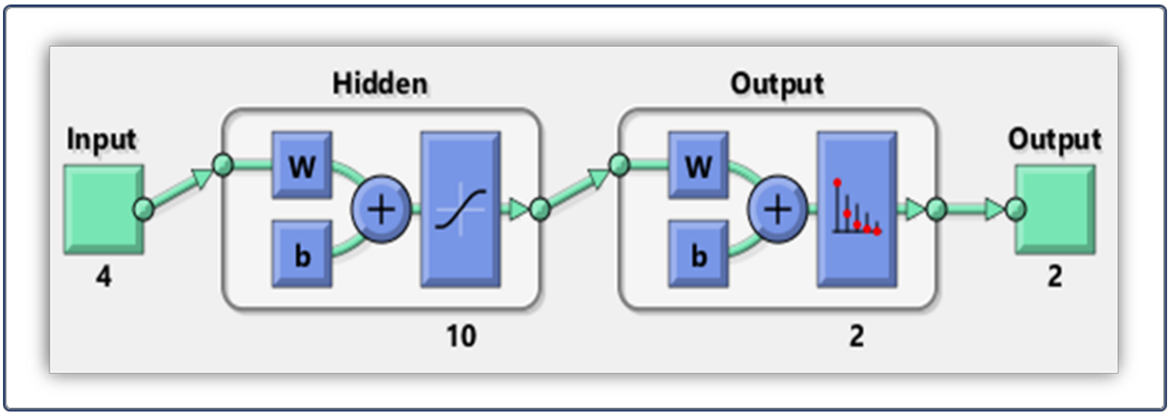


Figure 7.22: Network diagram of ANN Model C [Source: generated using MATLAB software]

The predictors are T_{room}, T_{rad}, and window status of main bedroom window, and T_{out}. The target is occupant behaviour based on the predictors. In this model, the window status is binary, represented by 2 variables. Window closed is represented as 01 and window open is represented as 10. Depending on the chosen predictors, the house is categorised as *'Good practice'* house (GP) or *'Bad Practice'* house. GP houses have low overall window open percentage (WOP) leading to low energy demand (ED) and BP houses have high WOP and ED.

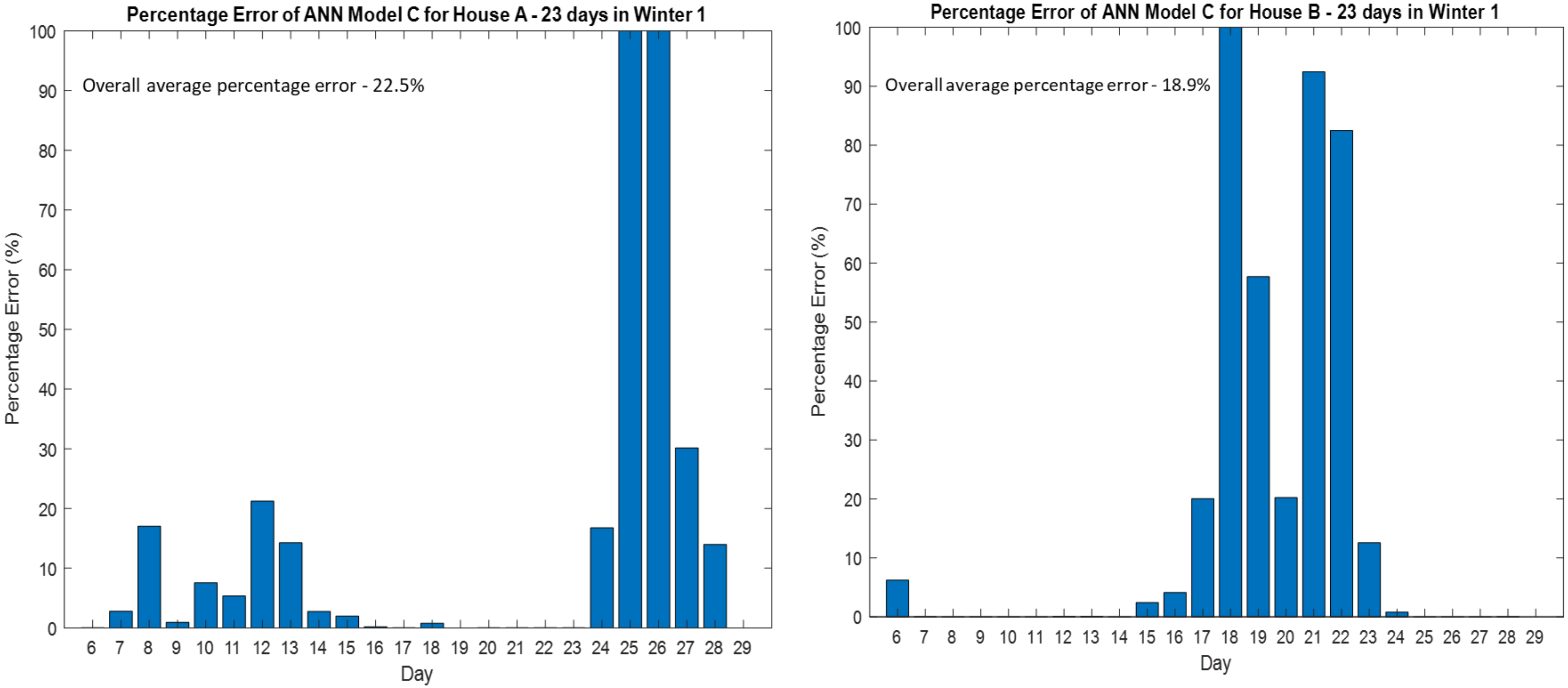


Figure 7.23: Model C - Percentage Error between actual and predicted occupant behaviour for House A and B - Winter 2

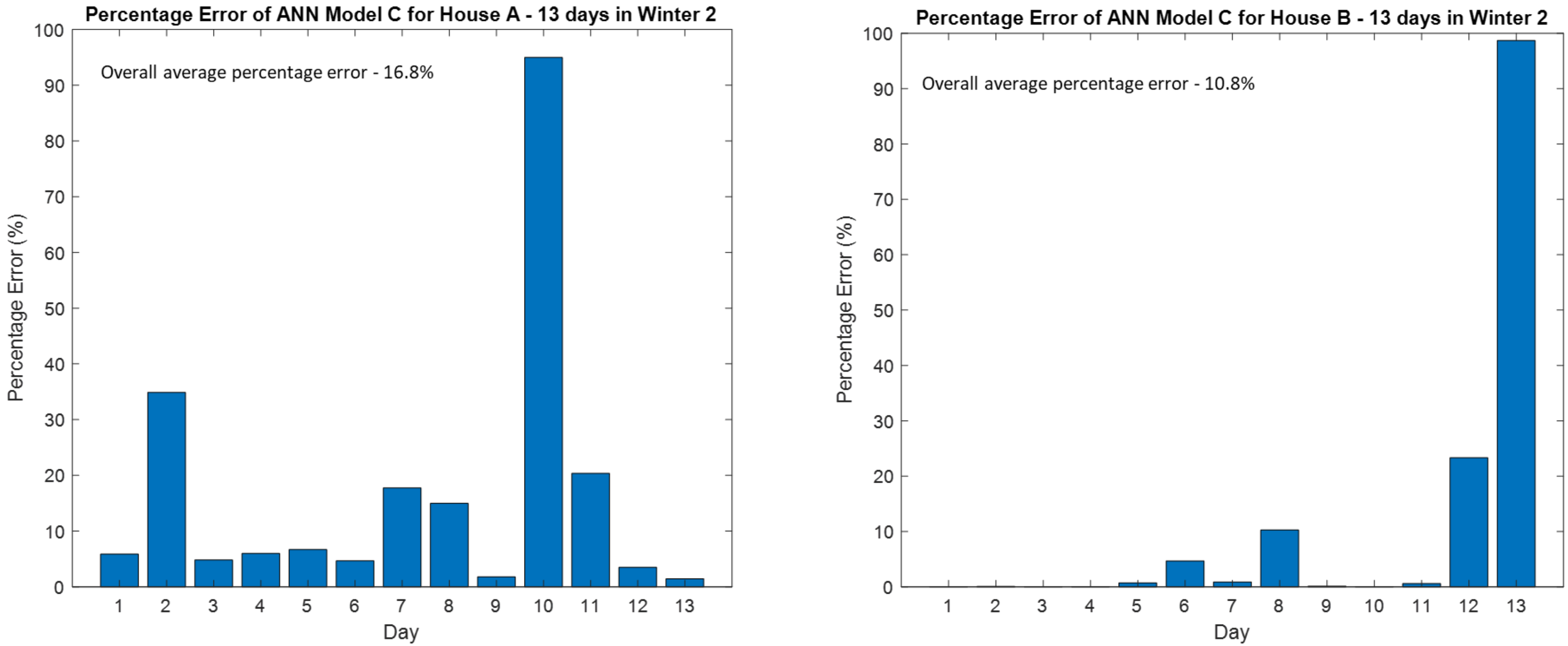


Figure 7.24: Model C - Percentage Error between actual and predicted occupant behaviour for House A and B - Winter 2

Good practice is when the correlation between radiator temperature, window status and room temperature is such that the energy demand will not be high. Bad practice is when the correlation between radiator temperature, window status and room temperature is such that window is open and radiator is ON and the thermal comfort temperature or the ambient temperature of the room is high, leading to high energy consumption. The target is binary, with good practice represented as 0 and bad practice represented as 1. The criterion for categorisation is based on the characteristics of House A and House B. The block diagram and network diagram of developed ANN Model C is shown in Figure 7.21. The neural network architecture for Model C, generated by the neural network app in MATLAB software, is shown in Figure 7.22, showing 4 inputs/predictors, 10 hidden layers, and 2 output/target variables.

Table 7.2: Selection of training data for Model C

Training data	**Training data is matrix containing**		
		House A	**House B**
1		day 1 data	day 1 data
2	Training data 1	day 2 data	day 2 data
3	Training data 2	day 3 data	day 3 data
4	Training data 3	day 4 data	day 4 data
5	Training data 4	day 5 data	day 5 data
6	Training data 5	day 6 data	day 6 data

The relationship between the room temperature, radiator temperature, window status and the outside ambient temperature determines characteristic of the house, in this neural network model. Table 7.2 shows the selection of training data for ANN Model C. winter 1 data is taken for training. Training data 1 is Winter 1 day 1 data of House A and House B, training data Winter 1 day 2 data of House A and House B and so on. The model is tried for up to training data 6 which is Winter 1 day 6 data of House A and House B. Model C with 6 days data taken for training is seen to have the best results. The target class for this model, which is the occupant behaviour is binary, with 0 for good practice and 1 for bad practice, represented as a logical array. The total error for each day is the number of times the characteristic, depending on occupant behaviour, is predicted wrong. The percentage error is calculated using the formula

$$e_{ob} = (ob_{predicted} \sim= ob_{measured}) \qquad (8.1)$$

$$e_{pob} = \frac{\sum_{i=0}^{n} e_{ob}}{n} \times 100 \qquad (8.1)$$

where n= 83, e_{ob} is error in house characteristic prediction for one day. The average percentage error, that is the prediction of the practice or characteristic of the days taken for testing, for House A and House B, is calculated. The developed pattern recognition neural network model is tested with the rest of the days data. The average percentage error for predicting characteristic of the house on that day, depending on the general characteristic of the house, based on training data, is calculated for the testing data which is day 7 to day 29 for winter 1, for House A and House B. Similarly, the average percentage error for prediction of practice of 13 days in Winter 2 is calculated for House A and House B. Figure 7.23 shows the percentage error in predicting occupant behaviour of House A and House B, for Winter 1. The overall average percentage error for House A for Winter 1 is 22.5% and that for House B for Winter 1 is 18.9%. Figure 7.24 shows the percentage error in predicting occupant behaviour of House A and House B, for Winter 2. The overall average percentage error for House A for Winter 2 is 16.8% and that for House B for Winter 2 is 10.8%. considering Winter 1 and Winter 2 together, the overall average percentage error for Model C for House A is 19.6% and the overall average percentage error for House B, considering Winter 1 and winter 2 together, is 14.8%. Based on the prediction, the occupants can be made aware of the consequent increase in energy usage, prompting them to change their pattern of window opening. Figure 7.23 shows the percentage error for House B for winter 1 and Figure 7.24 shows the percentage error for House A Winter 2 and House B Winter 2. The total average percentage error for both winters, for House A is 19.7% and that for House B is 14.9%. This means that depending on the internal temperatures of the house (including the radiator temperature), the window status, and the outside ambient temperature, data of a day, Model C can predict of the occupants have followed good practice or bad practice on the day. Model C can potentially be developed to a tool that helps provide occupants with information on their practice and their behaviour leading to increase in energy consumption in the house.

7.6. Summary

Based on analysis of social housing, artificial neural network models were developed to predict energy demand, window status and general occupant behaviour in the main bedroom of high insulation window open house and high insulation window closed house. Literature review showed that machine learning models are effective in predicting window opening behaviour of occupants in residential building. Although the variables used in modelling vary, room temperature, window status and outdoor ambient temperature are some of the most common predictors used. Including radiator temperature in predicting energy demand and window opening behaviour of occupants, has not been carried out extensively. This chapter describes the development of artificial neural network models developed. Three models were developed:

- Model A, to predict energy demand per day, in kWh, of main bedroom of high insulation window open house and high insulation window closed house. The predictors are room temperature, radiator temperature, window status and outside ambient temperature. The model predicted energy demand with 92.4% accuracy (7.6% error) for high insulation window open house and 99% accuracy (0.25% error) for high insulation window closed house.

- Model B, to predict window status of the house in a day, for high insulation window open house and high insulation window closed house. The predictors are room temperature, radiator temperature, energy demand and outside ambient temperature. The model predicted window status with 78.2% accuracy (21.8% error) for high insulation window open house and 73.9% accuracy (26.1% error) for high insulation window closed house.
- Model C, to categorise the house as a good practice house or bad practice house, depending on the relationship between room temperature, radiator temperature, window status and outside ambient temperature. Depending on the general characteristic of the house, the tested days for the house was categorised as good practice day or bad practice day. The model predictor the characteristic of high insulation window open house, with (19.75% error).

The above findings relate to the findings of existing studies in the field (Gill *et al.*, 2010; Haldi and Robinson, 2011; Jones, Fuertes and de Wilde, 2015),discussed in detail in Chapter 2. The developed models can be developed further to understand the patterns of energy usage in well insulated and poorly insulated houses and to compare them to see the effect of window opening behaviour of occupants.

The validity of any developed model increases with increase in number of real-life scenarios they are tested. Due to time constraints, the developed models in this study were tested with the 4 houses that were chosen for analysis previously in the study. Future work can include validating the results with a greater number of real-life scenarios.

Chapter 8 | Discussion and Conclusion

8.1. Introduction

Occupant behaviour plays a critical role in managing the energy efficiency of a residential building, arguably more than insulation property of the building. There is no single solution to achieve energy efficiency, there are some general areas to be considered and some general principles that can be followed to increase the energy efficiency in buildings. Getting the right balance can be done by having a holistic approach, considering a building in its context, significance and all the factors affecting energy use as the starting point for an optimum energy efficiency strategy. To achieve this, a clear understanding of why people open windows in residential buildings is necessary. Understanding the impact of occupant behaviour on energy usage and implementing it in building simulation models helps predict energy usage in realistic terms.

The aim and objectives of the research was fulfilled by following a systematic methodology. The results of this research confirm the hypothesis that OB is one of the key reasons for discrepancies between actual predicted energy consumption in residential buildings. This chapter discusses the results of the research concisely, comparing it with the objectives of the research. The key findings and contribution to knowledge are summarised. Limitations of the work and recommendations for future work are also presented.

8.2. Achievement of Research Aims and Objectives

The aim of this research was to study impact of occupant behaviour on the energy consumption of residential buildings and to identify the key factors that influence occupant behaviour that affect energy efficiency and to provide ideas to improve energy efficiency, by suggesting mathematical techniques and artificial intelligence. The primary focus of the thesis was to evaluate the effect of window opening on the energy efficiency of a residential building, regardless of the insulation property of the house. To achieve the aim, it was broken down into objectives which were attained with the help of the formulated research questions. The achievement of the objectives of the research are:

- Study the impact of occupant behaviour on the energy consumption of residential buildings:

This objective was achieved with the help a comprehensive literature review starting with review of energy efficiency in buildings and covering effect of insulation, energy gap and summarising the impact of occupant behaviour and ending with review of existing models of predicting window opening behaviour was done. It brought to light the explicate relationship between occupant behaviour and energy efficiency in buildings. This helped in making informed decision about the direction of research.

- Further enhance the understanding of the energy efficiency of buildings and to validate the information regarding the building fabrics, and its relationship to occupant behaviour of window opening, by obtaining thermal images of buildings:

Literature review followed by preliminary research helped achieve this objective. Thermal images of residential buildings across Nottingham were collected. The images helped visualise loss of heat due to opening of windows. The exercise validated the assumption that window opening behaviour occurred in houses especially in well insulated buildings.

- Identify the key factors that influence occupant behaviour that effect the energy efficiency:

Preliminary research phase was further enhanced by conducting a survey, which helped achieve this objective. Questions focussing window opening in winter were included in the survey questionnaire. Data was collected from a representative sample of people across UK. Results of the survey showed the wide-ranging set of reasons that prompted people to open windows of their dwelling in winter. The findings highlight the fact that OB in their house is strictly based on personal comfort and interrelated to IEQ and the energy efficiency of the building.

- Provide ideas to improving energy efficiency of residential buildings, by mathematical techniques:

Chapter 6 elaborates on the achievement of this objective. Energy efficiency in social housing was analysed. The window opening pattern in several houses of different building insulation properties were compared to understand the difference between the actual and predicted energy usage. This gave an insight into the impact of WOB in energy usage. It also helped compare the difference between energy usage in well insulated and poorly insulated buildings with windows open and closed.

- Design and develop models with the help of artificial neural networks, that help predict window opening and closing behaviour of occupants, and energy demand:

Chapter 7 explains the achievement of this objective. Artificial Neural Network Models were developed to predict the energy usage and the difference between actual and predicted energy usage when window is open. The models gave a clear indication of the energy gap occurring due to WOB of occupants.

8.3. Key Findings

The key findings obtained by achieving the aim and objectives through a set of structured research questions are:

- There is a strong relationship between energy efficiency of a building and the behaviour of occupants in the building.
- From the thermal image of buildings, it was inferred that thermal image of residential buildings can enhance the understanding and validate the impact of occupant behaviour in energy efficiency of a building.

- The survey provided an insight into the frequency of window opening in winter, and the wide range of reasons as to why people open windows in winter. 43% of the respondents open their windows in winter at least once a day, with 7.3% of them leaving it open always. 47% of the participants open their window when heating is ON. The survey revealed that energy consumption in houses is influenced to a great extent by occupant behaviour. People open window in their houses in winter due to diverse range of reasons, regardless of the type of insulation of their house.
- A comparative study four specific houses based on two categories (window opening and house insulation property) was carried out. with high insulation and window open behaves almost as badly as a house with poor insulation.
- The theory of first order control system can be used to understand building characteristics based on window opening and closing.
- In high insulation houses, the energy demand of one room increases by a factor of 2.9, when comparing a window open and window closed house.
- Consequently, the energy cost increases by £1 for one room per day, between two high insulation houses with window open and window closed.
- In poorly insulated houses, energy demand of one room increases by a factor of 1.5, in winter months, in a house with windows open, causing an increase of £0.65 for one day.
- Considering the average energy demand of one month, in high insulation houses, there is a difference of £30 in energy costs between a high insulation window open house and high insulation window closed house, for one room in a month.
- There is only a difference of 13% in energy demand of a high insulation window open house and a low insulation window closed house.

- As of April 2022, the gas prices will increase from £0.04 to £0.07. Based on this, the energy cost in a high insulation and window open house will increase by £1.73 for one day when compared toa high insulation and window closed house, which will account for an increase of £52.57 for one month.

ANN feed forward neural network model to predict energy consumption based on the room temperature, radiator temperature and outside ambient temperature was developed. 6 days data was taken for training. The model predicted energy consumption with 98.8% accuracy for high insulation, window closed house and 92% accuracy for high insulation, window open house.

- Artificial neural network model to predict window status based on radiator temperature, room temperature, outside ambient temperature and window status and EC, was developed. Pattern recognition algorithm was used. The model worked best with 10 hidden layers and 2 days data taken for training, with an accuracy of 76%. The models predict window status with an overall average error of 24.2% for high insulation, window open house and 23.6% for high insulation, window closed house.
- Artificial neural network model to predict general occupant behaviour regarding window opening, (or practice of window opening) based on radiator temperature, room temperature, outside ambient temperature was developed. Pattern recognition algorithm was used. The model worked best with 10 hidden layers and 6 days data taken for training. The models predict window status with an overall average error of 19.7% for high insulation, window open house and 14.9% for high insulation, window closed house

8.4. Contribution to Knowledge

The contributions to knowledge, from this research work are:

- Energy efficiency of a building holds an explicate relationship with the behaviour of occupants in the buildings, regardless of the building insulation properties.
- A highly insulated building could consume as much energy as a badly insulated house, due to people's behaviour. Hence the assumption that the more the insulation, the more the energy efficiency, might not be true
- People's behaviour could reduce the effect of insulation. So what theoretically is a well-insulated building might behave like a badly insulated house in terms of energy efficiency, depending on the behaviour of occupants
- Thermal imaging is a helpful tool in visualising the impact of window opening. The same can be used to make occupants aware of the effect of their behaviour.
- The survey acts as guidance helping policy makers understand the effect of a variety of window open behaviour. This stochastic nature is one of the main reasons for the discrepancies between actual energy usage and energy usage predicted by building simulation models. The survey shows that insulating a building alone cannot improve energy efficiency of a building.

Development of a mathematical model to characterise performance of a building based on opening and closing of windows using first order system modelling.

- Mathematical model to predict energy usage in a building.
- Artificial neural network architecture to predict energy usage based in window status.
- Artificial neural network architecture to predict window status based on internal and external temperatures and energy usage.
- The developed ANN models will aid post-occupancy evaluations of performance of buildings, thereby help explain commonly observed discrepancies between actual and predicted energy use, as the energy efficiency white papers of the UK does not account for occupant behaviour as a factor of energy loss.

8.5. Limitations and Recommendations for Future Work

The window monitoring system used in this research collected data regarding the state of the window and not the position, which indicates the degree of window opening. Only one house of each type has been considered based on data availability. The study can be further enhanced by including more houses of each type.

Although the objectives of the pilot study were achieved, the sample size can be considered small. A bigger sample size would provide an in-depth analysis and explicit correlations between the variables considered in the study.

ANN models were the only models tried for this study, other machine learning models like SVM and XGBoost etc can be used to develop models to compare the results to choose an optimum model to be represented.

The thermography survey can in future include input from the residents of the buildings to obtain more benefit

Although the government studies in UK agree that occupant behaviour has a large influence over the gas consumption in the domestic sector, and that external temperature is one of the most influential variables, it does not account occupant behaviour as one of the drivers concerning these two important factors that account for gas consumption variations (Department for Business Energy & Industrial Strategy, 2021). The findings from this study can be used to emphasise the importance of including occupant behaviour in housing energy consumption surveys and policy making.

The research analysis, interpretations and developed models must be taken as starting point for future research in the field of occupant behaviour analysis, for the development of robust stochastic building simulations models. Testing of the developed models with new data can be done, to strengthen the validity of the model. Implementing a more accurate statistical model by including the window opening angle can be done for a more precise prediction of energy use.

Going forward, indoor air quality must be the primary focus of the research. The humidity, CO_2 and ppm in the rooms will be considered to suggest a suitable ventilation practice.

8.6. Final Conclusion

The main aim of the research was to understand the impact of occupant behaviour on energy efficiency of buildings. Energy consumption pattern in similar insulated buildings differed based on occupant behaviour, was one of the key findings of the research. This chapter provides an overall summary of the thesis, focussing on the achievement of aims and objectives. The key findings are presented along with the contribution to knowledge, limitations of the research and recommendations for future work. The aim and objectives of the thesis was achieved by answering the research questions. The overall argument and key findings of the study have been summarised. The entire PhD has been a learning process, helping the author understand the impact a minor action like window opening can have on the energy usage of a dwelling. The PhD journey proved to be an insightful one to the author, with lessons on patience, resilience, and commitment.

Reference

Air Change Rate Calculator | Estimate air change | WindowMaster. (n.d.). Retrieved March 13, 2022, from https://www.windowmaster.com/resources/calculators/air-change-rate-calculator/#

Al-Habaibeh, A., Sen, A. and Chilton, J. (2021) 'Evaluation tool for the thermal performance of retrofitted buildings using an integrated approach of deep learning artificial neural networks and infrared thermography', Energy and Built Environment, 2(4), pp. 345–365. Available at: https://doi.org/10.1016/j.enbenv.2020.06.004.

Andersen, R. et al. (2013) 'Window opening behaviour modelled from measurements in Danish dwellings', Building and Environment, 69, pp. 101–113. Available at: https://doi.org/10.1016/j.buildenv.2013.07.005.

Andersen, R.K., Fabi, V. and Corgnati, S.P. (2016) 'Predicted and actual indoor environmental quality: Verification of occupants' behaviour models in residential buildings', Energy and Buildings, 127, pp. 105–115. Available at: https://doi.org/10.1016/j.enbuild.2016.05.074.

Andersen, R.V. et al. (2009) 'Survey of occupant behaviour and control of indoor environment in Danish dwellings', Energy and Buildings, 41(1), pp. 11–16. Available at: https://doi.org/10.1016/J.ENBUILD.2008.07.004.

Andersen, R.V., Olesen, B. and Toftum, J. (2007) 'Simulation of the Effects of Occupant Behaviour on Indoor Climate and Energy Consumption', Clima2007 [Preprint].

ANSI/ASHRAE Standard 55-2004 (2004) Thermal Environmental Conditions for Human Occupancy. Atlanta. Available at: www.ashrae.org (Accessed: 24 April 2019).

Attar, R. et al. (2011) 'Sensor-enabled Cubicles for Occupant-centric Capture of Building Performance Data'.

Bahadori-Jahromi, A. et al. (2022) ‘The Effect of Occupants’ Behaviour on the Building Performance Gap: UK Residential Case Studies’, MDPI Sustainability [Preprint]. Available at: https://doi.org/10.3390/su14031362.

Bahaj, A.S., James, P.A.B., 2007. Urban energy generation: The added value of photovoltaics in social housing. Renewable and Sustainable Energy Reviews, 11(9), pp.2121–2136. 10.1016/j.rser.2006.03.007.

Balvedi, B.F., Ghisi, E. and Lamberts, R. (2018) ‘A review of occupant behaviour in residential buildings’, Energy and Buildings, 174, pp. 495–505. Available at: https://doi.org/10.1016/j.enbuild.2018.06.049.

Barthelmes, V.M. et al. (2017) ‘Occupant behaviour lifestyles and effects on building energy use: Investigation on high and low performing building features’, in Energy Procedia. Elsevier Ltd, pp. 93–101. Available at: https://doi.org/10.1016/j.egypro.2017.11.126.

BBC News (2021) ‘Climate change: Is the UK on track to meet its targets? - BBC News’, BBC News, 10 November.

BBC News (2022) ‘Warm Home Discount Scheme - GOV.UK’. Available at: https://www.gov.uk/the-warm-home-discount-scheme (Accessed: 3 February 2022).

Belaïd, F. (2017) ‘Untangling the complexity of the direct and indirect determinants of the residential energy consumption in France: Quantitative analysis using a structural equation modeling approach’, Energy Policy, 110, pp. 246–256. Available at: https://doi.org/10.1016/j.enpol.2017.08.027.

Bennett, G., Elwell, C. and Oreszczyn, T. (2019) “Space heating operation of combination boilers in the UK: The case for addressing real-world boiler performance,” *Building Serv. Eng. Res. Technol*, 40(1), pp. 75–92. doi:10.1177/0143624418794552.

Breezeway, 2012. Comparative Ventilation Openings Of Various Window Types.

van den Brom, P., Meijer, A. and Visscher, H. (2018) ‘Performance gaps in energy consumption: household groups and building characteristics’, Building Research and Information, 46(1). Available at:

https://doi.org/10.1080/09613218.2017.1312897.

Bruce-Konuah, A., Jones, R. v. and Fuertes, A. (2019) “Physical environmental and contextual drivers of occupants’ manual space heating override behaviour in UK residential buildings,” Energy and Buildings, 183, pp. 129–138. doi:10.1016/j.enbuild.2018.10.043.

Brundrett, G. W. (1977). Ventilation: A behavioural approach. *International Journal of Energy Research*, *1*(4), 289–298. https://doi.org/10.1002/er.4440010403

Clarke, J.A. et al. (2008) ‘The role of built environment energy efficiency in a sustainable UK energy economy’, Energy Policy, 36(12), pp. 4605–4609. Available at: https://doi.org/10.1016/J.ENPOL.2008.09.004.

Climate Change Act 2008 (2008). Available at: http://www.legislation.gov.uk/ukpga/2008/27/pdfs/ukpga_20080027_en.pdf (Accessed: 5 March 2018).

Cozza, S., Chambers, J. and Patel, M.K. (2020) ‘Measuring the thermal energy performance gap of labelled residential buildings in Switzerland’, Energy Policy, 137(November 2019), p. 111085. Available at: https://doi.org/10.1016/j.enpol.2019.111085.

Cozza, S. *et al.* (2021) “In search of optimal consumption: A review of causes and solutions to the Energy Performance Gap in residential buildings,” *Energy and Buildings*, 249, p. 111253. doi:10.1016/J.ENBUILD.2021.111253.

Cuce, E. (2017). Role of airtightness in energy loss from windows: Experimental results from in-situ tests. *Energy and Buildings*, *139*, 449–455. https://doi.org/10.1016/j.enbuild.2017.01.027

Cuerda, E. *et al.* (2019) “Comparing the impact of presence patterns on energy demand in residential buildings using measured data and simulation models,” *Building Simulation*, 12(6), pp. 985–998. doi:10.1007/s12273-019-0539-z.

Dai, X., Liu, J. and Zhang, X. (2020) ‘A review of studies applying machine learning models to predict occupancy and window-opening behaviours in smart buildings’, Energy and Buildings, 223, p. 110159. Available at: https://doi.org/10.1016/j.enbuild.2020.110159.

Darby, S. (2008) ‘Why, What, When, How, Where and Who? Developing UK Policy on Metering, Billing and Energy Display Devices’, in ACEEE Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA, pp. 70–81. Available at: https://aceee.org/files/proceedings/2008/data/papers/7_137.pdf (Accessed: 9 April 2019).

Davies, G. (2021) Green Homes Grant Voucher Scheme. London.

Dear, R.J. de and Brager, G.S. (1998) ‘Developing an adaptive model of thermal comfort and preference’, in 1998 ASHRAE winter meeting. San Francisco. Available at: https://www.osti.gov/biblio/653186.

Delzendeh, E. et al. (2017) ‘The impact of occupants’ behaviours on building energy analysis: A research review’, Renewable and Sustainable Energy Reviews, 80, pp. 1061–1071. Available at: https://doi.org/10.1016/j.rser.2017.05.264.

Denzin, N. K. and Lincoln, Y. S. (2011) The SAGE handbook of qualitative research. Sage.

Department for Business Energy & Industrial Strategy (2018a) SMART METER CUSTOMER EXPERIENCE STUDY A report on post-installation and longer-term experiences of smart meter customers. London. Available at: www.nationalarchives.gov.uk/doc/open-government- (Accessed: 18 October 2019).

Department for Business Energy & Industrial Strategy (2018b) SMART METER CUSTOMER EXPERIENCE STUDY A report on post-installation and longer-term experiences of smart meter customers. London.

Department for Business Energy and Industrial Strategy (2017) ‘Energy Trends December 2017’, (DECEMBER). Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/669750/Energy_Trends_December_2017.pdf.

Department for Business Energy and Industrial Strategy (2019) ‘Energy Trends December 2018’, (July), pp. 111–153. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/736148/DUKES_2018.pdf.

Department for Business Energy & Industrial Strategy (2019) Annual Fuel Poverty Statistics in England, 2019 (2017 data).

Department for Business Energy & Industrial Strategy (2021a) Annual Fuel Poverty Statistics in England, 2021 (2019 data). UK Government. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/966509/Annual_Fuel_Poverty_Statistics_LILEE_Report_2021__2019_data_.pdf.

Department for Business Energy & Industrial Strategy (2021b) Green Homes Grant Voucher Scheme - National Audit Office (NAO) Report. Available at: https://www.nao.org.uk/report/green-homes-grant/ (Accessed: 15 August 2022).

Department for Business Energy & Industrial Strategy (2021c) UK Energy Brief in 2021. Available at: www.gov.uk/government/statistics/uk-energy-in-brief-2021.

Department for Business Energy & Industrial Strategy (2021d) 'UK local authority carbon dioxide emissions estimates 2018', HM Department for Business, Industry and Industrial Strategy, (June 2021), pp. 1–34. Available at: https://geoportal.statistics.gov.uk/datasets/standard-area-measurements-2019-for-administrative-areas-in-the-.

Department of Energy and Climate Change (2011) The Carbon Plan: Delivering our low carbon future.

Diakaki, C. et al. (2010) 'A multi-objective decision model for the improvement of energy efficiency in buildings', Energy, 35(12), pp. 5483–5496. Available at: https://doi.org/10.1016/j.energy.2010.05.012.

D'Oca, S. and Hong, T. (2014) 'A data-mining approach to discover patterns of window opening and closing behavior in offices', Building and Environment, 82, pp. 726–739. Available at: https://doi.org/10.1016/j.buildenv.2014.10.021.

Dowson, M. et al. (2012) 'Domestic UK retrofit challenge: Barriers, incentives and current performance leading into the Green Deal', Energy Policy, 50, pp. 294–305. Available at: https://doi.org/10.1016/j.enpol.2012.07.019.

Dziedzic, J.W., Da, Y. and Novakovic, V. (2019) 'Indoor occupant behaviour monitoring with the use of a depth registration camera', Building and Environment, 148(7491), pp. 44–54. Available at:

https://doi.org/10.1016/j.buildenv.2018.10.032.

Dubrul, C., 1988. Inhabitant Behaviour with Respect to Ventilation - A Summary Report of IEA Annex VIII [online]. AIVC Technical Reports, TN 23, pp.1–63. Available at: http://www.aivc.org/Publications/publications.html#Technical reports%5Cnhttp://www.aivc.org/Subscriptions/aivc_subscriptions.htm.

Energy Act 2011 (no date). Available at: https://www.legislation.gov.uk/ukpga/2011/16/contents/enacted (Accessed: 9 February 2022).

Esmaeilimoakher, P. et al. (2016) 'Identifying the determinants of residential electricity consumption for social housing in Perth, Western Australia', Energy and Buildings, 133, pp. 403–413. Available at: https://doi.org/10.1016/j.enbuild.2016.09.063.

Esmaeilimoakher, P. (2019) The Impact of Implicit and Explicit Occupants' Behaviour on the Efficient Use of Energy in Low-Income Households. Murdoch University.

European Union (2009) 'DIRECTIVE 2009/28/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL', Official Journal of the European Union , 140(16), pp. 16–62.

Estiri, H. (2015) 'The indirect role of households in shaping US residential energy demand patterns', Energy Policy, 86, pp. 585–594. Available at: https://doi.org/10.1016/j.enpol.2015.08.008.

Fabi, V. et al. (2013) 'A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings Article History', Building Simulation /, 6(4), pp. 415–427. Available at: https://doi.org/10.1007/s12273-013-0119-6.

Fernández-Agüera, J. et al. (2019) 'Thermal comfort and indoor air quality in low-income housing in Spain: The influence of airtightness and occupant behaviour', Energy and Buildings, 199, pp. 102–114. Available at: https://doi.org/10.1016/J.ENBUILD.2019.06.052.

FLIR. (2013). User's manual FLIR T6xx series. FLIR Systems. https://www.instrumart.com/assets/FLIR-T620-T640-Manual.pdf

Fox, J. (2008) 'A study of occupant controlled ventilation within UK dwellings', PQDT - Global, p. 385. Available at: https://manchester.idm.oclc.org/login?url=https://search.proquest.com/docview/1427203194?accountid=12253%0Ahttp://man-fe.hosted.exlibrisgroup.com/openurl/44MAN/44MAN_services_page?genre=dissertations+%26+theses&atitle=&author=Fox%2C+Jacquelyn&volume=&issu.

Fritsch, R. et al. (1990) 'A stochastic model of user behaviour regarding ventilation', Building and Environment, 25(2), pp. 173–181. Available at: https://doi.org/10.1016/0360-1323(90)90030-U.

Fulton, M.K. and Bsme, P.E. (2004) 'Western Mechanical Solutions, llc'. Available at: http://docshare01.docshare.tips/files/7792/77926535.pdf (Accessed: 27 February 2018).

Gill, Z.M. et al. (2010) 'Low-energy dwellings: The contribution of behaviours to actual performance', Building Research and Information, 38(5), pp. 491–508. Available at: https://doi.org/10.1080/09613218.2010.505371.

Goodhew, J. et al. (2015) "Making Heat Visible: Promoting Energy Conservation Behaviors Through Thermal Imaging," Environment and Behavior, 47(10), pp. 1059–1088. doi:10.1177/0013916514546218.

Goodhew, J. et al. (2017) "Mental models: Exploring how people think about heat flows in the home," Energy Research & Social Science, 31, pp. 145–157. doi:10.1016/J.ERSS.2017.06.012.

Gravetter, F. ., & Forzano, L. . (2006). Research methods for the behavioral sciences. In Thomson Wadsworth. https://doi.org/10.5860/choice.197263

Green Deal: energy saving for your home - GOV.UK (no date). Available at: https://www.gov.uk/green-deal-energy-saving-measures (Accessed: February 9, 2022).

Greene, J. C. (2006). Toward a Methodology of Mixed Methods Social Inquiry. Research in the Schools, 13(1), 93–98.

Guerra-Santin, O. and Itard, L. (2010) 'Occupants' behaviour: determinants and effects on residential heating consumption Occupants' behaviour: determinants and e¡ects on residential heating consumption', Building Research and

Information, 38(3), pp. 318–338. Available at: https://doi.org/10.1080/09613211003661074.

Gul, M.S. and Patidar, S. (2015) 'Understanding the energy consumption and occupancy of a multi-purpose academic building', Energy and Buildings, 87, pp. 155–165. Available at: https://doi.org/10.1016/j.enbuild.2014.11.027.

Gupta, R., Kapsali, M. and Howard, A. (2018) "Evaluating the influence of building fabric, services and occupant related factors on the actual performance of low energy social housing dwellings in UK," *Energy and Buildings*, 174, pp. 548–562. doi:10.1016/J.ENBUILD.2018.06.057.

Haldi, F. *et al.* (2017) "Modelling diversity in building occupant behaviour: a novel statistical approach," *Journal of Building Performance Simulation*, 10(6), pp. 527–544. doi:10.1080/19401493.2016.1269245.

Haldi, F. and Robinson, D. (2008) 'On the behaviour and adaptation of office occupants', Building and Environment, 43(12), pp. 2163–2177. Available at: https://doi.org/10.1016/j.buildenv.2008.01.003.

Haldi, F. and Robinson, D. (2009) 'Interactions with window openings by office occupants', Building and Environment, 44(12), pp. 2378–2395. Available at: https://doi.org/10.1016/j.buildenv.2009.03.025.

Haldi, F. and Robinson, D. (2011) 'The impact of occupants' behaviour on building energy demand', Journal of Building Performance Simulation, 4(4), pp. 323–338. Available at: https://doi.org/10.1080/19401493.2011.558213.

Hamilton, E.M. (2018) Positive Sustainable Built Environments: The Cognitive and Behavioral Affordances of Environmentally Responsible Behavior in Green Residence Halls. University of Michigan.

Harrje, D.J. and Kempton, W.M. (1986) 'Ventilation, Air Infiltration and Building Occupant Behaviour', in Occupant interaction with ventilation systems, p. 18.

Hong, T. et al. (2015) 'An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework', Building and Environment, 92, pp. 764–777. Available at: https://doi.org/10.1016/J.BUILDENV.2015.02.019.

Hong, T. et al. (2016) 'Advances in research and applications of energy-related occupant behavior in buildings', Energy and Buildings, 116, pp. 694–702. Available at: https://doi.org/10.1016/j.enbuild.2015.11.052.

Hong, T. et al. (2017) 'Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs', Building Simulation [Preprint]. Available at: https://doi.org/10.1007/s12273-017-0396-6.

How the UK is progressing - Committee on Climate Change (2017). Available at: https://www.theccc.org.uk/tackling-climate-change/reducing-carbon-emissions/how-the-uk-is-progressing/ (Accessed: 8 March 2018).

