Using the Internal/External Temperature Difference as a Proxy for Energy Efficiency of Homes in the IDEAL Dataset

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4th Year Project Report
Artificial Intelligence
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2023

Abstract

Energy Efficiency in homes is an important factor to consider with the world's goal of stopping climate change. The main way that this is measured currently in the UK is through EPC which takes significant time and is often considered inaccurate. In this project, I investigated the application of Newton's Law of Cooling which states that the rate of temperature change of an object is expected to be correlated with the temperature of its surroundings. This relationship was evaluated on three prediction tasks namely classification of EPC Energy Efficiency Rating, Regression of EPC Annual Predicted Energy Use and Regression of Monthly Real Gas Usage of a Home. The application was found to have little use with the first of these prediction tasks as there was only a little separation between the two most common ratings while it was found to be of use on the latter two; namely 4.983 RMSE on annual predicted energy use and 0.741 RMSE on December 2017 real gas usage. Thus it was concluded that this proxy provided some use as a proxy for energy efficiency, however by itself it did not perform greatly. It remains that additional work into fine-tuning the metric to improve its performance is possible if additional data were available on the shape of rooms as well as other possible improvements.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Connor Deeley*)

Acknowledgements

Firstly I would like to thank my supervisor Nigel Goddard for his support in providing ideas, answering many questions no matter how stupid some of them may have been, and his general support.

Next, I would like to thank my family for their support throughout my education and the sacrifices that they have made to allow me to be the person I am today. All of your words of wisdom have helped me make many decisions over the past few years.

I would also like to thank my flatmates Jordan, Harry, Nathan, and Josh for making university so much more fun. They made the university a much more enjoyable experience especially when it was only the five of us in the flat during the pandemic, I am not sure how I would have gotten through online university without you guys, those days are truly special to me.

Finally, I would like to thank my girlfriend Giulia for her constant support in writing this dissertation and the completion of the project. I am struggling to find the words, to sum up her support so I guess I'll just say it was non male.

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Chapter 1

Introduction

1.1 Motivation

With the world's, UK government's, and Scottish government's goal of reaching Net Zero, it is crucial that we find new ways to improve energy efficiency. In 2021, the UK government reported that a third of fuel consumption in the UK comes from the domestic sector [20]. Thus, it remains important that we look into new ways of improving energy efficiency in the domestic sector and, by proxy, look into improved techniques of evaluating efficiency.

Currently, in the UK, the main method to evaluate a building's energy efficiency is its Energy Performance Certificate (EPC). This is a document that provides an Energy Efficiency Rating (EER) ranging from A to G[1] - with A being the most efficient. As well as an EER, an EPC also contains information about the building's predicted energy usage, predicted cost of energy usage and recommendations on methods to reduce these. [3][19].

A previous student project looked into how well basic building description data can be used to predict the EPC rating and estimated annual energy use but failed to find a good method of prediction. Moreover, this student did not use sensor data for prediction. One of the main uses of energy in the domestic sector in the UK is for the heating of spaces with the UK government reporting that it is the source of 55% of domestic energy usage. [20]. This means that EPCs are significantly concerned with the thermal performance of a building.

Bearing all that is mentioned above in mind, in this project, I explored the use of internal/external temperature differences to develop a metric based on the fact that as the temperature difference between the inside and outside of the home increases, the heat loss will increase roughly in proportion to the buildings insulation levels. It is important to mention that Newton's Law of Cooling was used as a base for developing a model. This work is based on the IDEAL dataset consisting of detailed temperature, energy, structure, and demographic data for 255 homes in the Edinburgh region. For

[1] These letters come from a more fine-grained rating system of 1 - 100 where the letter corresponds with an asymmetric range of numeric rating

this project, I had 2 initial aims which were to evaluate the use of the possible metrics for predicting, **EPC Energy Efficiency Rating**, and **EPC Predicted Energy Use**. I also explored the additional aim to evaluate the use of the possible metric for predicting the **Real Gas Usage**.

1.2 Achievements of the Project

In this project, I achieved several objectives, of which I would like to highlight the following:

- Explored heating patterns of homes in the IDEAL dataset.
- Extracted a number of features including gas usage, home size, and cooling events.
- Investigated two methods of extracting cooling events.
- Investigated two models of measuring thermal performance.
- Investigated scaling the models for use in prediction.
- Explored both methods and both models used in 3 separate investigating tasks.

1.3 Project Report Structure

The overall structure of the remainder of the report is described below. In Chapter 2 I provide background information that is helpful to understand the project fully as well as highlight related work and data sets. In Chapter 3 I discuss the methodology of the project. Then in Chapter 4, I talk about the initial data analysis and some data processing that was done. In Chapter 5 I examine the creation of the energy efficiency measure and justify the decision that was made around its calculation. In Chapter 6 I explain the results that this energy efficiency measure produced on the three prediction tasks. Finally, in Chapter 7 I conclude the report and discuss possible future work.

Chapter 2

Background and Related Work

In this chapter, several points are discussed, Firstly, I give a brief description of the IDEAL dataset that this work is based on. Secondly, I provide additional information on EPCs as well as introduce Newton's Law of Cooling. Additionally, I summarise some key work that has inspired aspects of my project. Finally, I highlight other data sets that have not been used but are of interest and could be of use for future work in this area.

2.1 IDEAL data-set

The IDEAL household energy dataset [11] [15] as mentioned in the introduction is the data set on which this work is based. It contains a vast and detailed collection of energy-related data, including room temperature and humidity readings of each individual room of the home as well as a variety of readings from the boiler. The dataset also contains additional metadata describing the occupants, rooms, homes and sensors. There is also additional data for 39 of the 255 homes on individual devices and appliances. Data was collected on the homes ranging from almost two years to two months with the data being published up until June 2018; there is additional collected data but this has not been publicly released yet. In addition to this data, I was also provided with EPC data on 153 of the homes.

2.2 Background

2.2.1 Energy Performance Certificates (EPCs)

Energy Performance Certificates (EPCs) were introduced in Scotland in "The Energy Performance of Buildings (Scotland) Regulations 2008". This regulation made an EPC required for most buildings when they were built, sold, or rented. The current method to calculate EPC for homes is the "Standard Assessment Procedure for dwellings (SAP 2012)". This model uses physical building features and assumptions on the use of the building to estimate the energy use of a building [17]. This policy was introduced in response to the 2007 EU Energy Performance of Buildings Directive (EPBD), which required member states to introduce mandatory residential energy labelling as part of the EU's policy to combat global warming [19].

The Scottish Government reported that 82% of Scottish homes were rated as C or D – 41% each. They also state that less than 5% of homes have an EER of B or higher. This highlights the difficulty of providing precise classifications predictor as so much of the data is skewed to the centre of the rating system. The Scottish Government aims for all homes to be at least rated C by 2033 with the aim to reach Net Zero [16].

As well as the requirement discussed above, as of April 2020, the Domestic Minimum Energy Efficiency Standard (DMEES) was introduced to require that privately rented properties have a minimum EER of E [18]. In addition to this requirement there are current proposed changes to the DMEES to extend the minimum EER to C. [12].

One of the major problems with EPC is they are widely considered to not be accurate. Few et al [7], a pre-published paper from 2023, found that homes with a C EPC energy efficiency rating used significantly more energy than the EPC predicted energy use. It suggests that more work is needed to refine EPCs so that the discrepancies that it found are not as large. Furthermore, another paper from 2021 by Samantha Organ [13] talks about the limitations of EPC and how they may be misleading government policy to meet climate change targets. This general distrust in EPCs inhibits their ability to effectively fulfil their role in informing people if their homes are energy efficient. This means that they are often ignored as they do not reflect real-life performance enough.

2.2.2 Newton's Law of Cooling

As this project focuses on the use of temperature it is important to have a base model to work with. For this, I used Newton's Law of Cooling which states that "*the rate of heat loss of a body is proportional to the difference in temperatures between the body and its surroundings*"[8]. In terms of the context of this paper, it translates to that a room will cool down quicker in proportion to the temperature difference between it and its surrounding. This cool-down happens at a rate of a constant that is proportional to the insulation and the room shape. In one of its simplest forms, it can be written as seen below in Equation 2.1,

$$\frac{dT}{dt} = k(T_{environment}(t) - T_{object}(t)) \tag{2.1}$$

Where,

- $\frac{dT}{dt}$ - is the rate of change of temperature of the room.
- $T_{environment}$ - is the temperature of the environment at time t.
- T_{object} - is the temperature of the object at time t.
- k - is a constant thermal transmission factor.

2.3 Relevant Work

2.3.1 Research into Energy Usage in UK Households

Huebner et al [6] investigated the modelled household heating patterns of homes to the actual habits of English homes finding significant differences. The modelled estimate of the household living room temperature was 21C while they found that on average it was 19C. Further, the authors discovered that assumptions made about heating differences between weekdays and weekends were too drastic and that the actual difference was much less significant.

Hamilton et al [5] explored the causes of the temperature of homes during cold conditions. They found that indoor temperature was not particularly affected by outside temperature. In addition to this, they found that low energy efficiency homes were on average 1.7C and 1C colder in the living room and bedroom, respectively.

2.3.2 Other Relevant Work

A previous student also used the IDEAL data-set to perform similar prediction tasks using easily available building data and energy consumption for their prediction. To make this prediction they use four different machine-learning models but found that none of them performed particularly well.

Aguilera et al [1] tried to predict indoor temperature using building attributes and weather data. They found success when predicting on previously known conditions, but were particularly unsuccessful when it came to making predictions on unknown conditions. Of these unknown conditions, Aguilera et al [1] found that their predictions were particularly bad on different climates, thus suggesting that we would need to develop a different model if we were to use data outside of the UK.

Pullinger et al [14] also used the IDEAL data-set and investigated the behaviour of how household heated their homes. They discovered that similar to what Huebner et all [6] found in English homes, indoor temperatures are lower than those assumed by the SAP model as well as the lack of variation between weekdays and weekends. In addition to this, they also determine there was little variation on how different rooms in homes were heated.

Goddard et al [4] worked on the following energy use of households as affected by external factors. This paper further demonstrates the relationship between energy use, time, building characteristics and human behaviour.

Williams [21] used a variety of machine learning techniques to predict energy efficiency for homes in Wales. They created a model which used 20 variables mostly about the building's characteristics which created a model with 69% accuracy. Their model performs particularly badly with extreme EPC Energy Efficiency Rating, but this is to be expected as similarly to Scottish homes, Energy Efficiency Ratings concerning Welsh homes are mostly either C or D. Of the 20 variables, Williams [21] found that none of them by themselves were a particularly good indicator of a home's EER but required the combination of all the variables. However, when they tried to apply this model using other data sources, they found little success.

Lomas et al [9] developed Domestic Operational Rating (DOR) using smart meter data. It was designed to be used alongside SAP. DOR also considers the behaviour of occupants and other dynamic factors so that a more relevant rating than an EPC can be given. Although this method by Lomas et al. is not used currently, it does highlight the downfalls of EPCs and how they could be improved to be more dynamic.

2.3.3 Other Data Sets

Finally, in this background section, I mention the existence of two other data sets of similar data - although there are many more. The first of these is a data set released by the University College London Energy Institute in 2021 of homes in the UK [10]. This contains half-hourly data about the consumption of gas, electricity, and information on weather data from 13'000 homes. This data set is from a much larger sample of homes than the IDEAL dataset, and the sample is representative of UK homes and households. However, it does not contain nearly as much data on each of the homes.

Another data set that I believe is important to mention is that all EPC data was made available online by the British government for households in England and Wales to the public so that it can be used for research on energy efficiency. This could be combined with the potential future data sets so that work similar to this could be done on a much wider group of homes. [2]

Chapter 3

Methodology

In this chapter, I outline the methodology used throughout this project. The project can be split into three distinct stages. The first stage focuses on Data Analysis and Data Extraction; while the second one is on the Creation of an Energy Efficiency Measure; and finally, the third one is on the Use of the Measure for Prediction.