Innovate UK (2016) Building Performance Evaluation Programme: Findings from domestic projects. Swindon.

Insulate Britain (2021) 'Insulating Britain'. Available at: www.insulatebritain.com.

International Energy Agency (2016a) Total Energy Use in Buildings: Analysis and Evaluation Methods (Annex 53).

International Energy Agency (2016b) Total Energy Use in Buildings: Analysis and Evaluation Methods (Annex 53).

International Energy Agency, 1986. Occupant Interaction With Ventilation Systems. In: 7th AIVC conference. Berkshire.

Islam, M.Z., Mamun, Q., Rahman, M.G., 2014. Data cleansing during data collection from wireless sensor networks. Conferences in Research and Practice in Information Technology Series, 158, pp.195–204.

Jack, R. et al., 2015. Quantifying the effect of window opening on the measured heat loss of a test house SEEDS International Conference Quantifying the Effect of Window Opening on the Measured Heat Loss of a Test House. International SEEDS Conference 2015: Sustainable Ecological Engineering Design for Society, pp.0–14.

Jang, H. and Kang, J. (2018) 'An energy model of high-rise apartment buildings integrating variation in energy consumption between individual units', Energy and Buildings, 158, pp. 656–667. Available at:

https://doi.org/10.1016/j.enbuild.2017.10.047.

Johnson, T. and Long, T. (2004) ‘Determining the frequency of open windows in residences: a pilot study in Durham, North Carolina during varying temperature conditions’, Journal of Exposure Science & Environmental Epidemiology 2005 15:4, 15(4), pp. 329–349. Available at: https://doi.org/10.1038/sj.jea.7500409.

Jones, R. v. et al. (2017) ‘Stochastic behavioural models of occupants’ main bedroom window operation for UK residential buildings’, Building and Environment, 118, pp. 144–158. Available at: https://doi.org/10.1016/j.buildenv.2017.03.033.

Jones, R. v, Fuertes, A. and de Wilde, P. (2015) ‘THE GAP BETWEEN SIMULATED AND MEASURED ENERGY PERFORMANCE: A CASE STUDY ACROSS SIX IDENTICAL NEW-BUILD FLATS IN THE UK’. Available at: http://hdl.handle.net/10026.1/4320 (Accessed: 14 February 2022).

Kelly, S. (2011) ‘Do homes that are more energy efficient consume less energy?: A structural equation model of the English residential sector’, Energy, 36(9), pp. 5610–5620. Available at: https://doi.org/10.1016/j.energy.2011.07.009.

Lam, K.P. et al. (2009) ‘OCCUPANCY DETECTION THROUGH AN EXTENSIVE ENVIRONMENTAL SENSOR NETWORK IN AN OPEN-PLAN OFFICE BUILDING’, in Eleventh International IBPSA Conference.

Larbi Youcef, M.H.A. *et al.* (2020) “In situ quantitative diagnosis of insulated building walls using passive infrared thermography,” *Quantitative InfraRed Thermography Journal* [Preprint]. doi:10.1080/17686733.2020.1805939.

Lilley, D. (2009) ‘Design for sustainable behaviour: strategies and perceptions’, Design Studies, 30(6), pp. 704–720. Available at: https://doi.org/10.1016/J.DESTUD.2009.05.001.

Liu, W. et al. (2021) ‘Modeling window and thermostat use behavior to inform sequences of operation in mixed-mode ventilation buildings’, Science and Technology for the Built Environment, 27(9), pp. 1204–1220. Available at: https://doi.org/10.1080/23744731.2021.1936629.

Lucchi, E. (2018) ‘Applications of the infrared thermography in the energy audit of buildings: A review’, Renewable and Sustainable Energy Reviews. Elsevier

Ltd, pp. 3077–3090. Available at: https://doi.org/10.1016/j.rser.2017.10.031.

'Machine Learning with MATLAB' (2020). Mathworks.

MathWorks, 2021. Principal Component Analysis (PCA) - MATLAB & Simulink - MathWorks United Kingdom [online]. Mathworks Documentation. Available at: https://uk.mathworks.com/help/stats/principal-component-analysis-pca.html [Accessed 31 July 2021].

Mallaburn, P.S. and Eyre, N. (2014) 'Lessons from energy efficiency policy and programmesin the UK from 1973 to 2013', Energy Efficiency, 7(1), pp. 23–41. Available at: https://doi.org/10.1007/s12053-013-9197-7.

Mangematin, E., Pandraud, G. and Roux, D. (2012) 'Quick measurements of energy efficiency of buildings', Comptes Rendus Physique, 13(4), pp. 383–390. Available at: https://doi.org/10.1016/j.crhy.2012.04.001.

Markovic, R. et al. (2018) 'Window opening model using deep learning methods', Building and Environment, 145, pp. 319–329. Available at: https://doi.org/10.1016/J.BUILDENV.2018.09.024.

Marshall, E. et al. (2016) 'Combining energy efficiency measure approaches and occupancy patterns in building modelling in the UK residential context', Energy and Buildings, 111, pp. 98–108. Available at: https://doi.org/10.1016/J.ENBUILD.2015.11.039.

MET Office UK. (2021, January 6). *NCIC Monthly Summary*. https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/uk-past-

Milne, J.M. and Reynolds, W.N. (1985) 'The Non-Destructive Evaluation Of Composites And Other Materials By Thermal Pulse Video Thermography', in Thermosense VII: Thermal Infrared Sensing for Diagnostics and Control. Available at: https://doi.org/10.1117/12.946141.

Ministry of Housing Communities & Local Government (2020) 'English Housing Survey 2019 to 2020', pp. 1–73. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/945013/2019-20_EHS_Headline_Report.pdf.

M.J. Sorgato, A.P. Melo, R.L.L. (2016) "The effect of window opening ventilation control on residential building energy consumption," *Energy and Buildings*, (133), pp. 1–13. Available at: https://reader.elsevier.com/reader/sd/pii/S0378778816309574?token=1820B5CEB45F35933EB78AE63A42E1ADC0C12C0252B427D32C93F89585BE1C7FD6DDB4DEE36EF1BD26BC897CCBFF5DF6&originRegion=eu-west-1&originCreation=20211231113523 (Accessed: December 31, 2020).

Mo, H. et al. (2019) 'Developing window behavior models for residential buildings using XGBoost algorithm', Energy and Buildings, 205. Available at: https://doi.org/10.1016/J.ENBUILD.2019.109564.

Moropoulou, A. et al. (2013) 'Non-destructive techniques as a tool for the protection of built cultural heritage', Construction and Building Materials, 48, pp. 1222–1239. Available at: https://doi.org/10.1016/j.conbuildmat.2013.03.044.

Morse, J. M. (2000) 'Determining Sample Size', Qualitative Health Research, pp. 3–5. doi: 10.1177/104973200129118183

Naspi, F. *et al.* (2018) "Measuring Occupants' Behaviour for Buildings' Dynamic Cosimulation." doi:10.1155/2018/2756542.

National Insulation Association. (n.d.). Retrieved January 17, 2019, from https://www.nia-uk.org/

Nevius, M.J. and Pigg, S. (2000) "Programmable thermostats that go berserk? Taking a social perspective on space heating in Wisconsin," *Proceedings ACEEE Summer Study on Energy Efficiency in Buildings*, 8, pp. 233–244.

Nicol, J.F. (2001) 'Characterising Occupant Behaviour in Building: Towards a Stochastic Model of Occupant Use of Windows, Lights, Blinds Heaters and Fans Human Factors 2 J. Fergus Nicol', in Seventh International IBPSA Conference. Rio de Janeiro, Brazil.

Nicol, J.F. and Humphreys, M.A. (2002) 'Adaptive thermal comfort and sustainable thermal standards for buildings', Energy and Buildings, 34(6), pp. 563–572. Available at: https://doi.org/10.1016/S0378-7788(02)00006-3.

O'Brien, W., Kapsis, K. and Athienitis, A.K. (2013) 'Manually-operated window shade patterns in office buildings: A critical review', Building and

Environment, 60, pp. 319–338. Available at: https://doi.org/10.1016/j.buildenv.2012.10.003.

Ofgem, 2022. Check if the energy price cap affects you | Ofgem [online]. Available at: https://www.ofgem.gov.uk/information-consumers/energy-advice-households/check-if-energy-price-cap-affects-you [Accessed 3 March 2022].

O'Kane, E. (2018) 'Mind the (Performance) Gap', Architectural Technology Journal, (127), p. 36.

Olesen, B.W. and Brager, G.S. (2004) 'A better way to predict comfort', ASHRAE Journal, 46(8), pp. 20–28.

Ouyang, J., Hokao, K., 2009. Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China. Energy and Buildings, 41(7), pp.711–720. 10.1016/j.enbuild.2009.02.003.

Padey, P. et al. (2021) 'Understanding the reasons behind the energy performance gap of an energy-efficient building, through a probabilistic approach and on-site measurements', Energies, 14(19). Available at: https://doi.org/10.3390/en14196178.

Pan, S. et al. (2019) 'A model based on Gauss Distribution for predicting window behavior in building', Building and Environment, 149, pp. 210–219. Available at: https://doi.org/10.1016/J.BUILDENV.2018.12.008.

Park, J. et al. (2021) 'Machine learning algorithms for predicting occupants' behaviour in the manual control of windows for cross-ventilation in homes', Indoor and Built Environment, 30(8), pp. 1106–1123. Available at: https://doi.org/10.1177/1420326X20927070.

Pasick, R.J. et al., 2009. Behavioral Theory in a Diverse Society: Like a Compass on Mars. Health Education and Behavior, 36(5_suppl), pp.11S-35S. 10.1177/1090198109338917.

Pigliautile, I. et al. (2020) 'Assessing occupants' personal attributes in relation to human perception of environmental comfort: Measurement procedure and data analysis', Building and Environment, 177, p. 106901. Available at: https://doi.org/10.1016/J.BUILDENV.2020.106901.

Pilkington, B., Roach, R. and Perkins, J. (2011) 'Relative benefits of technology and occupant behaviour in moving towards a more energy efficient, sustainable housing paradigm', Energy Policy, 39(9), pp. 4962–4970. Available at: https://doi.org/10.1016/j.enpol.2011.06.018.

Polinder, H. et al. (2013) 'Final Report Annex 53 - Occupant behavior and modeling (Separate Document Volume II)', p. 153. Available at: http://www.iea-ebc.org/fileadmin/user_upload/images/Pictures/EBC_Annex_53_Appendix_Volume_2.pdf.

Pretlove, S.E.C., 2000. Predicting Relative Humidity in UK dwellings. , (January).

Rea, M.S. (1984) 'Window blind occlusion: a pilot study', Building and Environment, 19(2), pp. 133–137. Available at: https://doi.org/10.1016/0360-1323(84)90038-6.

Reeves, S., Kuper, A. and Hodges, B. D. (2008) 'Qualitative research methodologies: ethnography', BMJ. British Medical Journal Publishing Group, 337, p. a1020. doi: 10.1136/BMJ.A1020.

Rijal, H.B. et al. (2008) 'Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings', Journal of Building Performance Simulation, 1(1), pp. 17–30. Available at: https://doi.org/10.1080/19401490701868448.

Rocha, P., Siddiqui, A. and Stadler, M. (2015) 'Improving energy efficiency via smart building energy management systems: A comparison with policy measures', Energy and Buildings, 88, pp. 203–213. Available at: https://doi.org/10.1016/j.enbuild.2014.11.077.

Salim, S. and Al-Habaibeh, A. (2019a) "The Effect of Insulation on Energy Savings in Residential Buildings - Myth or Reality?," in *The International Conference on Energy and Sustainable Futures (ICESF)*.

Salim, S. and Al-Habaibeh, A. (2019b) "The Effect of Insulation on Energy Savings in Residential Buildings - Myth or Reality?," in *The International Conference on Energy and Sustainable Futures (ICESF)*.

Salim, S. and Al-Habaibeh, A. (2020) 'How Often Do You Open Your House Windows When Heating is ON? An Investigation of the Impact of Occupants'

Behaviour on Energy Efficiency of Residential Buildings', in International Conference of Energy and Sustainable Futures. Hatfield, Hertfordshire, pp. 233–240. Available at: https://doi.org/10.1007/978-3-030-63916-7_29.

Schakib-Ekbatan, K. *et al.* (2015a) "Does the occupant behavior match the energy concept of the building? – Analysis of a German naturally ventilated office building," *Building and Environment*, 84, pp. 142–150. doi:10.1016/J.BUILDENV.2014.10.018.

Schakib-Ekbatan, K. *et al.* (2015b) "Does the occupant behavior match the energy concept of the building? – Analysis of a German naturally ventilated office building," *Building and Environment*, 84, pp. 142–150. doi:10.1016/J.BUILDENV.2014.10.018.

Schweiker, M. (2010a) *Occupant Behaviour and the Related Reference Levels for Heating and Cooling*.

Schweiker, M. (2010b) *Occupant Behaviour and the Related Reference Levels for Heating and Cooling*.

Schweiker, M. et al. (2011) 'Verification of stochastic models of window opening behaviour for residential buildings', Journal of Building Performance Simulation, 5(1), pp. 55–74. Available at: https://doi.org/https://doi.org/10.1080/19401493.2011.567422.

Schweiker, M. (2017) 'Understanding Occupants' Behaviour for Energy Efficiency in Buildings'. Available at: https://doi.org/10.1007/s40518-017-0065-5.

Sen, A. and Al-Habaibeh, A. (2020) The Effect of Covid-19 Pandemic on Energy Demand, Carbon Emission and Household Budget of Households in England due to Working from Home.

Shi, Z. et al. (2018) 'Seasonal variation of window opening behaviors in two naturally ventilated hospital wards', Building and Environment, 130, pp. 85–93. Available at: https://doi.org/10.1016/J.BUILDENV.2017.12.019.

Shipworth, D. (2012a) 'Carbon, Control and Comfort | UCL Energy Institute - UCL - London's Global University'. Available at: https://www.ucl.ac.uk/bartlett/energy/carbon-control-and-comfort (Accessed: 9 April 2019).

Shipworth, D. (2012b) Carbon, Control and Comfort: User-centred control systems for comfort, carbon saving and energy management. Available at: https://gtr.ukri.org/projects?ref=EP%2FG000395%2F1 (Accessed: 9 April 2019).

Shipworth, M. *et al.* (2009) "Building Research & Information Central heating thermostat settings and timing: building demographics." doi:10.1080/09613210903263007.

Shipworth, M. (2011) 'Thermostat settings in English houses: No evidence of change between 1984 and 2007', Building and Environment, 46(3), pp. 635–642. Available at: https://doi.org/10.1016/J.BUILDENV.2010.09.009.

Steg, L. and Vlek, C. (2009) 'Encouraging pro-environmental behaviour: An integrative review and research agenda', Journal of Environmental Psychology, 29(3), pp. 309–317. Available at: https://doi.org/10.1016/J.JENVP.2008.10.004.

Tang, T. (2010) Towards Sustainable Use: An Exploration of Designing for Behavioural Change. Loughborough University.

Tashakkori, A., Newman, I., 2010. Mixed methods. International Encyclopedia of Education, (1989), pp.514–520. 10.1016/B978-0-08-044894-7.00287-6.

Timperley, J. (2018) UK homes need 'deep efficiency retrofit' to meet climate goals - Energy Post, energypost. Available at: https://energypost.eu/retrofitting-energy-efficiency-in-uk-homes/ (Accessed: 25 April 2019).

United Nations Economic Commission for Europe (2018) Exchange of experience on standards and guidelines to improve significantly energy efficiency in buildings.

UK Government (2021) 'Families and households in the UK: 2020', Office for National Statistics, (March), pp. 1–4.

UK Statutory Instruments (2019) The Climate Change Act 2008 (2050 Target Amendment) Order 2019.

United Nations (2015) PARIS AGREEMENT. Paris.

Valentina, F., Andersen, R.V. and Corgnati, S.P. (2012) 'Window opening behaviour: Simulations of occupant behaviour in residential buildings using models based on a field survey', in Proceedings of 7th Windsor Conference: The Changing Context of Comfort in an Unpredictable World.

Weather Observation Website, Met Office WOW - Home Page [online]. MET Office. Available at: https://wow.metoffice.gov.uk/ [Accessed 25 October 2021].

Wei, S., Jones, R. and de Wilde, P. (2014) 'Driving factors for occupant-controlled space heating in residential buildings', Energy and Buildings. Elsevier Ltd, pp. 36–44. Available at: https://doi.org/10.1016/j.enbuild.2013.11.001.

Wei, S. et al. (2017) 'Impact of occupant behaviour on the energy-saving potential of retrofit measures for a public building in the UK', Intelligent Buildings International, 9(2), pp. 97–106. Available at: https://doi.org/10.1080/17508975.2016.1139538.

Wilson, G.T., Bhamra, T. and Lilley, D. (2010a) 'Reducing domestic energy consumption: a user-centred design approach', in Knowledge Collaboration & Learning for Sustainable Innovation ERSCP-EMSU Conference, Delft, The Netherlands, 25th-29th October 2010,. Delft, The netherlands: Delft University of Technology; The Hague University of Applied Sciences; TNO (c the authors), pp. 200–222.

Wilson, G.T., Bhamra, T. and Lilley, D. (2010b) 'Reducing domestic energy consumption: a user-centred design approach', in Knowledge Collaboration & Learning for Sustainable Innovation ERSCP-EMSU Conference, Delft, The Netherlands, 25th-29th October 2010,. Delft, The netherlands: Delft University of Technology; The Hague University of Applied Sciences; TNO (c the authors), pp. 200–222. Available at: https://dspace.lboro.ac.uk/2134/10912 (Accessed: 1 April 2019).

Wilson, G.T., Lilley, D. and Bhamra, T. (2013) 'DESIGN FEEDBACK INTERVENTIONS FOR HOUSEHOLD ENERGY CONSUMPTION REDUCTION', in 16th Conference of the European Roundtable on Sustainable Consumption and Production (ERSCP) & 7th Conference of the Environmental Management for Sustainable Universities (EMSU) (ERSCP-EMSU 2013). Istanbul, Turkey. Available at: https://dspace.lboro.ac.uk/ (Accessed: 1 April 2019).

World Business Council for Sustainable Development (2007) Energy Efficiency in Buildings Business realities and opportunities. Washington DC.

Yan, D. et al. (2017) 'IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings', Energy and Buildings, 156, pp. 258–270. Available at: https://doi.org/10.1016/j.enbuild.2017.09.084.

Yan, D., O'Brien, W., et al. (2015) 'Occupant behavior modeling for building performance simulation: Current state and future challenges', Energy and Buildings [Preprint]. Available at: https://doi.org/10.1016/j.enbuild.2015.08.032.

Yan, D., O'brien, W., et al. (2015) 'Occupant behavior modeling for building performance simulation: Current state and future challenges', Energy and Buildings, 107, pp. 264–278. Available at: https://doi.org/10.1016/j.enbuild.2015.08.032.

Yoshino, H., Hong, T. and Nord, N. (2017) 'IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods', Energy and Buildings, 152(July), pp. 124–136. Available at: https://doi.org/10.1016/j.enbuild.2017.07.038.

Yun, G.Y., Tuohy, P. and Steemers, K. (2009) 'Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models', Energy And Buildings, 41, pp. 489–499. Available at: https://doi.org/10.1016/j.enbuild.2008.11.013.

Zero Carbon Hub (2015) POST-OCCUPANCY EVALUATION. Gosport. Available at: www.zerocarbonhub.org (Accessed: 24 April 2019).

Zhang, W., Wu, Y. and Calautit, J.K. (2022) 'A review on occupancy prediction through machine learning for enhancing energy efficiency, air quality and thermal comfort in the built environment', Renewable and Sustainable Energy Reviews, 167. Available at: https://doi.org/10.1016/J.RSER.2022.112704.

Zheng, H. et al. (2019) 'Non-intrusive measurement method for the window opening behavior', Energy and Buildings, 197, pp. 171–176. Available at: https://doi.org/10.1016/j.enbuild.2019.05.052.

Zhou, X., Liu, T., et al. (2021) 'An action-based Markov chain modeling approach for predicting the window operating behavior in office spaces', Building Simulation,14, pp.301–315. Available at: https://doi.org/10.1007/s12273-020-0647-9.

Zhou, X., Ren, J., et al. (2021) 'Predicting open-plan office window operating behavior using the random forest algorithm', Journal of Building Engineering, 42. Available at: https://doi.org/10.1016/J.JOBE.2021.102514.

Appendix A

Online surveys

Survey on window opening behaviour of people

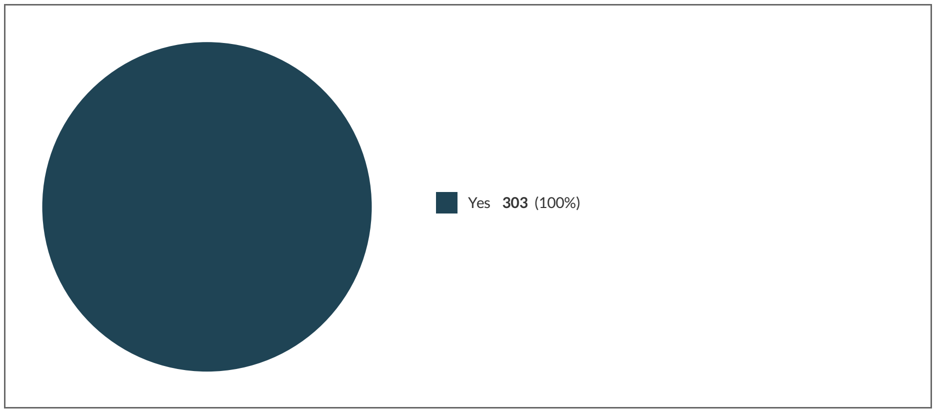
Showing 303 of 303 responses

With **4 responses excluded and 1 response deleted**

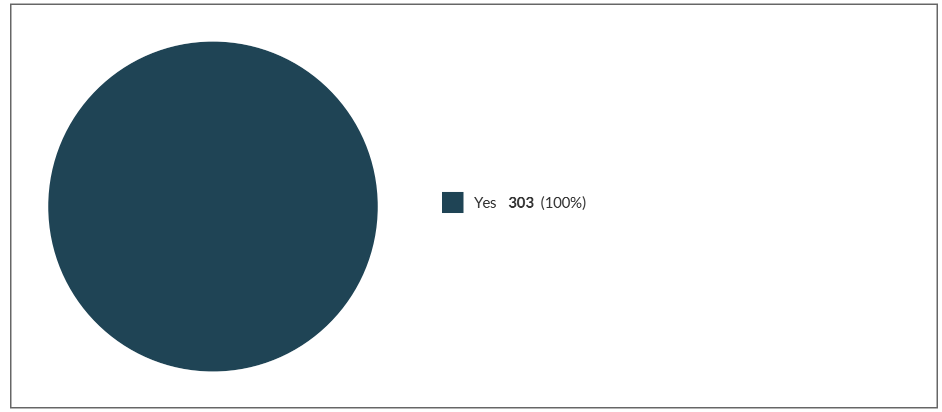
Showing **all** questions

Response rate: 303%

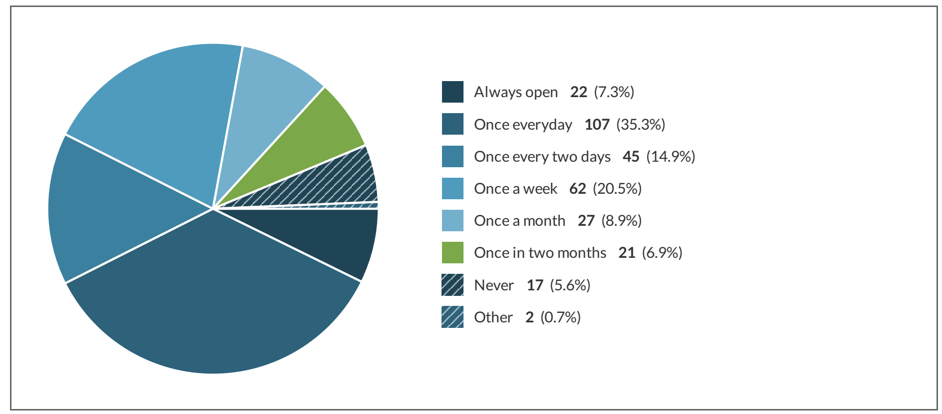
1 I agree to participate in the research study. I understand the purpose and nature of this study and I am participating voluntarily.



2 I grant permission for the data generated from this survey to be used in the researcher's publications on this topic



3 In winter, how often do you open windows in your house?

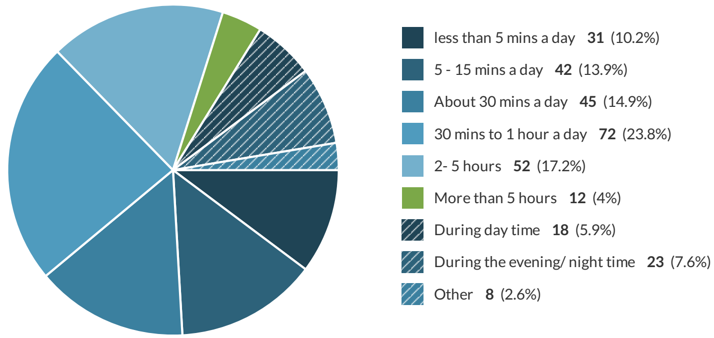


3.a If Other, please specify

Showing all 2 responses	
Twice a day	729640-729631-75505759
Whenever central heating isn't on and feel the need to do so (usually in the afternoons)	729640-729631-75510217

When windows are opened (in winter) how long are they left open for, usually?

4



4.a If Other, please specify

Showing all 8 responses	
Don’t open because I have a house cat.	729640-729631-75505723
Always locked open a crack	729640-729631-75506608
All the time	729640-729631-75507511
Never opened so no duration...	729640-729631-75506936
overnight and early morning	729640-729631-75509360
all day and night	729640-729631-75512700
Usually 2 windows 24/7 for ventilation. Another one during cooking.	729640-729631-75516912
If it’s frosty, not leaving windows open during the night, otherwise a slight opening of the window throughout the day and night is the norm in my house.	729640-729631-75537057

4.b Please add any additional comments for the above question, here

Showing all 98 responses	
I have my bedroom window open all night during the Winter. The heating is turned off at night. I open all our windows for an hour on Sundays as it's the only day I can safely air out the house due to lower traffic levels. Opening windows is also important to reduce viral spread.	729640-729631-75504884
Usually only bathroom window, after a shower or bath, occasionally kitchen window	729640-729631-75505391
Bathroom Windows & office windows stay open almost permanently except when in the bathroom.	729640-729631-75505911
I leave the bathroom window open (roughly a centimetre) on a latch all the time and fully open after a bath or shower, the bedroom window is always open (roughly a handspan) and the living room one is shut in winter and kitchen open when cooking	729640-729631-75506143
Depends on the room! Bathroom always open. Bedroom at night. Kitchen while cooking etc. Etc.	729640-729631-75506460
Only bedroom window is left open in winter	729640-729631-75506434
Can range from 15 mins to the whole daytime depending on which window or what the weather is like. Occasionally open them in the evenings as well.	729640-729631-75506086
Bedroom window is usually open all the time; sometimes on the draft setting, sometimes open. All other windows are usually closed most of winter	729640-729631-75506432
Usually when doing a deep clean	729640-729631-75506790
it's usually only cracked open a little bit	729640-729631-75506636
Kitchen windows are open during cooking as heat from oven and hob counter act the heat loss. Bedroom windows open for 2 mins per day to allow circulation	729640-729631-75506502
in the morning to get rid of smell and fog on windows after sleep	729640-729631-75506619
Usually when cleaning to get ventilation	729640-729631-75506683
Windows are usually left on the catch. Neither open or closed	729640-729631-75506730
these can sometimes be open during the day	729640-729631-75506650
have storage heaters, Would open bedroom windows for longer, but once the heat leaves the room, cannot turn the heating back on to reheat the room. Just cold all day.	729640-729631-75506173
Open to help with damp/mould in some rooms.	729640-729631-75506632
I overheat sometimes and will open and close windows often	729640-729631-75506445
just to let fresh air in and take condensate out.	729640-729631-75506933
Bedroom window throughout night	729640-729631-75507001
I'm opening my windows everyday, few times a day for 10 min	729640-729631-75506878
Bathroom window is left open longer	729640-729631-75507063
We have windows open while we are sleeping. Bathroom windows opened after showering	729640-729631-75506916
We live on a busy road	729640-729631-75507387
I open front and back to create a through draft	729640-729631-75507333
I have a house cat so only open 1 window she doesnt have access to, and that's for my tumble dryer hose.	729640-729631-75507250
Bedroom window always open	729640-729631-75507283

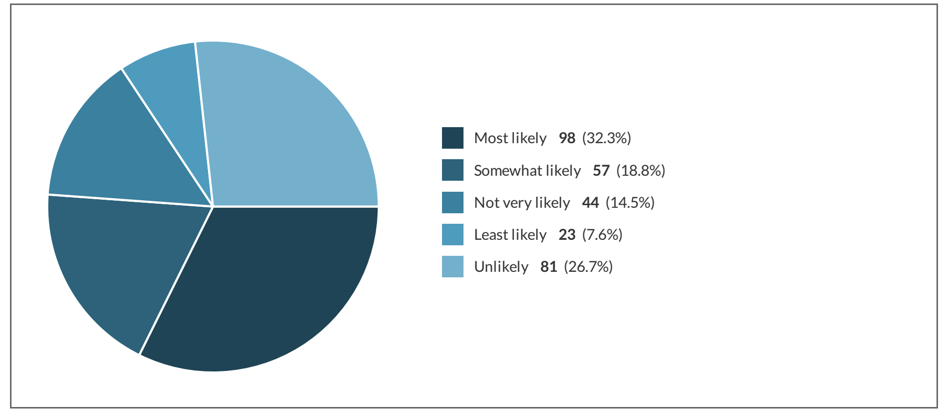
Its too cold in winter and lets all the heat out so i dont do it in winter	729640-729631-75507107
only in our bedroom	729640-729631-75507443
to clear condensation on the windows	729640-729631-75507470
Depends on how cold it is really. So would open the window on a "warmer day" during the week.	729640-729631-75507246
Windows may be opened to air out rooms for brief amounts of time that add up to 2+ hours	729640-729631-75507358
I always open the bedroom windows for a few hours.	729640-729631-75507357
It depends on whether I am home or at work.	729640-729631-75507361
length of time depends on weather/cold conditions	729640-729631-75507648
Bathroom slightly open all day and night, every day of the year	729640-729631-75507563
If it is extremely cold and windy then the above data does not apply	729640-729631-75507439
in bathroom to prevent windows streaming	729640-729631-75507809
Sometimes windows are open longer if my housemate has been cooking.	729640-729631-75507289
Open a few windows such as bathroom and kitchen but only very slightly	729640-729631-75507533
I tend to open the back door instead of our windows. Are windows are very old single glazed and on thier last legs	729640-729631-75507320
while I am cleaning	729640-729631-75507751
House is at 1400' and exposed.	729640-729631-75506936
bedroom windows always open	729640-729631-75507795
Mainly bedroom and bathroom windows	729640-729631-75507640
usually in response to cooking/smokey atmosphere	729640-729631-75507702
We usually leave a window open when we go out to run errands	729640-729631-75507224
I open the window to my balcony, maybe that is technicalyl a door?	729640-729631-75508166
If they are opened (smells etc) then it is for a short a time as possible.	729640-729631-75507388
This is dependent on how cold it is	729640-729631-75508167
We don't open all windows in winter. Usually just bedroom windows	729640-729631-75508210
Need to air out the place everyday	729640-729631-75508290
I open some windows more than others. The window in the kitchen gets open all the time as the cat goes in and out and I need to let out the smoke as I burn the food a lot (I am quite distracted person). The bedroom gets window open as my husband does not feel cold and that window stays open sometimes a day or two. The windows in the children's rooms get opened hardly ever. Maybe once a week a bit. The living room....not often as it is noisy and quite a bit of pollution.	729640-729631-75507972
I live in a very poorly insulated building, my upstairs neighbour is able to drop my temps by over 4c in winter by leaving windows open 24/7, as a	729640-729631-75508093

result I open mine as little as possible in order to not do the same to the bloke beneath me.	
Mainly opening bathroom windows after showers etc.,	729640-729631-75508521
It depends in how cold it is	729640-729631-75508672
Normally to dissipate steam in kitchen when cooking.	729640-729631-75508354
Windows are open for a few hours to all day in the bedroom to air out the bed. Rest of the house we tend to open windows in the bathroom for an hour or so after getting ready. Open windows in all other rooms when needs, e.g. when airing out laundry, get rid of smells, while cooking etc.	729640-729631-75508239
I mainly open bedroom window but usually open back door as well	729640-729631-75508512
I only open the windows when the heat in the house gets too much for me.	729640-729631-75508590
This is too fixed. What do I mean - depending on the weather I might open the windows less. In the kitchen, bathrooms I may well open windows daily.	729640-729631-75508395
Our bathroom window is open nearly every day and our bedroom most days but it depends on how cold it is outside. If mild, we open windows every day.	729640-729631-75507682
Open overnight in occupied bedrooms unless very cold or stormy	729640-729631-75508914
We like to have fresh air into the bedroom at night...just a little in the winter and wider in the summer	729640-729631-75508430
When cooking	729640-729631-75508955
Only in the bedroom	729640-729631-75508780
open small window in bedroom overnight all year round except in wet or windy conditions	729640-729631-75508724
usually bedroom & bathroom windows, upstairs	729640-729631-75509162
i only open the windows in the bedrooms	729640-729631-75509226
Bedroom and bathroom windows are open at all times. I have answered the previous question relating to living room windows only.	729640-729631-75508901
This might only be 1 window not all the windows in the house. If I leave them open it will only be partially. wins	729640-729631-75508556
I do sometimes have a window open all night as I like fresh air in the bedroom. Never with the heating on.	729640-729631-75508905
window trickle vents are left open to prevent condensation	729640-729631-75509699
I mean the kitchen and bathroom windows in the mornings in winter	729640-729631-75509470
The windows are opened only when drying clothes indoors, or cooking and it gets steamy.	729640-729631-75508979
We open quarter lights in our bedroom when we go to bed, unless extremely windy	729640-729631-75508906
I would only open the kitchen window to allow smoke to escape when cooking.	729640-729631-75509571

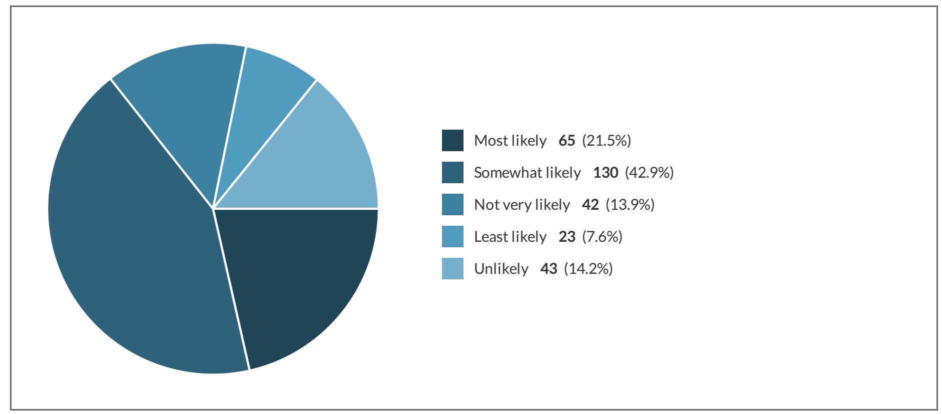
cooking.	
Unless very cold or windy a bedroom window is open when in bed.	729640-729631-75509638
We leave a small bedroom window (fanlight) constantly open	729640-729631-75509791
Heating would be off	729640-729631-75510017
During the daytime and a few times at night if the house is too stuffy.	729640-729631-75510216
I open my windows almost everyday for 20-30 minutes to let fresh air come in.	729640-729631-75509954
Tend to open the window to clear steam from the bathroom and more likely to do it on a sunny day. Don't bother in bad weather.	729640-729631-75509946
Usuall to air bedroom and bathroom	729640-729631-75510591
Windows open in master bedroom for fresh air while sleeping	729640-729631-75508560
I have at least one window slightly open about half and inch all day for air circulation.	729640-729631-75509766
weather permitting we mopen the windpws as much as we can upstairts not so much down staors	729640-729631-75510644
We only try to open windows in winter when we have turned off heating	729640-729631-75511182
I open only when I clean the window.	729640-729631-75510952
We don’t open all windows just some of them once a day	729640-729631-75511673
the windows would only be opened if it was a relatively warm day and to bring about a change of air in the house	729640-729631-75510367
the bathroom window is open all day and night, others are open during the day time only	729640-729631-75512700
depends on the weather outside	729640-729631-75514242
Not all windows, only kitchen and bathroom but not every day either.	729640-729631-75514121
I dont always remember to open them but we have a cleaner sometimes and she always opens them when she's working even in winter	729640-729631-75520326
Only open during cooking	729640-729631-75528665
Open in kitchen and bathroom	729640-729631-75508980
Since I have a weak chest I am cautious not to be in a draft directly, as a result when frosty outside I leave no windows open during the night, but need fresh air usually.	729640-729631-75537057

5 What time of the day are you most likely to open your windows, in winter?

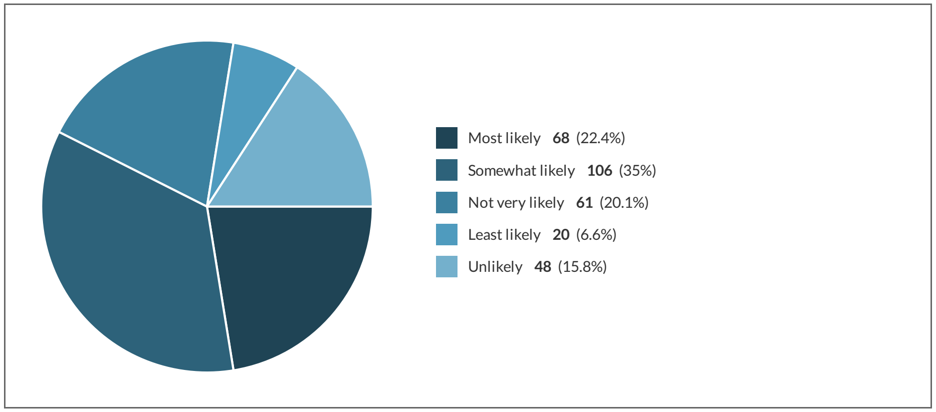
5.1 Early morning



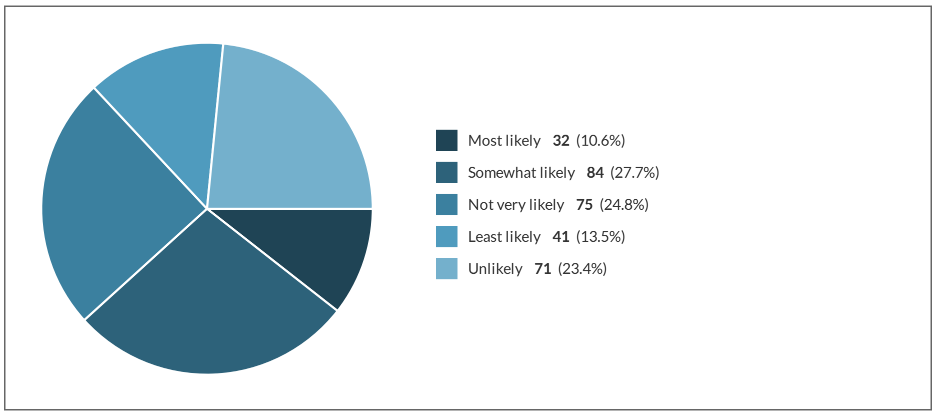
5.2 Late morning



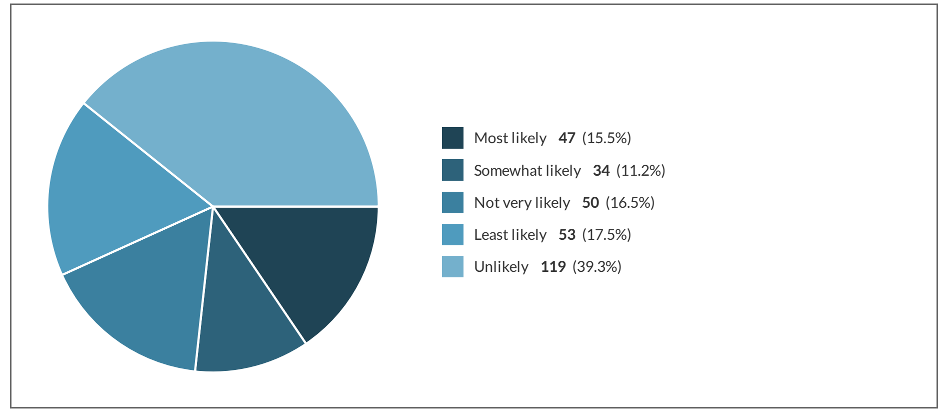
5.3 Early afternoon



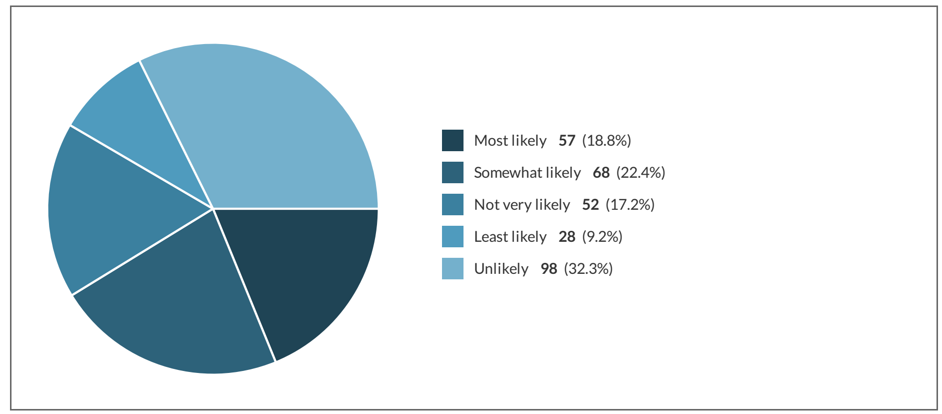
5.4 Late afternoon



5.5 Evening



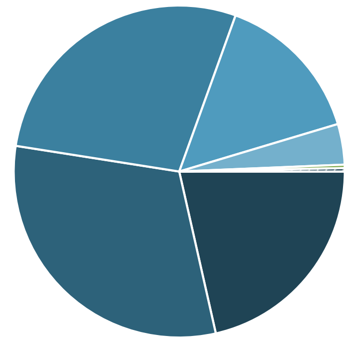
5.6 I open windows randomly



5.a Please add any additional comments for the above question, here

Showing all 24 responses	
before or after work, same reason as above	729640-729631-75505391
Bedroom only	729640-729631-75506434
Bedroom windows in morning and kitchen during evening dinner	729640-729631-75506502
Sometimes open all windows before we go out	729640-729631-75506916
Only when it snow	729640-729631-75507343
Kichen window will be opened randomlg	729640-729631-75507357
Bathroom window only, others are only opened occasionally in Winter but always in Summer	729640-729631-75507563
Windows would only be opened to ventilate due to say burnt toast.	729640-729631-75506936
Generally open windows when its too hot or when cooking / using shower	729640-729631-75507925
This will be as and when needed	729640-729631-75507388
Late evening - Most Likely - in the bedroom	729640-729631-75508430
More frequent is the toilet window for fresh air	729640-729631-75508037
Early afternoon south windows, late afternoon west windows.	729640-729631-75508600
These answers depend on the time of year.	729640-729631-75508905
Early morning - shower room and bathroom	729640-729631-75509335
sitting room windows randomly if the weather is good, i.e. sunshine	729640-729631-75509470
Occasionally open ceiling sky lights in kitchen if cooking and doing laundry	729640-729631-75508906
This would be to allow smoke to escape when cooking.	729640-729631-75509571
First thing in the morning if the weather isn't too bad	729640-729631-75509387
Unless very cold or windy a bedroom window is open when in bed.	729640-729631-75509638
I have at least one window slightly open about half and inch all day for air circulation.	729640-729631-75509766
Kitchen window is open in evening due to cooking	729640-729631-75511673
Depends on the window, bathroom window open nearly all day and night, bedroom windows when the last person leaves, the kitchen window is open during and after cooking then closed at the end of the day.	729640-729631-75512700
Only open if needed e.g. steam in bathroom, cooking in kitchen, this is random.	729640-729631-75514121

6 How often do you open windows when the heating is ON?



6.a If Other, please specify

Showing 1 response	
I switch off the radiator in the room in question and keep the door shut	729640-729631-75510581

6.b Please add any additional comments for the above question, here

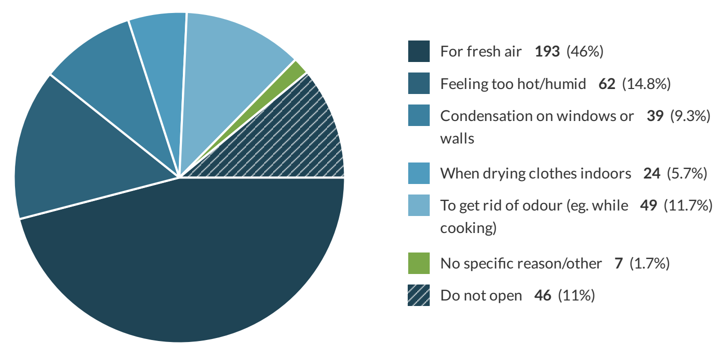
Showing all 44 responses	
My son sometimes decides his room is too warm and opens the window while heating is on.	729640-729631-75505035
I open windows on Sundays as traffic fumes are lower.	729640-729631-75504884
if bathroom window open then the door is closed to minimise heat loss for the rest of the house	729640-729631-75505391
As mentioned our bathroom windows & office windows are open mostly even when heating is on.	729640-729631-75505911
We don't use the heating often because we can't afford it and we all run hot anyway.	729640-729631-75506130
I'll open the windows if it gets too hot but only for a short time to keep the warmth.	729640-729631-75506574
Bedroom only	729640-729631-75506434
Mainly open before heating comes on	729640-729631-75506502
the odd windo could be open to llow air to flow	729640-729631-75506650
As said above, old storage heaters, which limits opening, because cannot turn up	729640-729631-75506173

Heating off in day time (9-5pm)	729640-729631-75506632
Usually bathroom window to prevent condensation	729640-729631-75507122
Bathroom windows may be opened for a short time while the heating is on, depends when we shower	729640-729631-75506916
It is for the tumble dryer as explained and sometimes heating is on too	729640-729631-75507250
Heating in general is on but windows open in bedrooms where radiators are off. Cant sleep with the central heating on!	729640-729631-75507212
would waste the heat i just dont do that	729640-729631-75507107
High thermal mass of building means the heating is never off, though it is under thermostatic control.	729640-729631-75506936
generally keep windows shut if heating on unless need to let steam etc out or when cooking etc	729640-729631-75507925
Only open in morning after sleeping and showering	729640-729631-75507640
Sometimes if the house gets too hot (rarely!) when the oven is on with the heating for example then i may open a window for a short amount of time.	729640-729631-75507388
I dont use my heating	729640-729631-75508233
I open the windows in order to create an air flow and get fresh air into the house. This may be during the time I have heating on, but I don't open the windows to bring the temperature down.	729640-729631-75507915
Thermostatic control mean the heating doesn't have a regular on/off cycle. So heating can come on while windows are open.	729640-729631-75508210
I tend to first open the windows, then put on the heating once I close them.	729640-729631-75507972
We use a thermostat to heating on off. Unless I open most windows I don't actively turn the heating down. If the house cools down too much and the heating comes on we can hear this so tend to close windows.	729640-729631-75508239
Just to let some fresh air in	729640-729631-75508546
We have no neating upstairs, open fire in living room and night-storage in kitchen so it's hard to say.	729640-729631-75507682
Our heating is turned off at 20.00 automatically	729640-729631-75508430
Especially the kitchen windows if for some reason there is some smoke	729640-729631-75508037
Try not to loose too much heat.	729640-729631-75508600
I get a lot of condensation and need to open the windows after cooking or bathing	729640-729631-75508556
Try not to waste energy so never with heating on.	729640-729631-75508905
exception is the bathroom ..always open during morning	729640-729631-75509470
Only if drying clothes indoors, or cooking.	729640-729631-75508979
Heating is off at night when we open windows going to bed, but underfloor	729640-729631-75508906

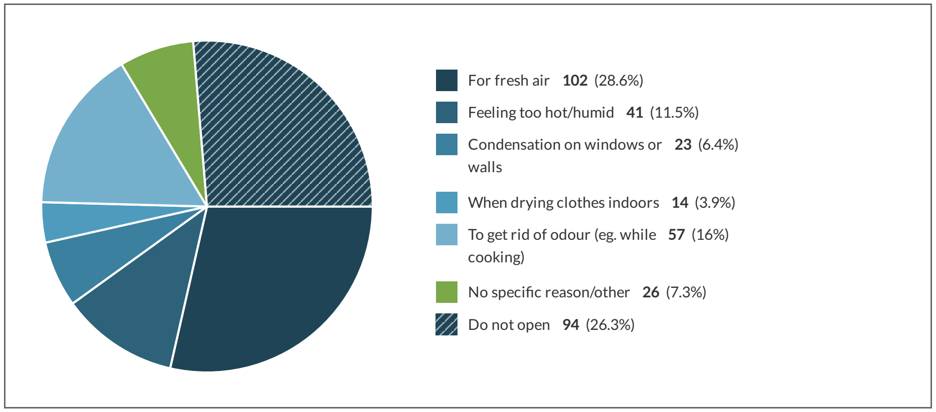
heating is always on thermostat	
Again just to allow smoke to escape.	729640-729631-75509571
During the winter period, I open the windows only 2-3 times in a few weeks while the heating is on.	729640-729631-75510168
I have at least one window slightly open about half and inch all day for air circulation.	729640-729631-75509766
I may open the windows when heating is on but it would never be intentionally.	729640-729631-75509725
occassions when this might occur would be possiblly to remove odours or smoke from cooking	729640-729631-75510367
These windows tend to be away from heat sources.	729640-729631-75512700
During cooking	729640-729631-75528665
bathroom and kitchen areas	729640-729631-75508980
But only very slightly, I do have drafty windows in some areas.	729640-729631-75537057

7 Select the reasons that prompt you to open windows.

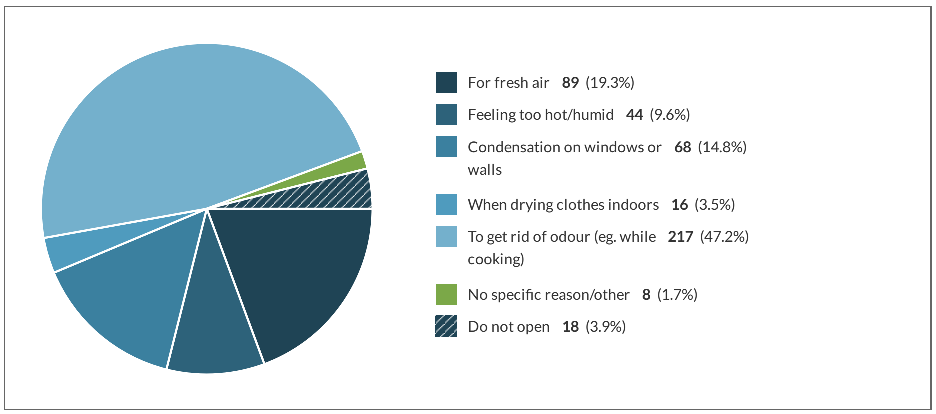
7.1 Living room/ open plan living room



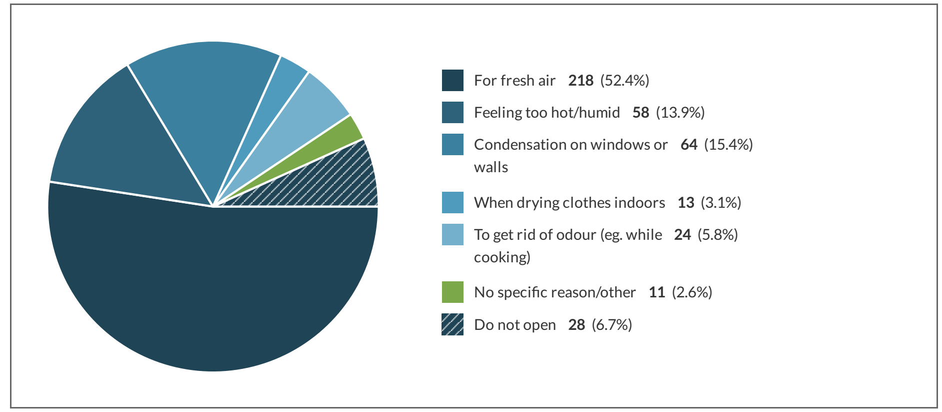
7.2 Dining room



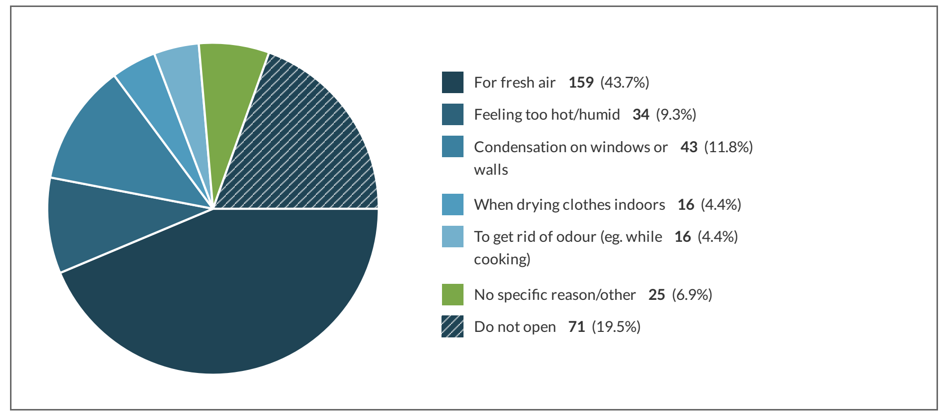
7.3 Kitchen



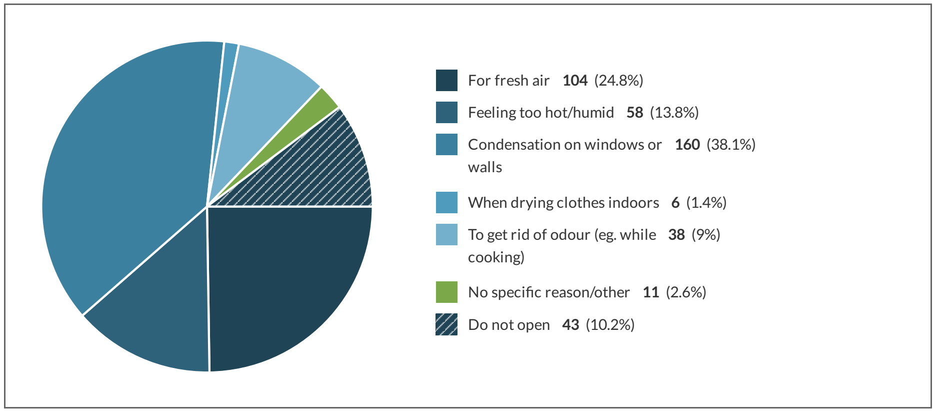
7.4 Main bedroom



7.5 Other bedrooms



7.6 Bathrooms



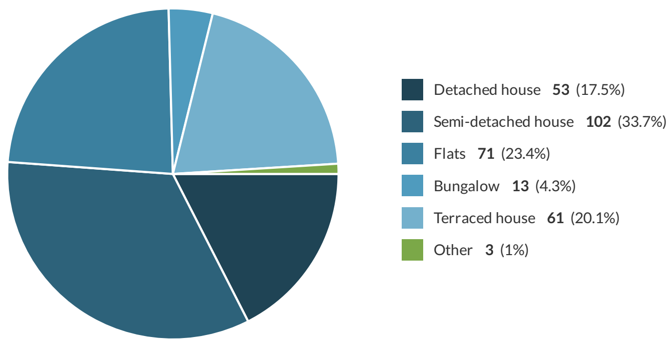
7.a Please write down any other reason for opening windows, not mentioned above

Showing all 43 responses	
help with damp	729640-729631-75505193
To reduce viral spread by ventilating the house. I'm extremely clinically vulnerable.	729640-729631-75504884
Dining room window ajar when drying clothes (tumble dryer on) closed shortly after drying cycle.	729640-729631-75505391
I also sometimes open when cleaning, depending on the products used	729640-729631-75506189
'No specific reason / other' - selected for rooms I don't have in my flat, so question does not apply.	729640-729631-75506086
Nice sunny day. Not too cold	729640-729631-75506502
To let out insects the have flown in	729640-729631-75506784
to allow smoke to go out	729640-729631-75506650
Aware of fresh air's role in keeping down coronavirus, always aware of that when opening windows now	729640-729631-75506173
I don't know more reasons	729640-729631-75506878
To watch snow	729640-729631-75507343
Get rid of smells eg the dogs	729640-729631-75507212
Bathroom has no window.	729640-729631-75507361
spring airing of whole building	729640-729631-75507648
To get rid of the smell of wet dog after winter walks!	729640-729631-75507798
Answers are for any time of the year not just winter. Winter would really	729640-729631-75506936

only see the kitchen window opened for cooking odours.	
We do not have a bathroom window.	729640-729631-75507224
none	729640-729631-75507388
I smoke inside	729640-729631-75508542
Teenage children get smelly. :-)	729640-729631-75507972
I open a bedroom for ventilation when on my exercise bike	729640-729631-75508354
To get rid of smell of smoke from open fire. To remove dusty smell after hoovering	729640-729631-75507682
no windows in bathrooms	729640-729631-75508973
No other reasons	729640-729631-75508635
We also open hallway windowsas this seems to effect the whole house refreshing it.	729640-729631-75508808
For fresh to limit COVID-19 infections among our big family members who include school going children	729640-729631-75508037
To refresh the air. We do not have a heat recovery system.	729640-729631-75508600
Cleaning	729640-729631-75508556
If decorating	729640-729631-75509523
There are no windows in the bathrooms, so this part of the question is not applicable for my home.	729640-729631-75508979
To get rid of musty smells	729640-729631-75509387
I open my windows almost everyday for 20-30 minutes to get fresh air.	729640-729631-75509954
Mostly for a short time to get rid of humidity and smells	729640-729631-75510365
Like the air during night time or when it rains	729640-729631-75510217
none	729640-729631-75510552
Bathroom has no windows, but only an extractor fan	729640-729631-75508560
I have at least one window slightly open about half and inch all day for air circulation.	729640-729631-75509766
we have an open plan kitchen/dining area/clothes drying area so need to open the door to garden for humidity reduction. However we tend to do that when heating is off	729640-729631-75511182
When clean the window.	729640-729631-75510952
To prevent mould	729640-729631-75511095
N/A	729640-729631-75510367
My policy is: windows and doors are closed and central heating is on permanently during winter. Windows and doors are open during the spring/summer with the heating off.	729640-729631-75514121

Clean fresh air in the house, I tend to leave the back door (bedroom door to patio), first thing for at least 10 minutes, whatever the weather and then leave the window open after closing that back bedroom door.	729640-729631-75537057

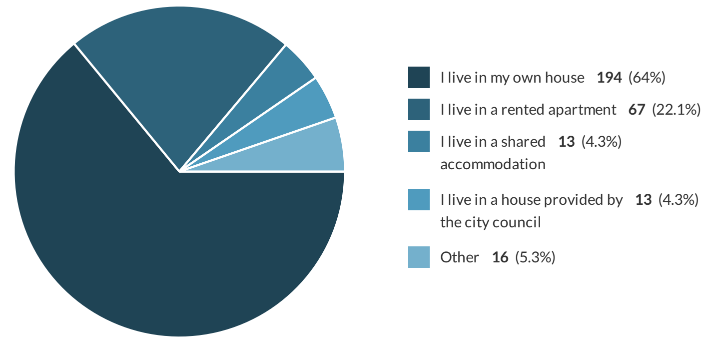
8 Please mention the type of accommodation you live in



8.a If you selected Other, please specify:

Showing all 3 responses	
Maisonette.	729640-729631-75508905
mobile home	729640-729631-75509470
upper maisonette	729640-729631-75524755

9 Please choose one of the following

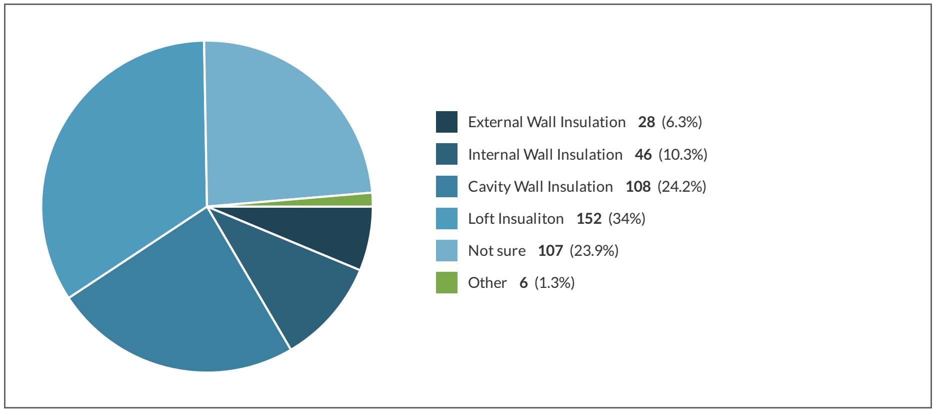


9.a If you selected Other, please specify:

Showing all 16 responses	
I live in a rented housing association house.	729640-729631-75504884
Rented house	729640-729631-75506139
Rented house	729640-729631-75506256
Flat owned with a mortgage	729640-729631-75506683
Live with parents	729640-729631-75506730
family	729640-729631-75507048
with parents	729640-729631-75507878
I live with my parents	729640-729631-75507956
Private rented house	729640-729631-75507640
rented house	729640-729631-75507682
privately rented bungalow	729640-729631-75508724
A rented flat with other family members	729640-729631-75508037
Rented house from private landlord	729640-729631-75509746
owned by a relative	729640-729631-75510217
Rent house	729640-729631-75508289
House rented from housing association	729640-729631-75508560

Please state the insulation properties of your house.

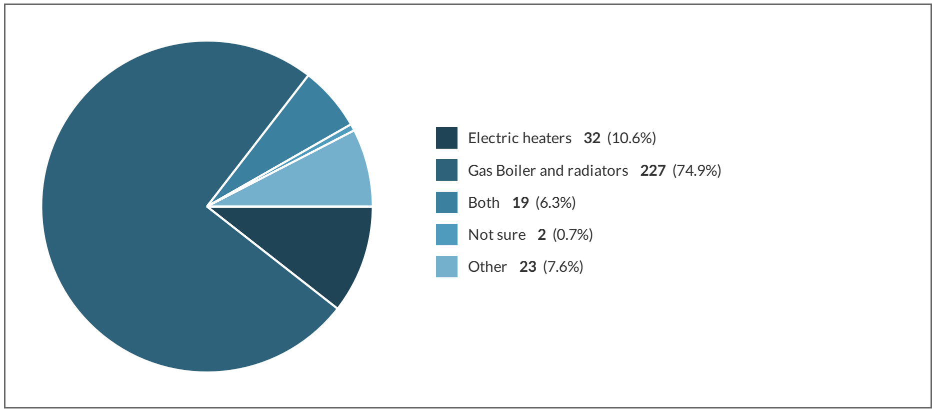
10



10.a If Other, please specify

Showing all 6 responses	
None	729640-729631-75504742
none of these. The house is over two hundred years old and has stone and very thick walls	729640-729631-75507320
There is none, we have cavity walls with no insulation between the flats, no plasterboard on the walls, no external insulation, worst housing I've ever had, no sound insulation either, it's so bad we can hear each others conversations.	729640-729631-75508093
I live in a grade 2 listed building. The original builder did very little insulation.	729640-729631-75508354
Mixed, no cavity wall insulation in original (1929) parts of house, but recent extension to side and rear complies to current building regs. Loft DIY insulated	729640-729631-75508906
none	729640-729631-75514242

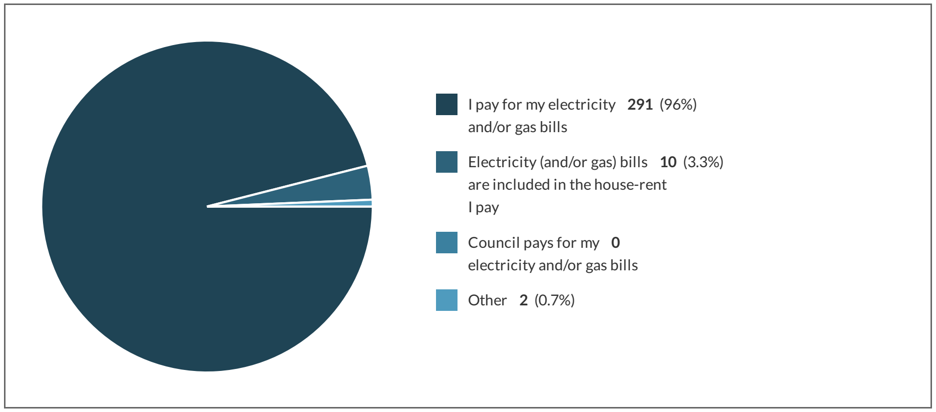
11 Please mention the type of heating used in your house.



11.a If Other, please specify

Showing all 23 responses	
Oil boiler and radiators	729640-729631-75505969
Small fan heater	729640-729631-75506172
Oil with radiators.	729640-729631-75505723
Vents	729640-729631-75507005
Coal central heating	729640-729631-75507122
Gas fires	729640-729631-75507226
Oil fired central heating	729640-729631-75507563
oil fired radiators and we also use two extra oil heaters in the winter, one at the back of the house and one near the front door which is drafty	729640-729631-75507320
Primary oil with solar thermal and wood burner all feeding a thermal store for part. Other part electric night storeage heaters.	729640-729631-75506936
oil boiler and radiators	729640-729631-75507795
Oil boiler and radiators	729640-729631-75507939
gas fire	729640-729631-75507702
Oil boiler and radiators	729640-729631-75508210
Log Burner	729640-729631-75508354
night-storage heater, electric heaters and open fire	729640-729631-75507682
Oil boiler and radiators	729640-729631-75509443
Oil boiler and radiators. Wood burner	729640-729631-75508556
Oil and radiators - no gas connections in village	729640-729631-75509335
oil	729640-729631-75509799
Gas boiler and radiators, underfloor heating in gf extension (half entire floor area)	729640-729631-75508906
Oil fired boiler	729640-729631-75509987
Air heat transfer system	729640-729631-75510688
oil fired boiler	729640-729631-75510644

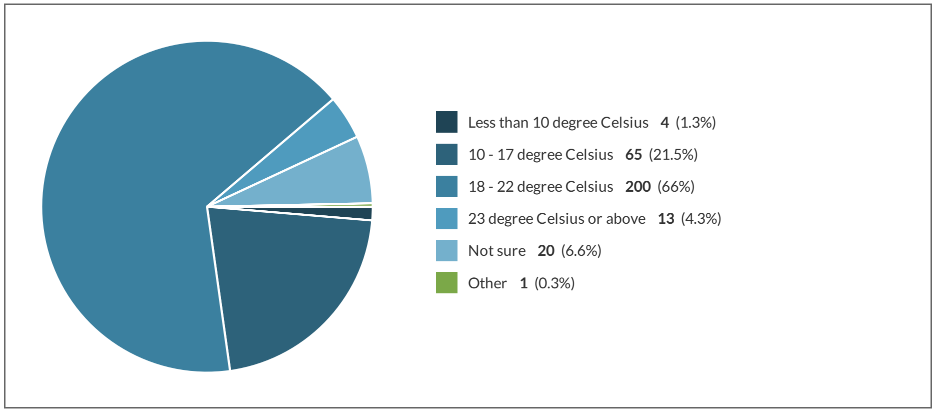
12 Please choose from the following options.



12.a If Other, please specify:

Showing all 2 responses	
Parents pay for electricity and gas bill	729640-729631-75506139
Parents pay	729640-729631-75506730

13 What is the preferred ambient temperature of your house.



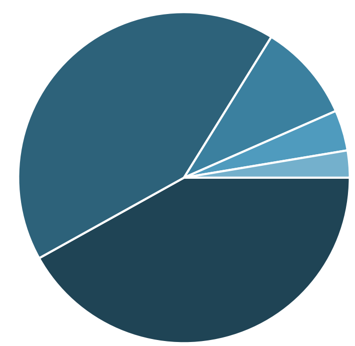
13.a If Other, please specify

Showing 1 response	
18 - 22 normally, but increased in winter if there is an easterly wind	729640-729631-75508906

13.b Please add any additional comments for the above question, here

Showing all 17 responses	
Lower temperature overnight.	729640-729631-75505035
At night I prefer a temperature of below 18 Deg. I use an air conditioner in the Summer as high temperatures negatively affect my sleep.	729640-729631-75504884
based on thermostat readings	729640-729631-75505391
depends on the weather, but usually 18 degrees, in summer it could go below.	729640-729631-75505911
House ancient, draughty, barely insulated. Coal fire plus storage heaters. Expensive and often too cold	729640-729631-75506173
I get very hot due to my age but we try not to open the windows too much to preserve the heat within the walls as it does get colder later. We tend to rely on our aga in the kitchen for heat as there is no other radiator in that room and our log burner in the evening. We keep our use of radiators etc to a minimum to keep the costs down. I only tend to open the windows when it is very hot and too hot to cook without opening one.	729640-729631-75507320
I prefer mine at 15 but everyone else favours 18	729640-729631-75507224
I like it hot and keep a heater in my study. My husband does not and keeps opening the windows in the rest of the house.	729640-729631-75507972
I'm rarely able to achieve my desired temps as the windows in the flat above are open all winter, I'm lucky if I can manage to get any part of my flat as high as 16c in the winter despite using a fan heater to supplement the central heating.	729640-729631-75508093
15-16 during the night, 18-20 during the day	729640-729631-75508239
It is often below 10 degrees in the hall, landing and bedrooms	729640-729631-75507682
Unused bedrooms - heating turned down when not in use	729640-729631-75509335
Sometimes use an efficient gas 'log fire' when very cold, especially in Spring/Autumn when central heating is off	729640-729631-75508906
Daytime usually set at 20.5 and down to 19 at night.	729640-729631-75509725
our incentive for reducing heating is financial to save money	729640-729631-75511182
In winter themostat is set to 20c during the day if cold and 15c at night on going to bed	729640-729631-75510367
I use additional paraffin heater to save using the central heating in the hallway and to save money.	729640-729631-75514121

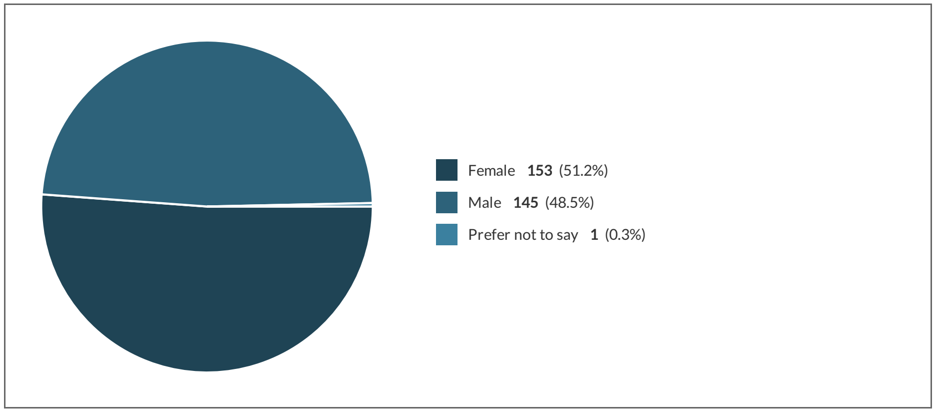
14 What kind of heating control do you use.



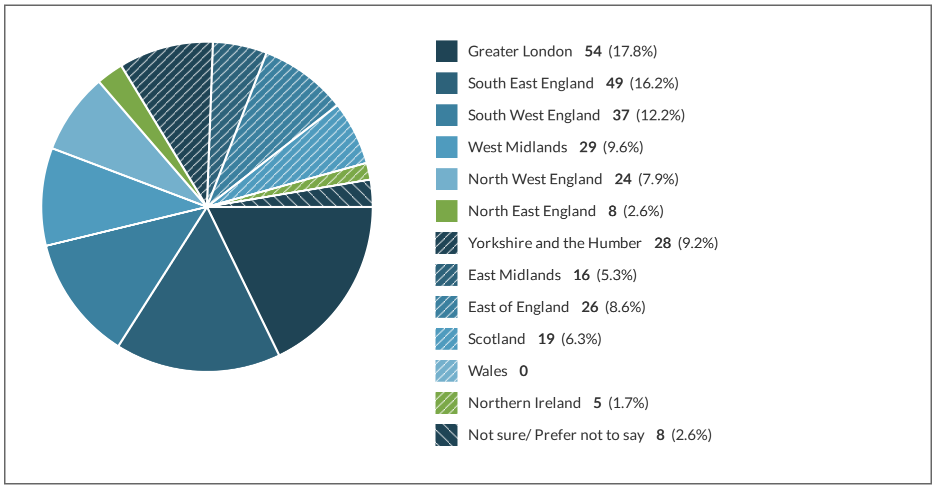
14.a If Other, please specify:

Showing all 8 responses	
Its a fan heater on the floor	729640-729631-75506172
Storage heaters	729640-729631-75506683
Hahaha. There is no control on our ancient heating system	729640-729631-75506173
Programmable thermostats automaticaly adjust set temperature according to time of day.	729640-729631-75506936
none	729640-729631-75507795
no thermostat	729640-729631-75507682
The landlord sets a fixed temperature for the shared central heating in the evening which I have no control over.	729640-729631-75509766
It is very old, so switch on and off manually	729640-729631-75508980

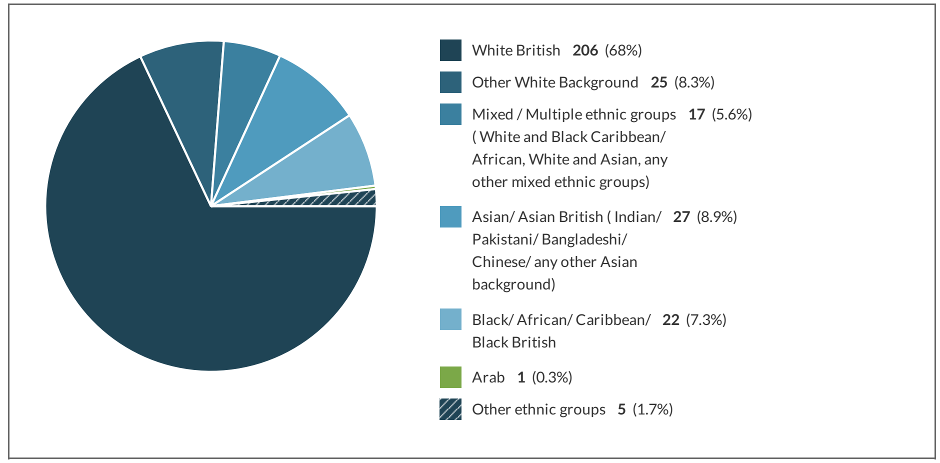
15 Please state your sex



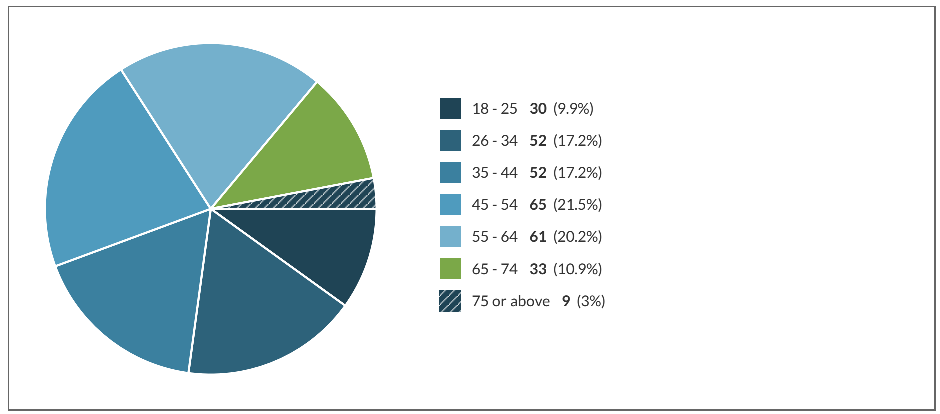
16 Which part of the UK do you currently reside in



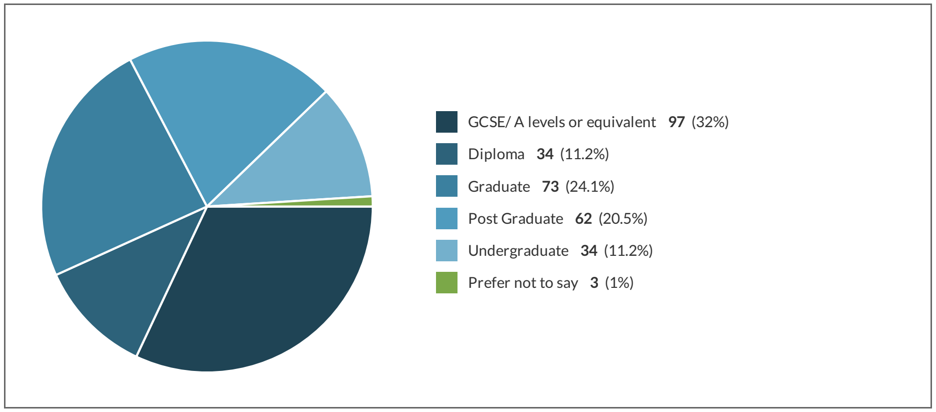
17 Please state your ethnicity.



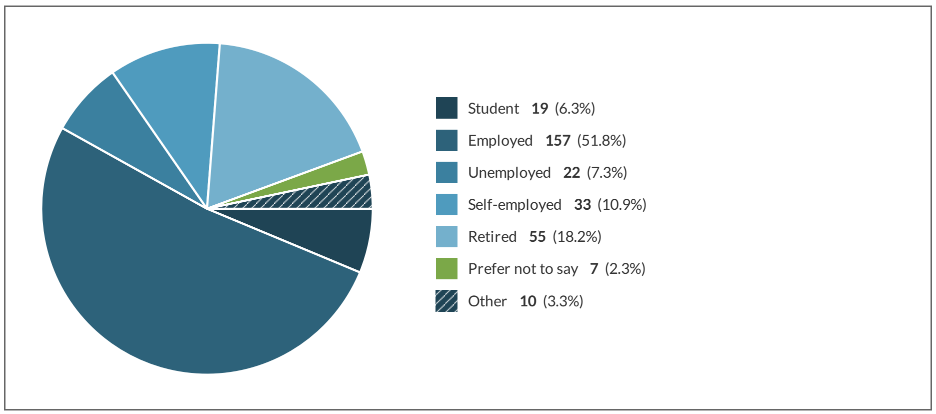
18 Please state your age group.