For this project, Python programming language (Version 3.11.2) was used due to the language's strengths in handling data as well as the advantage of my personal experience with this language in both university and personal environments. Further to this, Jupyter notebooks were used due to their ease of working with data, inline data visualisation capabilities, and the ease of documenting the notebook. The data was retrieved from Edinburgh Data Share[1] with the additional EPC data on the homes supplied by my supervisor Nigel Goddard.

3.1 Part 1 - Data Analysis and Data Extraction

In the first part of my project, the goal was to increase my understanding of the IDEAL dataset to best inform the creation of an energy efficiency measure as well as to develop methods to extract features. This part of the project took significant effort due to the vast amount of data in the IDEAL dataset for me to understand and work out how to extract the data by reading the documentation provided so that different sections could be combined. The initial focus of this part of the project was to investigate home 59 specifically. This home was chosen as it was the first home with a C EER and thus out of these homes had the most data available. This investigation involved looking into the heating patterns of each room in the home, the reliability of these sensors, and the weather data of the home as well. This involved developing a method for converting the raw data into a more usable format for the creation of the energy efficiency metric. Next, I extracted two features - home/room size, and real gas usage - that I also believed would be important for the creation of the energy efficiency metric and for the evaluation of its effectiveness in measuring a home's energy efficiency. Finally, in this part, I also investigated the EPC data that was available for the homes in the IDEAL dataset. This

[1] https://datashare.ed.ac.uk/handle/10283/3647

involved looking into the relationship between EER and EPC Predicted Energy Use as well as their relationship against other variables.

More details on this part can be found in Chapter 4.

3.2 Part 2 - Creation of Energy Efficiency Measure

In the second part of my project, the goal was to use the understanding that I gained from part 1 of the project and my background reading to develop an energy efficiency measure. In this section, I propose two different models that could be used for the extraction of the measure from data; one based solely on the difference between internal room temperature and the external outside temperature while the other also used the difference between the internal room temperature and the other room temperature. In addition to this, I propose two different methods for extracting the data used to fit these models; one based focusing on the early morning period of cooling and the other focusing on the period of cooling post-heating being turned off. Following this, I look into the application of these proposals to home 59 - as it was focused on in Chapter 4 - and then to the wider applications to all the homes in the IDEAL dataset. Finally, I look into the use of scaling this metric based on the room size.

More details on this part can be found in Chapter 5.

3.3 Part 3 - Use of Measure for Prediction

In the third and final part of my project, the goal was to investigate the use of the metric using the various proposed forms in part two at the three prediction tasks I defined these as,

- EPC Energy Efficiency Rating Classification (C or Greater vs D or Worse) using Cooling Metric
- EPC Predicted Energy Use Regression using Cooling Metric and Home Size
- EPC Real Energy Use using Cooling Metric and Home Size

For this part of the project, the homes were split into a training and testing set with an 80:20 split. Where the training set is used to train and validate the models and the testing set is to evaluate the final chosen models.

To choose the best of the prediction models 4-fold cross-validation was used to determine which selection of cooling metric model, cooling event data points, room type and scaling produced the best results. 4-fold cross-validation involved splitting the home training set into 4 sets using each to validate a prediction model on the model trained on the other sets then averaging the results over the 4 folds. For the first prediction task, accuracy - as defined in Equation 3.1 - was used to choose the best prediction model while for the other two tasks root mean squared error (RMSE) - as defined in Equation 3.2 - was used.

$$Accuracy = \frac{TP + TN}{N} \tag{3.1}$$

Where,

- TP - is for True Positive, meaning that the model predicted it is C or above and it was.
- TN - is for True Negative, meaning that the model predicted it is not C or above and it was not.
- N - is the number of homes.

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{N}} \tag{3.2}$$

Where

- y_i - is the actual value.
- $\hat{y}_i$ - is the predicted value
- N - is the number of homes.

The reason for choosing to use 4-fold cross-validation was due to the low number of homes in the IDEAL dataset and in contrast the number of possible prediction models. This, along with limiting the number of models evaluated using cross-validation would reduce the model's chance of being particularly bad or particularly good when it was neither. Despite this, I do recognise the chance that cross-validation can sometimes be misleading but I believe that it was unavoidable due to the size of the dataset.

Finally, in this section, the best two models for each of the prediction tasks were evaluated on the testing set to produce a final result.

More details on this part can be found in Chapter 6.

Chapter 4

Data Analysis and Data Extraction

In this chapter, I give a description of the investigation into Home 59 which focuses on the indoor temperature and the outside weather conditions. I then proceed to explain two key features (room/home size and gas usage) that were extracted. Finally, I look into the EPC data of the homes in the IDEAL data-set.

4.1 Home 59 Exploration

From the initial background research, the first focus of the project was to get a better understanding of heating in an individual house. This focus was chosen as such to discover features that could inspire ideas to be used on a wider number of houses and to gain an understanding of the data of each home. The home id of the chosen house was 59. This home has an EER of C and a Predicted Energy Use of 13 MWh/yr.

4.1.1 Home 59 Temperature

In the IDEAL dataset there is a sensor which should measure the temperature every 12 seconds. This means that for each day, a sensor should record 7200 temperature readings. Their readings are recorded to an accuracy of $0.1C$. These 12-second readings recorded very little change and were often the same over short periods of time. Thus, one of the first steps I took to make the analysis faster was to take the average reading over a 15-minute time period. This reduced the expected number of readings over a one-year period from 2.627 million to 35 thousand which significantly increased the running speed of the code. This reduction also had the advantage of compensating for missing readings as was often the case in the living room of Home 59.

Following this reduction, the average temperature in these 15-minute periods was calculated over the course of the entire data collection period. This can be seen in Figure 4.1. This figure highlights some interesting regularity in the temperature of the living room in this house. One of the things that can be noticed from this graph is that there are two periods of cooling. The smaller one is between approximately 1 pm and 4 pm while the second large one is between 9 pm and 6 am. These two periods make sense intuitively as the heating from the sun results in the midday peak and then the later period is the result of the heating being turned off at night until the morning.

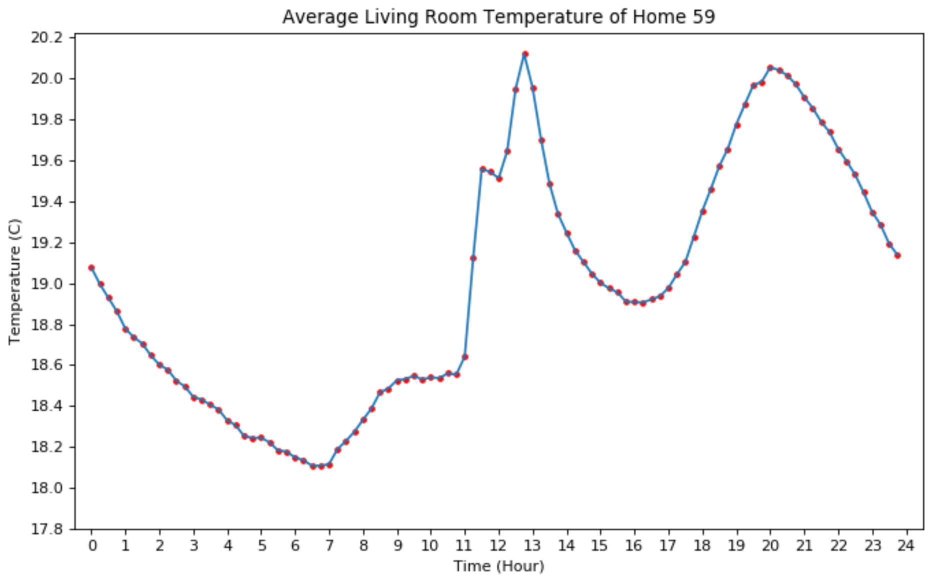
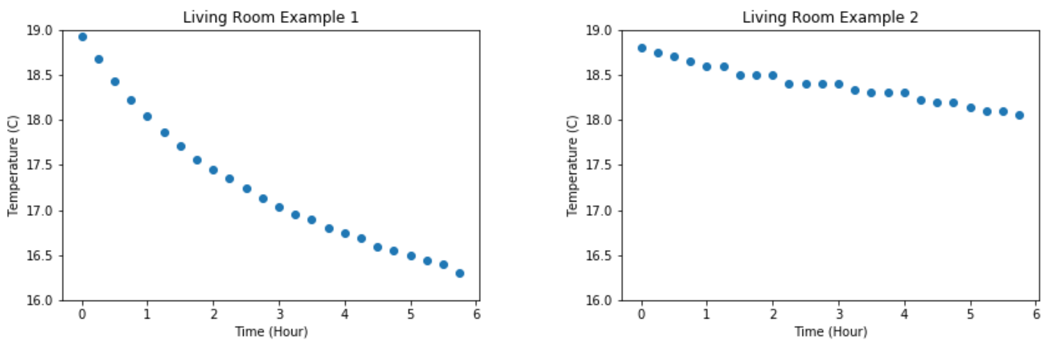


Figure 4.1: Home 59 Average Temperature

Next, looking more closely at two example days that can be seen in Figure 4.2. Despite the two examples starting at approximately the same temperature, the temperature of the first drops almost 3C compared to the second example 1C. One of the reasons for this could be that in the first example is the day the average outside temperature between 12 pm and 6 am was 4.4C while in the second the average outside temperature is 8.2C. This hints at the relationship between internal/external temperature.



(a) Example 1 (b) Example 2

Figure 4.2: The temperature of the living room in home 59 on 2 different days.

Finally, in this section, I look more generally at the trends in the whole home. This can be seen in Figure 4.3. From this we can see that the living room (blue line) temperature is unique in its roughness - this is due to Home 59 having a relatively unreliable living room sensor; this can be seen from Figure 4.4 which shows that this sensor often drops out. This figure also visualises the difference in the heating requirements of rooms with the living room and the kitchen being the most heated rooms.

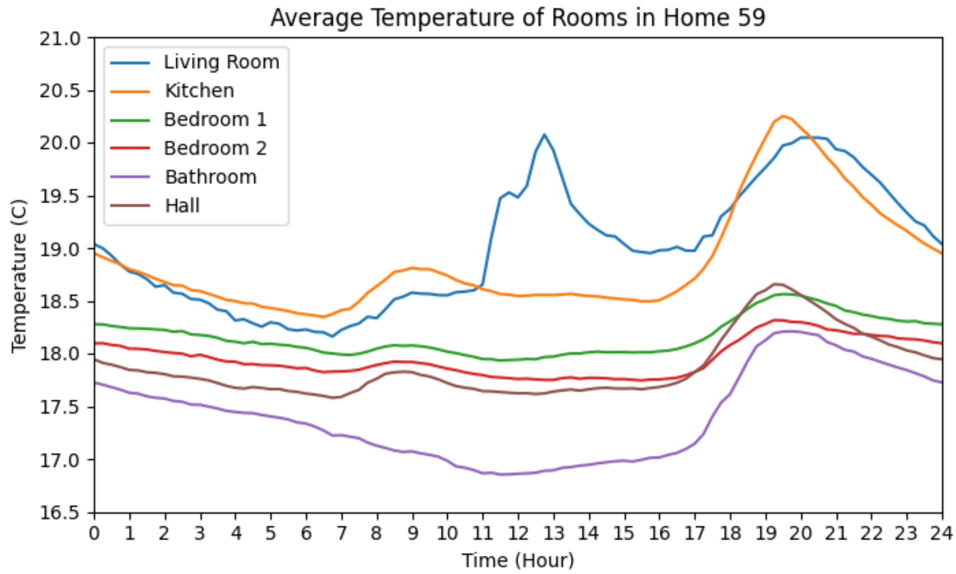


Figure 4.3: Home 59 All Room Average Temperatures

Figure 4.5 shows the correlations of temperatures between all rooms in Home 59 and the outside temperature. It can be seen that there is a high correlation between the different rooms in the house. The room with the lowest correlations with others is the living room. This may be due to it being the main room in the home and thus more affected by other activities. The correlation is much lower between the room and outside, this is somewhat expected due to the likelihood of the home being heated at certain points and the relative ease of transfer of heat between rooms. Two of these rooms have particularly low correlations. One of these is the bathroom which has no exterior walls, and the other is the kitchen which is where this home drys clothes.