19 Please state your level of education



20 Please state your employment status

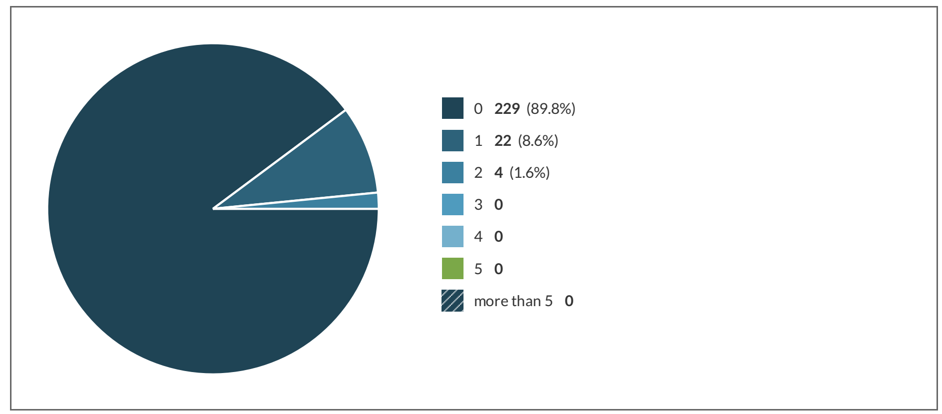


20.a If you selected Other, please specify:

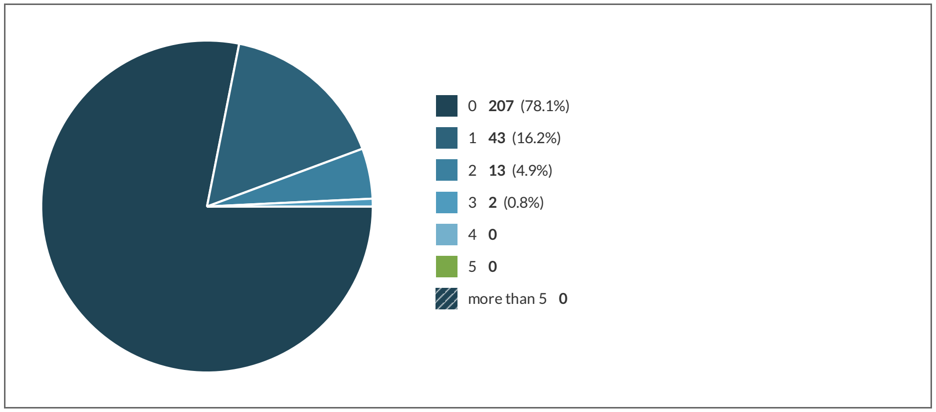
Showing all 10 responses	
Housewife	729640-729631-75504884
Volunteer	729640-729631-75506730
Stay at home parent	729640-729631-75506784
Unable to work	729640-729631-75507250
homemaker	729640-729631-75507585
Born disabled	729640-729631-75507224
Part Time	729640-729631-75508290
Part-time employment	729640-729631-75508037
Disabled	729640-729631-75509443
Freelancer	729640-729631-75511095

21 Please state the number of people in your house.

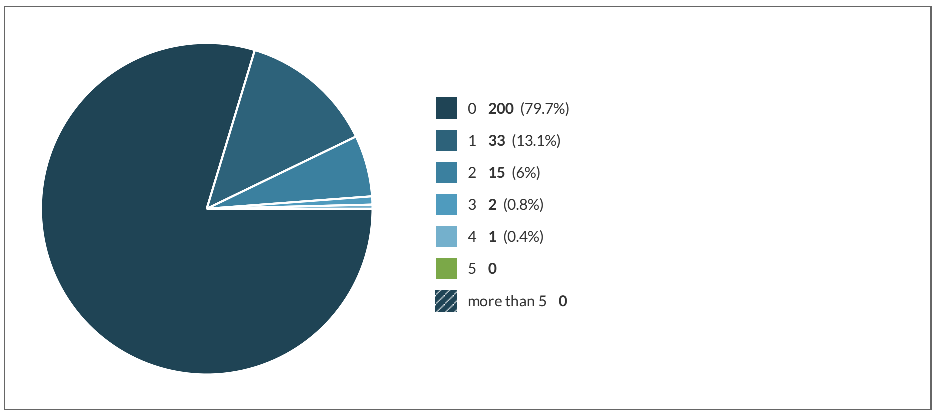
21.1 Babies(aged 0 - 2 yrs)



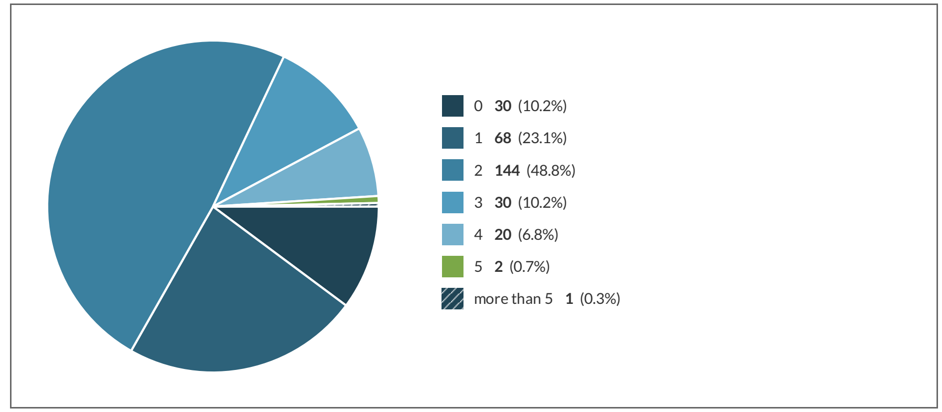
21.2 Children (aged 3 -12 yrs)



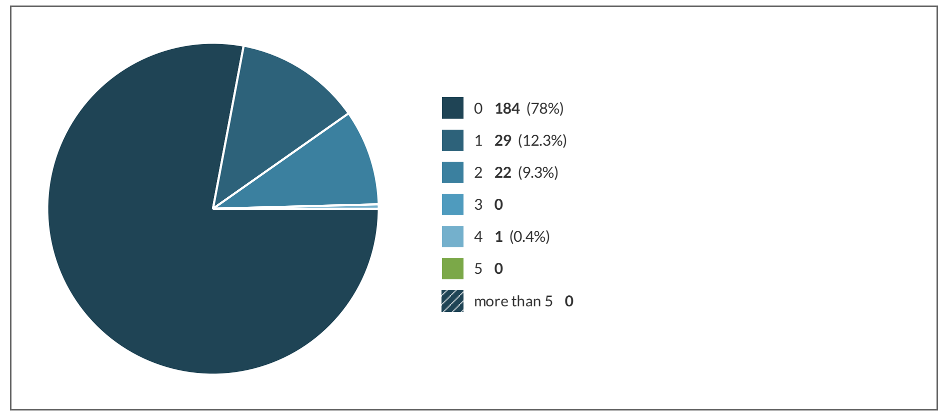
21.3 Youth (13 - 18)



21.4 Adults (aged 19 - 64 yrs)



21.5 Senior citizens (aged 65 yrs or older)



Appendix B

Comparison of Energy Demand in 4 types of Houses

House A - House 11 - High Insulation and Window Open
House B - House 2 - High Insulation and Window Closed
House C - House 16 - Low Insulation and Window Open
House D - House 5 - Low Insulation and Window Closed

1

Winter 1

Feb – March 2013

2

Instances

Inst1 = [18-Feb-2013 00:00:0018-Feb-2013 23:59:00]

Inst2 = [19-Feb-2013 22:00:0020-Feb-2013 22:00:00]

Inst3 = [22-Feb-2013 09:00:0023-Feb-2013 09:00:00]

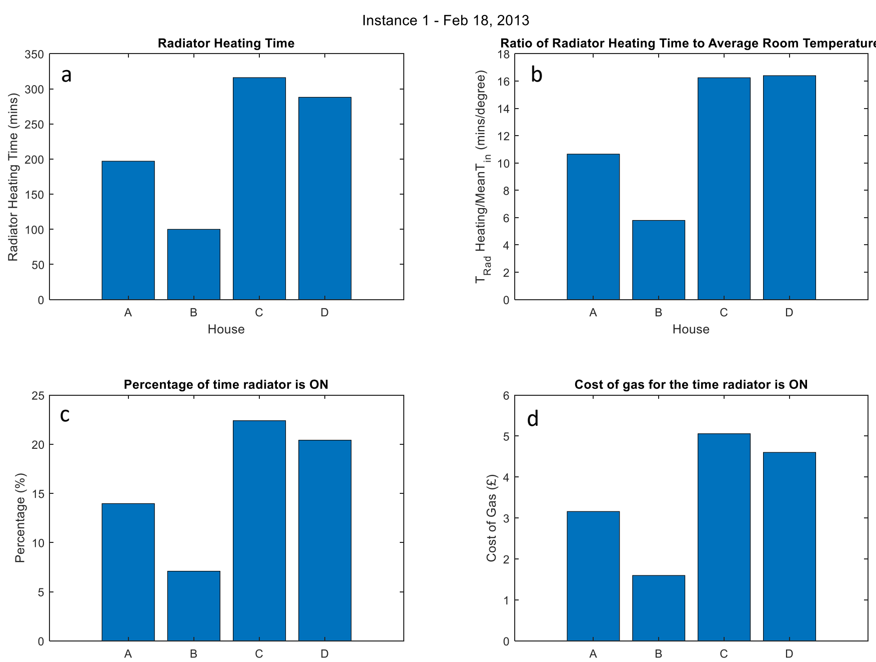
Inst4 = [02-Mar-2013 00:00:0002-Mar-2013 23:59:00]

Inst5 = [03-Mar-2013 00:00:0003-Mar-2013 23:59:00]

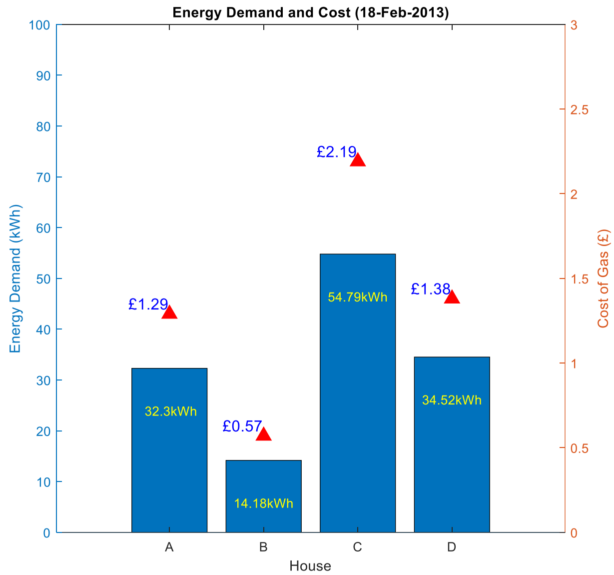
Inst6 = [04-Mar-2013 15:00:0005-Mar-2013 15:00:00]

Inst7 = [09-Mar-2013 00:00:0009-Mar-2013 23:59:00]

3

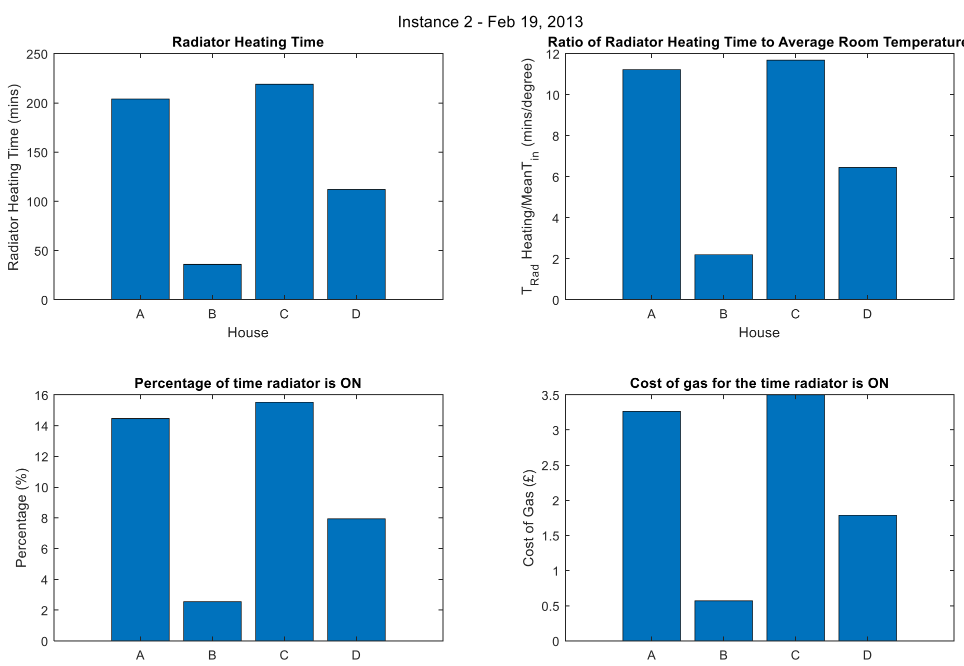


4



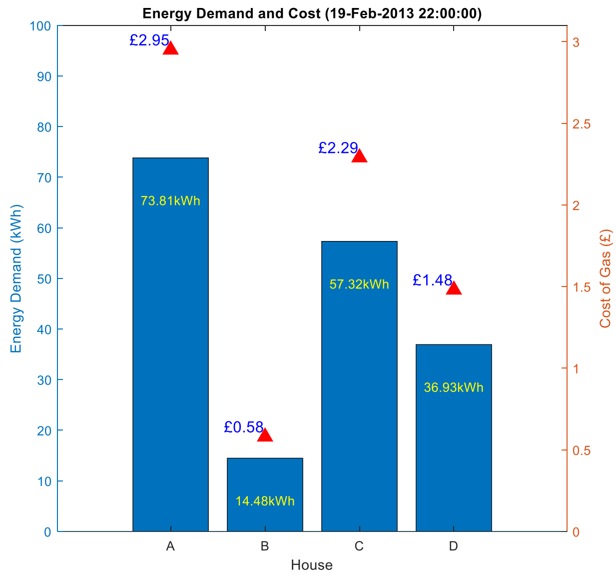
Energy Demand and Cost (18-Feb-2013)
Energy Demand (kWh)
Cost of Gas (£)
£1.29
£0.57
£2.19
£1.38
32.3kWh
14.18kWh
54.79kWh
34.52kWh
House

5

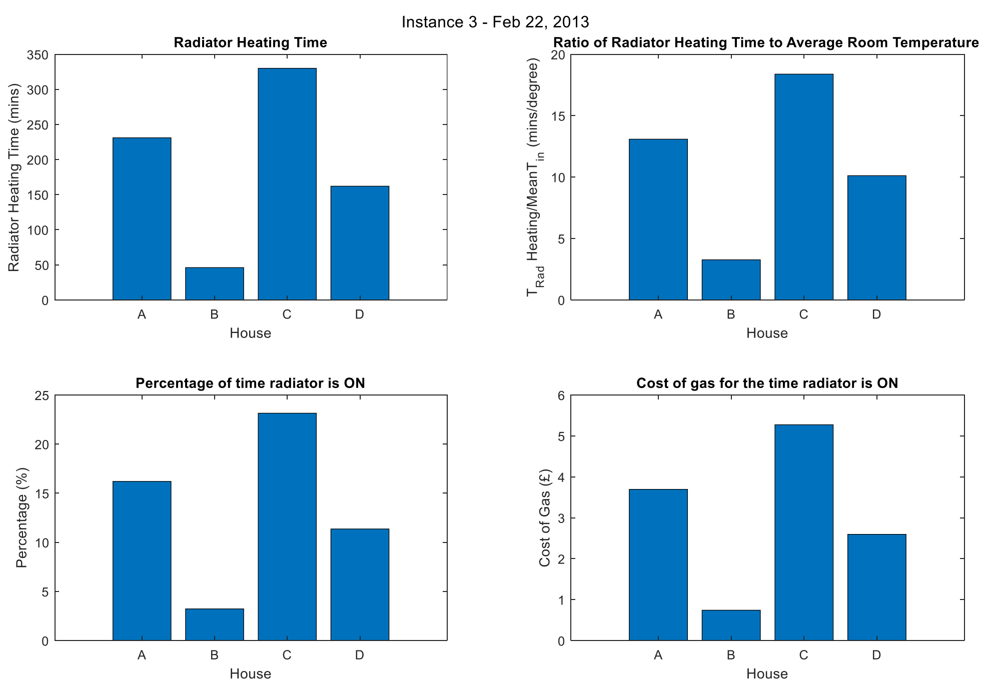


Instance 2 - Feb 19, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
House

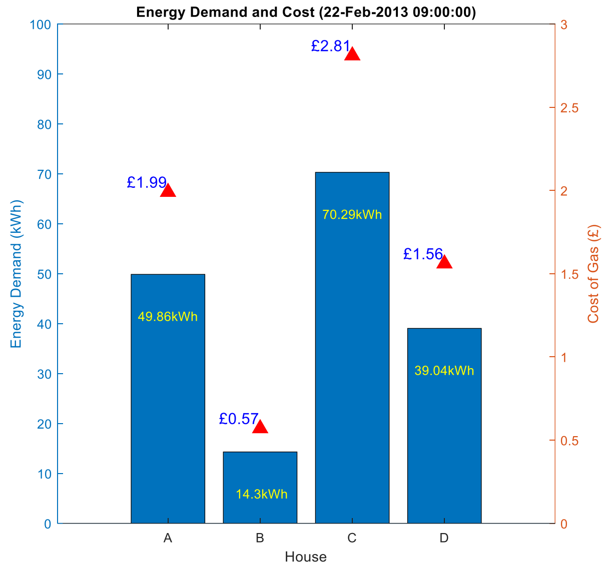
6


Energy Demand and Cost (19-Feb-2013 22:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£2.95
£2.29
£1.48
£0.58
73.81kWh
57.32kWh
36.93kWh
14.48kWh
A
B
C
D
House

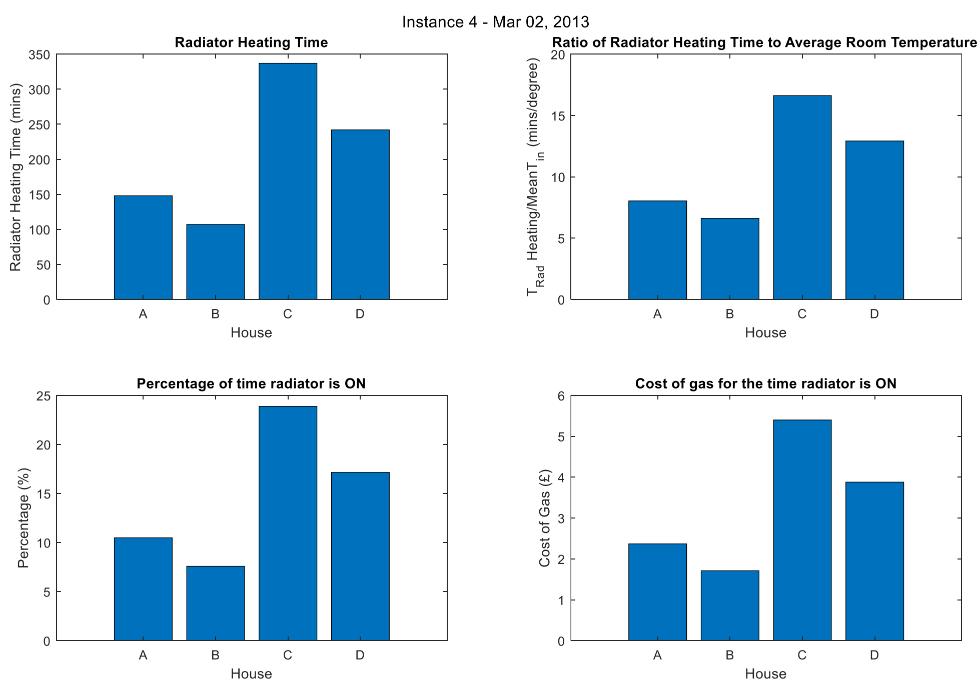
7


Instance 3 - Feb 22, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

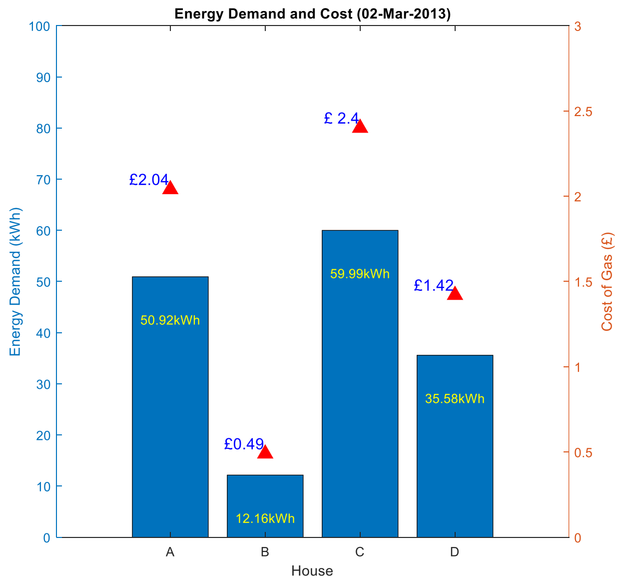
8


Energy Demand and Cost (22-Feb-2013 09:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£1.99
£0.57
£2.81
£1.56
49.86kWh
14.3kWh
70.29kWh
39.04kWh

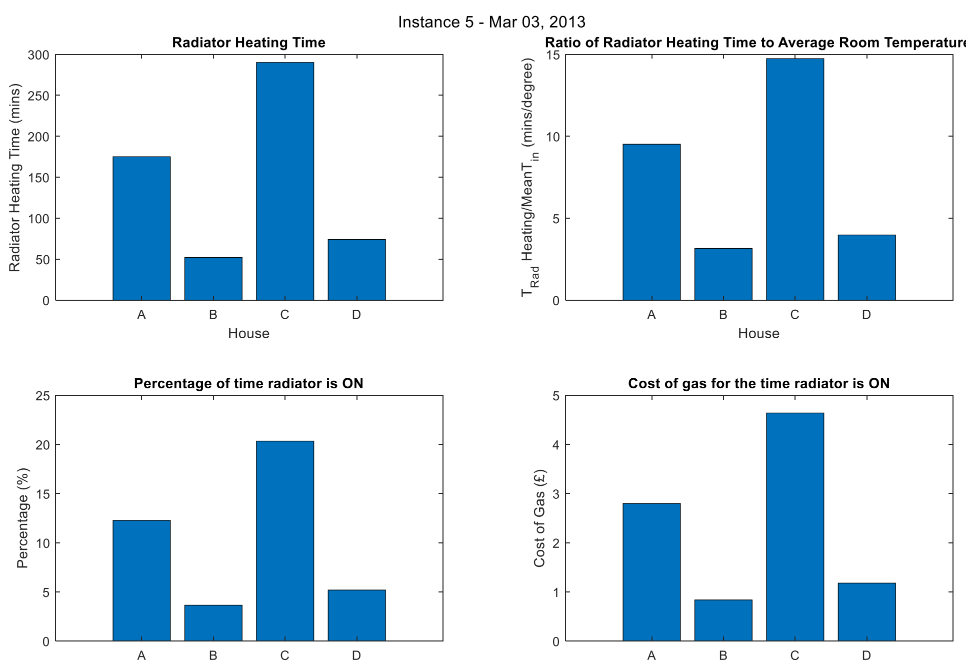
9


Instance 4 - Mar 02, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
House
A
B
C
D

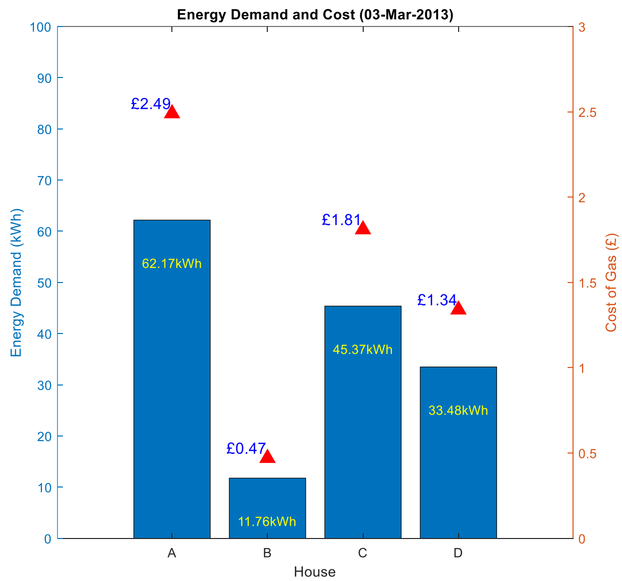
10


Energy Demand and Cost (02-Mar-2013)
Energy Demand (kWh)
Cost of Gas (£)
£2.04
£0.49
£ 2.4
£1.42
50.92kWh
12.16kWh
59.99kWh
35.58kWh
A
B
C
D
House

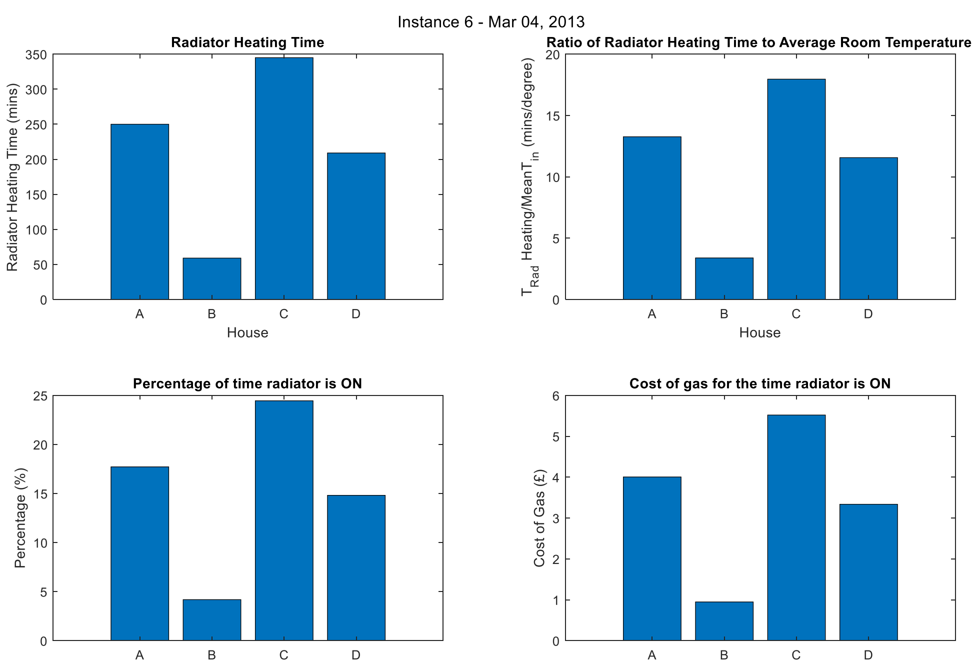
11


Instance 5 - Mar 03, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T Rad Heating/MeanT in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

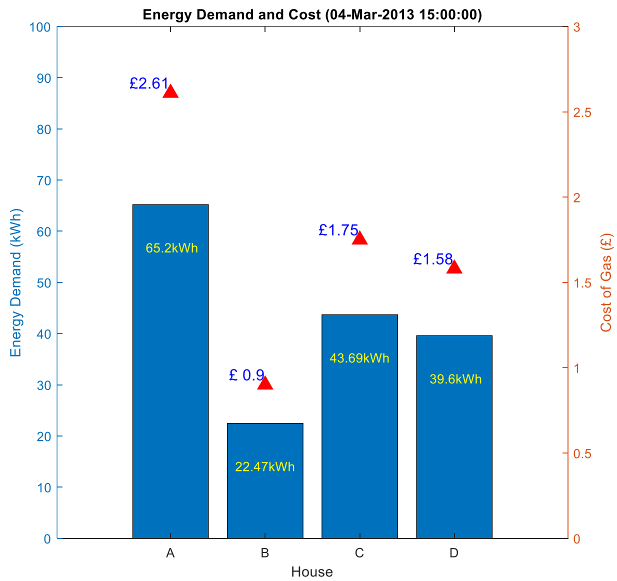
12


Energy Demand and Cost (03-Mar-2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
62.17kWh
11.76kWh
45.37kWh
33.48kWh
£2.49
£0.47
£1.81
£1.34

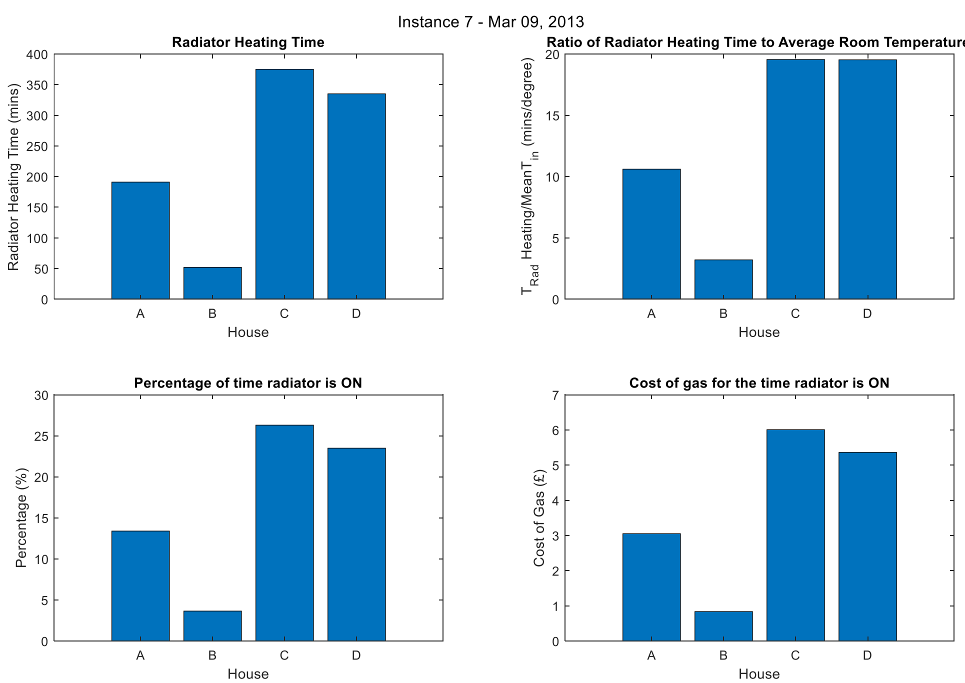
13


Instance 6 - Mar 04, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
House
A
B
C
D

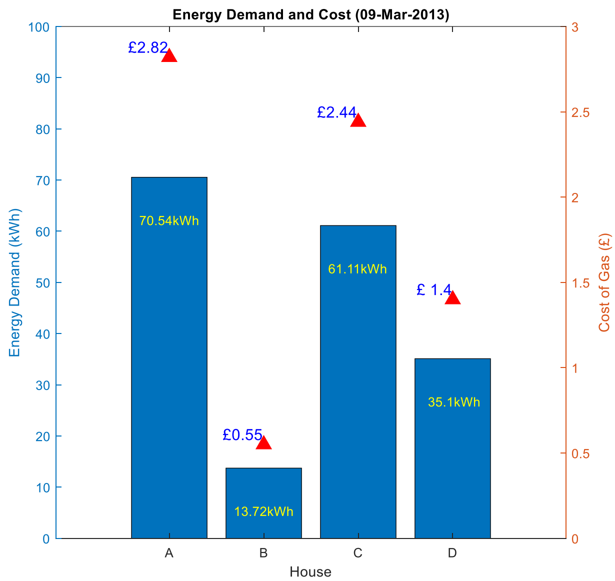
14


Energy Demand and Cost (04-Mar-2013 15:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£2.61
£ 0.9
£1.75
£1.58
65.2kWh
22.47kWh
43.69kWh
39.6kWh
A
B
C
D
House

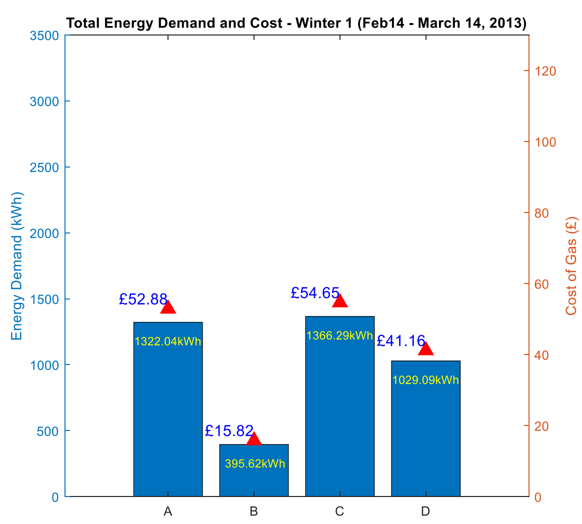
15


Instance 7 - Mar 09, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

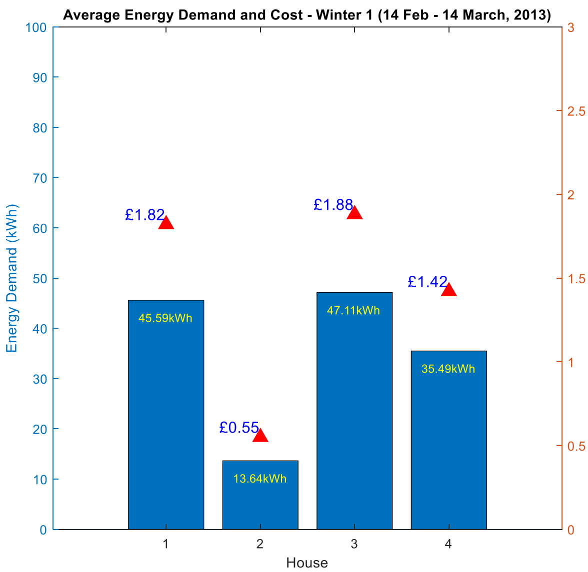
16

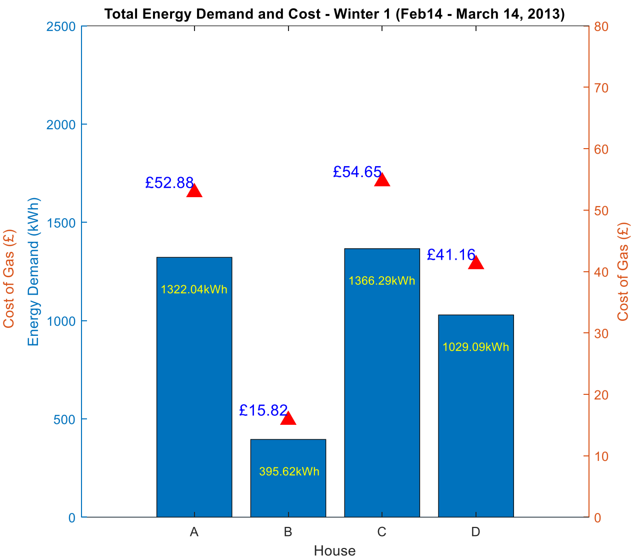

Energy Demand and Cost (09-Mar-2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£2.82
£0.55
£2.44
£ 1.4
70.54kWh
13.72kWh
61.11kWh
35.1kWh

17


Total Energy Demand and Cost - Winter 1 (Feb14 - March 14, 2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£52.88
£15.82
£54.65
£41.16
1322.04kWh
395.62kWh
1366.29kWh
1029.09kWh