4.1.2 Home 59 Weather

Another aspect that I explored in my data analysis was the weather of Home 59. In Figure 4.6 I have shown the weather on the 11th of November 2016 around Home 59. The key aspect that I want to highlight from this graph is the variation in the weather even in just one day with it having clear skies for a large part of the day and also raining, 6+C temperature changes in an hour, and the varying wind speeds.

4.2 Data Extraction

The next focus of the project was to extract both the room sizes, and real gas usage that could be calculated. The first was extracted as it was thought to be useful for the development of the cooling metric, whereas the second was extracted so that it could be used for the final prediction task.

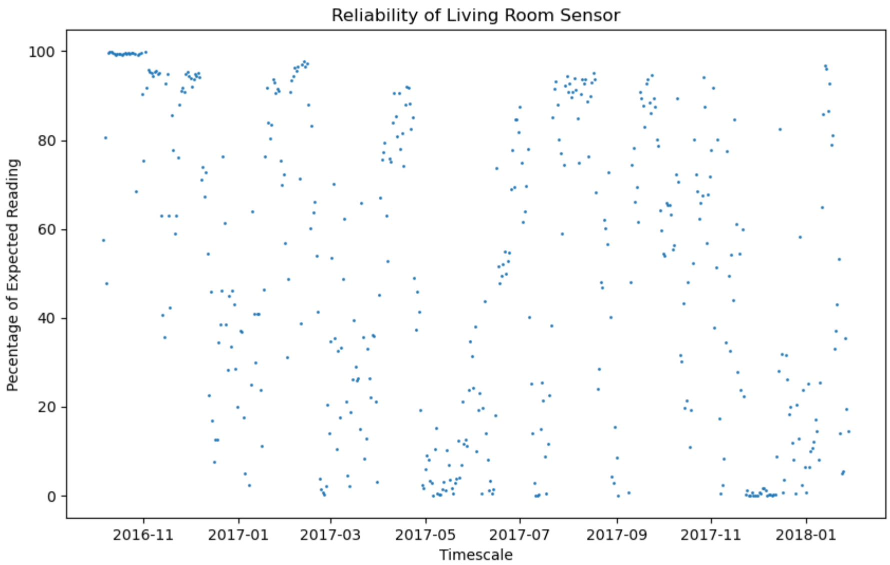


Figure 4.4: Number of Readings from Home 59 Living Room Sensor

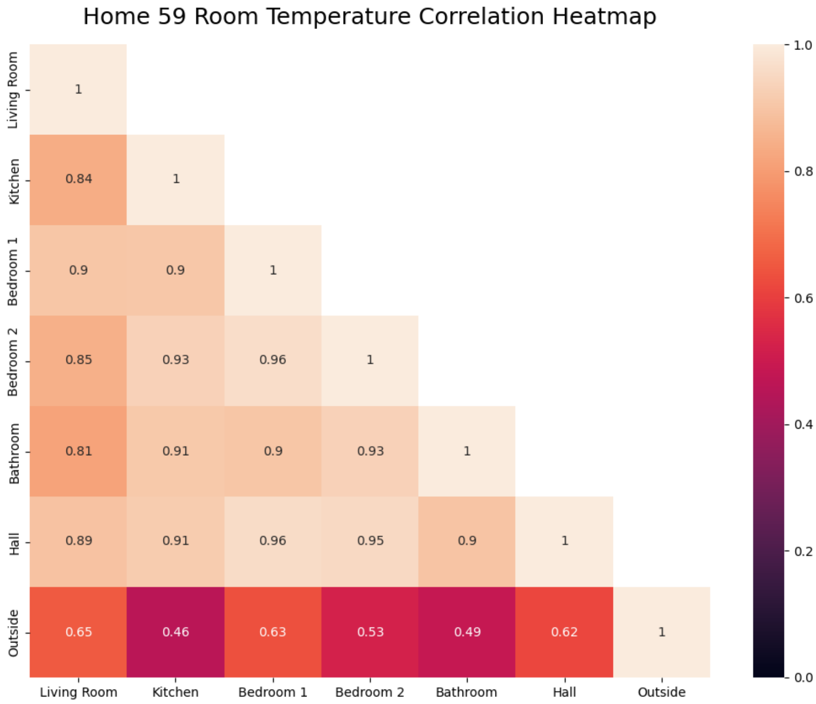


Figure 4.5: Home 59 All Room and Outside Temperature Correlations

4.2.1 IDEAL Home and Room Size

The home size of each home was calculated using the room metadata file in the IDEAL data-set. This file contained the floor area of the room in square metres and the average

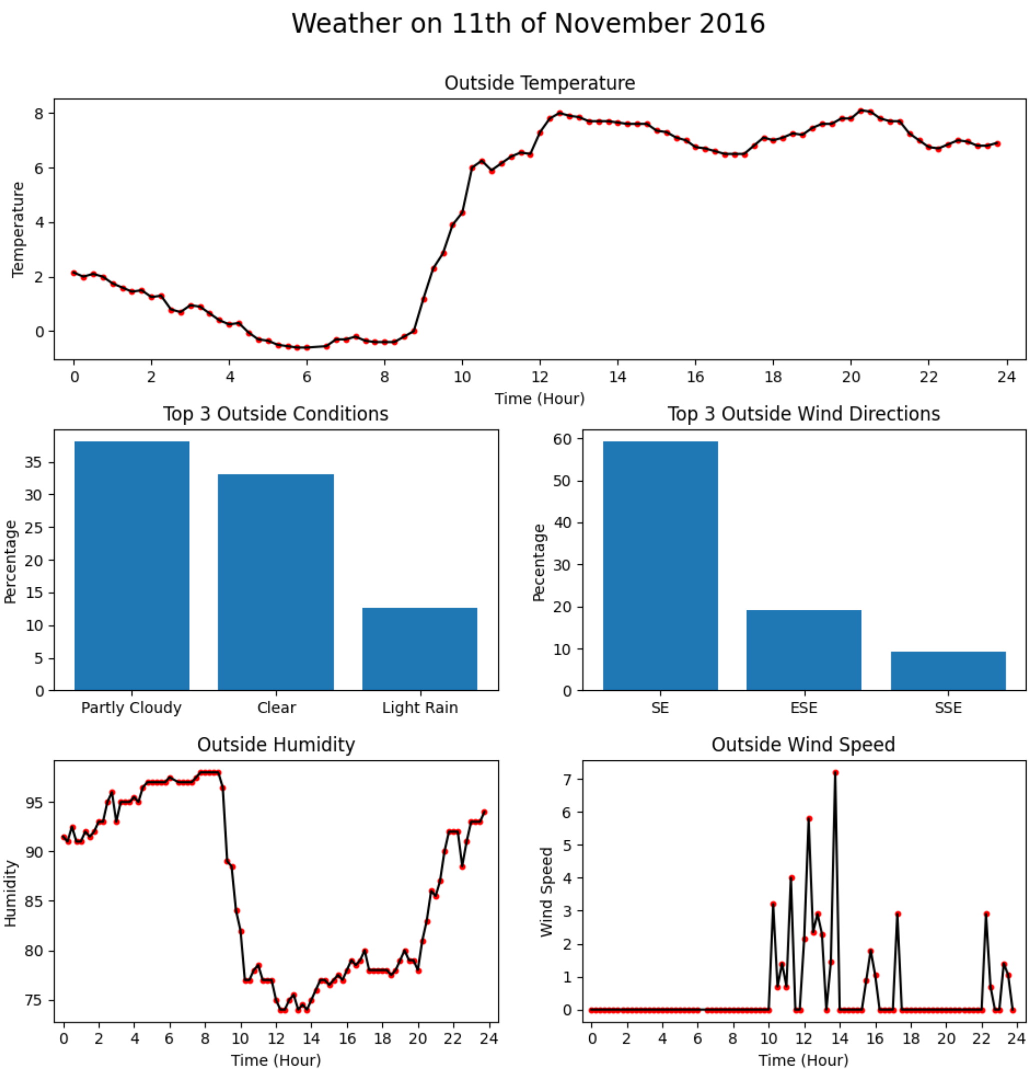


Figure 4.6: Home 59 Weather Data on the 11th of November 2016. It includes the data from each of the 5 available feeds (Outside Temperature, Weather Conditions, Wind Directions, Outside Humidity, and Outside Wind Speed)

height of a room in cm. Thus for each room there could be a size calculated then the rooms of each could be combined to get the total area of rooms in the home could be combined.

In addition to this, I also approximated the surface area of the room. This was done by assuming the room was a cuboid. Although this is not the case for most rooms there was no data available on room shape and I deemed it was necessary to make some approximation.

4.2.2 IDEAL Home Real Gas Usage

The gas usage was calculated using the gas pulse sensor data. For this we combined the pulse data of each home removing unusually high error readings - these were mentioned to happen in the IDEAL dataset paper. This part provided a challenge with deciding what would count as an anomaly. For this, I decided to remove readings greater than 5 pulses as these were rare and often very high. Another problem with working with the real gas data is that some houses would drop in and out so it was difficult to take a total over a large period due to inconsistencies so one-month periods were targeted. In Figure 4.7 we can see the amount of gas used in December 2017 against the size of homes in the IDEAL dataset. This will be used later as a comparison against the EPC Predicted energy use.

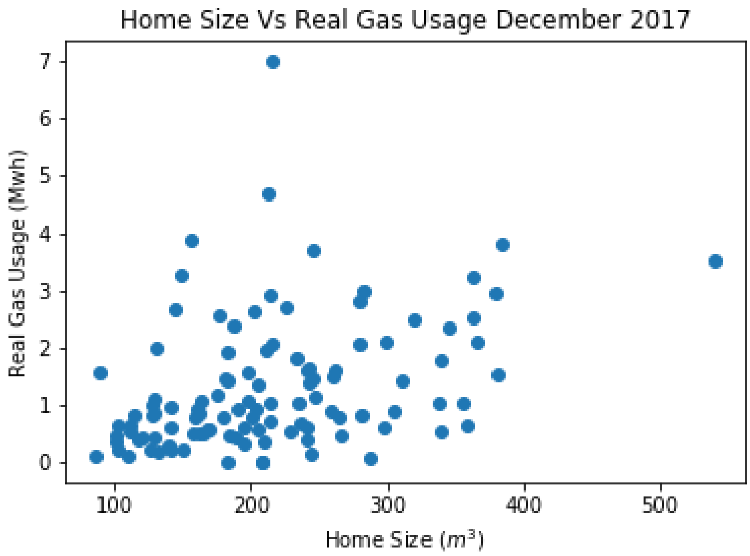


Figure 4.7: Size of Home compared with Real Gas Usage in December 2017

4.3 EPCs of the IDEAL data-set

The final focus of this section of the project was to look into the distribution of the EPCs of the home in the IDEAL data-set. Of the 255 homes in the IDEAL data-set there is EPC data for 153 homes. This data contains 3 separate elements for each of the homes. These are the Energy Efficiency Rating (EER), Predicted Energy Use, and the built-form of each home. The first two are the focus of the prediction task while the latter is not focused on in my project but additional work on it can be seen in Appendix A.

4.3.1 EPC Energy Efficiency Rating

Firstly, below is the distribution of EERs in the homes, which is shown in Figure 4.8.

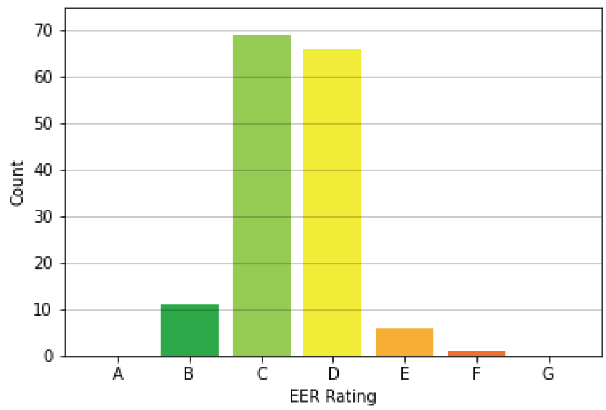


Figure 4.8: Distribution of EERs in IDEAL data-set

From this we can see that the majority of homes have an EER of either C or D - 69 and 66 respectively - and none of them had the lowest (A) or highest (G) rating. This means that C and D make up 88% of the ratings, which is approximately in line with the 82% of all homes in Scotland as stated in Section 2.2.1. However, this distribution places limits on what could be achieved in this project, as it would be impractical to attempt to distinguish between anything that is neither C nor D.