18





19

Winter 2

Nov - Dec 2013

20

Instances

```
Inst1 = ['20-Nov-2013 00:00:00';'20-Nov-2013 23:59:00'];
Inst2 = ['21-Nov-2013 00:00:00';'21-Nov-2013 23:59:00'];
Inst3 = ['22-Nov-2013 00:00:00';'22-Nov-2013 23:59:00'];
Inst4 = ['23-Nov-2013 18:00:00';'24-Nov-2013 18:00:00'];
Inst5 = ['24-Nov-2013 18:00:00';'25-Nov-2013 18:00:00'];
Inst6 = ['25-Nov-2013 18:00:00';'26-Nov-2013 18:00:00'];
Inst7 = ['26-Nov-2013 18:00:00';'27-Nov-2013 18:00:00'];
Inst8 = ['27-Nov-2013 18:00:00';'28-Nov-2013 18:00:00'];
Inst9 = ['28-Nov-2013 18:00:00';'29-Nov-2013 18:00:00'];
Inst10 = ['30-Nov-2013 00:00:00';'30-Nov-2013 23:59:00'];
Inst11 = ['01-Dec-2013 20:00:00';'02-Dec-2013 20:00:00'];
Inst12 = ['02-Dec-2013 20:00:00';'03-Dec-2013 20:00:00'];
Inst13 = ['19-Dec-2013 19:00:00';'20-Dec-2013 19:00:00'];
Inst14 = ['24-Dec-2013 9:00:00';'25-Dec-2013 9:00:00'];
Inst15 = ['26-Dec-2013 00:00:00';'26-Dec-2013 23:59:00'];
Inst16 = ['27-Dec-2013 20:00:00';'28-Dec-2013 20:00:00'];
Inst17 = ['29-Dec-2013 17:00:00';'30-Dec-2013 17:00:00'];
Inst18 = ['30-Dec-2013 17:00:00';'31-Dec-2013 17:00:00'];
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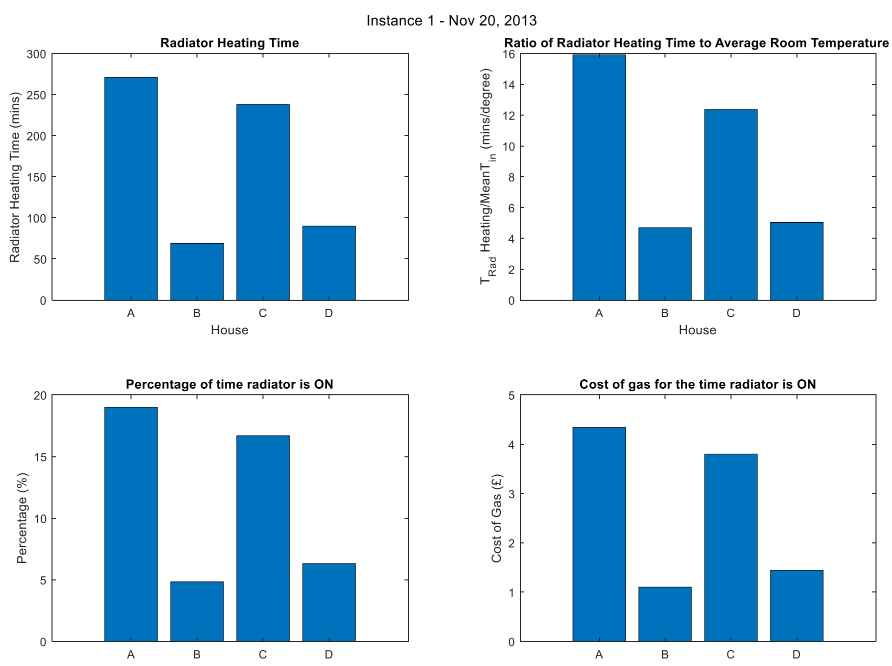
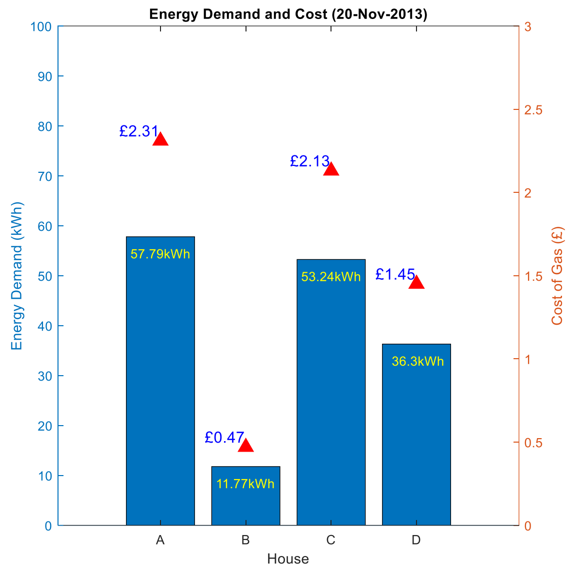
21

Instance 1

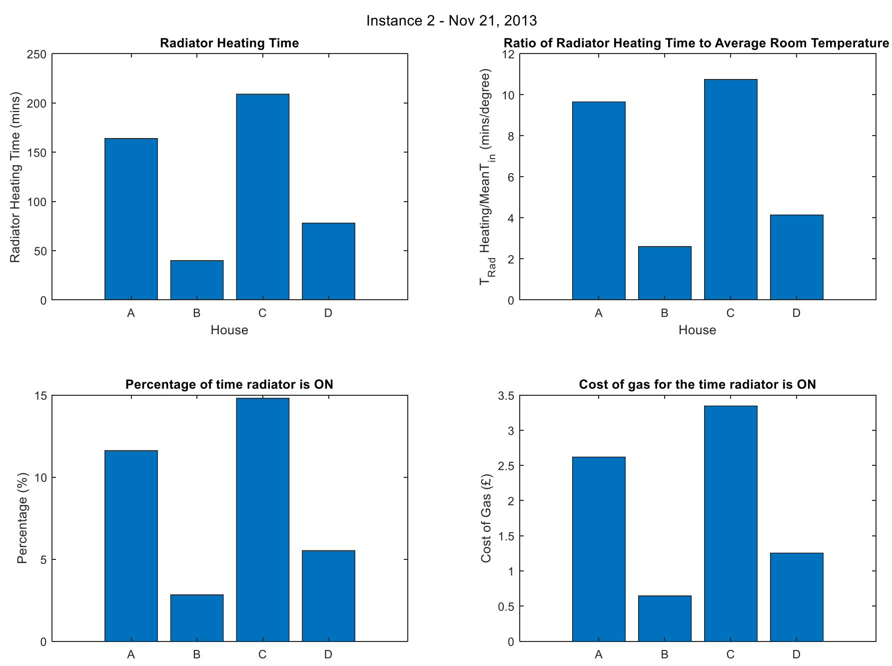


22



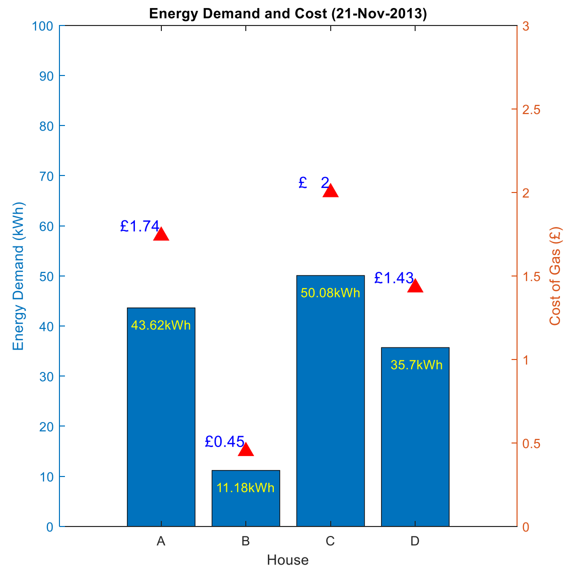
Energy Demand and Cost (20-Nov-2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
57.79kWh
11.77kWh
53.24kWh
36.3kWh
£2.31
£0.47
£2.13
£1.45

23



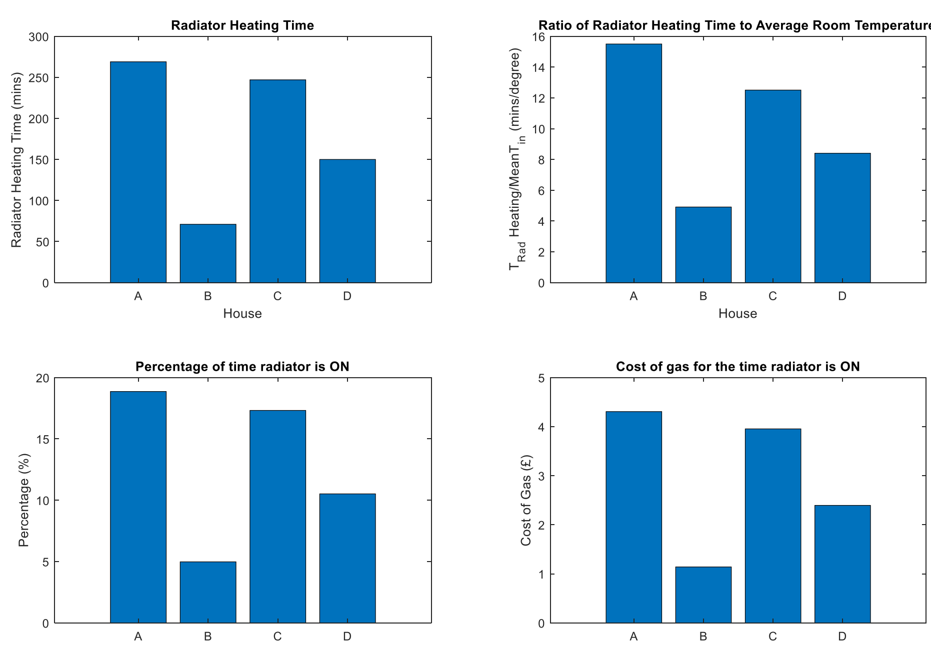
Instance 2 - Nov 21, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T Rad Heating/MeanT in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
House
A
B
C
D

24

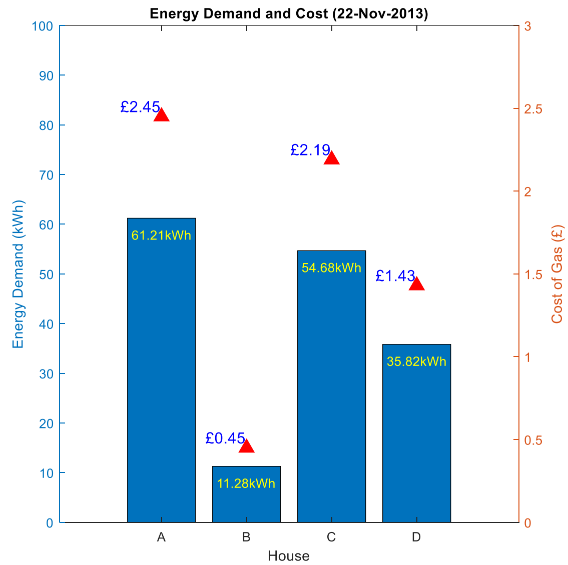


25

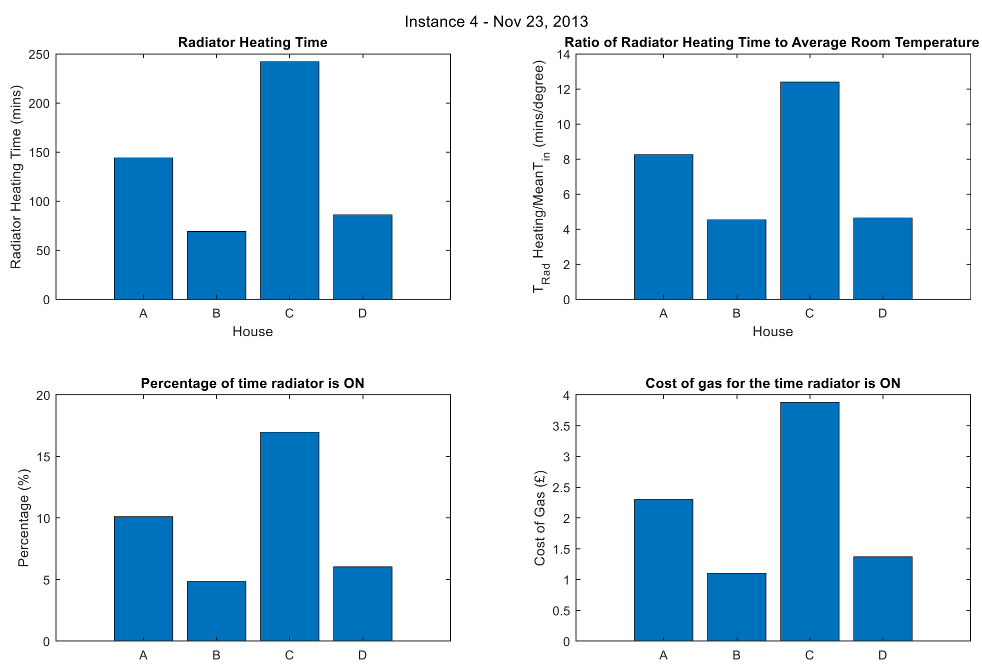
Instance 3



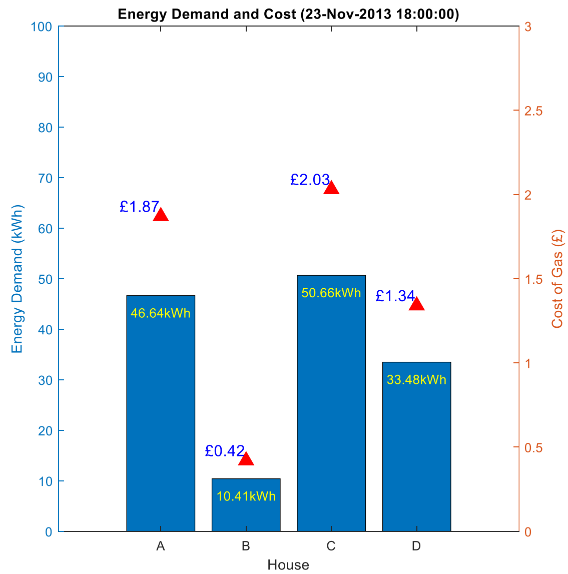
26


Energy Demand and Cost (22-Nov-2013)
Energy Demand (kWh)
Cost of Gas (£)
£2.45
£2.19
£1.43
£0.45
61.21kWh
54.68kWh
35.82kWh
11.28kWh
A
B
C
D
House

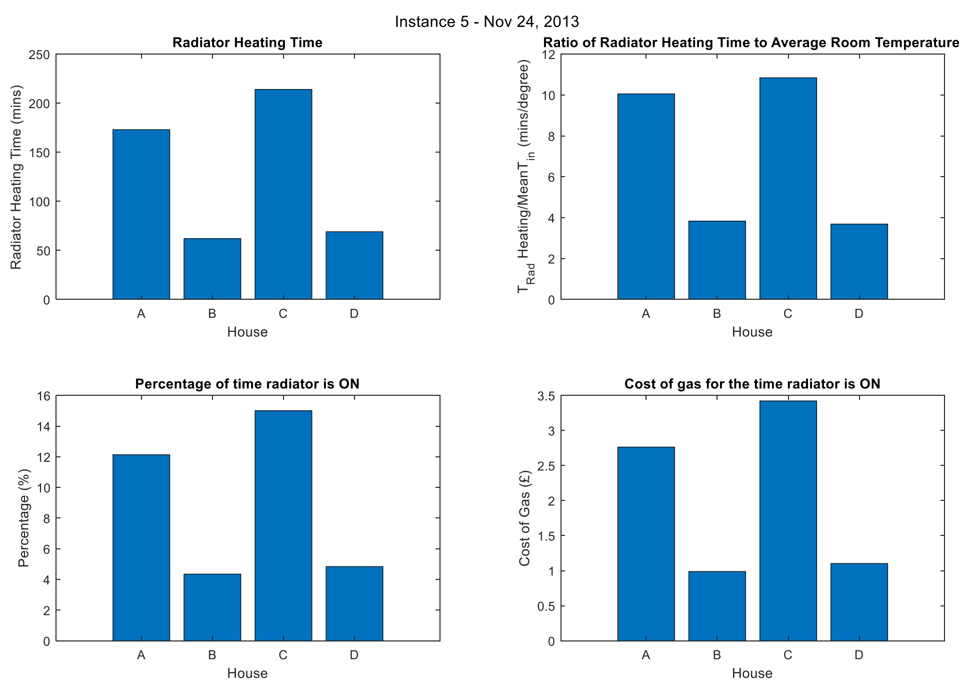
27


Instance 4 - Nov 23, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

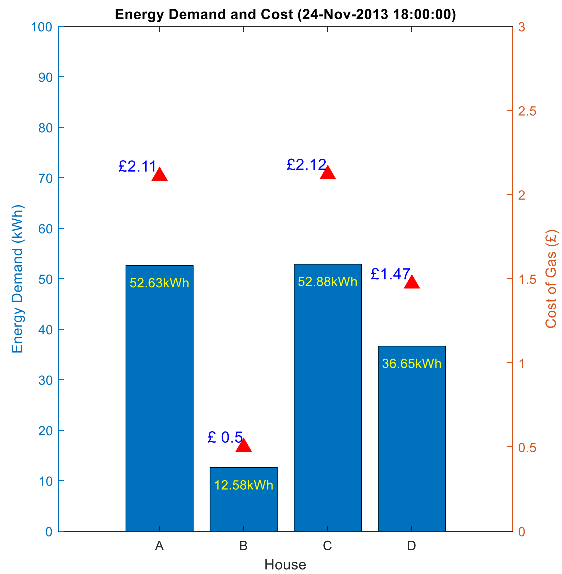
28


Energy Demand and Cost (23-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£1.87
£0.42
£2.03
£1.34
46.64kWh
10.41kWh
50.66kWh
33.48kWh
A
B
C
D
House

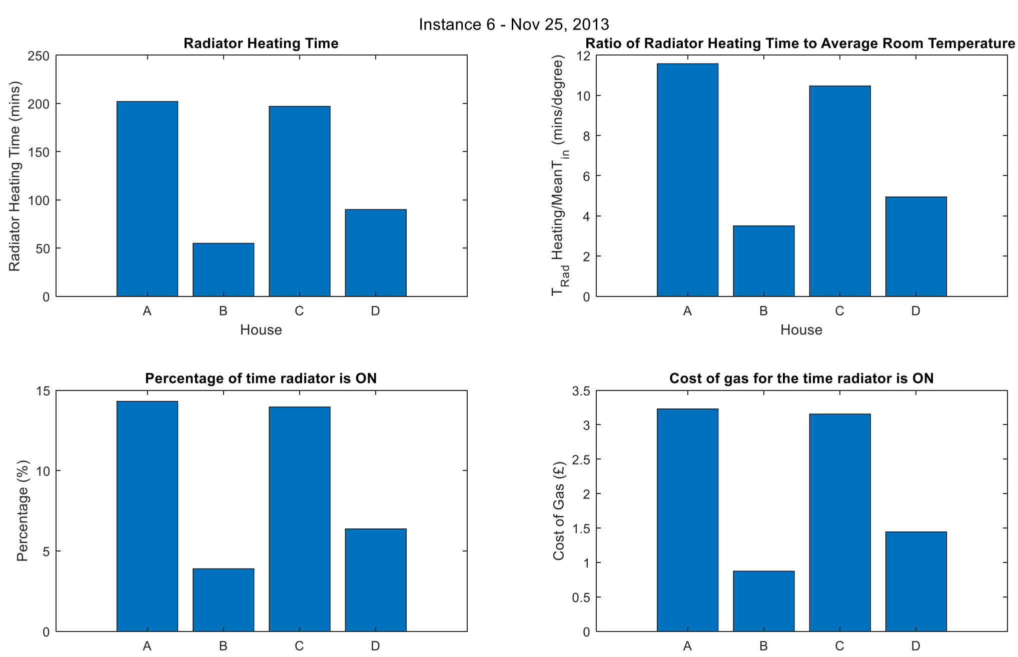
29


Instance 5 - Nov 24, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

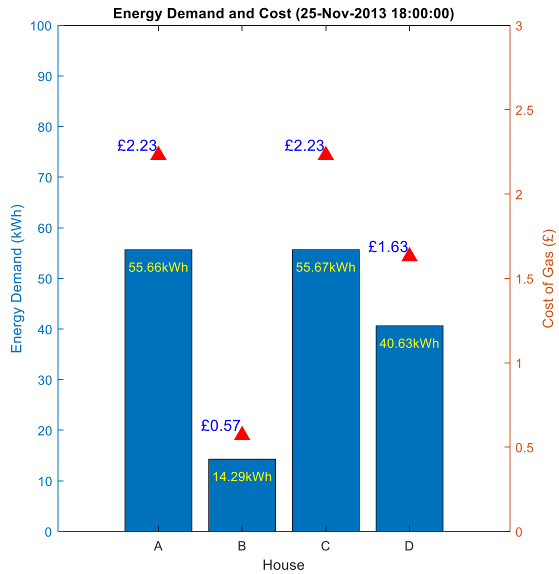
30


Energy Demand and Cost (24-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£2.11
£2.12
£1.47
£ 0.5
52.63kWh
12.58kWh
52.88kWh
36.65kWh
House
A
B
C
D

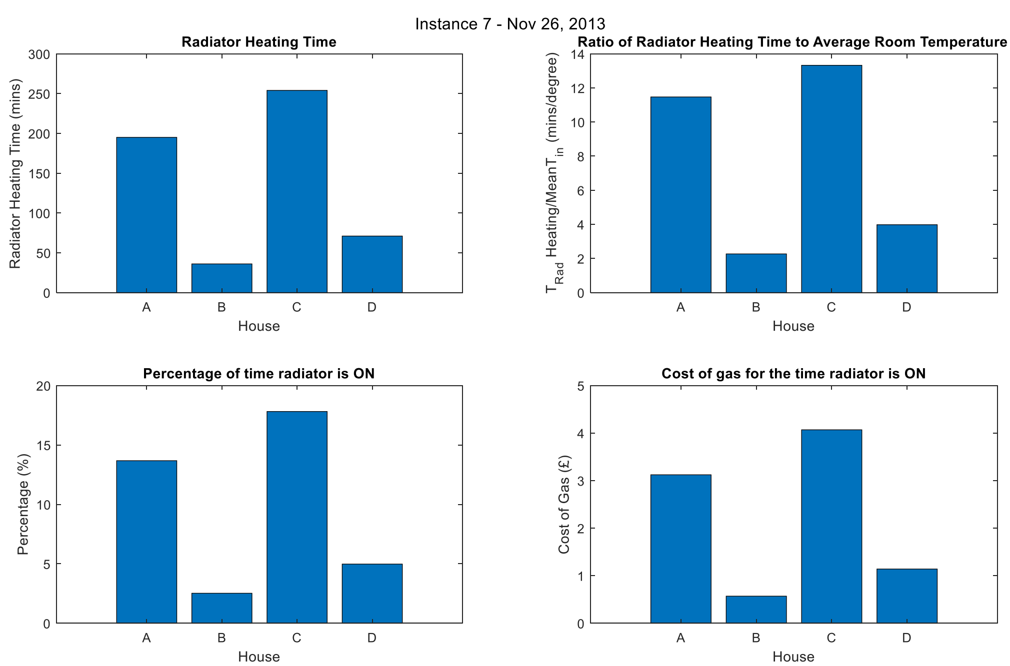
31


Instance 6 - Nov 25, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
House
A
B
C
D

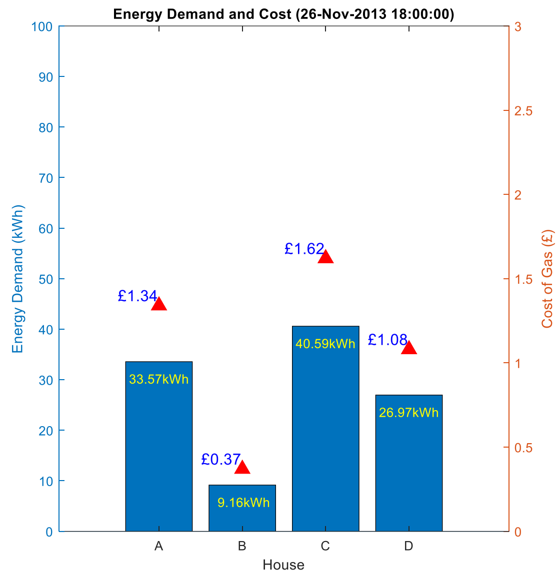
32


Energy Demand and Cost (25-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£2.23
£2.23
£1.63
£0.57
55.66kWh
55.67kWh
40.63kWh
14.29kWh
A
B
C
D
House

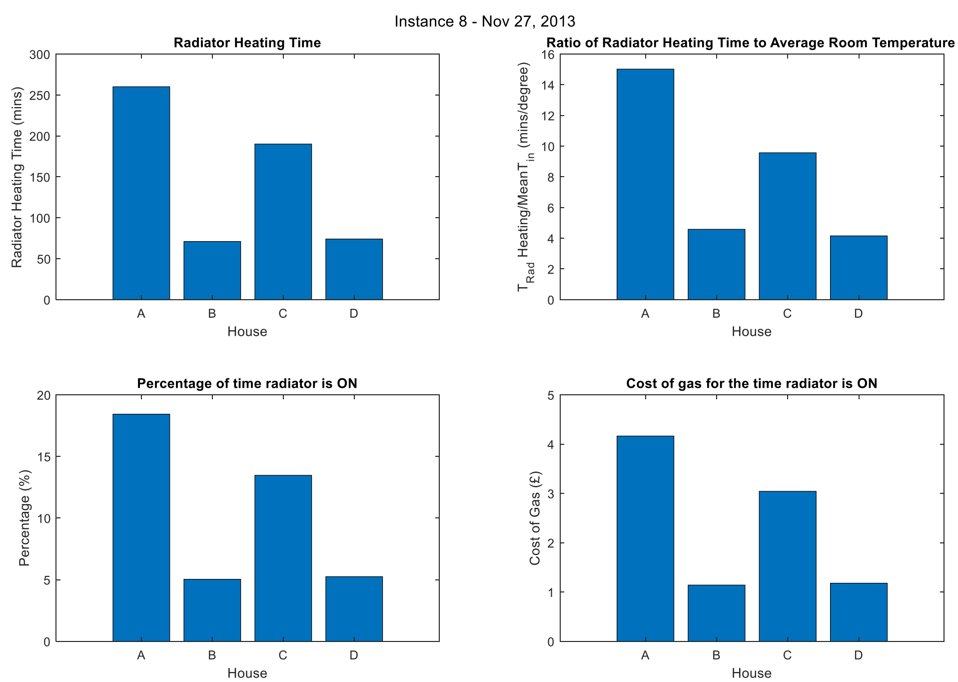
33


Instance 7 - Nov 26, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

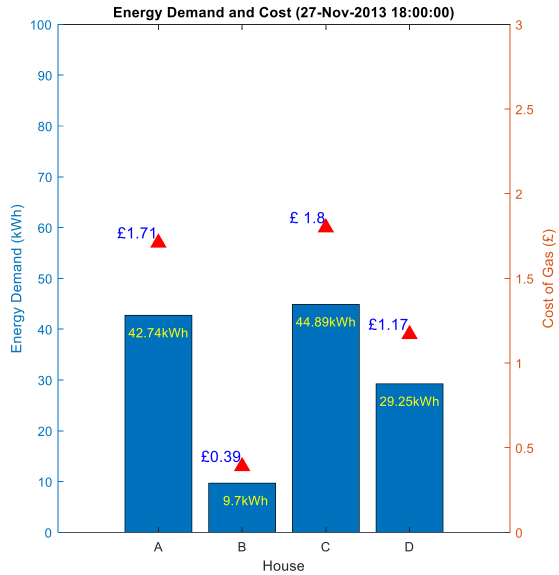
34


Energy Demand and Cost (26-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£1.34
£0.37
£1.62
£1.08
33.57kWh
9.16kWh
40.59kWh
26.97kWh
A
B
C
D
House

35

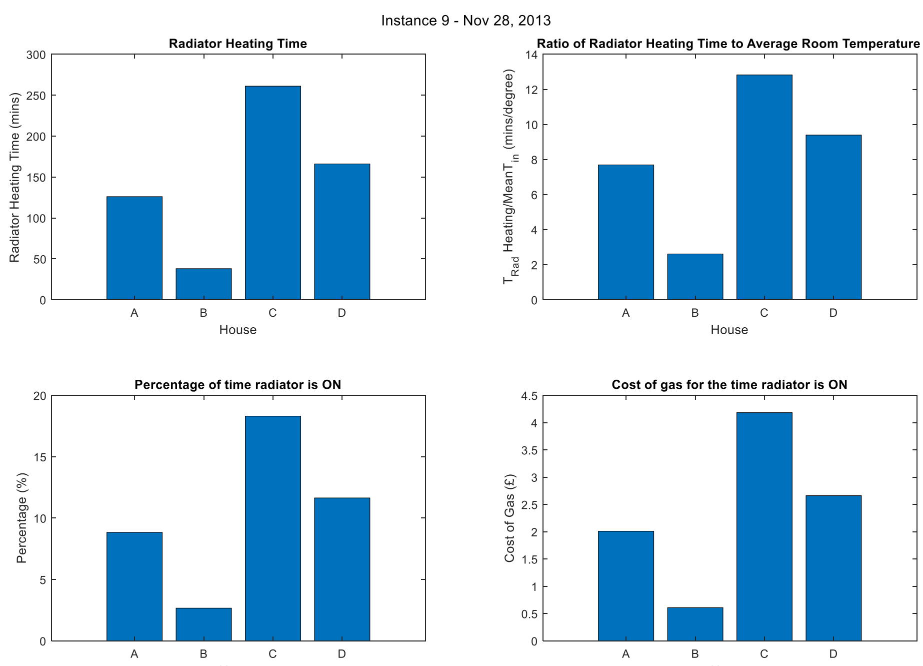

Instance 8 - Nov 27, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

36



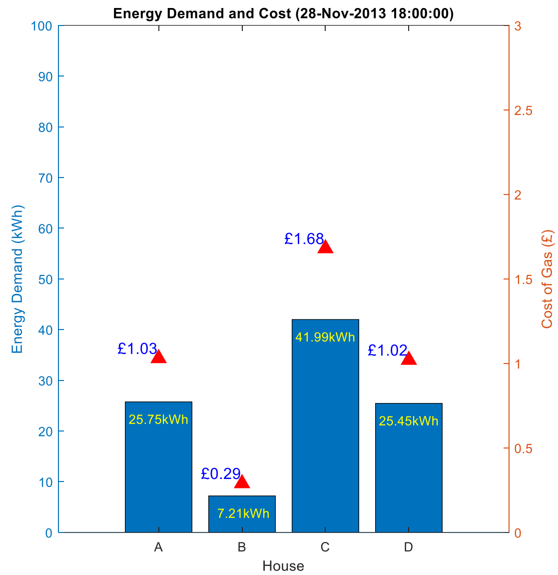
Energy Demand and Cost (27-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£1.71
£0.39
£ 1.8
£1.17
42.74kWh
9.7kWh
44.89kWh
29.25kWh
A
B
C
D
House

37

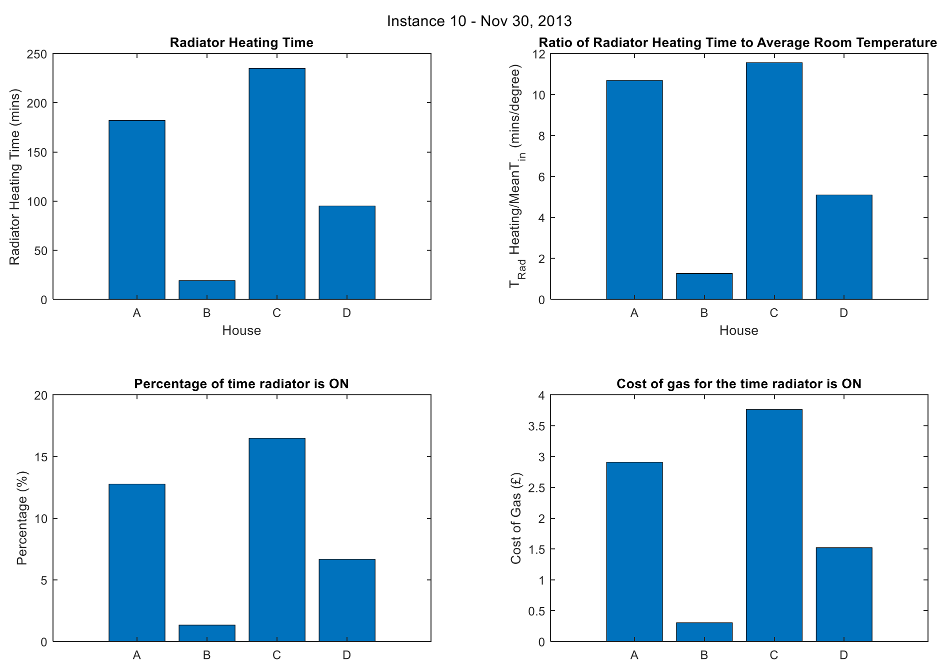


Instance 9 - Nov 28, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_Rad Heating/MeanT_in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

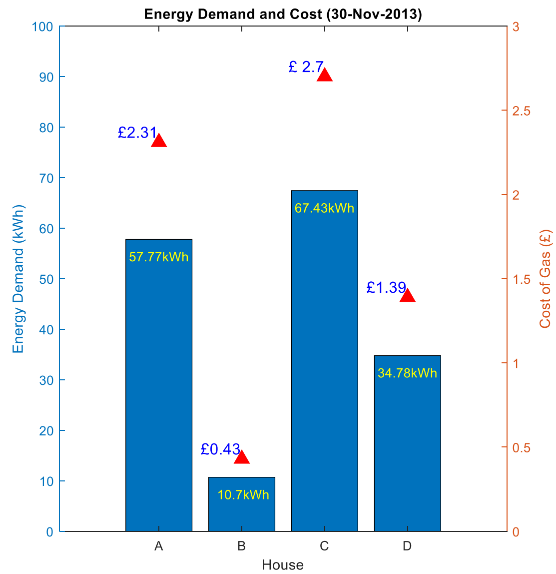
38


Energy Demand and Cost (28-Nov-2013 18:00:00)
Energy Demand (kWh)
Cost of Gas (£)
£1.03
£0.29
£1.68
£1.02
25.75kWh
7.21kWh
41.99kWh
25.45kWh
A
B
C
D
House

39

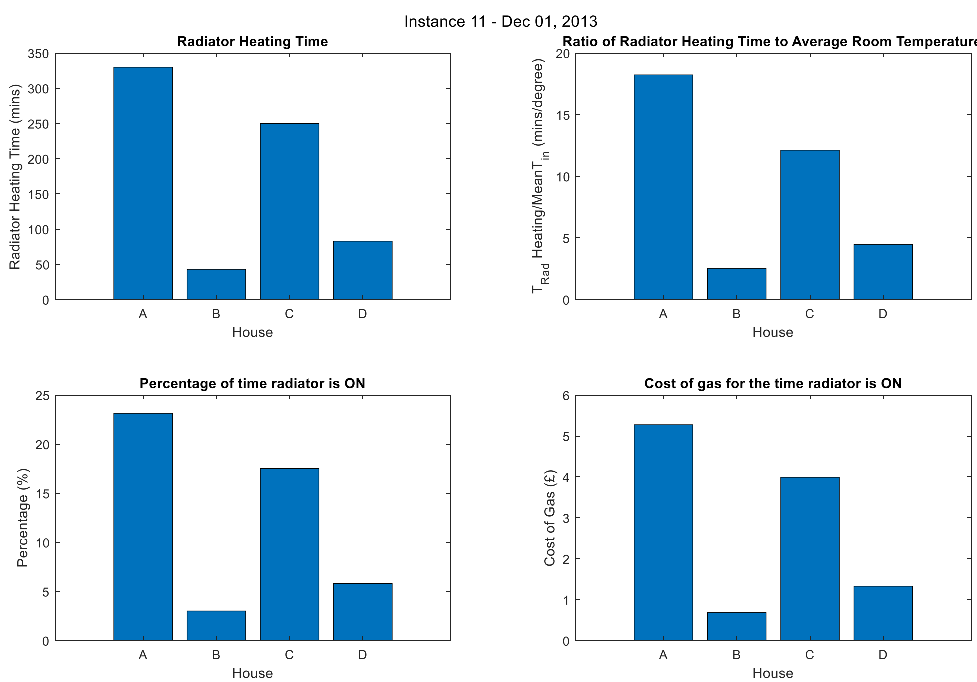

Instance 10 - Nov 30, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T Rad Heating/MeanT in (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

40



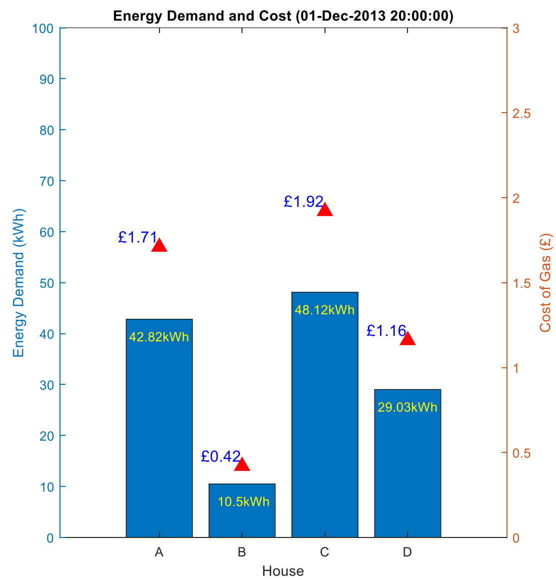
Energy Demand and Cost (30-Nov-2013)
Energy Demand (kWh)
Cost of Gas (£)
£2.31
£0.43
£ 2.7
£1.39
57.77kWh
10.7kWh
67.43kWh
34.78kWh
A
B
C
D
House

41

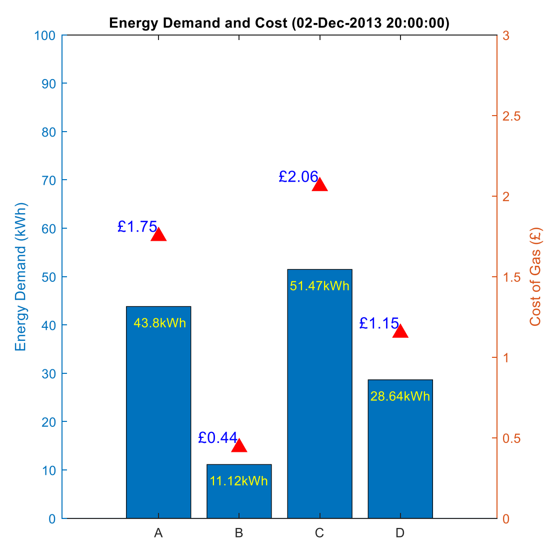


Instance 11 - Dec 01, 2013
Radiator Heating Time
Radiator Heating Time (mins)
Ratio of Radiator Heating Time to Average Room Temperature
T_{Rad} Heating/MeanT_{in} (mins/degree)
Percentage of time radiator is ON
Percentage (%)
Cost of gas for the time radiator is ON
Cost of Gas (£)
A
B
C
D
House

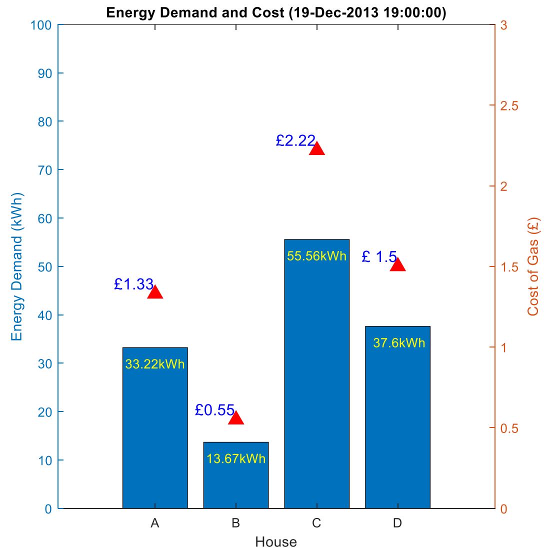
42


Energy Demand and Cost (01-Dec-2013 20:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£1.71
£0.42
£1.92
£1.16
42.82kWh
10.5kWh
48.12kWh
29.03kWh

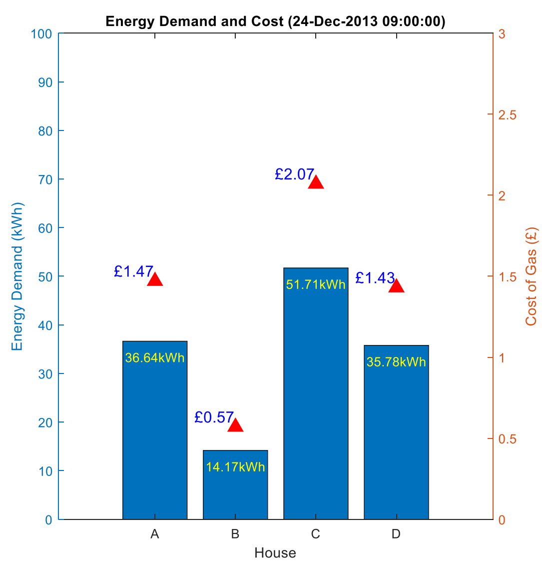
43


Energy Demand and Cost (02-Dec-2013 20:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£1.75
£0.44
£2.06
£1.15
43.8kWh
11.12kWh
51.47kWh
28.64kWh

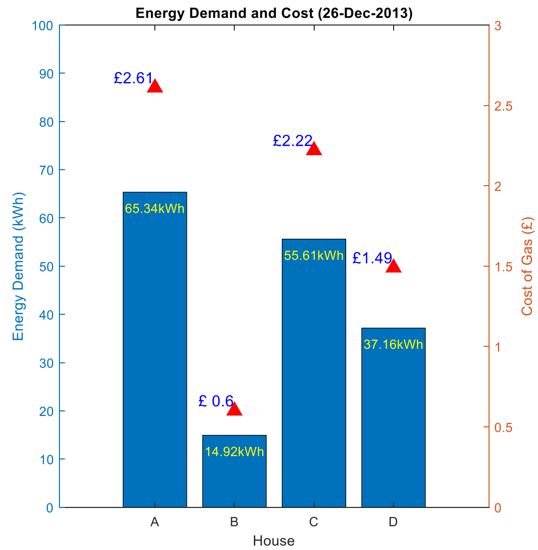
44


Energy Demand and Cost (19-Dec-2013 19:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
33.22kWh
13.67kWh
55.56kWh
37.6kWh
£1.33
£0.55
£2.22
£ 1.5

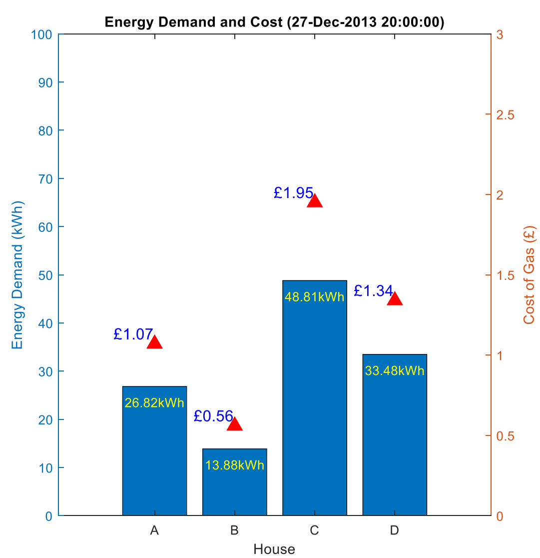
45


Energy Demand and Cost (24-Dec-2013 09:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
36.64kWh
14.17kWh
51.71kWh
35.78kWh
£1.47
£0.57
£2.07
£1.43

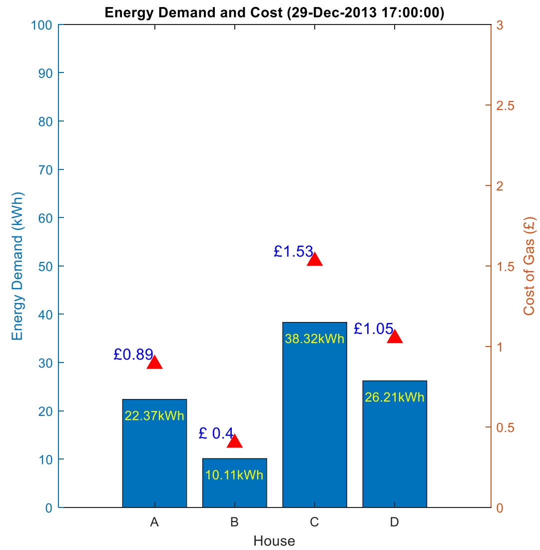
46


Energy Demand and Cost (26-Dec-2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£2.61
£2.22
£1.49
£ 0.6
65.34kWh
14.92kWh
55.61kWh
37.16kWh

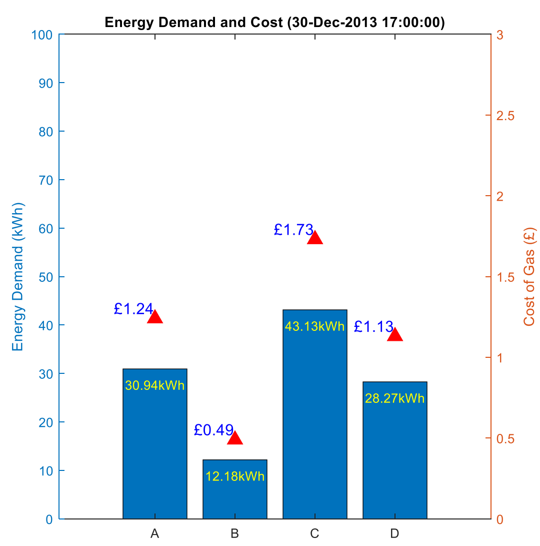
47


Energy Demand and Cost (27-Dec-2013 20:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£1.95
£1.34
£1.07
£0.56
26.82kWh
13.88kWh
48.81kWh
33.48kWh

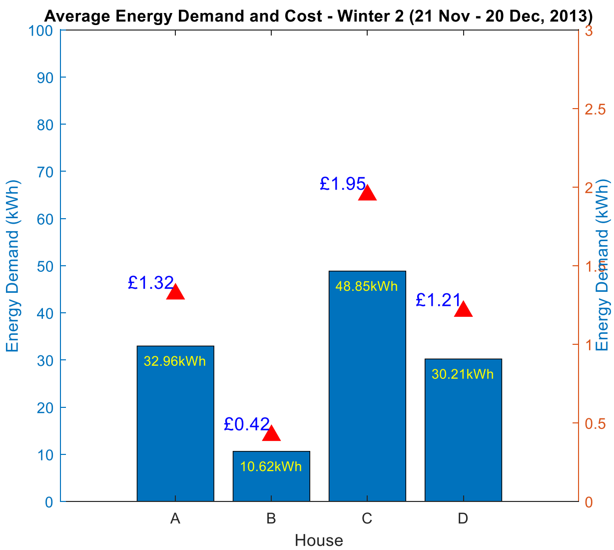
48

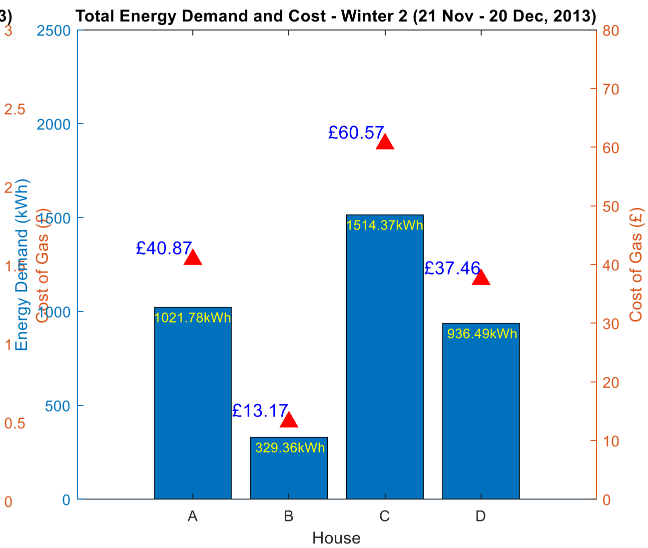

Energy Demand and Cost (29-Dec-2013 17:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£0.89
22.37kWh
£ 0.4
10.11kWh
£1.53
38.32kWh
£1.05
26.21kWh

49

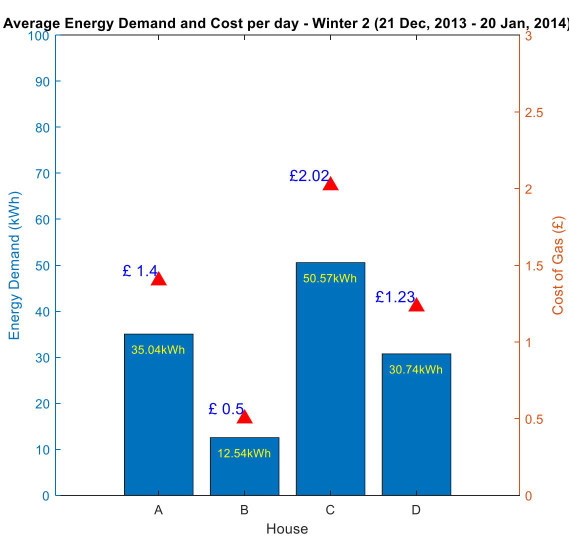

Energy Demand and Cost (30-Dec-2013 17:00:00)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
£1.24
30.94kWh
£0.49
12.18kWh
£1.73
43.13kWh
£1.13
28.27kWh

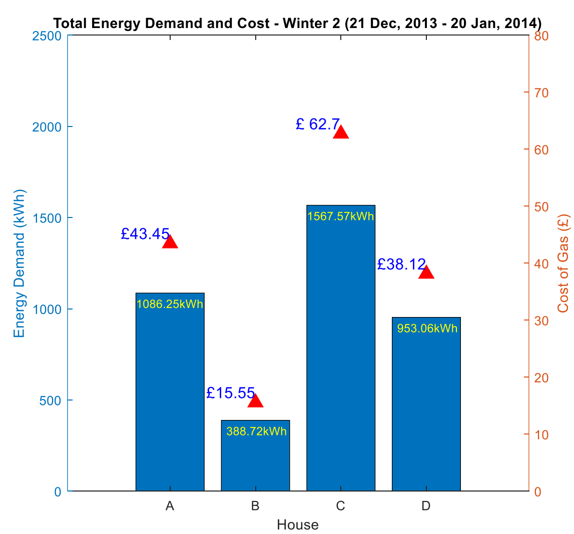
50


Average Energy Demand and Cost - Winter 2 (21 Nov - 20 Dec, 2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
32.96kWh
10.62kWh
48.85kWh
30.21kWh
£1.32
£0.42
£1.95
£1.21

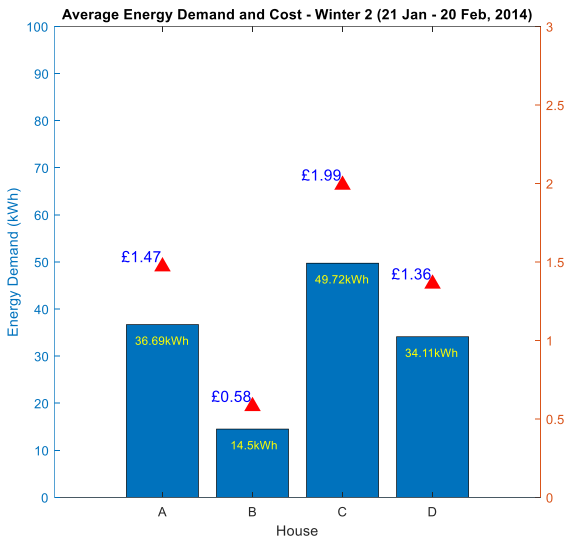

Total Energy Demand and Cost - Winter 2 (21 Nov - 20 Dec, 2013)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
1021.78kWh
329.36kWh
1514.37kWh
936.49kWh
£40.87
£13.17
£60.57
£37.46

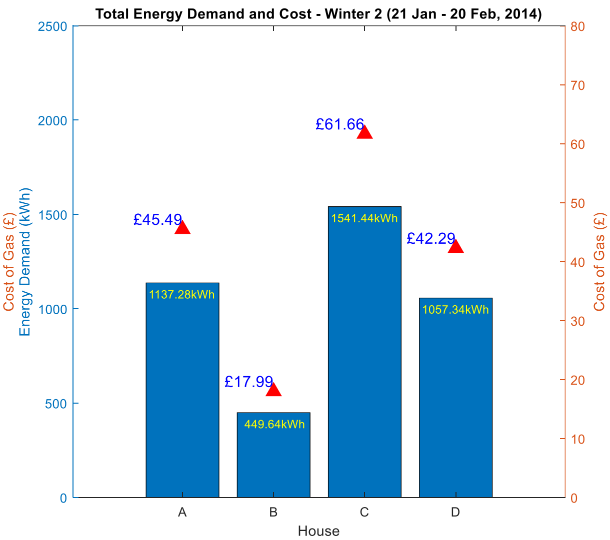
51


Average Energy Demand and Cost per day - Winter 2 (21 Dec, 2013 - 20 Jan, 2014)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
35.04kWh
12.54kWh
50.57kWh
30.74kWh
£ 1.4
£ 0.5
£2.02
£1.23


Total Energy Demand and Cost - Winter 2 (21 Dec, 2013 - 20 Jan, 2014)
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
1086.25kWh
388.72kWh
1567.57kWh
953.06kWh
£43.45
£15.55
£ 62.7
£38.12

52

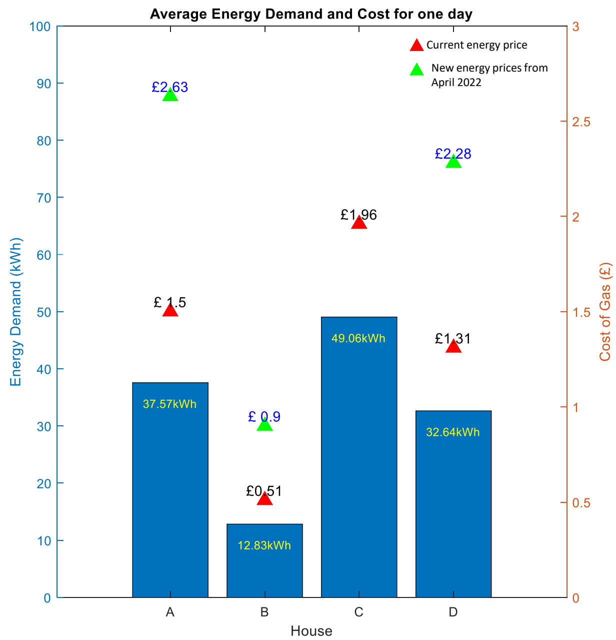




53

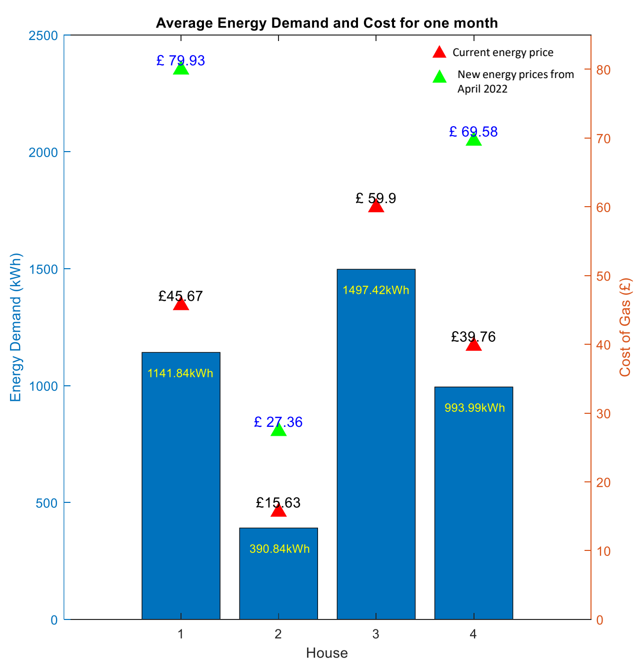
Average Values

54



Average Energy Demand and Cost for one day
Current energy price
New energy prices from April 2022
£2.63
£2.28
£1.96
£ 1.5
£1.31
£ 0.9
£0.51
37.57kWh
12.83kWh
49.06kWh
32.64kWh
Energy Demand (kWh)
Cost of Gas (£)
House
A
B
C
D
100
90
80
70
60
50
40
30
20
10
0
3
2.5
2
1.5
1
0.5
0

55



Average Energy Demand and Cost for one month
Current energy price
New energy prices from April 2022
£ 79.93
£ 69.58
£ 59.9
£45.67
£39.76
£ 27.36
£15.63
1141.84kWh
390.84kWh
1497.42kWh
993.99kWh
Energy Demand (kWh)
Cost of Gas (£)
House
1
2
3
4
2500
2000
1500
1000
500
0
80
70
60
50
40
30
20
10
0

56

Appendix C

NCH Analysis
Time Response

House 11,2,16,5

House	New No.	Old No.	Window Status
House A	11	32	HIP and Window Open
House B	2	15	HI and WC
House C	16	22	LI and WO
House D	5	21	LI and WC

1

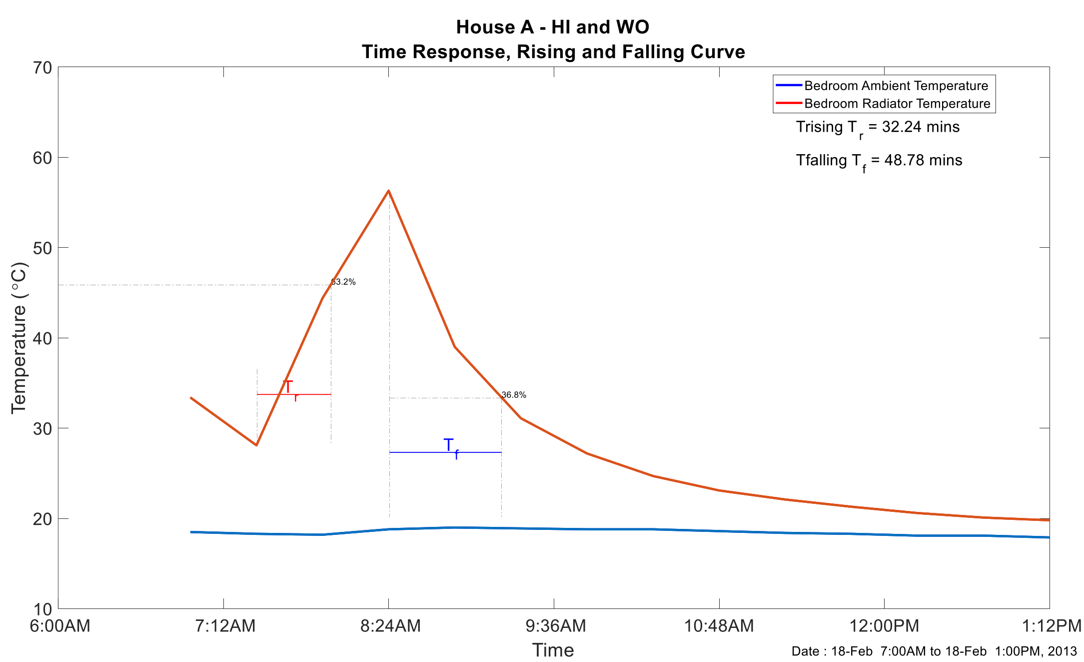
Time Response Instances - Winter 1

- TRInst1 = ['18-Feb-2013 04:40:00' ;'18-Feb-2013 13:00:00'];
- TRInst2 = ['20-Feb-2013 05:00:00' ;'20-Feb-2013 12:00:00'];
- TRInst3 = ['22-Feb-2013 16:00:00' ;'23-Feb-2013 01:50:00'];
- TRInst4 = ['02-Mar-2013 14:00:00' ;'03-Mar-2013 01:59:00'];
- TRInst5 = ['03-Mar-2013 05:00:00' ;'03-Mar-2013 11:59:00'];
- TRInst6 = ['05-Mar-2013 04:00:00' ;'05-Mar-2013 11:59:00'];
- TRInst7 = ['09-Mar-2013 04:30:00' ;'09-Mar-2013 14:59:00'];
-

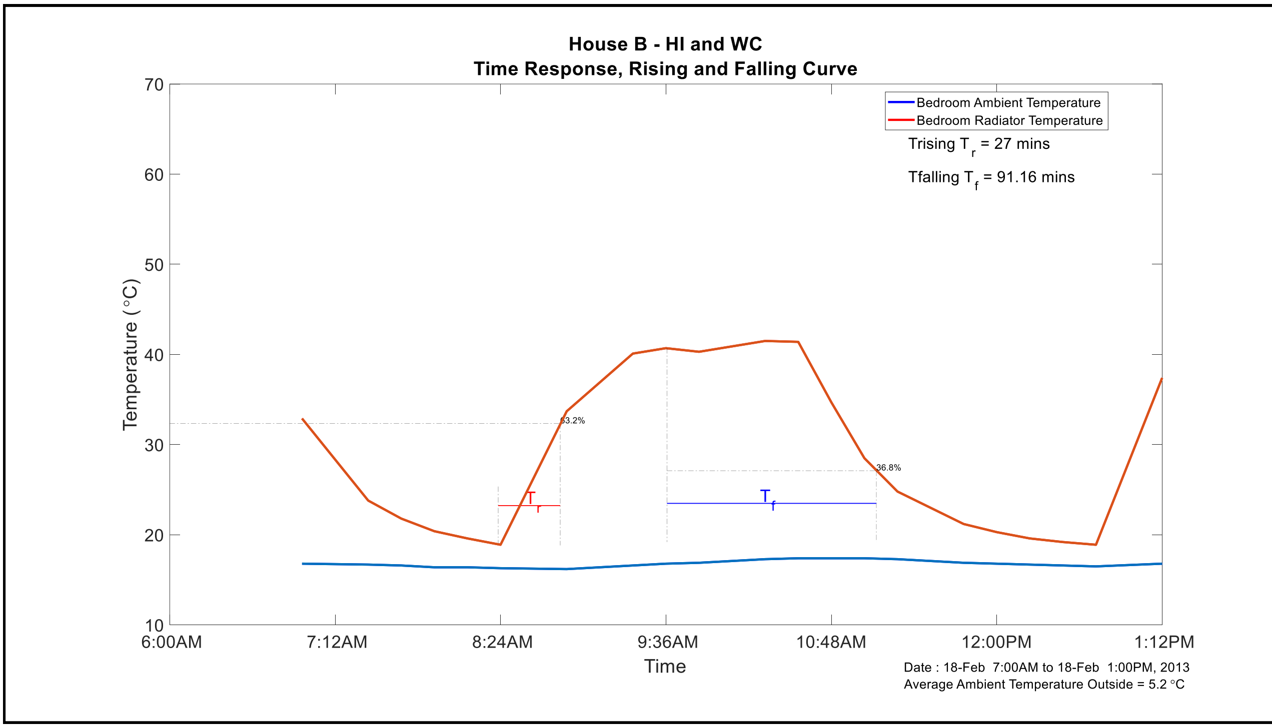
2

TRINstance 1

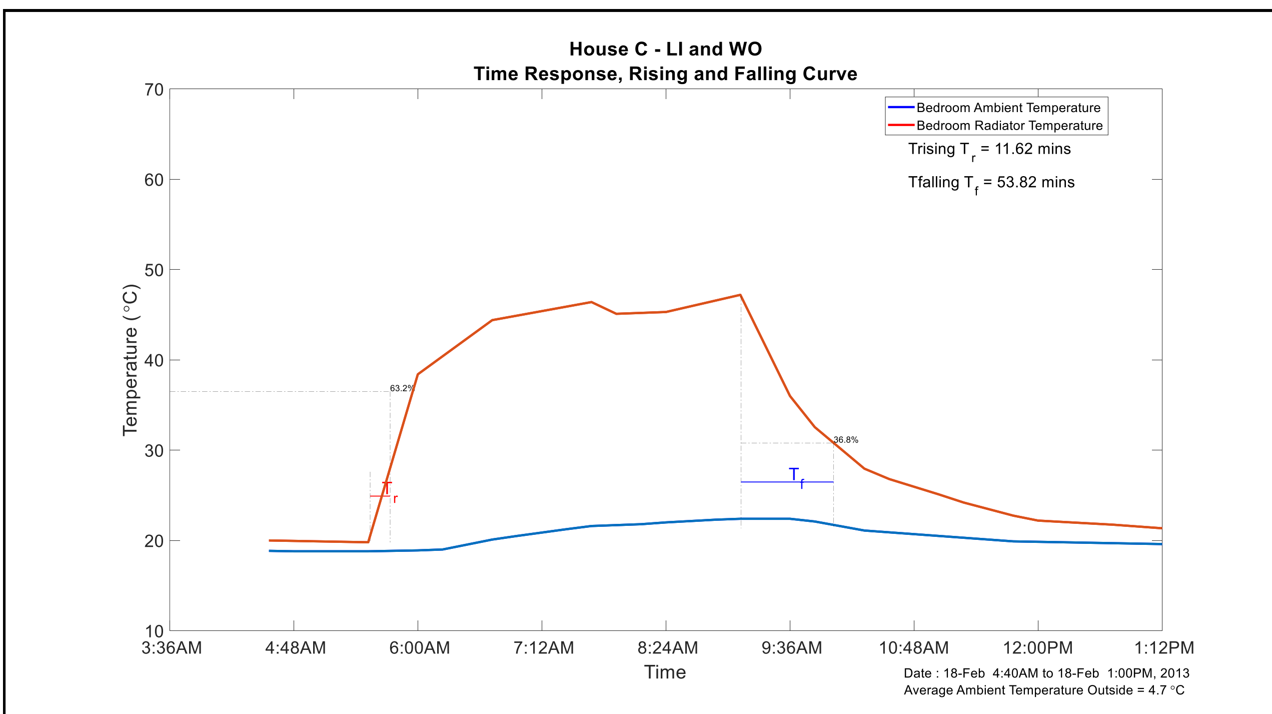
3



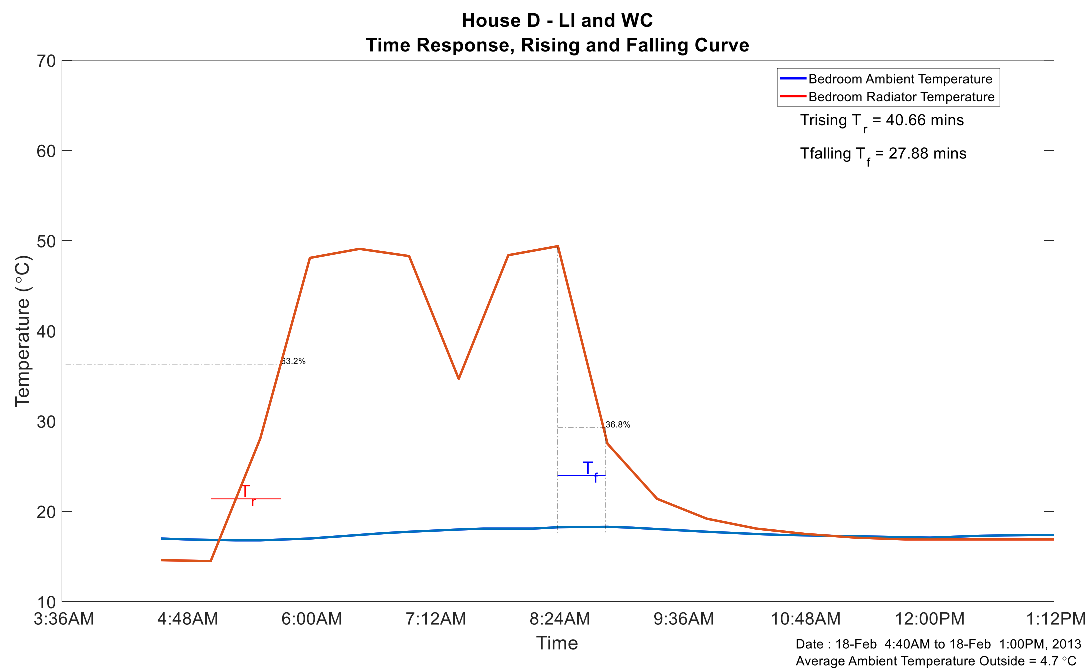
4


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T r = 27 mins
Tfalling T f = 91.16 mins
63.2%
36.8%
T r
T f
Temperature (°C)
70
60
50
40
30
20
10
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
Time
Date : 18-Feb 7:00AM to 18-Feb 1:00PM, 2013
Average Ambient Temperature Outside = 5.2 °C

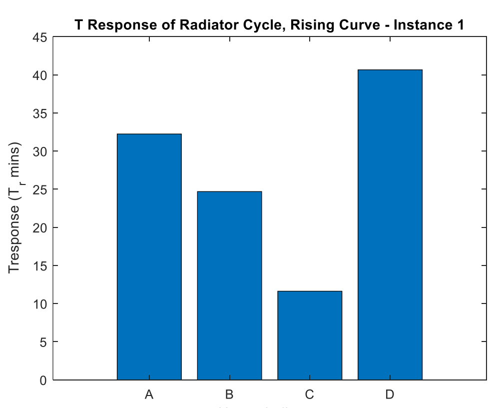
5

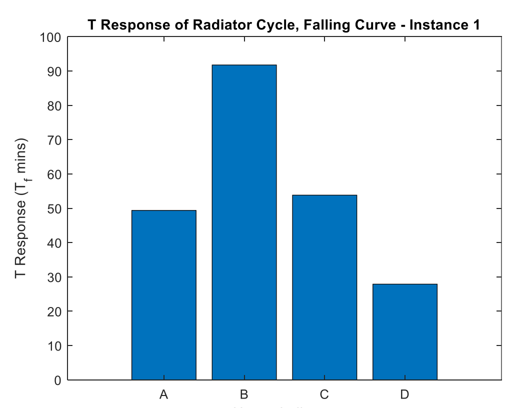

House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T r = 11.62 mins
Tfalling T f = 53.82 mins
63.2%
36.8%
T r
T f
Temperature (°C)
70
60
50
40
30
20
10
3:36AM
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
Time
Date : 18-Feb 4:40AM to 18-Feb 1:00PM, 2013
Average Ambient Temperature Outside = 4.7 °C

6


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 40.66 mins
Tfalling T_f = 27.88 mins
Temperature (°C)
70
60
50
40
30
20
10
63.2%
36.8%
T_r
T_f
3:36AM
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
Time
Date : 18-Feb 4:40AM to 18-Feb 1:00PM, 2013
Average Ambient Temperature Outside = 4.7 °C

7

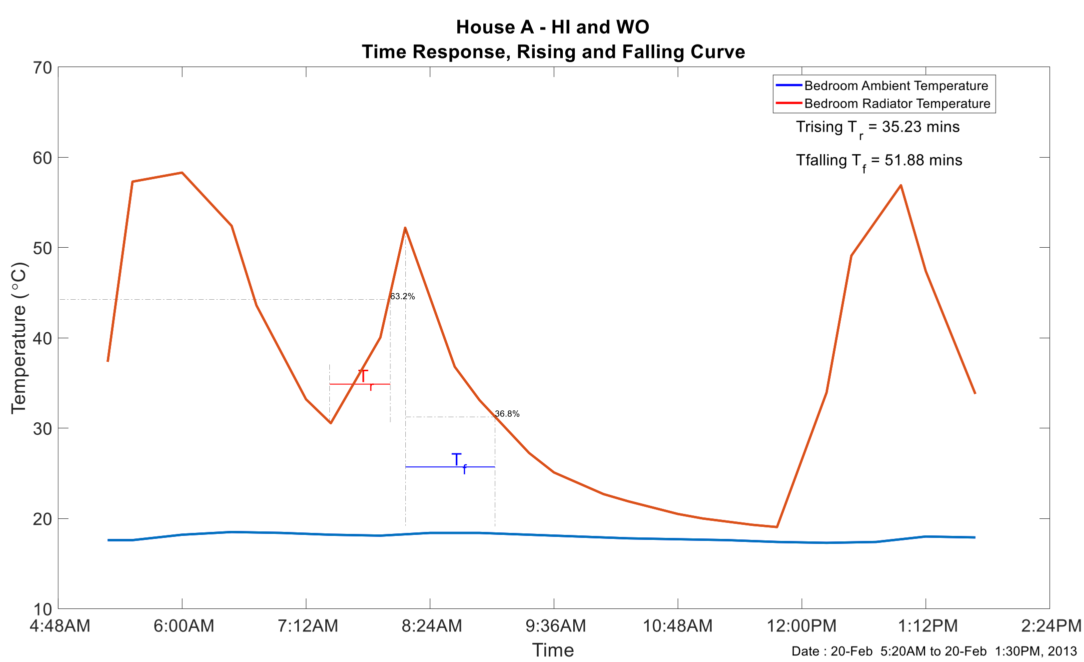

T Response of Radiator Cycle, Rising Curve - Instance 1
Tresponse (T_r mins)
45
40
35
30
25
20
15
10
5
0
A
B
C
D
House Indicator


T Response of Radiator Cycle, Falling Curve - Instance 1
T Response (T_f mins)
100
90
80
70
60
50
40
30
20
10
0
A
B
C
D
House Indicator

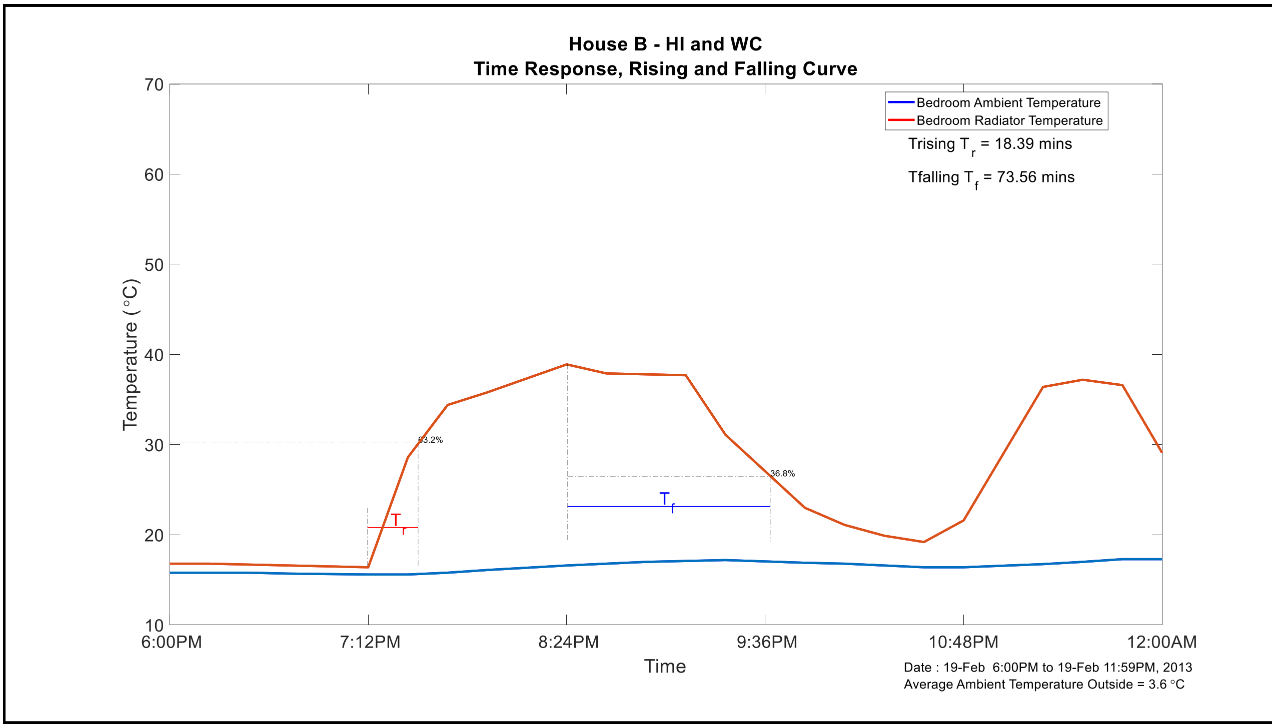
8

TR Instance 2

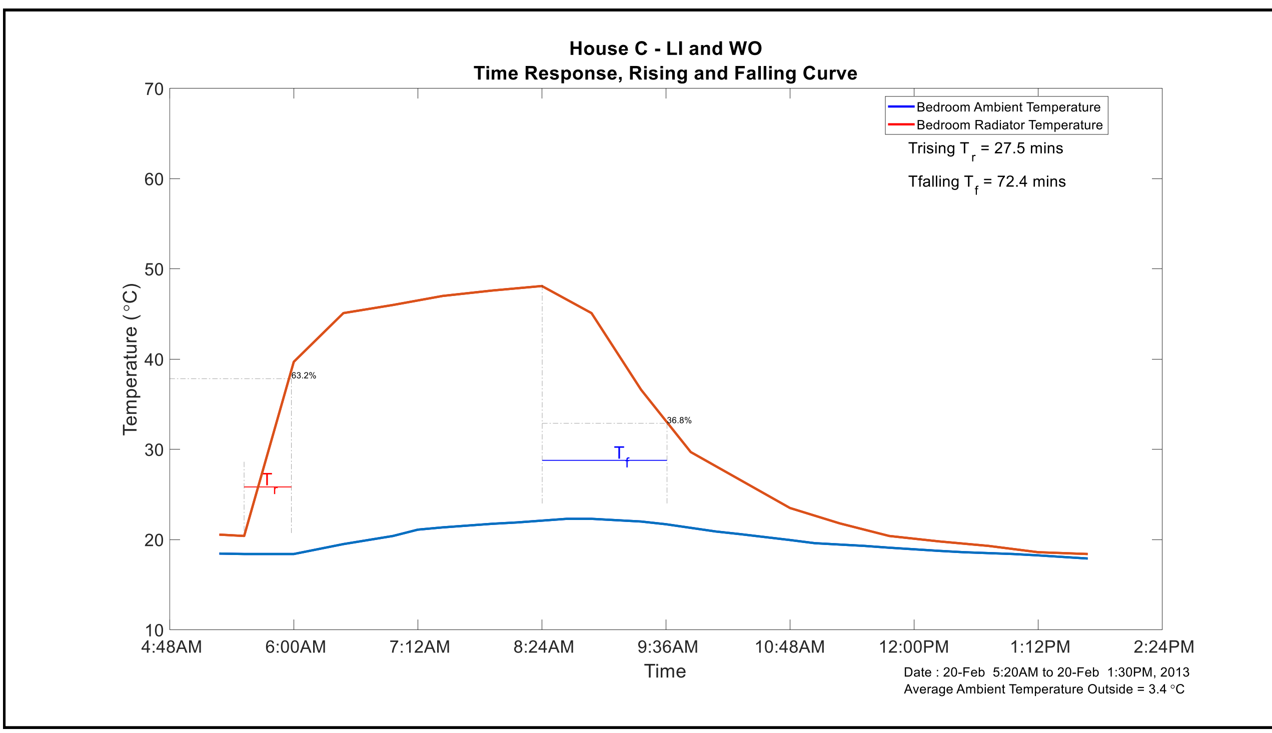
9



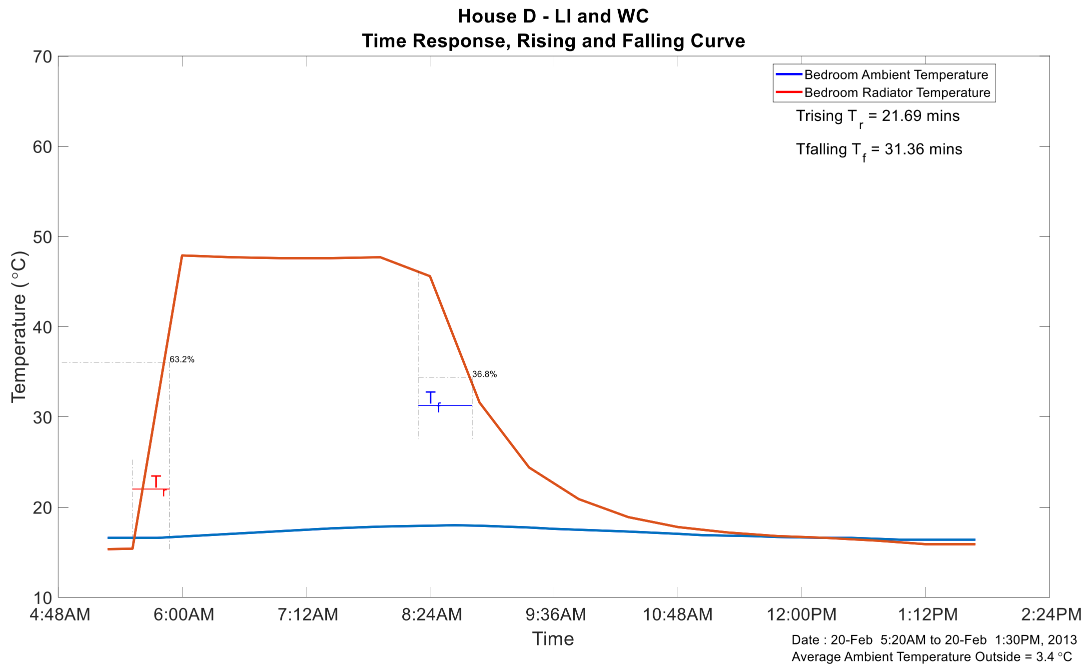
10


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 18.39 mins
Tfalling T_f = 73.56 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
Time
Date : 19-Feb 6:00PM to 19-Feb 11:59PM, 2013
Average Ambient Temperature Outside = 3.6 °C

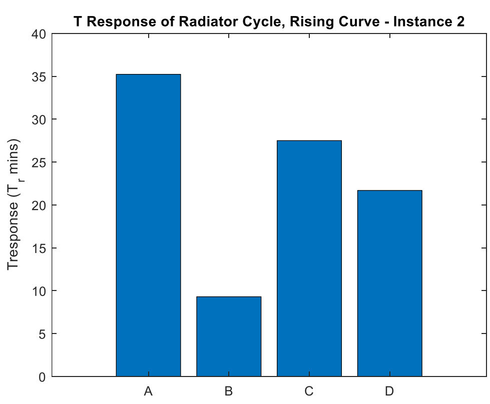
11

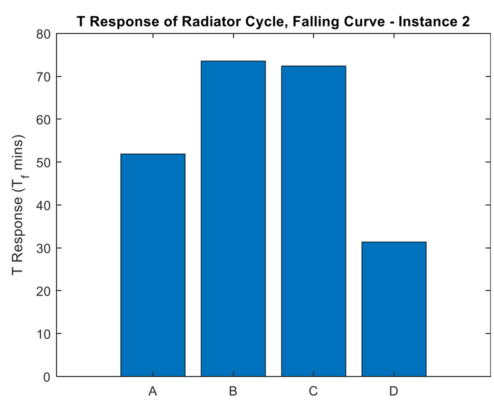

House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 27.5 mins
Tfalling T_f = 72.4 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
2:24PM
Time
Date : 20-Feb 5:20AM to 20-Feb 1:30PM, 2013