Subsequently, when looking at a comparison between the EERs and the real gas usage we can see the distinction between the two ratings. Nevertheless, it is not as clear as one would expect. This can be seen in Figure 4.9.

4.3.2 EPC Predicted Energy Use

Secondly, I explore how the Predicted Energy Use in the homes compares to both home size and EER. The distribution of the Predicted Energy Use can be seen in Figure 4.10. This shows that there is a fairly even spread of Predicted Energy Uses in the homes in the IDEAL dataset although there are fewer homes that are predicted to use $30+Mwh/yr$.

Comparing the Predicted Energy Use against Home Size shows the expected relationship that a larger home is anticipated to use more energy. This can be seen in Figure 4.11. This relationship is clearer than that of the real gas usage, as seen in Figure 4.7 which suggests that the predicted energy usage is more related to home size than it should be. This difference highlights why there is distrust of EPCs ability to do their job correctly.

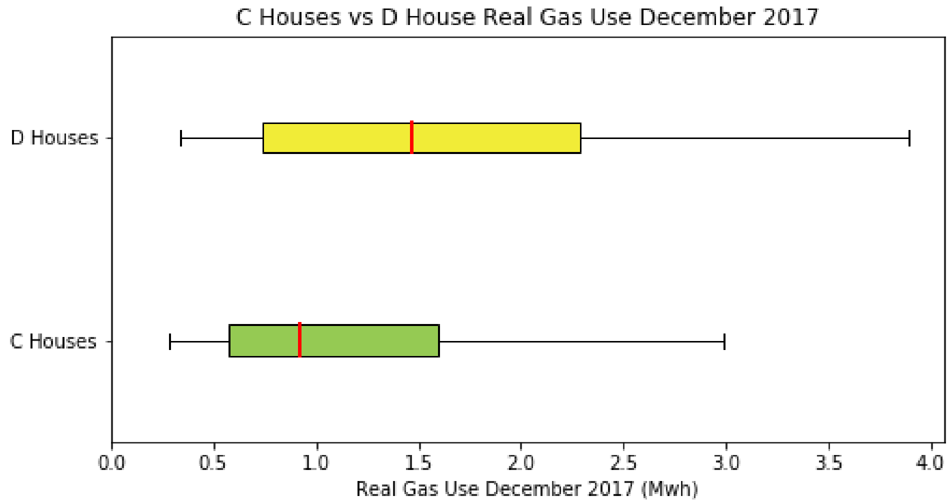


Figure 4.9: Real Gas Usage December 2019 of homes with C and D ratings. Note that homes with low gas usage have been removed $<$ 0.25 MWh and also outliers.

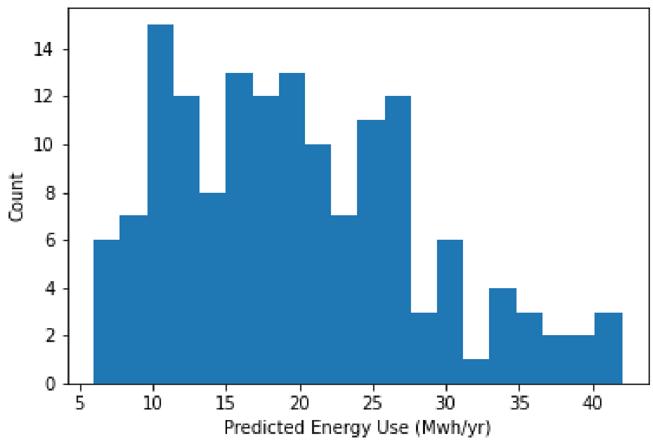


Figure 4.10: Distribution of Predicted Energy Uses in IDEAL data-set

Finally, comparing the EPC Predicted Energy Use against the EPC Energy Efficiency Rating. This can be seen in Figure 4.12 which shows a clear separation in the EPC Predicted Energy Use compared with the real gas usage. This hints at the inaccuracy of the assumptions that are made during EPC home evaluations.

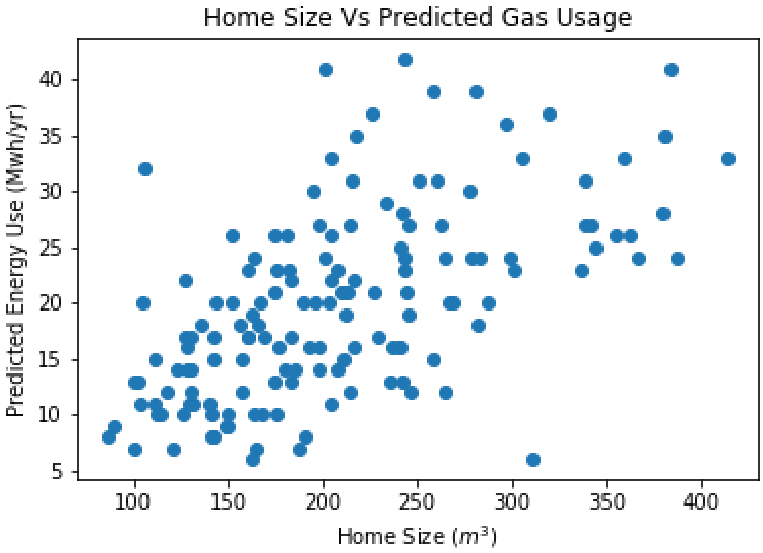


Figure 4.11: Home Size compared with Predicted Energy Use

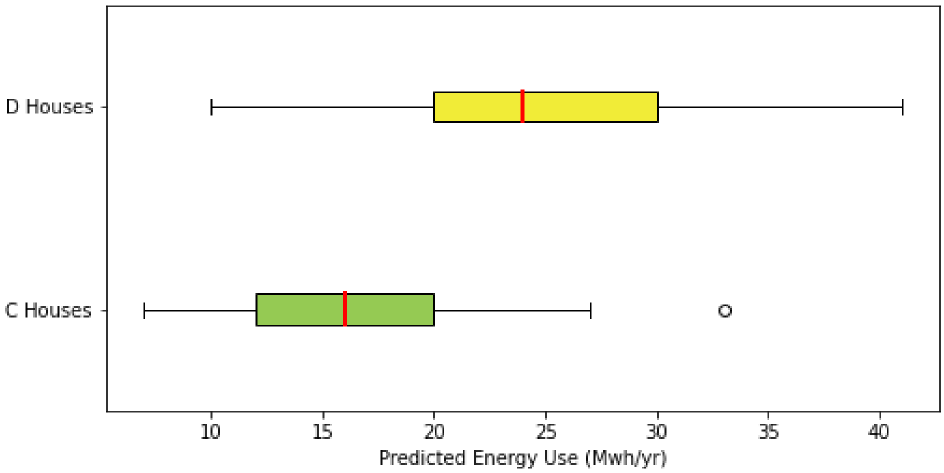


Figure 4.12: Distribution of C and D EER Houses Predicted Energy Use (Mwh/yr) in IDEAL data-set

Chapter 5

Creation of Energy Efficiency Measure

In this chapter, I explain the two proposed models based on Newton's Law of Cooling. Moreover, I describe the methods used for the extraction of cooling events and the advantages and disadvantages of both. Following that, I look into the results that each combination of each proposed models and cooling events extraction produce. Finally, I also propose a method of scaling the models based on the size of the rooms.

5.1 Proposed Models

In this section, I discuss the two proposed models that I chose to investigate. The first method can be seen in Equation 5.1 and can be described as the simpler model based on solely the difference between the internal room temperature and the external outside temperature. The second method can be seen in Equation 5.2 and can be described as the more complicated model base on both the difference between the internal room and both the external temperature outside and the average of other rooms. Both models have a constant factor C which would take into account other constant heating such as an appliance. These models however are not able to capture factors such as occupant activity or activity of connecting buildings in the case where the home is a flat connected to a business and other flats which will contribute noise to the model.

Proposed Model 1 - Simple Model

$$\frac{dT}{dt} = k(T_{outside}(t) - T_{room}(t)) + C \tag{5.1}$$

Proposed Model 2 - Complex Model

$$\frac{dT}{dt} = k_1(T_{outside}(t) - T_{room}(t)) + k_2(T_{otherrooms}(t) - T_{room}(t)) + C \tag{5.2}$$

The first model, as seen in Equation 5.1, has the main advantage of requiring a heating sensor only in the room in which the cooling constant is required. However, variations in other rooms will not be accounted for which has shown to have a significant correlation as shown in Section 4.1.1. The second model, as seen in Equation 5.2, has the main advantage of being able to adapt to the internal temperature of other rooms which was shown in Section 4.1.1 to have significant correlations with the room. This would however mean that if the model was to be deployed to a real-world scenario then there would be a larger number of resources required for additional sensors. Another aspect to consider is that if a door was open then the effect of k_2 especially if it is inconsistent on whether the door would be different but this problem still persists if a window was open with both models.

The values of the equation are calculated as follows,

- $\frac{dT}{dt}$ is calculated using the difference between the temperature of the room at the end of the cooling event and the start of the cooling event.
- $T_{outside}(t) - T_{room}(t)$ is calculated using the difference between the average temperature of the room during the cooling event and the average external outside temperature during the cooling event.
- $T_{otherrooms}(t) - T_{room}(t)$ is calculated using the difference between the average temperature of the room during the cooling event and the average temperature of other rooms during the cooling event.

One of the things that should be noted about the values for both these models is that they are not fitted using the traditional form of differential equations where dt is small instead are fitted using a larger dt. This is a rough approximation as essentially I fitted a straight line instead of a more traditional exponential decay. This decision was based on two reasons, the first of these is that the temperature sensors only measure in 0.1C increments thus their change over small periods can often be zero. The second was based on that the outside temperature and other room temperatures are changing which makes an exponential model more difficult to fit.

5.2 Data Points for Fitting Models

In order to fit these models I need to have data points of periods of cooling in homes. In this project, I proposed two sources for extracting these events. Similar to the proposed models, there is a simpler method and more complex method. In this section, I explain both methods along with their advantages and disadvantages as well as compare the number of events each method produces.

When I initially looked at this task I was focusing on shorter periods of only 15 minutes but found them to be very variable because the sensors would only measure changes of 0.1C or more. I initially looked into smoothing based on the rates of changes of the previous 15-minute periods but settled on taking larger periods - 6 hours for method 1 and at least three hours for method 2. This decision was based on the fact that it didn't involve changing the real data to make 'fake' rates of change. I have included a graph of this smoothing in Appendix C.

5.2.1 Method 1 - Early Morning Period

The first method that was used to extract cooling data points consisted of getting the period of cooling in each home between 12 am and 6 am on each day. It was found, both in my personal analysis of the IDEAL dataset and in a number of studies on other UK-based data, that this period of cooling in the early morning was common in many UK homes. This is due to most people not heating their homes at night when they are not active. Another advantage of this method is that during this period of the day, on average the temperature is lower than the day allowing for there to be a greater internal/external temperature between inside and outside. However, a disadvantage of this method is that is there a few situations where it could go badly wrong. These are when the room,

- is cold, to begin with, and thus does not have a significant drop in temperature during this early morning period.
- is being heated for the whole period and thus it could result in the room temperature changing at a different rate than it would without this heat.
- does not have any external walls

5.2.2 Method 2 - Central Heating Off Period

The second method that was used to extract cooling data points comprised getting the period immediately following the central heating is turned off. For this, I looked into the central heating flow[1] of each of the homes in the data set looking for periods where the flow temperature was above a threshold - 50 degrees was chosen[2] - and then below this threshold in the next reading to generate potential cooling events. Once the possible cooling events were found they were verified that they met the following 3 conditions,

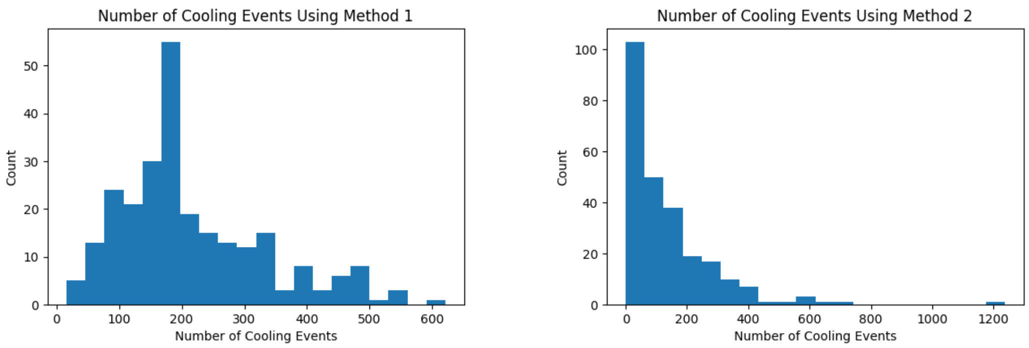
- Final flow temperature was below 30 degrees.
- Any reading in a cooling event was at most 5 degrees warmer than the lowest previously recorded flow temperature in that event.
- Cooling Event was at least 1.5 hours.

The reason for the first two of these conditions was to make sure that the heating was turned off and remained off. The second condition was chosen as when I looked into splitting the cooling event in the first method I found that there was a significant amount of noise in events less than three hours long.

One of the biggest problems I found with this method was that there was high variability between houses with the number of cooling events that were detected which I expected but not to such a large degree. The conditions that were placed for the detection of heating events were fairly strict and it could be argued that they could be loosened. However, I discovered that the events that were already detected had their own problems

[1] flow is the supply of hot water to the radiators

[2] this was chosen as most central heating pipes peaked at 60C so it allowed for a bit of fluctuation not to be treated as the heating being turned off.



(a) Method 1 (b) Method 2

Figure 5.1: Comparison of the Distribution of the Number of Cooling Events Extracted by Method 1 and Method 2

of sometimes not resulting in a decrease in room temperature despite the heating being turned off.

5.2.3 Comparison of Methods

A comparison of the number of events that each of these methods has generated can be seen in Table 5.1. This shows that on average the first method had a larger number of events. However, it should be noted that the second method generated 1237 events for one home. Looking at Figures 5.1 it can be seen that the distribution of the number of cooling events is much more spread when using method 1 as well as highlighting the frequency that method 2 detects a lower number of events. Figure 5.1b also highlight how the home with 1237 events is an exception rather than a common theme from this method.

	Method 1	Method 2
Mean	**215.9**	131.7
Median	**187**	94
Minimum	**16**	0
Maximum	620	**1237**

Table 5.1: Comparison of the number of possible cooling events per home between method 1 and method 2.

One of the parts of this project I believe could be better is the verification that these events are cooling events. On the other hand, however, cleaning the data to not include data points where the temperature decreases may give a false sense of correctness.

5.3 Application to Home 59

To verify the application of the models I applied them firstly to Home 59. This was chosen as it was also the focus of the initial analysis in Chapter 4. To fit each of the models I used least squares to minimise the error in each of the data points. The application to Home 59's living rooming of model 1 using method 1's cooling events can be seen in Figure 5.2.

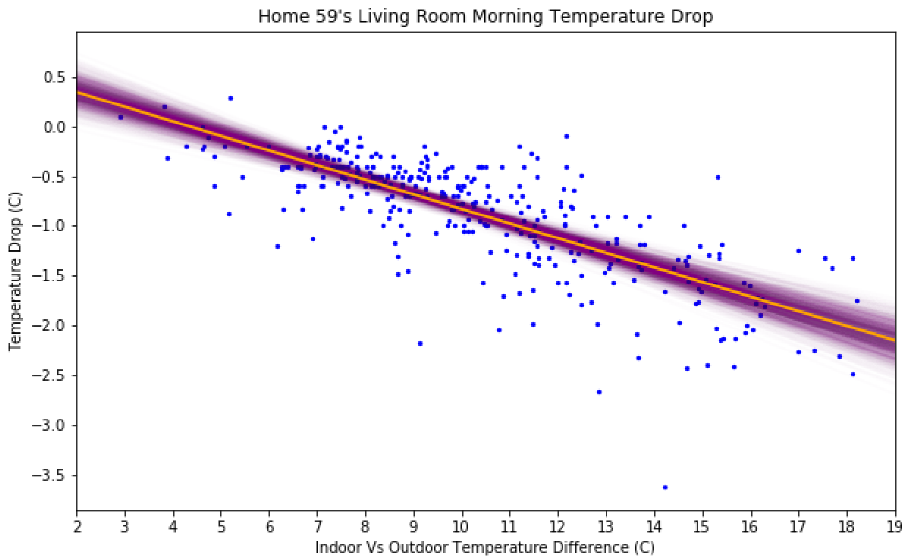


Figure 5.2: Temperature Difference vs Temperature Drop between 12 pm and 6 am of Home 59's Living Room Using Cooling Events from Method 1

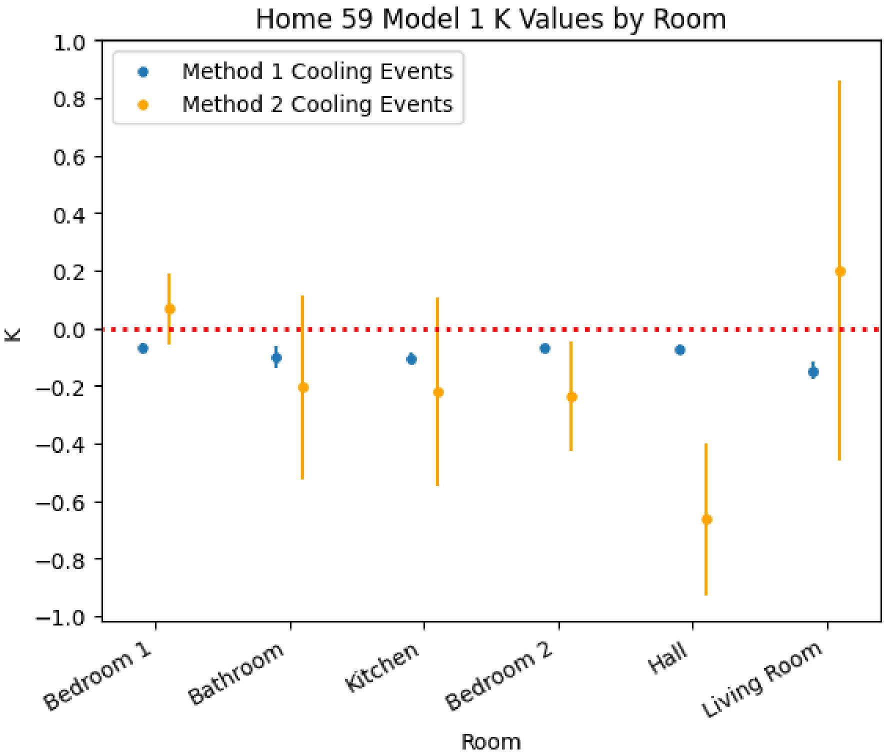
The orange line is the line of best fit. Looking at the data it is clear that the data points are noisy thus to quantify this noise I choose to fit 1000 potential lines using 90 randomly selected data points (3 months of data points) each time. These are represented by the opaque purple lines in Figure 5.2.

5.3.1 Model 1

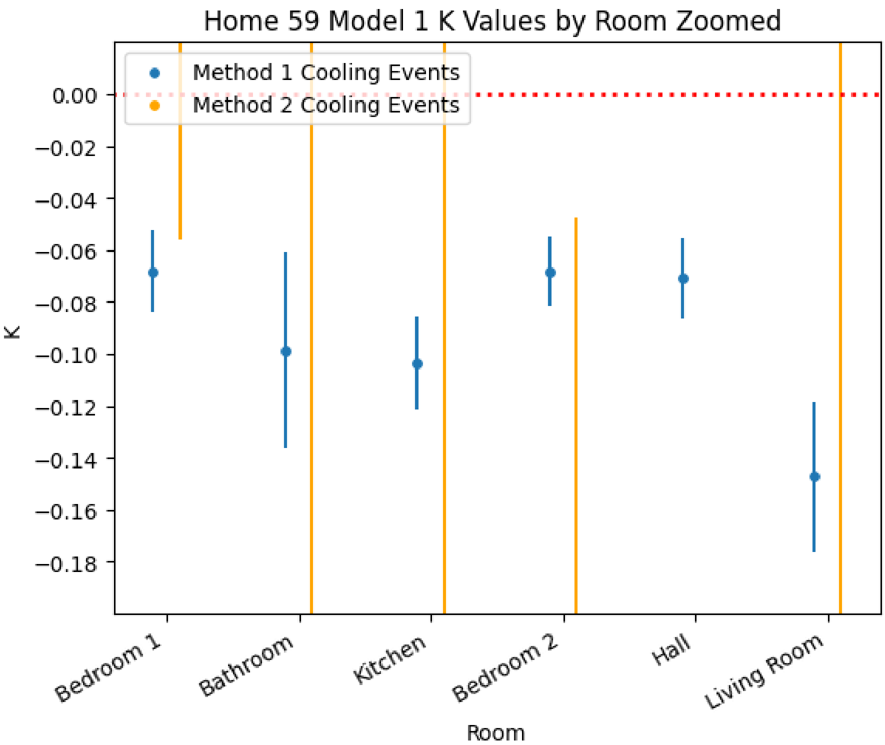
Figure 5.3 shows the K values of for each of the rooms for model 1 using the cooling events as determined by each of the two methods in sections 5.2.1 and 5.2.2. From Figure 5.3a we can see that the uncertainty around the values calculated from method 2 cooling events are much larger than those calculated from method 1 cooling events. In fact, the error bars only become clear for the models fitted from method 1 cooling events when the figure is enlarged as seen in Figure 5.3b. Another problem that we can see with the second set of cooling events is that there are some values that are the opposite of what we expect suggesting as if the room is colder than the external temperature then it will heat up. It can also be seen that the results from method 1 cooling events are all negative - including the 95% confidence interval - which is the expected polarity.

5.3.2 Model 2

Looking more closely at model 2, the values and the 95% certainty range can be seen for method 1 cooling events in Table 5.2 and for method 2 cooling events in Table 5.3.



(a) Original



(b) Zoomed

Figure 5.3: Comparison of K Values of Model 1 for Home 59 Between Method 1 Cooling Events and Method 2 Cooling Events. Error Bars Represented 2 standard deviations which is 95% certainty.

For method 1 cooling events, the K1 values are negative as expected even within 95% certainty as well as the C values are positive which is mostly as expected. However, the K2 values are positive for some which is not the expected relationship, other rooms being colder should result in a drop in the room temperature, which hints that this model doesn't capture the expected behaviour for this home.

	K1	K2	C
Bedroom 1	-0.068 ± 0.016	0.069 ± 0.157	0.422 ± 0.15
Bathroom	-0.094 ± 0.036	-0.142 ± 0.681	0.397 ± 0.621
Kitchen	-0.091 ± 0.019	-0.248 ± 0.137	0.527 ± 0.163
Bedroom 2	-0.032 ± 0.014	-0.396 ± 0.101	0.022 ± 0.142
Hall	-0.068 ± 0.016	0.209 ± 0.106	0.424 ± 0.129
Living Room	-0.134 ± 0.034	0.102 ± 0.149	0.448 ± 0.392

Table 5.2: Home 59 Model 2 Results from Method 1 Cooling Events

	K1	K2	C
Bedroom 1	0.018 ± 0.15	-0.378 ± 0.932	-1.619 ± 1.095
Bathroom	-0.367 ± 0.514	1.545 ± 2.999	2.333 ± 5.863
Kitchen	-0.368 ± 0.418	0.747 ± 2.001	-0.295 ± 2.625
Bedroom 2	-0.198 ± 0.188	0.545 ± 0.735	0.203 ± 1.239
Hall	-0.672 ± 0.274	-1.106 ± 2.624	0.953 ± 2.269
Living Room	0.126 ± 0.569	-1.648 ± 4.509	-1.232 ± 6.809

Table 5.3: Home 59 Model 2 Results from Method 2 Cooling Events

For method 2 cooling events, the K1 values are positive which is counter-intuitive, these are positive values for the same rooms that the K parameter was positive for model 1 fitted with method 2 cooling events suggesting that this is not to do with the model but the cooling events. It can also be seen that the K2 parameter (internal room and external other rooms temperature parameter) has a much larger absolute value for all rooms. In addition to this, there is a large degree of uncertainty for the C values. Moreover, it seems that the values are much more extreme in this case.