Average Ambient Temperature Outside = 3.4 °C

12


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 21.69 mins
Tfalling T_f = 31.36 mins
Temperature (°C)
Time
63.2%
36.8%
T_r
T_f
10
20
30
40
50
60
70
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
2:24PM
Date : 20-Feb 5:20AM to 20-Feb 1:30PM, 2013
Average Ambient Temperature Outside = 3.4 °C

13

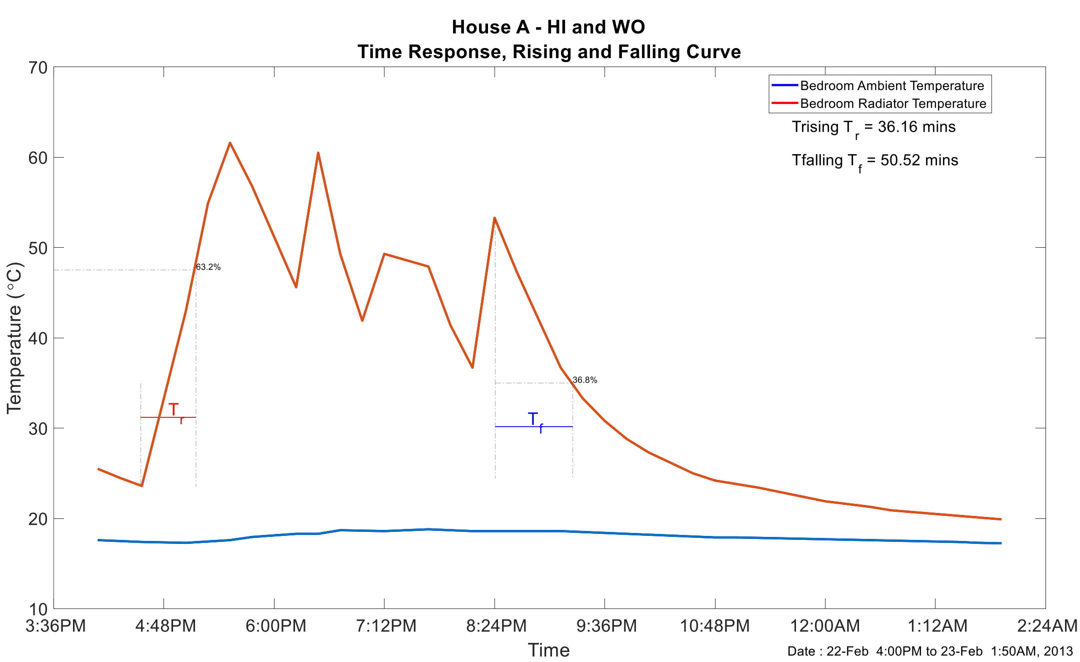

T Response of Radiator Cycle, Rising Curve - Instance 2
Tresponse (T_r mins)
House Indicator
A
B
C
D
0
5
10
15
20
25
30
35
40


T Response of Radiator Cycle, Falling Curve - Instance 2
T Response (T_f mins)
House Indicator
A
B
C
D
0
10
20
30
40
50
60
70
80

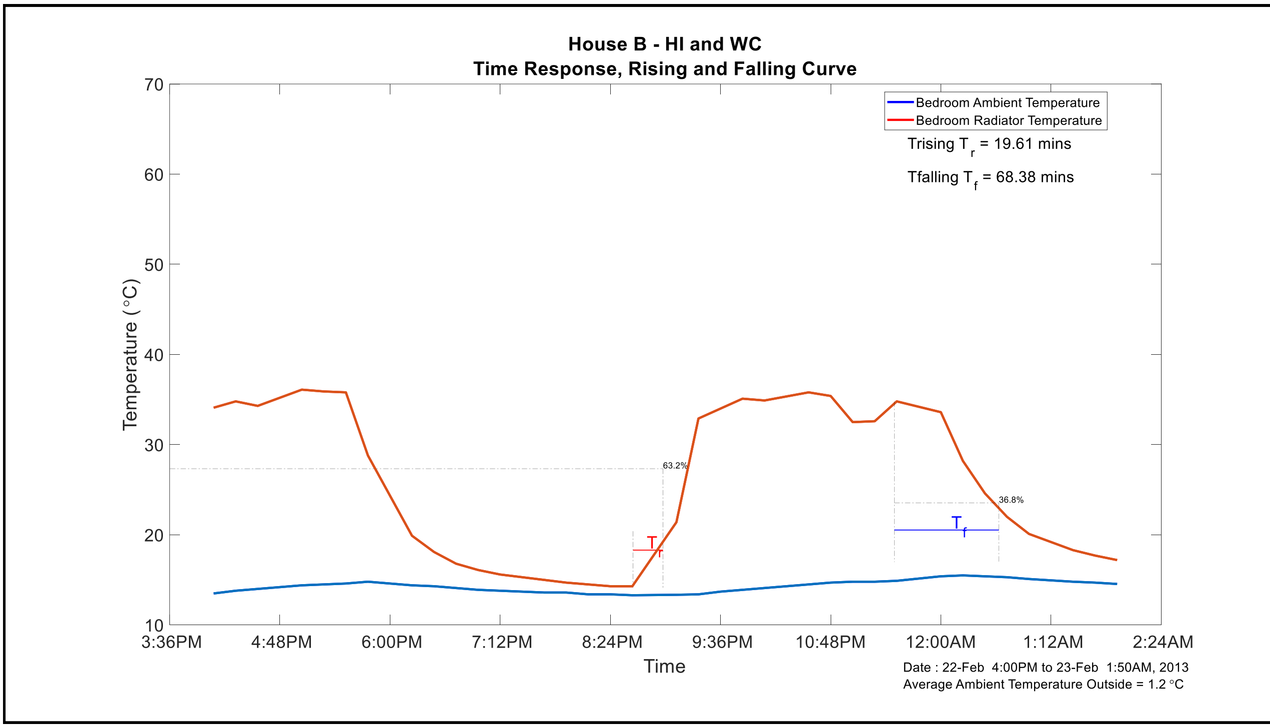
14

TR Instance 3

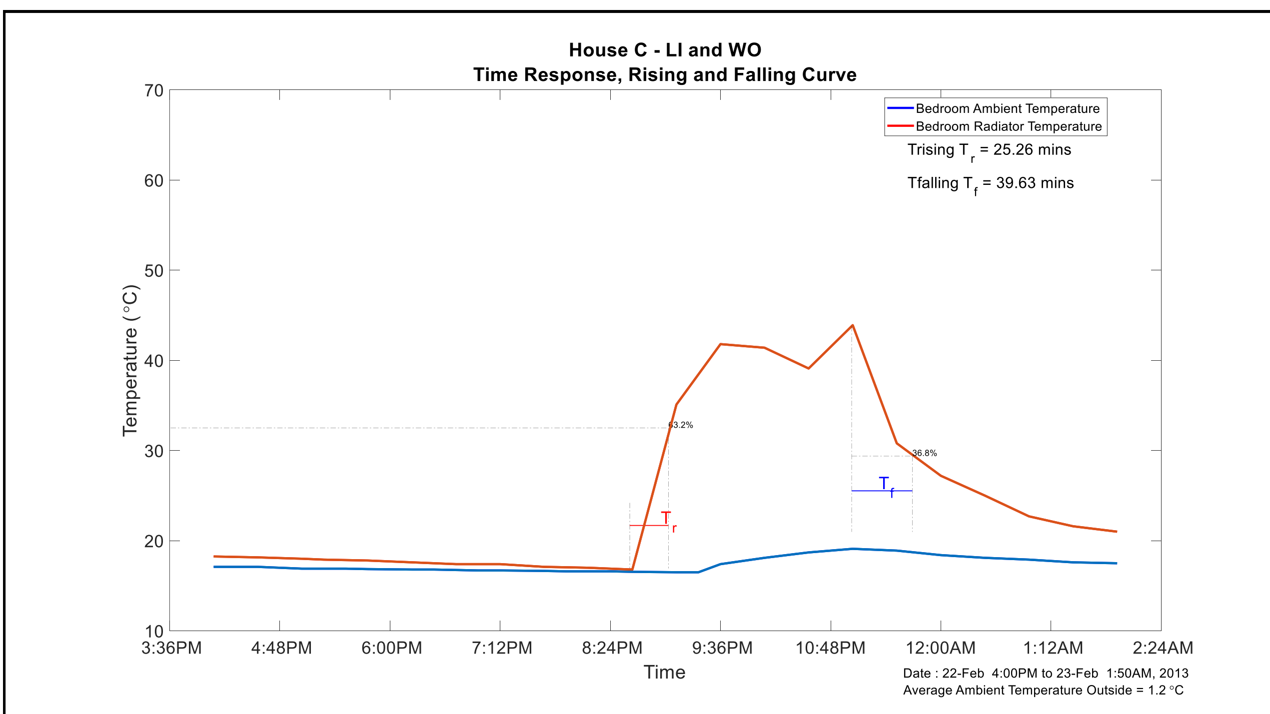
15



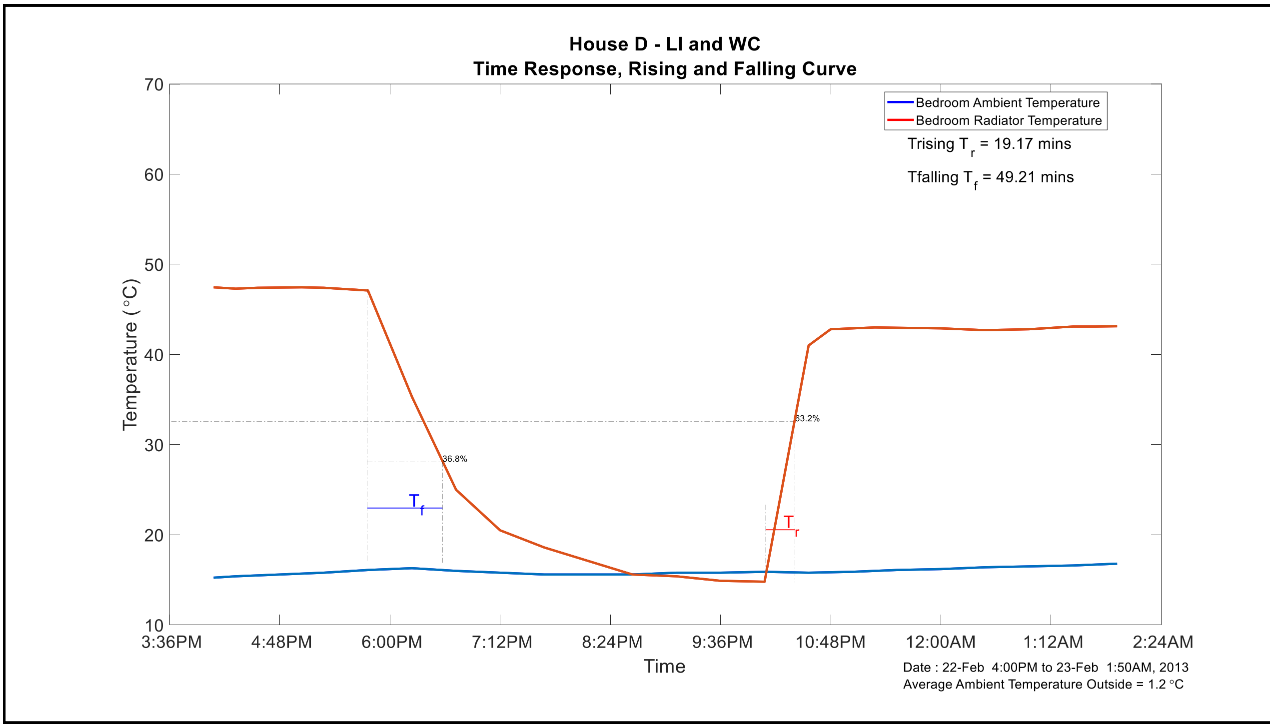
16


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 19.61 mins
Tfalling T_f = 68.38 mins
Temperature (°C)
70
60
50
40
30
20
10
63.2%
36.8%
T_r
T_f
3:36PM
4:48PM
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
1:12AM
2:24AM
Time
Date : 22-Feb 4:00PM to 23-Feb 1:50AM, 2013
Average Ambient Temperature Outside = 1.2 °C

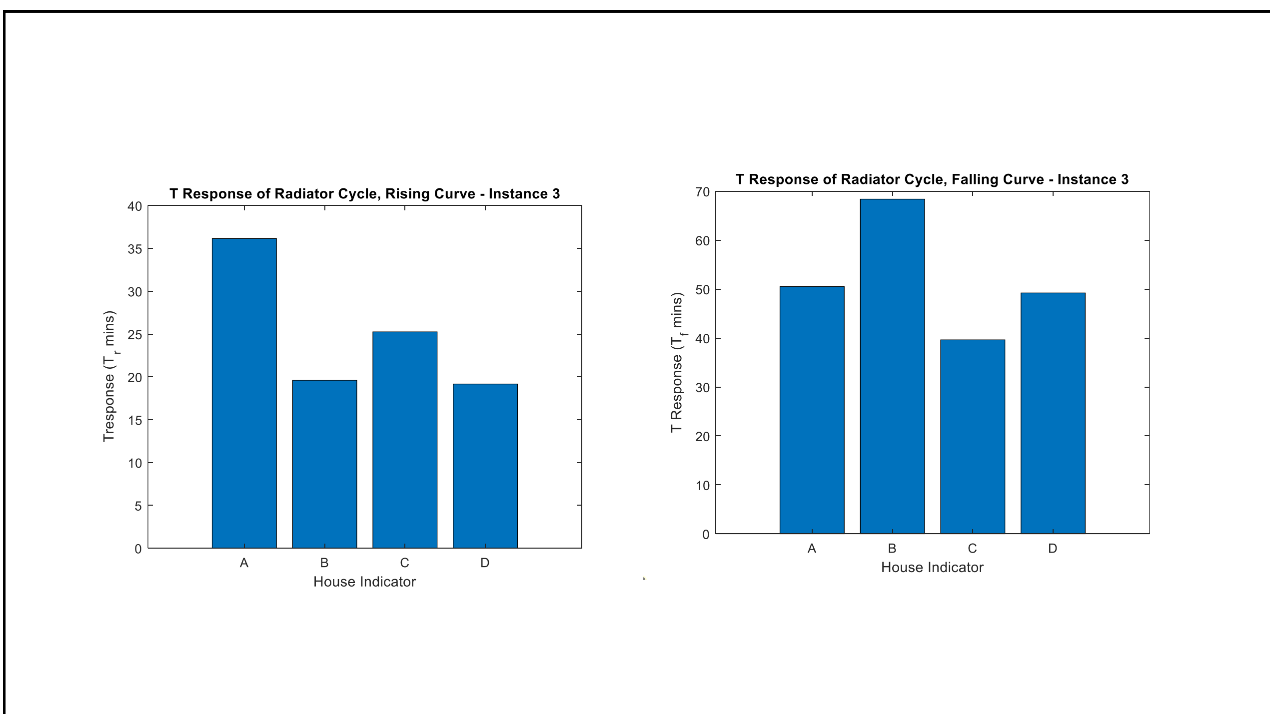
17


House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 25.26 mins
Tfalling T_f = 39.63 mins
Temperature (°C)
70
60
50
40
30
20
10
63.2%
36.8%
T_r
T_f
3:36PM
4:48PM
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
1:12AM
2:24AM
Time
Date : 22-Feb 4:00PM to 23-Feb 1:50AM, 2013
Average Ambient Temperature Outside = 1.2 °C

18


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 19.17 mins
Tfalling T_f = 49.21 mins
Temperature (°C)
Time
Date : 22-Feb 4:00PM to 23-Feb 1:50AM, 2013
Average Ambient Temperature Outside = 1.2 °C
63.2%
36.8%
T_f
T_r

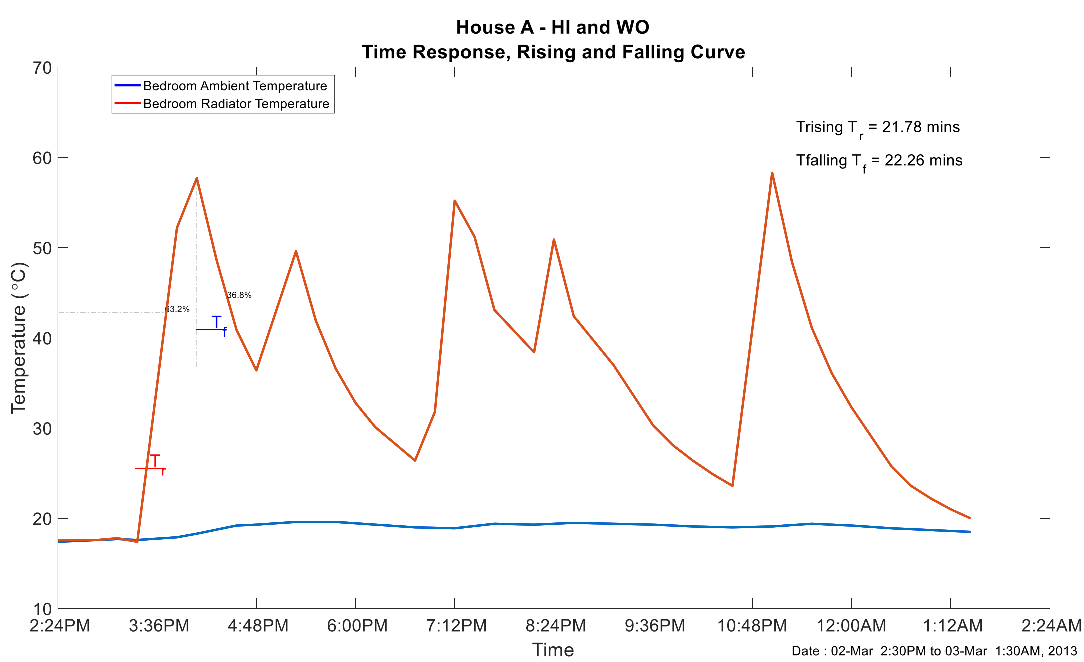
19


T Response of Radiator Cycle, Rising Curve - Instance 3
Tresponse (T_r mins)
House Indicator
T Response of Radiator Cycle, Falling Curve - Instance 3
T Response (T_f mins)
House Indicator

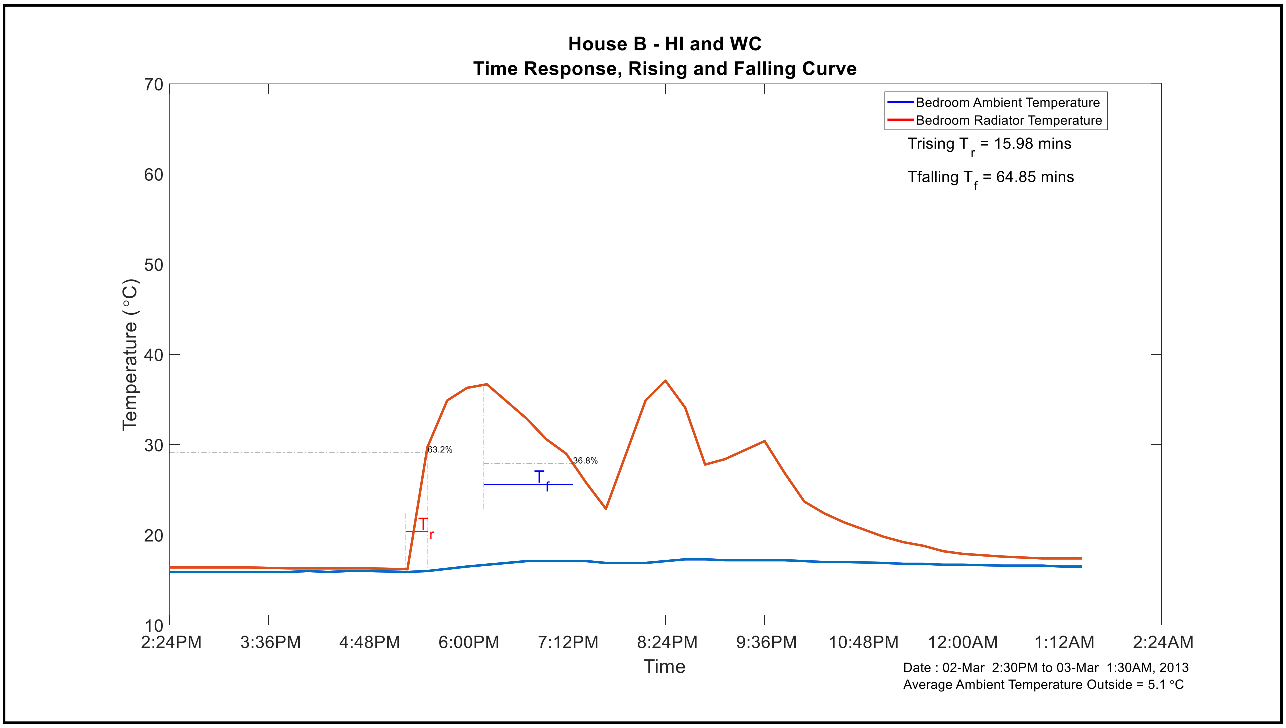
20

TR Instance 4

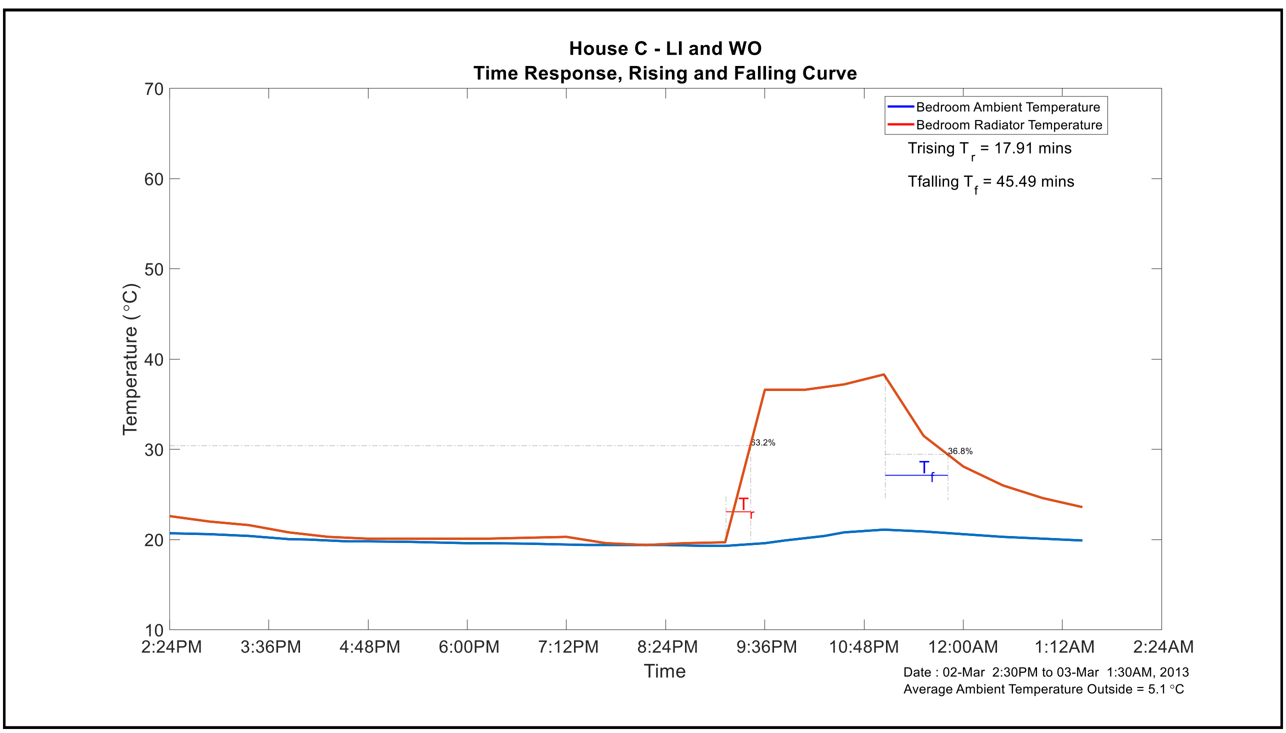
21



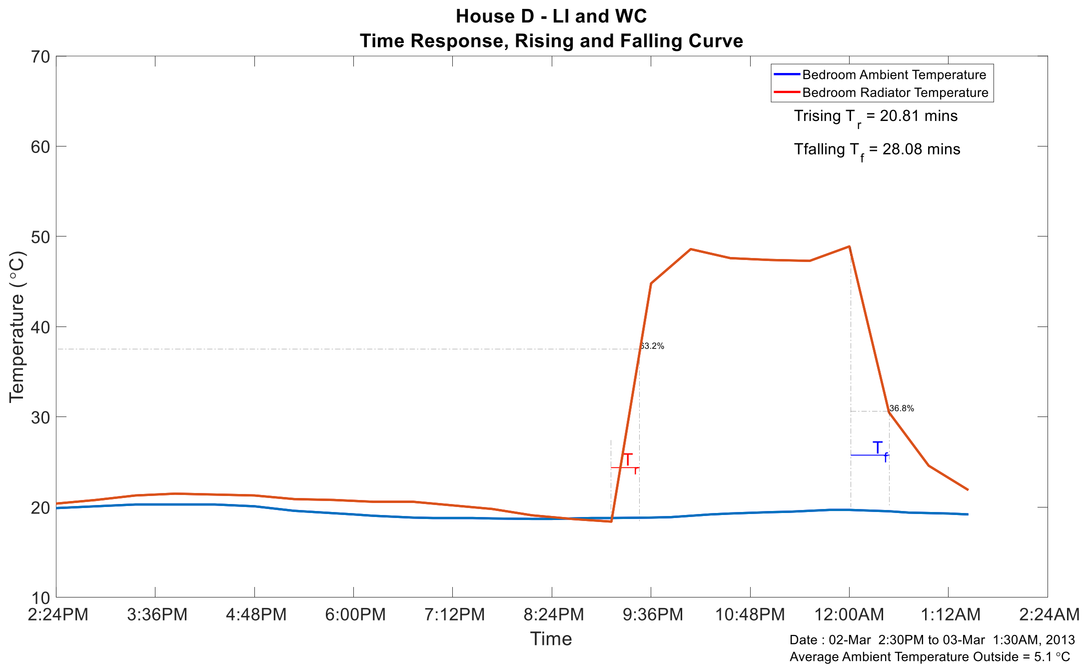
22


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 15.98 mins
Tfalling T_f = 64.85 mins
Temperature (°C)
Time
63.2%
36.8%
T_r
T_f
70
60
50
40
30
20
10
2:24PM
3:36PM
4:48PM
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
1:12AM
2:24AM
Date : 02-Mar 2:30PM to 03-Mar 1:30AM, 2013
Average Ambient Temperature Outside = 5.1 °C

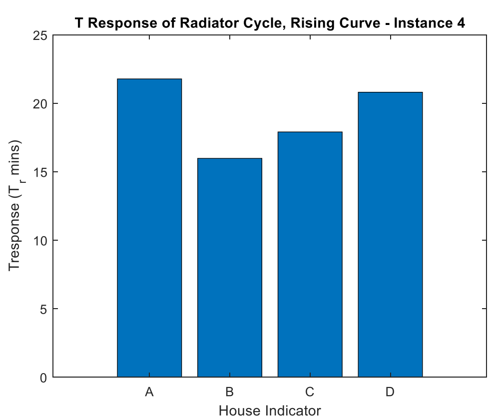
23

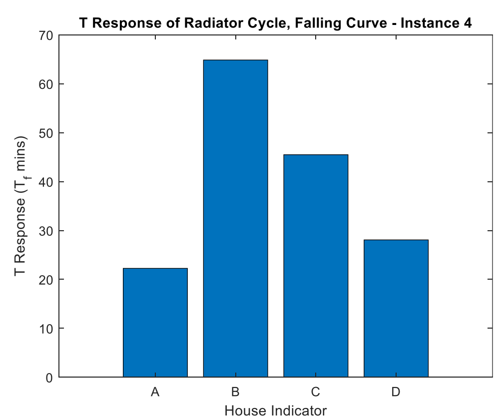

House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 17.91 mins
Tfalling T_f = 45.49 mins
Temperature (°C)
Time
63.2%
36.8%
T_r
T_f
70
60
50
40
30
20
10
2:24PM
3:36PM
4:48PM
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
1:12AM
2:24AM
Date : 02-Mar 2:30PM to 03-Mar 1:30AM, 2013
Average Ambient Temperature Outside = 5.1 °C

24


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 20.81 mins
Tfalling T_f = 28.08 mins
Temperature (°C)
70
60
50
40
30
20
10
63.2%
36.8%
T_r
T_f
2:24PM
3:36PM
4:48PM
6:00PM
7:12PM
8:24PM
9:36PM
10:48PM
12:00AM
1:12AM
2:24AM
Time
Date : 02-Mar 2:30PM to 03-Mar 1:30AM, 2013
Average Ambient Temperature Outside = 5.1 °C

25

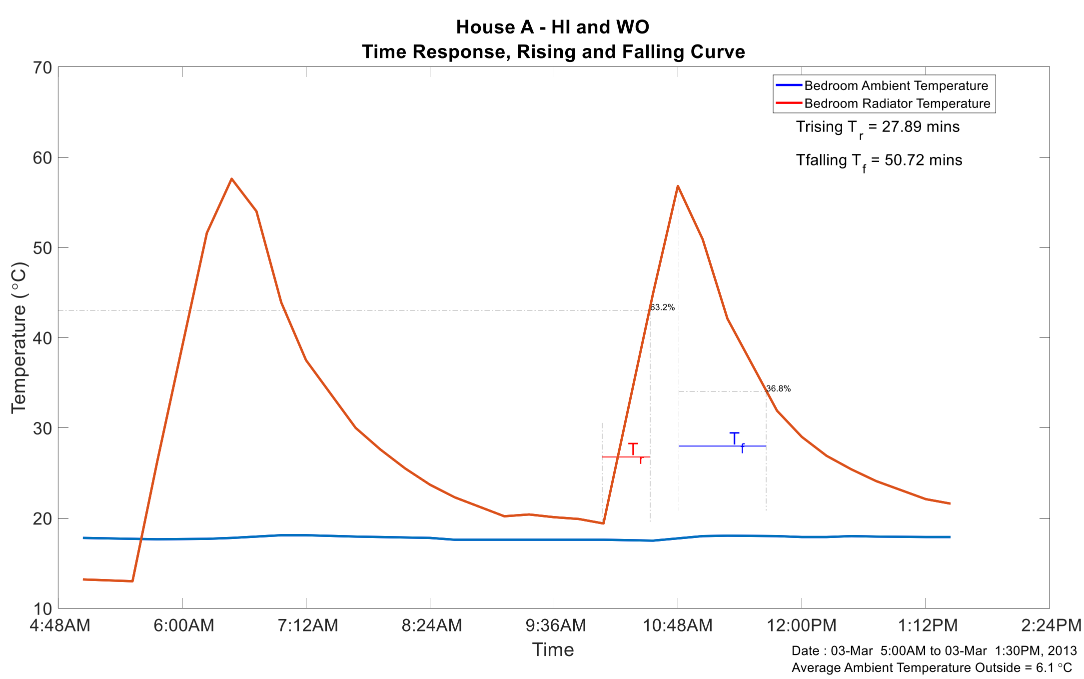

T Response of Radiator Cycle, Rising Curve - Instance 4
Tresponse (T_r mins)
25
20
15
10
5
0
A
B
C
D
House Indicator


T Response of Radiator Cycle, Falling Curve - Instance 4
T Response (T_f mins)
70
60
50
40
30
20
10
0
A
B
C
D
House Indicator

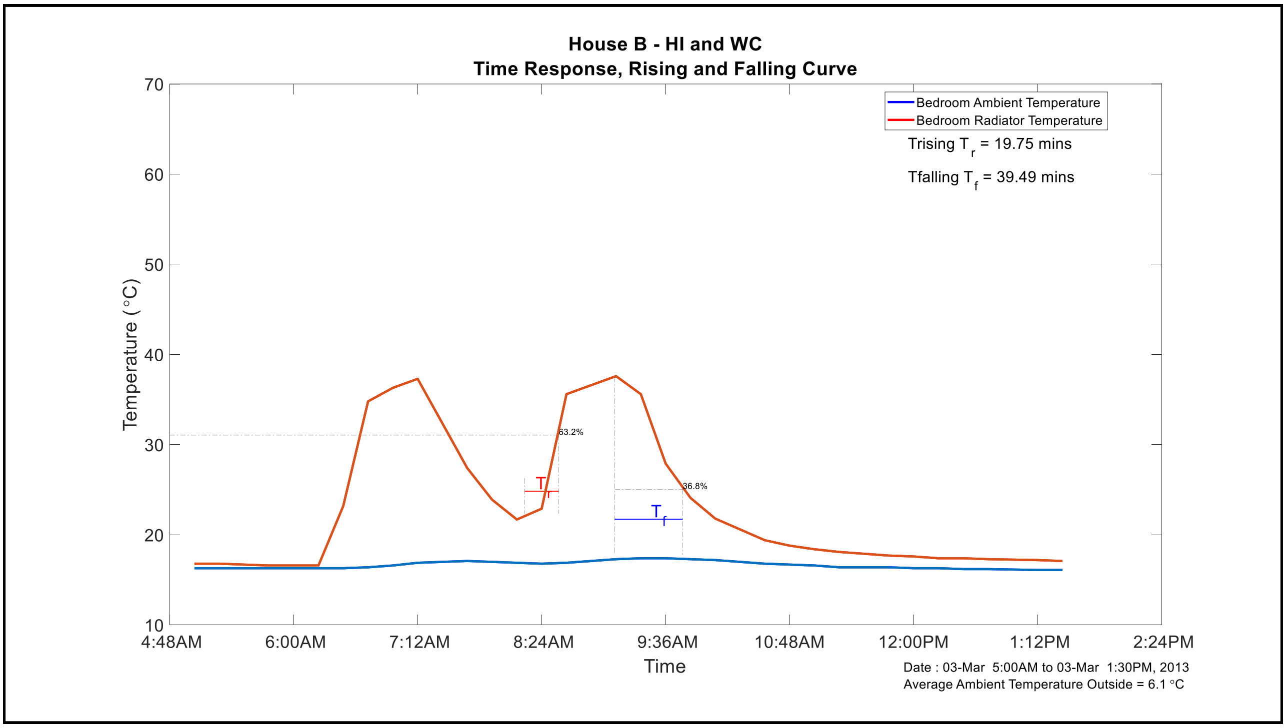
26

TR Instance 5

27

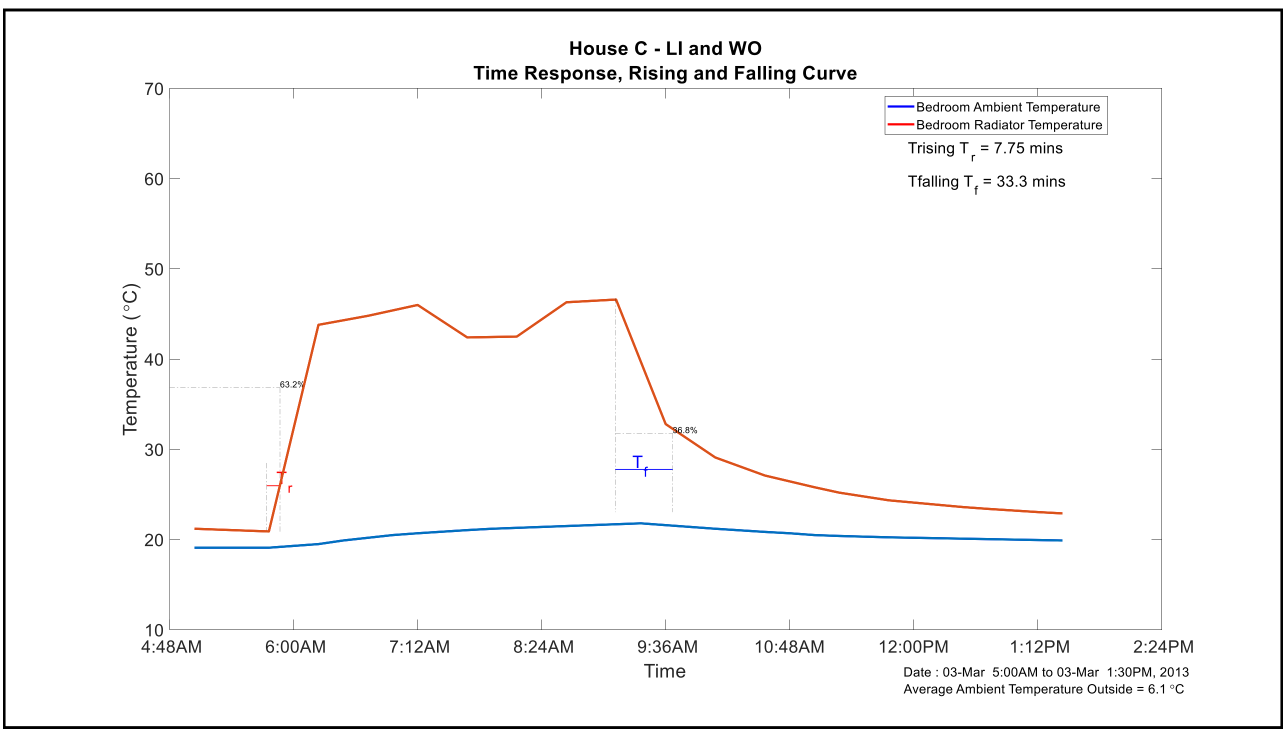


28



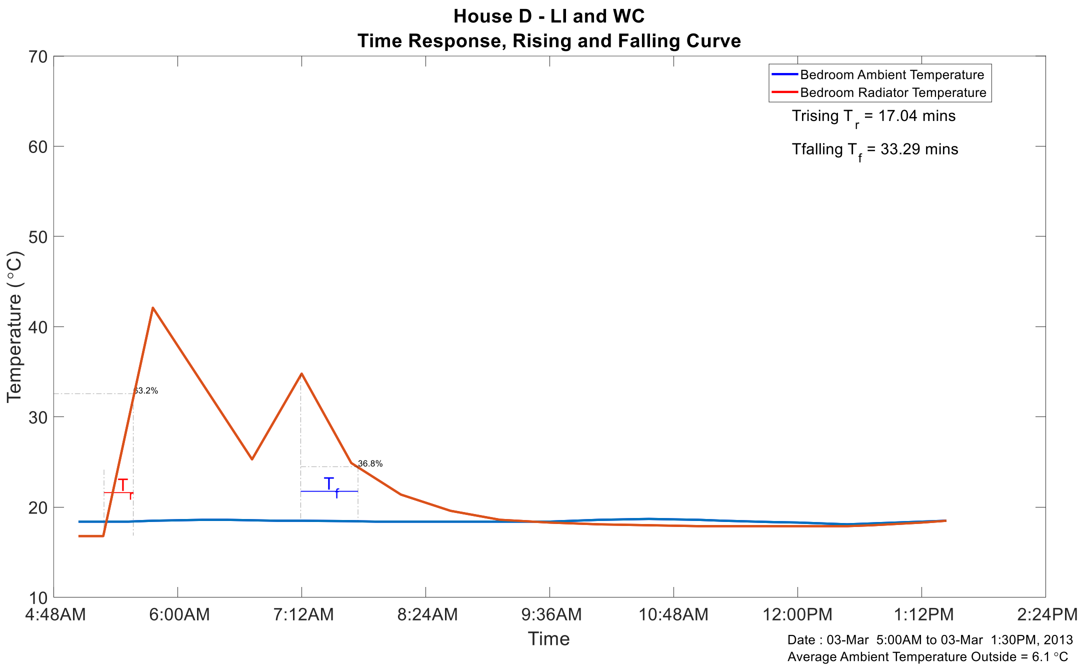
House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 19.75 mins
Tfalling T_f = 39.49 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
2:24PM
Time
Date : 03-Mar 5:00AM to 03-Mar 1:30PM, 2013
Average Ambient Temperature Outside = 6.1 °C

29

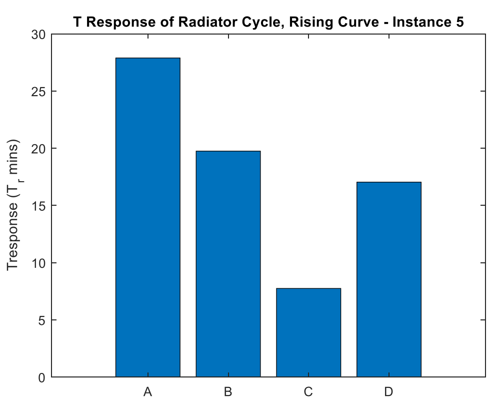


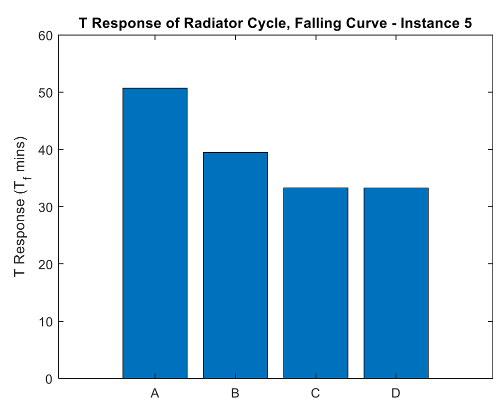
House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 7.75 mins
Tfalling T_f = 33.3 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
2:24PM
Time
Date : 03-Mar 5:00AM to 03-Mar 1:30PM, 2013
Average Ambient Temperature Outside = 6.1 °C

30


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T r = 17.04 mins
Tfalling T f = 33.29 mins
63.2%
36.8%
T r
T f
Temperature (°C)
70
60
50
40
30
20
10
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
1:12PM
2:24PM
Time
Date : 03-Mar 5:00AM to 03-Mar 1:30PM, 2013
Average Ambient Temperature Outside = 6.1 °C

31

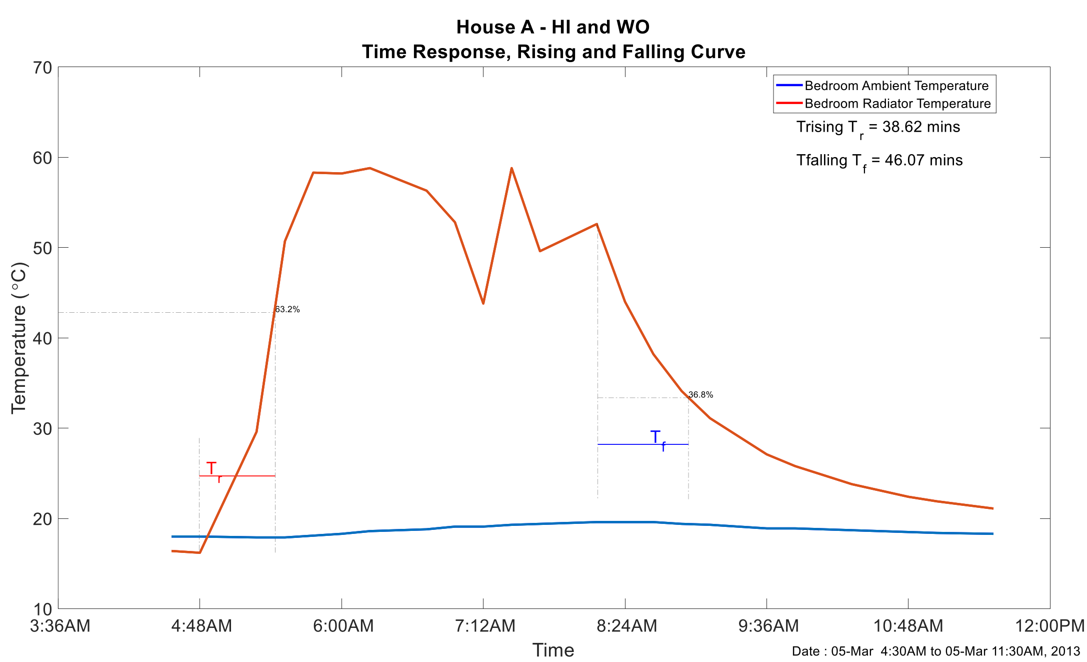

T Response of Radiator Cycle, Rising Curve - Instance 5
Tresponse (T r mins)
30
25
20
15
10
5
0
A
B
C
D
House Indicator


T Response of Radiator Cycle, Falling Curve - Instance 5
T Response (T f mins)
60
50
40
30
20
10
0
A
B
C
D
House Indicator

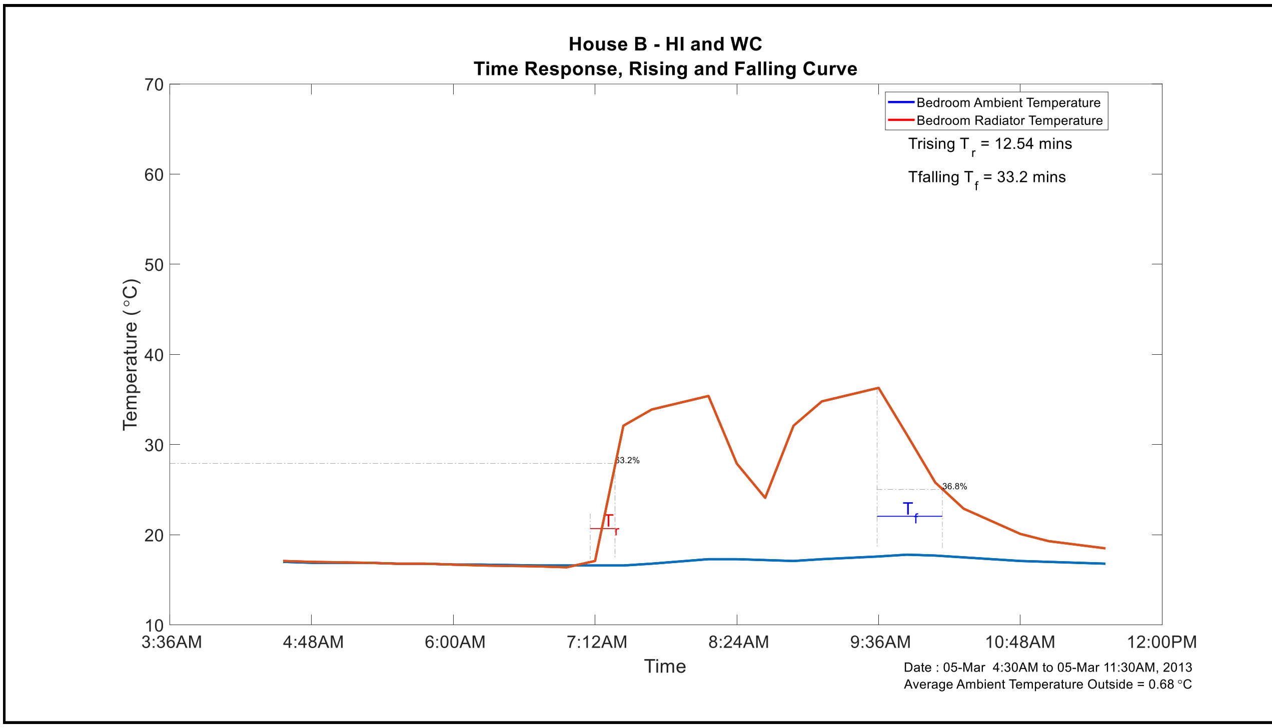
32

TR Instance 6

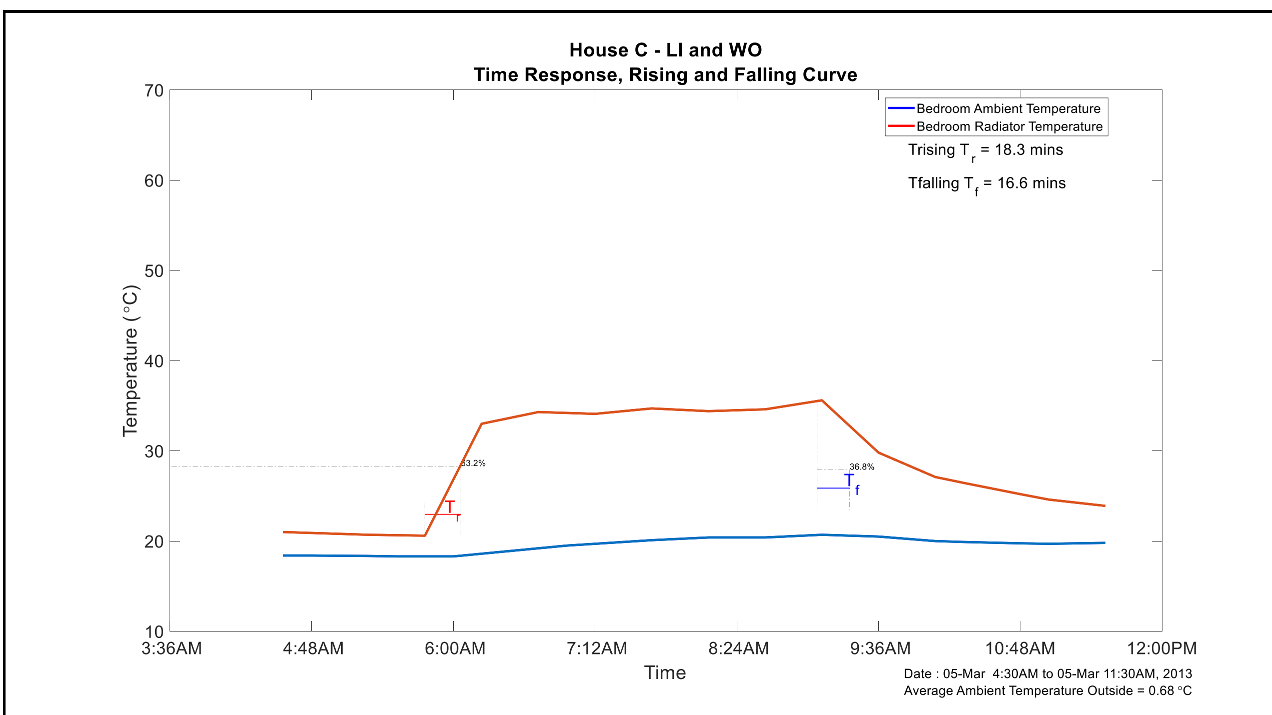
33



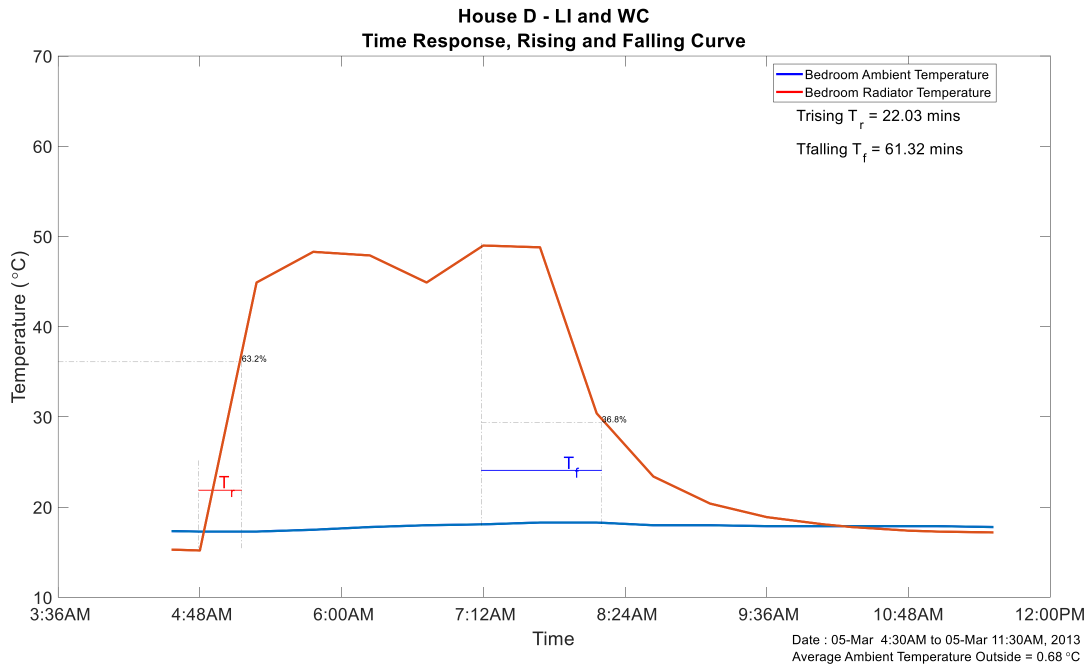
34


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 12.54 mins
Tfalling T_f = 33.2 mins
Temperature (°C)
Time
Date : 05-Mar 4:30AM to 05-Mar 11:30AM, 2013
Average Ambient Temperature Outside = 0.68 °C

35

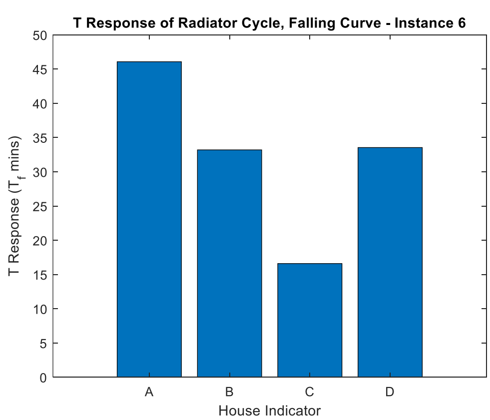

House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 18.3 mins
Tfalling T_f = 16.6 mins
Temperature (°C)
Time