5.3.3 Comparison of Internal/External Parameter

In Figure 5.4 a comparison between the internal room and external outside temperature parameter - K for model 1 and K1 for model 2. The difference between K and K1 can also be seen in Table 5.4. From this, we can see that for every room there is an increase in the value of the parameter from model 1 to model 2. This is expected as there is the addition of the room difference which is what we would suspect. Of particular interest is bedroom 2 as this has a more dramatic increase of 0.0363; almost 3 times greater than the Living room which is the second highest change. Bedroom 2 also has the largest K2 value; this is the parameter between the internal room and external other room temperature parameter for model 2.

Room	Difference Between K and K1
Bedroom 1	0.0006
Bathroom	0.0047
Kitchen	0.0127
Bedroom 2	**0.0363**
Hall	0.0033
Living Room	0.0137

Table 5.4: Difference Between K and K1 (internal room vs outside temperature) parameter of Model 1 and Model 2 for rooms in Home 59 from method 1 cooling events

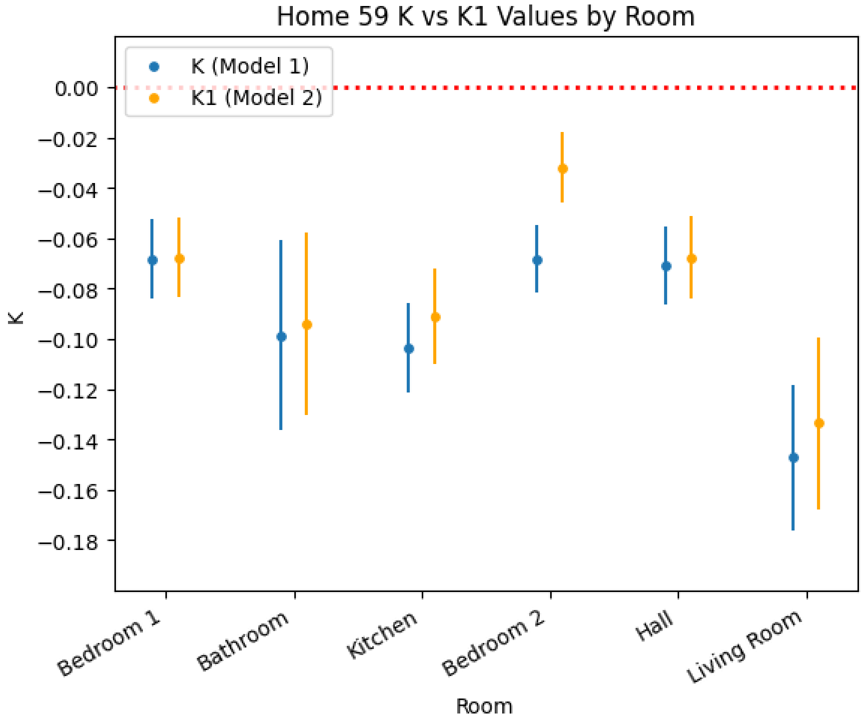


Figure 5.4: Comparison of K Vs K1 (internal room vs outside temperature) parameter of Model 1 and Model 2 for rooms in Home 59 from cooling event method 1

5.4 Application to All Homes

Following the application to the single home I applied the models to the full set of homes.

5.4.1 Model 1

Looking more closely at the application of model 1 we can see in Figure 5.5 the distribution of the K factor between the models fitted from method 1 cooling events and method 2 cooling events. From this figure, we can see the difference in the variance of the K's generated with method 2 cooling events being significantly more spread. There is also a larger number of K's who have a value above 0; which shouldn't be the case as it is expected that the surroundings should not work like this. One similarity between the two sets of cooling events is that they both peak in similar locations suggesting that the mean value of K is between -0.1 and -0.2.

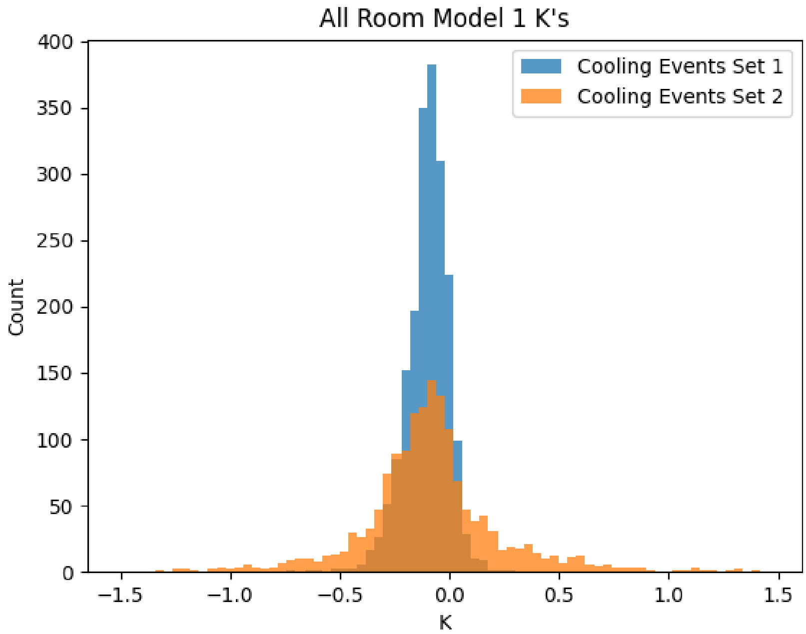


Figure 5.5: Comparison of the distribution of K values from model 1 of all homes between those generated from method 1 cooling events and method 2 cooling events.

Next looking at Figure 5.6 a comparison of the distributions of homes with C and D EPC Energy Efficiency Ratings can be seen. From this we can see that their distribution is significantly overlapping, however, they peak at different points with D Homes on average losing temperature faster according to the model. The amount of overlaps was a disappointing result and the inspiration for the more complicated models that were introduced however significant overlap remained.

	Value	Std	Min	Max
Method 1 Cooling Factor (K)	-0.100	0.024	-0.175	-0.019
Method 1 Constant (C)	0.188	0.261	-0.691	1.048
Method 2 Cooling Factor (K)	-0.084	0.093	-0.402	0.272
Method 2 Constant (C)	-0.546	0.914	-3.885	2.63

Table 5.5: Comparison of the Parameters Average Value, Average Standard Deviation, Average Minimum and Average Maximum produced for model 1 from both sets of cooling events

Finally looking at Table 5.5 we can see the average K, K Std, as well the average minimum and maximum values for the models. This further highlights the high variability of the results produced from method 2 cooling events. It also shows that the average maximum from method 1 cooling events is below 0 while this is not the case for method

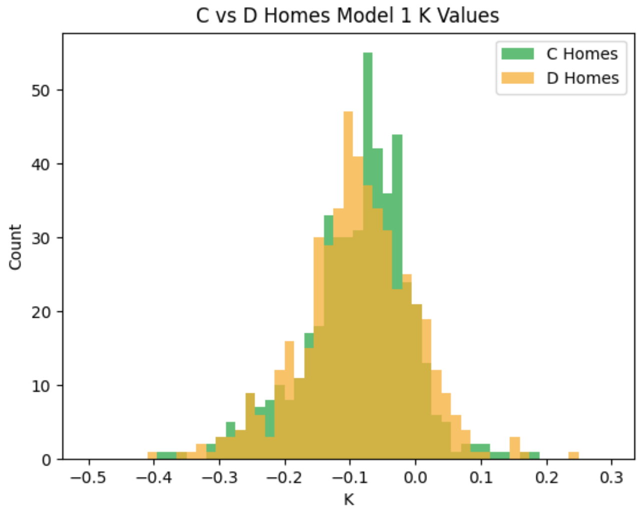


Figure 5.6: Comparison of K Values for homes with C and D EPC Energy Efficiency Rating Model 1 from Cooling Event Set 1

2 cooling events. This supports that method 2 cooling events are more likely to produce unplausible results.

5.4.2 Model 2

From Figure 5.7 it can be seen that in comparison with model 1, we can see the distribution of the C and D homes peaks are much closer together however there is slightly less overlap suggesting that they may be able to separate the different ratings more easily.

In Table 5.6 we can see the average values of each of the parameters. This shows that on average method 2 cooling events have a smaller internal/external parameter for both models. We can see that the polarity of the constant is similar between the two sets of cooling events for both models.

	Value	Std	Min	Max
Method 1 Cooling Factor 1 (K1)	-0.090	0.026	-0.174	-0.002
Method 1 Cooling Factor 2 (K2)	-0.088	-0.702	0.532	0.188
Method 1 Constant (C)	0.161	0.284	-0.787	1.104
Method 2 Cooling Factor 1 (K1)	-0.075	0.183	-0.956	0.649
Method 2 Cooling Factor 2 (K2)	-0.719	1.475	-6.782	6.375
Method 2 Constant (C)	-1.211	2.03	-8.892	10.241

Table 5.6: Comparison of the Parameters Average Value, Average Standard Deviation, Average Minimum and Average Maximum produced for model 1 from both sets of cooling events

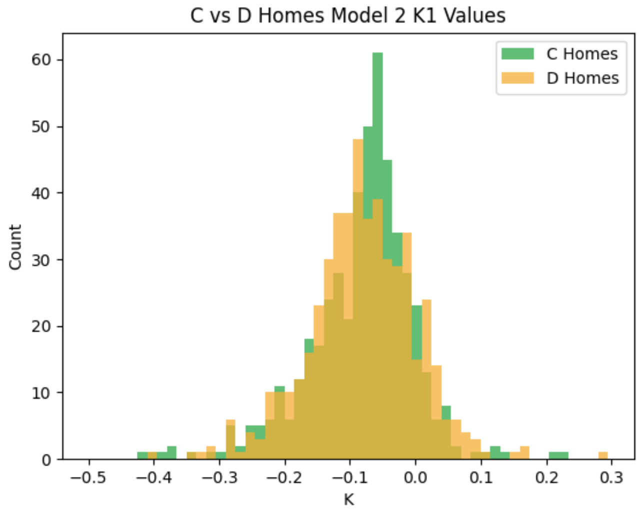


Figure 5.7: Comparison of K1 Values for homes with C and D EPC Energy Efficiency Rating Model 2 from Method 1 Cooling Events

5.5 Comparison Between Room Types

Following the application of the models I investigated the relationship between different room types and the K factor. In Figure 5.8 the distribution of the K factor of the five most common room types can be seen. From this, it can be seen that they are approximately similar however the most noticeable difference is in the mean of the living room which can be seen that living rooms have the lowest K value.

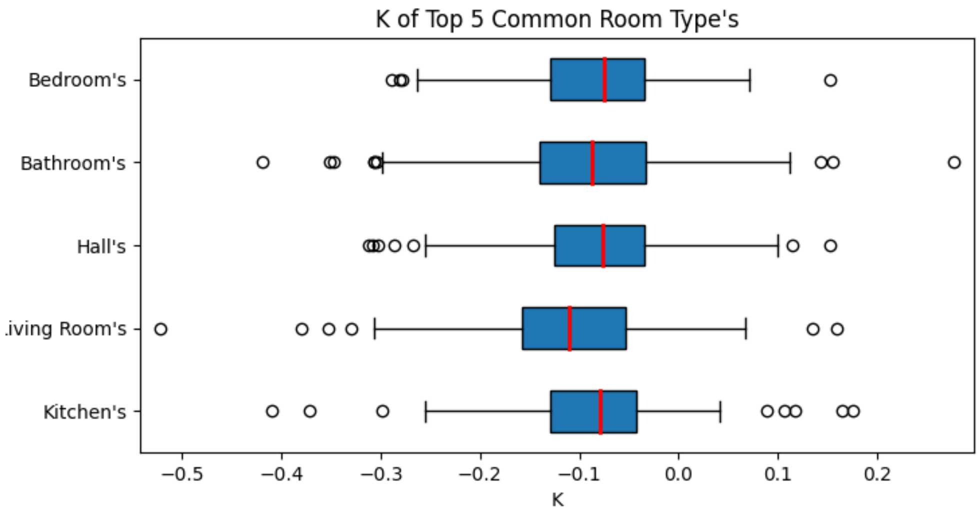


Figure 5.8: K Values of Various Room Types for Model 1 from Method 1 Cooling Events

In the next sections, I compare the cooling constant of three types of rooms. These are the two most common social rooms in homes - the living room and kitchen - as well as the thermostat room - the room where the thermostat that monitors the home's heat is located. Graphs on other rooms can be seen in Appendix B.

5.5.1 Living Rooms

In Figure 5.9 we can see the distribution of K factors for the living rooms of homes in the IDEAL dataset with EPCs. The living room was chosen to be looked into further due to it being the main social space for many households. Thus the living room is a space that is often heated and is best suited for a metric of this type.

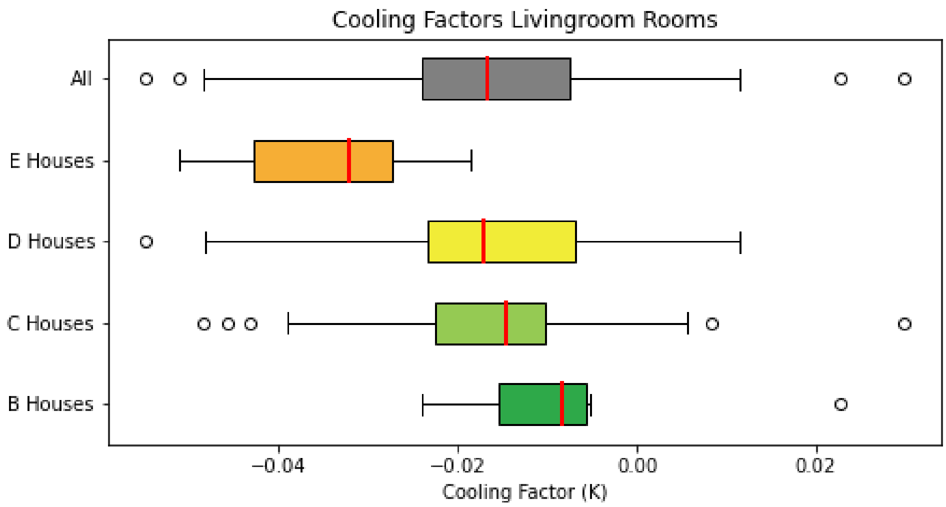


Figure 5.9: K Values of Living Rooms for Model 1 from Method 1 Cooling Events

From this figure, it can be seen that there is a clear separation in the median K factor of the home with different EPC ratings. However, there still remains significant overlap, especially between the C and D ratings. However, it provides promise that there may be a way to distinguish these values but perhaps not just with this simple model.

5.5.2 Kitchens

Another common room of activity in homes is the kitchen as this is where people make food and often where it is consumed as well. This means that it is also likely to be heated including by non-heating-centred uses such as cooking. From this figure, it can be seen that there is less overlap between the C and D homes; this is as the D homes for the living rooms range encompasses those of C which is not the case for C homes.

5.5.3 Thermostat Rooms

Finally, in this section, I looked at the thermostat rooms. These are rooms where the thermostat is located and thus if it has a lower temperature it will result in the heating being turned on. Thus I wanted to find out if this room itself and therefore the thermostat in itself would be useful for the prediction tasks. However, from this, we can see that the distribution of C and D homes are very similar however it still keeps the trend of the medians being as expected.

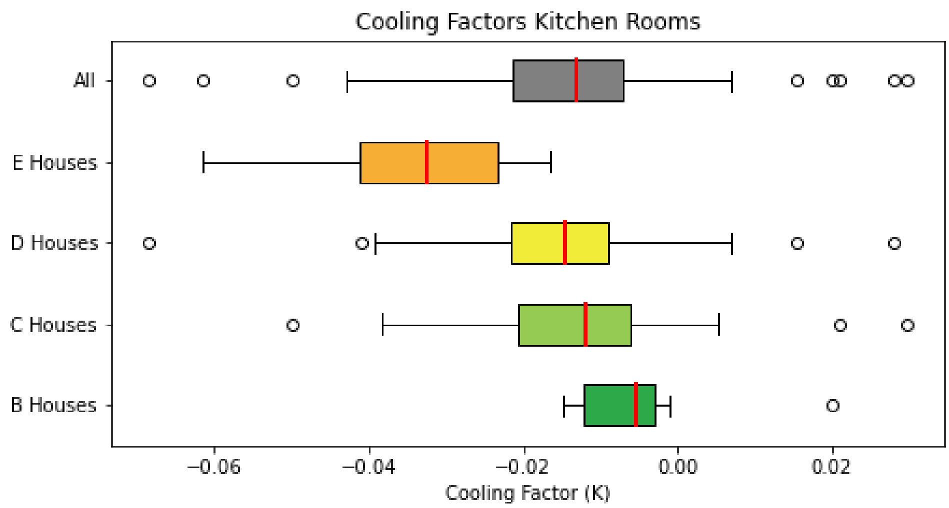


Figure 5.10: K Values of Kitchens for Model 1 from Method 1 Cooling Events

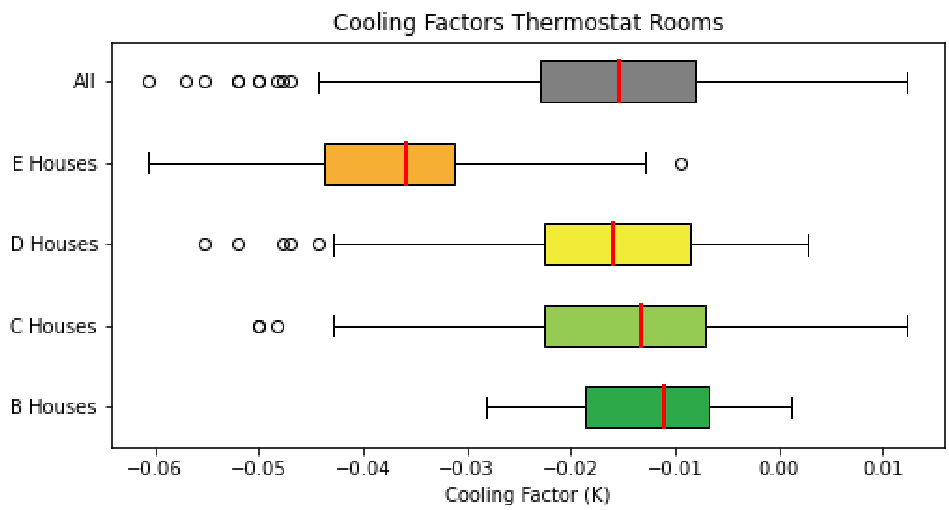


Figure 5.11: K Values of Thermostat Rooms for Model 1 from Method 1 Cooling Events

5.6 Scaling of Metric

The final aspect I investigated was scaling the metric according to its volume and approximate surface area. This is due to the amount of gas in a room and therefore its capacity to store energy (temperature) is based on its volume and the rate it can transfer is based on its surface area. This scaling was done using the following formulas,

$$K\ Scaled = K * \frac{Scaling\ Factor}{Mean\ Scaling\ Factor} \tag{5.3}$$

Where,

$$Scaling\ Factor = \frac{Approx\ Surface\ Area}{Room\ Volumne} \tag{5.4}$$

In Figure 5.12 a comparison of the distributions can be seen showing that they are similar. It also shows that there are some slightly less extreme values which were the intention of this scaling however it didn't have the complete desired effect. One of the reasons this may have not worked as desired was that surface area was an approximation based on the volume. Looking at the effect of the scaling on individual rooms can be seen in Figure 5.13. This shows that the values are not changed dramatically and the scaling has a minor effect.

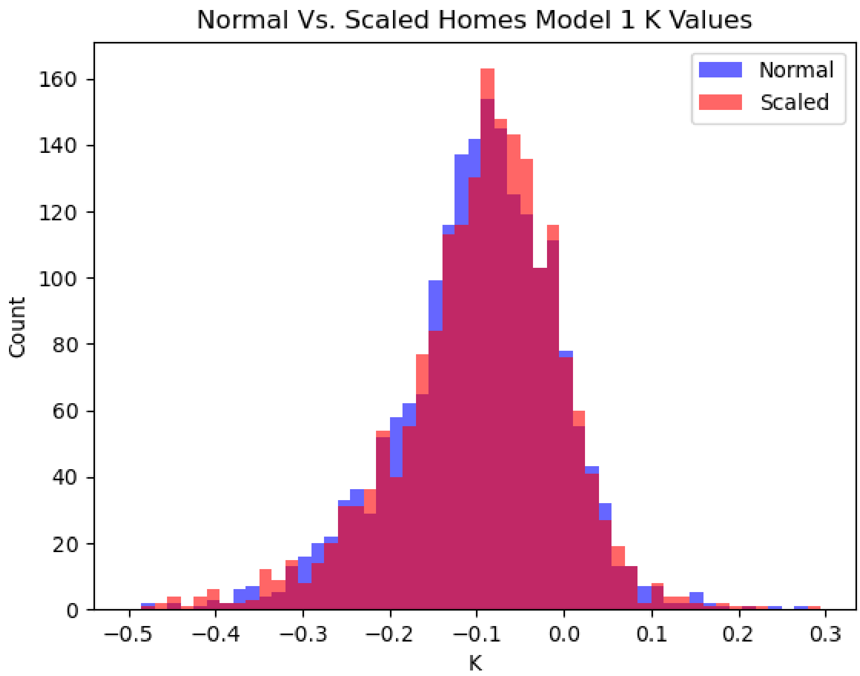


Figure 5.12: Normal Vs Scaled Distributions of K for model 1 from Method 1 Cooling Events

This scaling was used on K, K1, and K2 of their respective models in the predictive tasks. The constant was not scaled as it was assumed that it could be based on factors internal to the rooms.

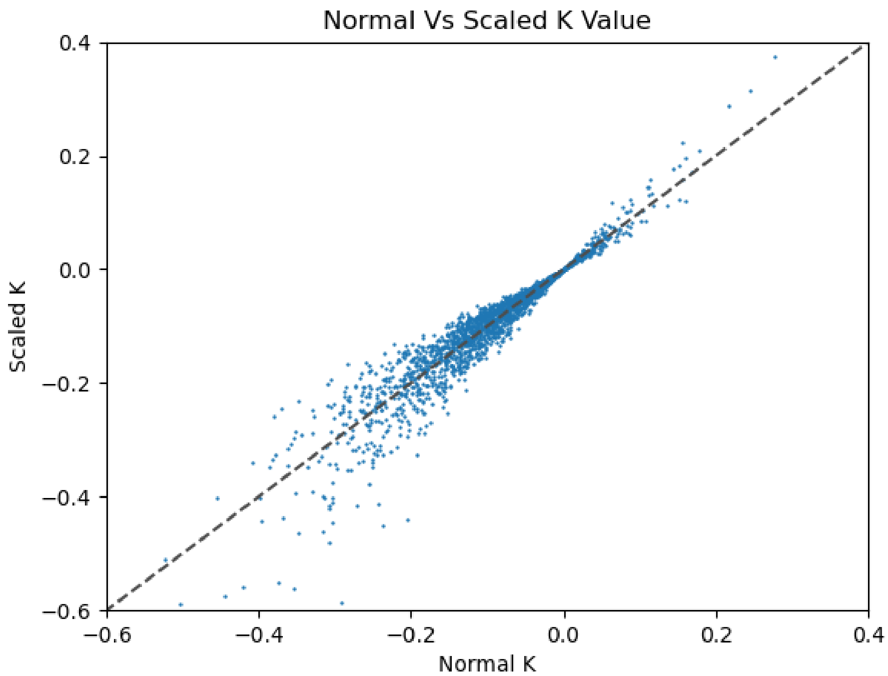


Figure 5.13: Normal Vs Scaled of each K for model 1 from Method 1 Cooling Events

Chapter 6

Use of Measure for Prediction

In this chapter, I look into the results produced by the proposed metrics using both cooling event sets and models for the 3 prediction tasks mentioned in Chapter 1. These were to predict the following,

- EPC Energy Efficiency Rating
- EPC Predicted Energy Use
- Real Gas Usage

6.1 EPC Energy Efficiency Rating Classification

The baseline chosen for predicting the EPC Energy Efficiency Rating was to predict everything as C, the most common class in the training data. This produced a training accuracy of 0.512 and a validation accuracy of 0.496

Table 6.1 shows the results from method 1 cooling events. From this, we can see that all of the potential models performed better on the training set but performed worse on the validation set suggesting that the models will not generalise well. It is also clear even from the training accuracy that the cooling models parameters have little predictive power and by themselves are not enough to correctly predict an EPC.