Date : 05-Mar 4:30AM to 05-Mar 11:30AM, 2013
Average Ambient Temperature Outside = 0.68 °C

36

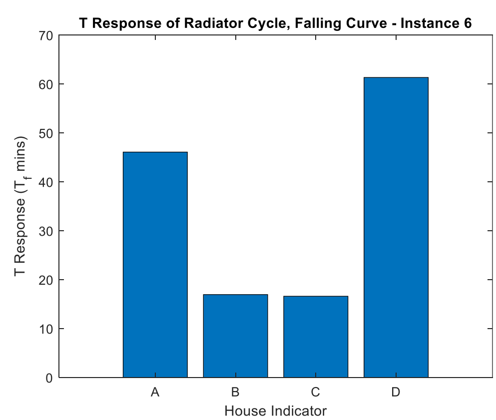


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 22.03 mins
Tfalling T_f = 61.32 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
3:36AM
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
Time
Date : 05-Mar 4:30AM to 05-Mar 11:30AM, 2013
Average Ambient Temperature Outside = 0.68 °C

37



T Response of Radiator Cycle, Falling Curve - Instance 6
T Response (T_f mins)
50
45
40
35
30
25
20
15
10
5
0
A
B
C
D
House Indicator

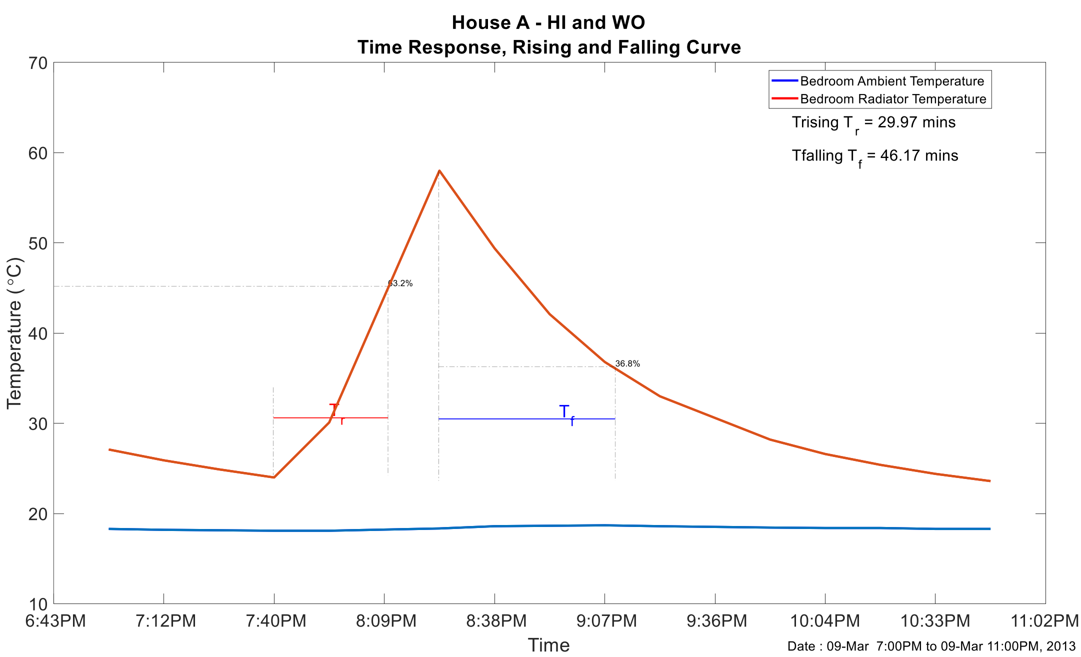


T Response of Radiator Cycle, Falling Curve - Instance 6
T Response (T_f mins)
70
60
50
40
30
20
10
0
A
B
C
D
House Indicator

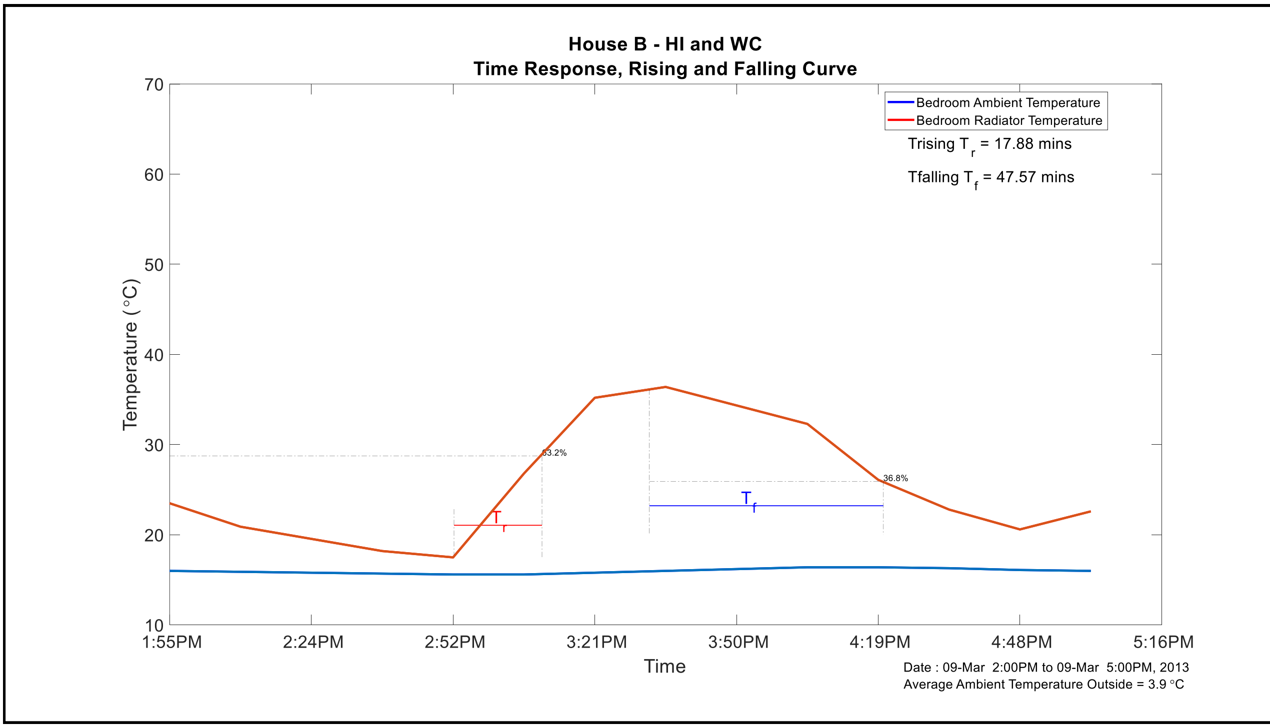
38

TR Instance 7

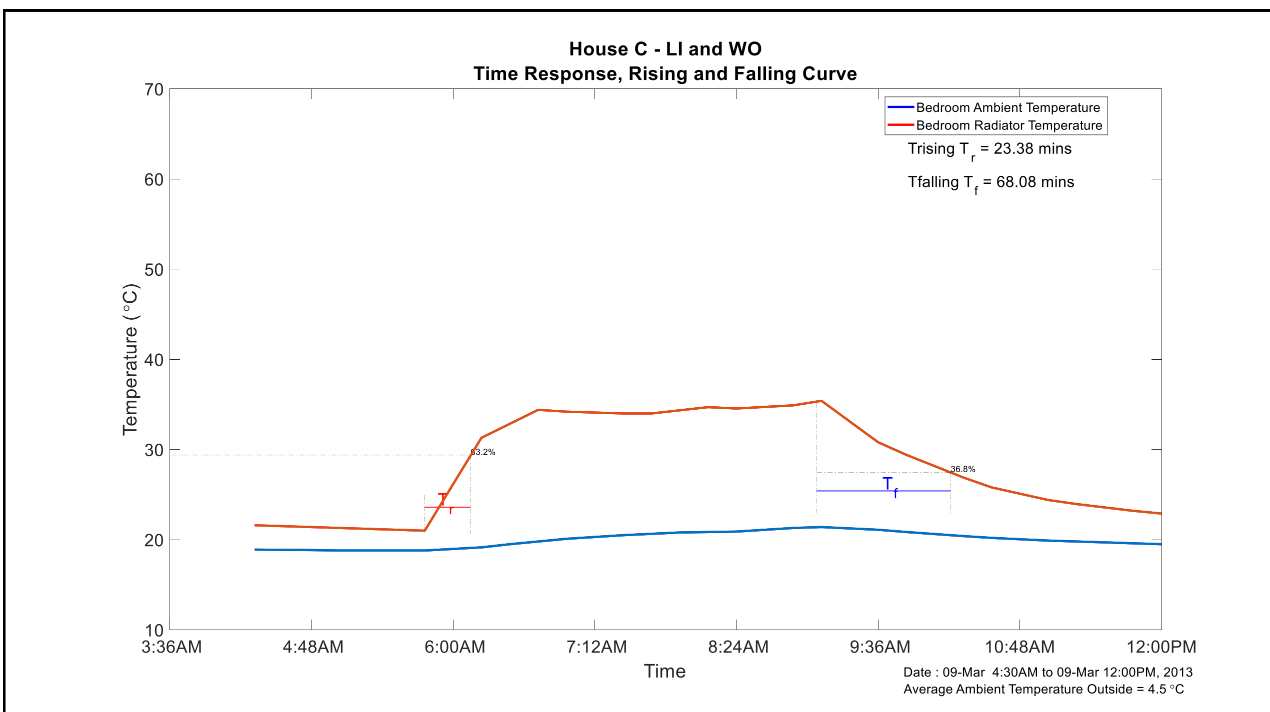
39



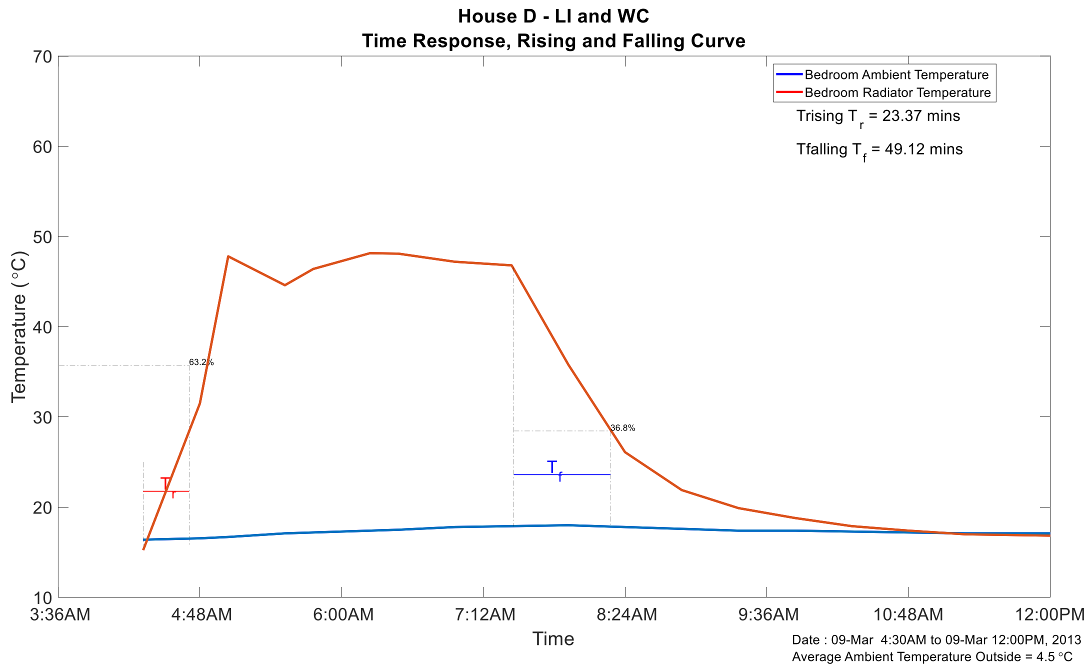
40


House B - HI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 17.88 mins
Tfalling T_f = 47.57 mins
Temperature (°C)
70
60
50
40
30
20
10
1:55PM
2:24PM
2:52PM
3:21PM
3:50PM
4:19PM
4:48PM
5:16PM
Time
Date : 09-Mar 2:00PM to 09-Mar 5:00PM, 2013
Average Ambient Temperature Outside = 3.9 °C

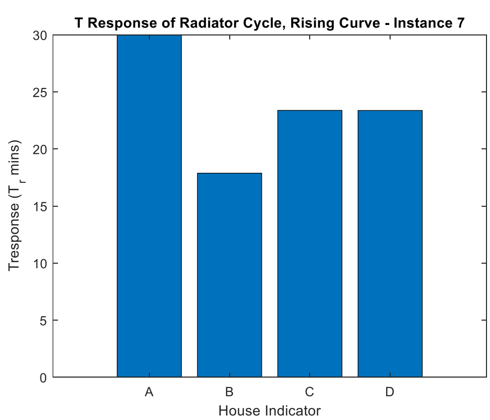
41

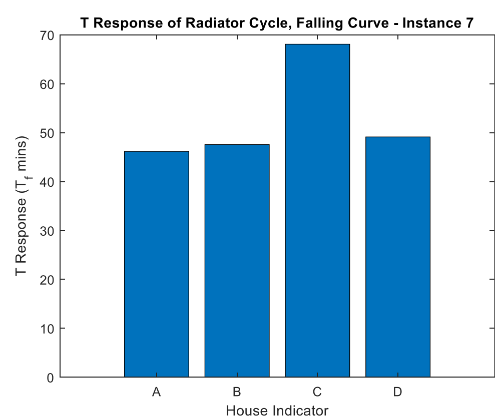

House C - LI and WO
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 23.38 mins
Tfalling T_f = 68.08 mins
Temperature (°C)
70
60
50
40
30
20
10
3:36AM
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
Time
Date : 09-Mar 4:30AM to 09-Mar 12:00PM, 2013
Average Ambient Temperature Outside = 4.5 °C

42


House D - LI and WC
Time Response, Rising and Falling Curve
Bedroom Ambient Temperature
Bedroom Radiator Temperature
Trising T_r = 23.37 mins
Tfalling T_f = 49.12 mins
63.2%
36.8%
T_r
T_f
Temperature (°C)
70
60
50
40
30
20
10
3:36AM
4:48AM
6:00AM
7:12AM
8:24AM
9:36AM
10:48AM
12:00PM
Time
Date : 09-Mar 4:30AM to 09-Mar 12:00PM, 2013
Average Ambient Temperature Outside = 4.5 °C

43


T Response of Radiator Cycle, Rising Curve - Instance 7
Tresponse (T_r mins)
30
25
20
15
10
5
0
A
B
C
D
House Indicator

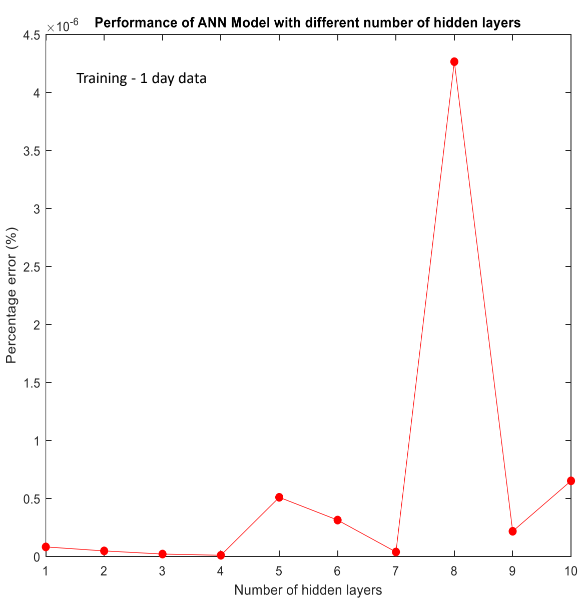

T Response of Radiator Cycle, Falling Curve - Instance 7
T Response (T_f mins)
70
60
50
40
30
20
10
0
A
B
C
D
House Indicator

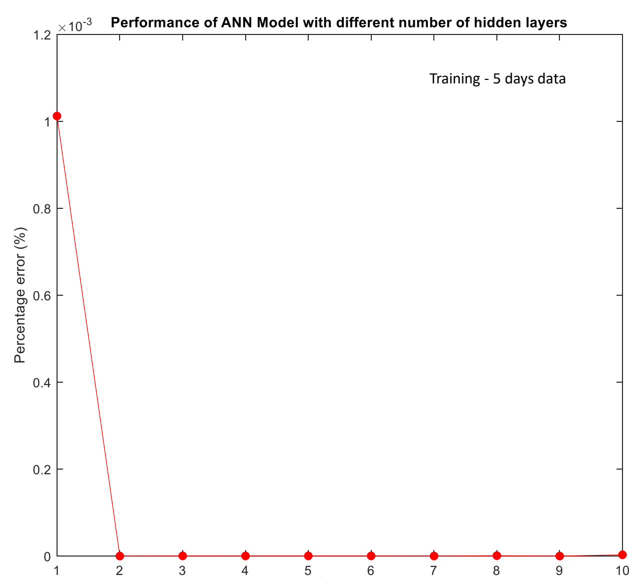
44

Appendix D

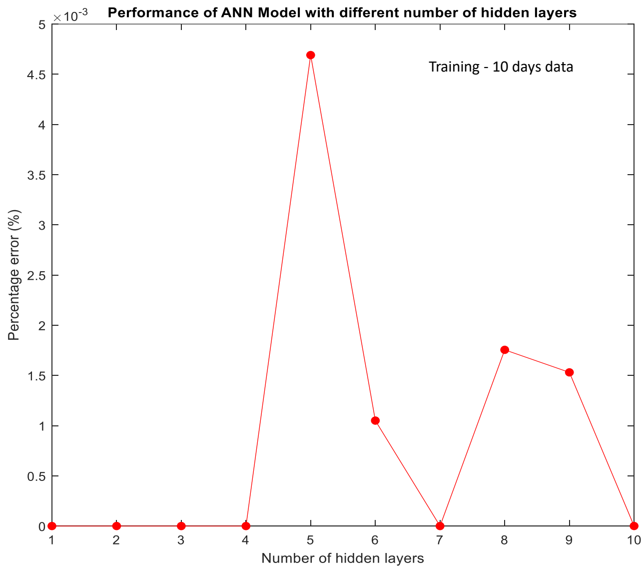
Grpahs from trials and training of ANN Model

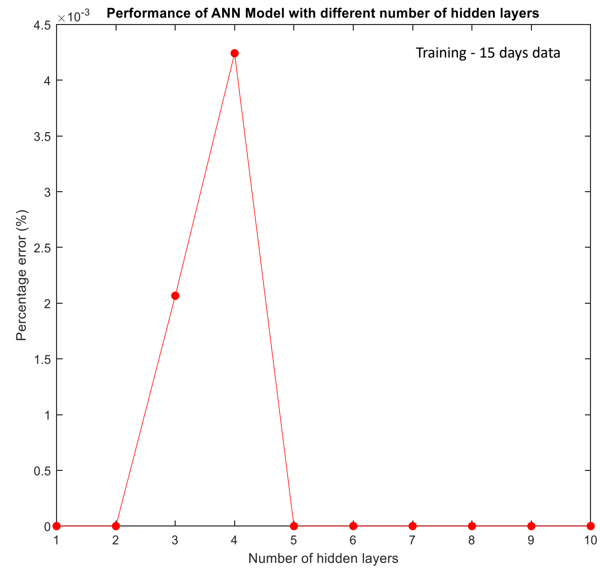
1



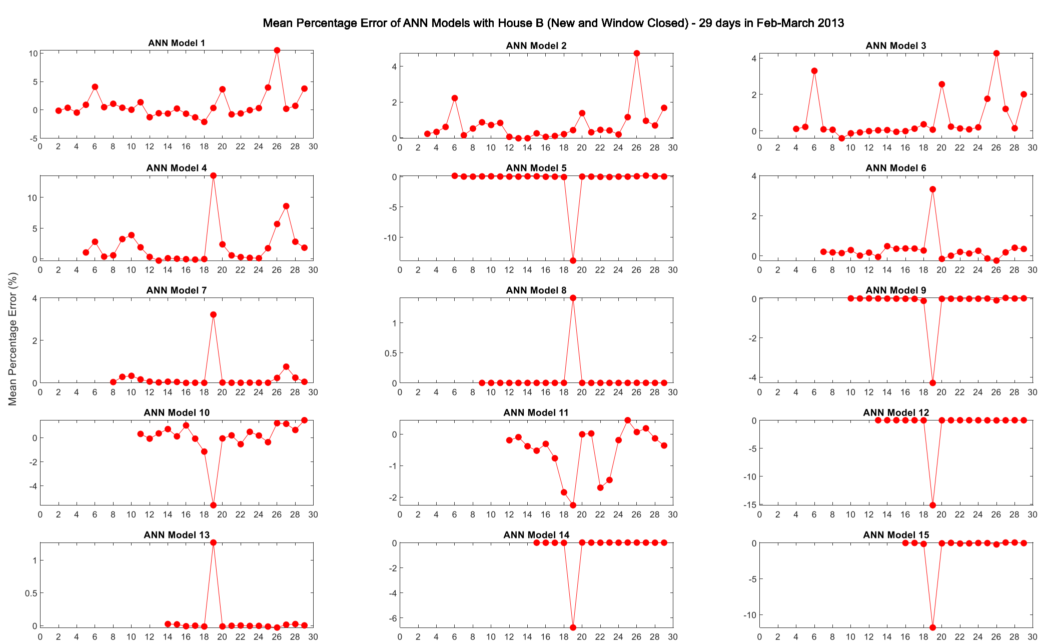


2

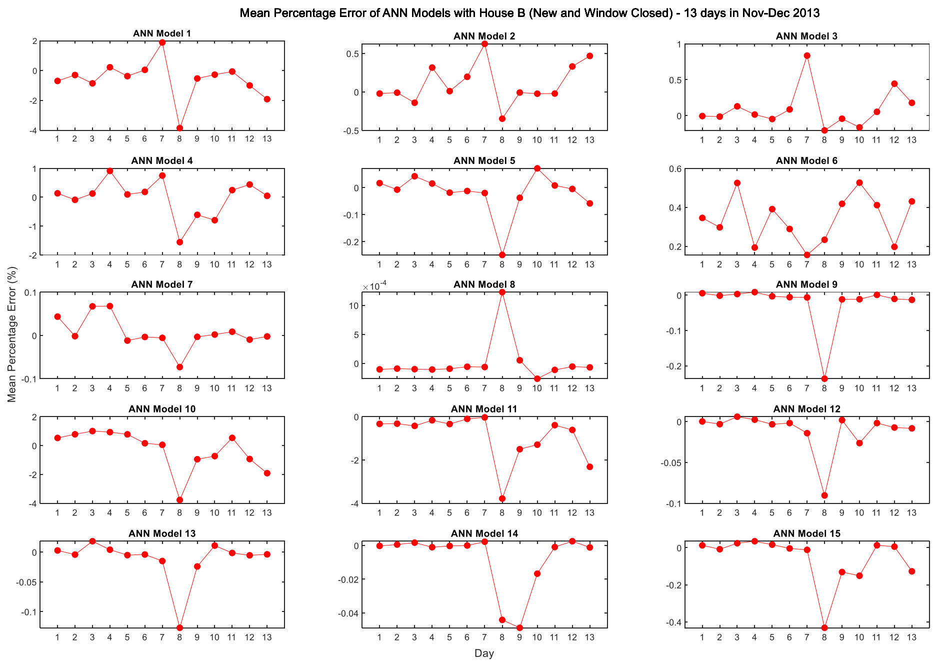

Performance of ANN Model with different number of hidden layers
Training - 10 days data
$\times 10^{-3}$
Percentage error (%)
Number of hidden layers


Performance of ANN Model with different number of hidden layers
Training - 15 days data
$\times 10^{-3}$
Percentage error (%)
Number of hidden layers

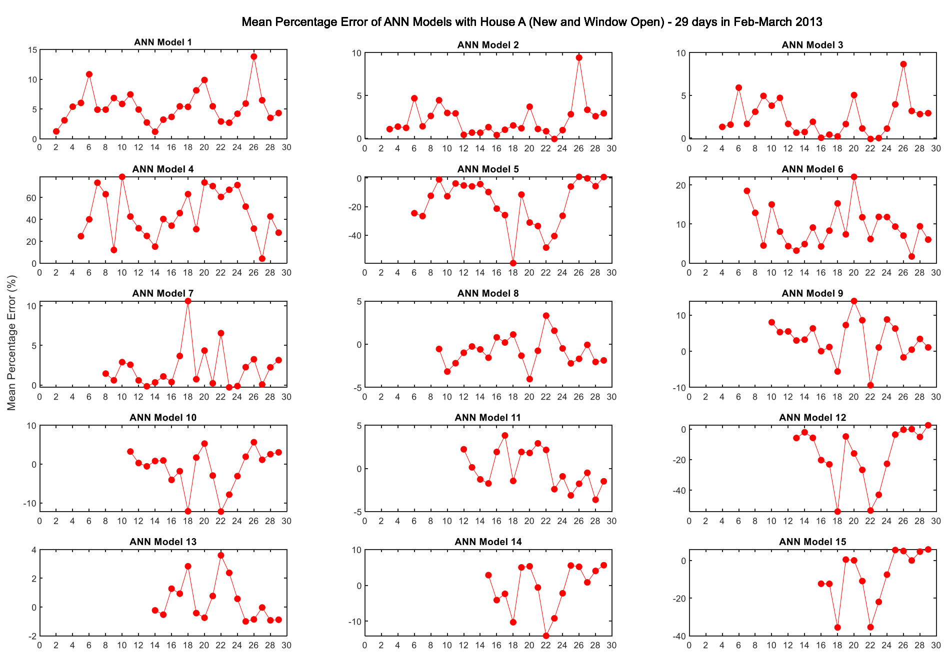
3


Mean Percentage Error of ANN Models with House B (New and Window Closed) - 29 days in Feb-March 2013
ANN Model 1
ANN Model 2
ANN Model 3
ANN Model 4
ANN Model 5
ANN Model 6
ANN Model 7
ANN Model 8
ANN Model 9
ANN Model 10
ANN Model 11
ANN Model 12
ANN Model 13
ANN Model 14
ANN Model 15
Mean Percentage Error (%)
Day

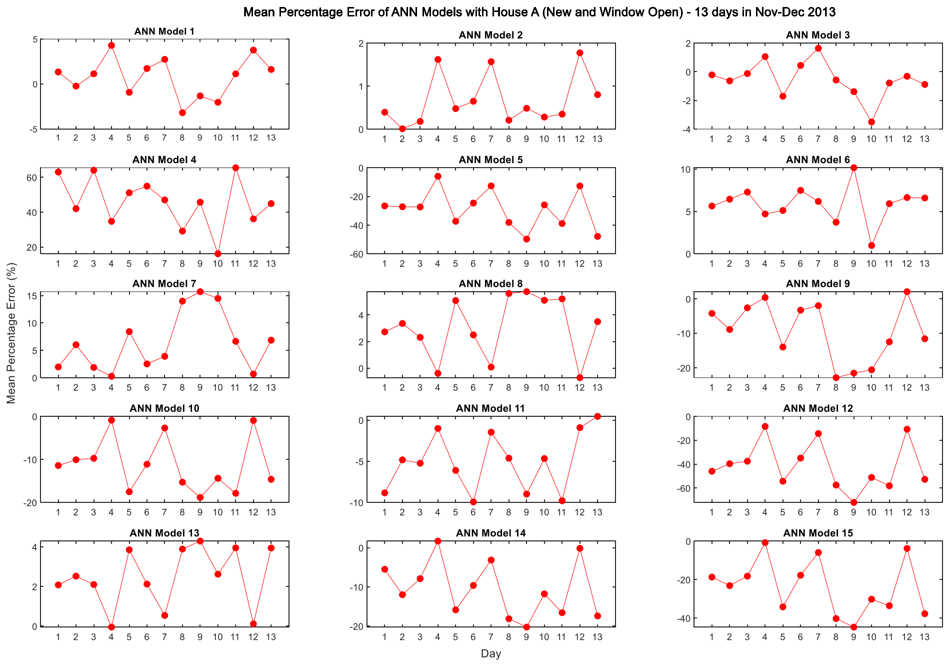
4


Mean Percentage Error of ANN Models with House B (New and Window Closed) - 13 days in Nov-Dec 2013
ANN Model 1
ANN Model 2
ANN Model 3
ANN Model 4
ANN Model 5
ANN Model 6
ANN Model 7
ANN Model 8
ANN Model 9
ANN Model 10
ANN Model 11
ANN Model 12
ANN Model 13
ANN Model 14
ANN Model 15
Mean Percentage Error (%)
Day

5


Mean Percentage Error of ANN Models with House A (New and Window Open) - 29 days in Feb-March 2013
ANN Model 1
ANN Model 2
ANN Model 3
ANN Model 4
ANN Model 5
ANN Model 6
ANN Model 7
ANN Model 8
ANN Model 9
ANN Model 10
ANN Model 11
ANN Model 12
ANN Model 13
ANN Model 14
ANN Model 15
Mean Percentage Error (%)
Day

6



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ANN pattern recognition_for thesis

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Training data

- Training is done separate for winter 1 and winter 2.
- Winter 1:
- Training data 1 is
  - House 2 Winter 1, day 1 data + House 11 Winter 1, day 7 data (day 7 is full open)
- Training data 2 is
  - Training data 1 + House 2 Winter 1, day 2 data + House 11 Winter 1 day 10 data (day 10 is the next full open day)

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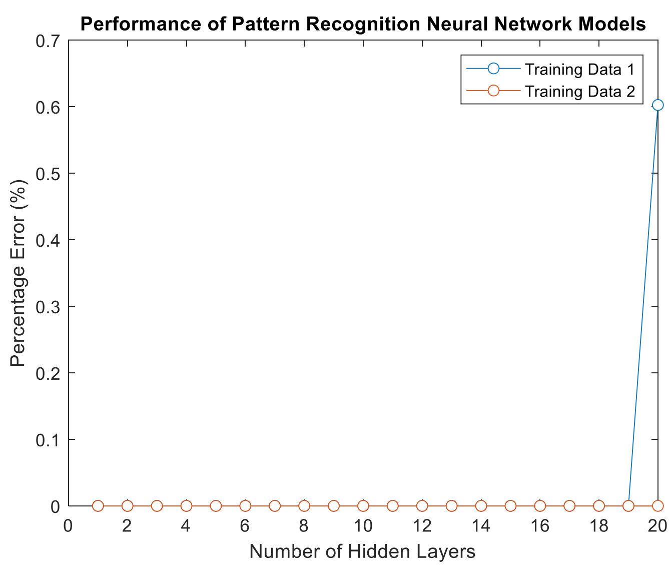

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Training data winter 2

Winter 2

- Training data 1 is
  - House 2 Winter 2, day 1 data + House 11 Winter 2, day 11 data (day 11 is 100% open)
- Training data 2 is
  - Training data 1 + House 2 Winter 1, day 2 data + House 11 Winter 1 day 28 data (day 28 is the 100%)

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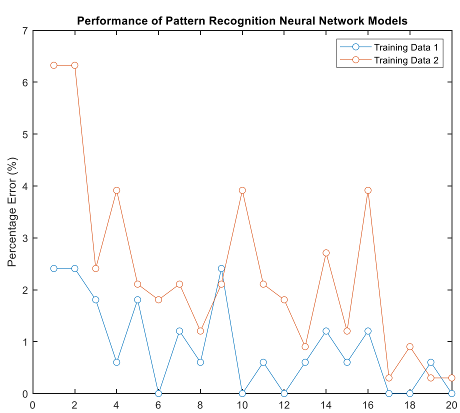
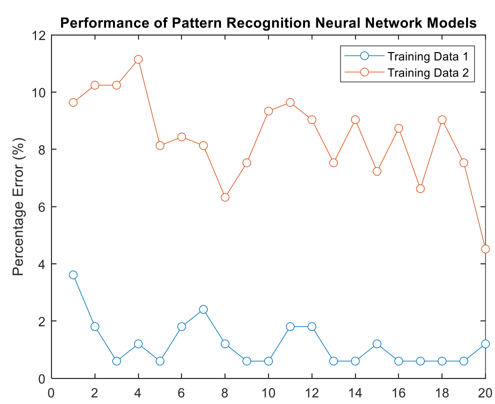
Training data 1 is
House 2 Winter 2, day 1 data + House 11 Winter 2, day 1 data (day 1 is 87% open)
Training data 2 is
Training data 1 + House 2 Winter 1, day 2 data + House 11 Winter 1 day 3 data (day 28 is the 92%)



Training data 1 is
House 2 Winter 2, day 1 data + House 11 Winter 2, day 1
data (day 11 is 100% open)
Training data 2 is
Training data 1 + House 2 Winter 1, day 2 data + House 1
Winter 1 day 28 data (day 28 is the 100%)



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