Table 6.2 shows the results from method 2 cooling events. The table shows that once again all of the potential models performed better on the training set but in contrast to the first set of models, a number of these models performed slightly better than the base model. However, these models still have low predictive power.

Despite these low results I chose to take the two best-performing models from method 2 cooling events, these were,

- Model 1, Scaled using the Living Room
- Model 1, Scaled using the Kitchen

The first of these final models produced a testing accuracy of 0.412. While the second of these final models produced a testing accuracy of 0.529. Both of these results are

Model	Scaled	Room Type	Training Acc	Validation Acc
Baseline			0.512	**0.496**
1	No	Living	0.571	0.414
1	Yes	Living	0.589	0.499
2	No	Living	0.577	0.404
2	Yes	Living	0.574	0.414
1	No	Kitchen	0.531	0.489
1	Yes	Kitchen	0.562	0.499
2	No	Kitchen	0.570	0.399
2	Yes	Kitchen	0.561	0.408
1	No	Thermostat	0.557	0.435
1	Yes	Thermostat	0.557	0.422
2	No	Thermostat	**0.596**	0.480
2	Yes	Thermostat	0.588	0.459

Table 6.1: Results of Method 1 Cooling Events for the Classification of EPC Energy Efficiency Ratings

Model	Scaled	Room Type	Training Acc	Validation Acc
Baseline			0.507	0.514
1	No	Living	0.590	0.495
1	Yes	Living	0.604	**0.545**
2	No	Living	0.532	0.337
2	Yes	Living	0.528	0.419
1	No	Kitchen	**0.634**	0.454
1	Yes	Kitchen	0.619	0.524
2	No	Kitchen	0.587	0.514
2	Yes	Kitchen	0.576	0.545
1	No	Thermostat	0.568	0.508
1	Yes	Thermostat	0.573	0.510
2	No	Thermostat	0.549	0.502
2	Yes	Thermostat	0.539	0.500

Table 6.2: Results of Method 2 Cooling Events for the Classification of EPC Energy Efficiency Ratings

disappointing but highlight the variance in performance of the model due to the low sample size. It is therefore clear that the models provided do not perform well at predicting the EPC Energy Efficiency Rating.

One aspect to consider with this task is that EPC Energy Efficiency Ratings come from an asymmetric mapping to a numeric scale thus a possible better prediction task could have been a regression of this numeric scale. However, this data was not available.

6.2 EPC Predicted Energy Use Regression

The baseline chosen for predicting the EPC Predicted Energy Use was regression by simply using the size of the home. This produced a training RMSE of 5.6 and a validation RMSE of 5.676.

Table 6.3 shows the results from method 1 cooling events. The table illustrates that all models performed better than the baseline on both the training set and the validation set. From this, we can see that the more complicated model 2 performs better on the training set but the more simple model 1 outperforms it in comparison when using both thermostat and living room on the validation set. Of particular interest from this set of experiments is that the model performs relatively better on the living room than all others.

Model	Scaled	Room Type	Training RMSE	Validation RMSE
Baseline			5.600	5.676
1	No	Living	4.970	5.088
1	Yes	Living	4.950	**5.084**
2	No	Living	4.807	5.475
2	Yes	Living	4.823	5.397
1	No	Kitchen	5.041	5.228
1	Yes	Kitchen	5.116	5.278
2	No	Kitchen	**4.754**	5.128
2	Yes	Kitchen	4.889	5.255
1	No	Thermostat	5.202	5.401
1	Yes	Thermostat	5.233	5.500
2	No	Thermostat	4.935	5.613
2	Yes	Thermostat	4.980	5.359

Table 6.3: Results of Method 1 Cooling Events for the Regression of EPC Predicted Energy Use

Table 6.4 shows the results from method 2 cooling events. From this, we can see that all of the potential models performed better on the training set than the baseline however only model one on the living room - both scaled and not scaled - performed better on the validation set than the baseline. It can be seen that the models created using thermostat rooms performed particularly badly on the validation set with all RMSE being greater than 6.6; which is approximately 1 worse than the baseline validation RMSE.

The models that I choose to look at the test results were,

- Model 1, scaled using the living room and method 1 cooling events.
- Model 1, not scaled using the Living Room and method 2 cooling events.

The first of these final models produced a testing RMSE of 5.039. While the second of these final models produced a testing RMSE of 4.983

From these results, we can see that the performance against the test set is better than the performance on the validation set which could be a result of a larger number of training

Model	Scaled	Room Type	Training RMSE	Validation RMSE
Baseline			5.600	5.676
1	No	Living	5.194	**5.382**
1	Yes	Living	5.221	5.405
2	No	Living	5.321	5.811
2	Yes	Living	5.382	5.599
1	No	Kitchen	**5.047**	5.665
1	Yes	Kitchen	5.161	5.797
2	No	Kitchen	5.345	6.116
2	Yes	Kitchen	5.412	5.918
1	No	Thermostat	5.355	6.647
1	Yes	Thermostat	5.372	6.687
2	No	Thermostat	5.420	6.908
2	Yes	Thermostat	5.489	6.851

Table 6.4: Results of Method 2 Cooling Events for the Regression of EPC Predicted Energy Use

examples used for the final models or simply a quirk of this test set. Despite this, it does confirm that the cooling factor developed has some use at predicting the EPC predicted Energy Use. This is further supported by the result of the first model.

6.3 Real Gas Use Regression

For the final prediction task, the baseline chosen for predicting the EPC Predicted Energy Use was regression by simply using the size of the home. This produced a training RMSE of 0.944 and a validation RMSE of 0.962. This was an expansion of the original project to predict the real gas usage of homes; this was due to the relatively poor performance at the previous two tasks with the objective of validating the method more.

Table 6.5 shows the results from method 1 cooling events. The table illustrates that all models performed better than the baseline on both the training set and the validation set.

Table 6.6 shows the results from method 2 cooling events. The table shows that the more simple model 1 performs badly against most results. However, what is interesting is the performance of model 2 against the training set in most cases is particularly impressive. The result of model 2 with the thermostat room both scaled and not scaled also generalises well with the validation set.

The models are chosen,

- Model 2, scaled using the kitchen and method 1 cooling events.
- Model 2, not scaled using the Kitchen and method 2 cooling event.
- Model 2, scaled using the Thermostat Room and method 2 cooling events.

Model	Scaled	Room Type	Training RMSE	Validation RMSE
Baseline			0.944	0.962
1	No	Living	0.897	0.936
1	Yes	Living	0.899	0.952
2	No	Living	0.892	0.920
2	Yes	Living	0.893	0.924
1	No	Kitchen	0.871	0.915
1	Yes	Kitchen	**0.864**	0.895
2	No	Kitchen	0.868	0.902
2	Yes	Kitchen	0.865	**0.894**
1	No	Thermostat	0.916	0.949
1	Yes	Thermostat	0.911	0.941
2	No	Thermostat	0.913	0.954
2	Yes	Thermostat	0.912	0.958

Table 6.5: Results of Method 1 Cooling Events for the Regression of Real Gas Usage

Model	Scaled	Room Type	Training RMSE	Validation RMSE
Baseline			0.944	0.962
1	No	Living	0.941	0.997
1	Yes	Living	0.939	0.996
2	No	Living	0.797	0.996
2	Yes	Living	0.797	0.984
1	No	Kitchen	0.915	0.974
1	Yes	Kitchen	0.912	0.970
2	No	Kitchen	0.787	0.892
2	Yes	Kitchen	0.787	0.907
1	No	Thermostat	0.949	1.058
1	Yes	Thermostat	0.949	1.071
2	No	Thermostat	0.737	0.798
2	Yes	Thermostat	**0.736**	**0.791**

Table 6.6: Results of Method 2 Cooling Events for the Regression of Real Gas Usage

The first of these final models produced a testing RMSE of 0.868. While the second and third of these final models produced a testing RMSE of 0.792 and 0.741.

From these results, we can see that the results for the test sets show that the models generalise well. I also want to recognise that the more complicated options perform better against the real gas usage well perform worse against the predicted energy usage suggesting they are more able to capture the actual behaviour of the home. These results however cannot be directly compared as one is based on a month of high usage while the other is based on annual usage.

Chapter 7

Conclusions and Discussion

7.1 Overview

The climate crisis will continue to be a problem and therefore, solutions will be required and new ideas will be needed to solve it. This will require effort in many sectors but there will remain the need for the improvement of energy efficiency metrics in the energy efficiency.

In this project, I have provided an analysis of the homes of the IDEAL dataset. I have examined the relationship between the temperature difference of the inside and external temperature of homes to see if it can be used as a proxy for insulation and shown that the application of Newton's Law of Cooling is possible. The result on predicting EPC predicted energy use showed that the possible metrics could be used but not fully on their own with the best final model achieving a 4.983 RMSE. A similar result can be reported for the real gas usage that the possible metrics could not be used fully but could aid in a model with other parameters with the best final model achieving a 0.741 RMSE (on December 2017 usage). However, the results were underwhelming for the EPC rating with the best final model having only 0.529 accuracy; which is similar to the baseline. However, there is still room for these methods to be developed in the future and it opens an interesting avenue for future work.

7.2 Future Work

In this project, I have explored several different avenues on how a metric based on internal/external temperature difference can be adapted to improve its ability to predict the EPC Energy Efficiency Rating, EPC Predicted Energy Use, and real gas usage. However, there still remains a vast number of different aspects that could be investigated and provide an improved metric.

One aspect that I believe could provide an interesting avenue for future work is the second cooling events extraction method. Despite its rough performance in this project, it remains that it could be adapted to include elements such as human behaviour when modelling the heat loss rate which could decrease the massive variability. Furthermore, if there was sufficient labelled data created for these heating events then there would be potential to train a machine learning model to detect these events which perhaps would perform better than the threshold method used in this project. The way gas events are extracted could be a whole project in itself.

Another aspect that could provide interesting further work is to consider more elements of weather in the models than just temperature. Elements such as there being cloud coverage or a difference in humidity could affect the heat transferred to a home. The cloud coverage could have a different effect on every room due to if its external walls face the sun normally which would have a heating effect on the walls and as a consequence the room; this would change with the time of day and year which could affect the cooling parameter value. While the humidity can affect the amount of energy in the air thus affecting how much energy can be transferred before the temperature changes.

Following on from the expansion of the models based on weather there could also be an expansion into the model's consideration of the room. As mentioned, humidity can affect the amount of energy in the air so it could be useful to adapt the metric based on the humidity of the room. Further, one of the aspects of this project I believed performed particularly poorly was the scaling of the rooms. If there was more information on the room such as the surface area, and even the surface area of external facing surfaces vs the surface area of other facing surfaces then this metric could be improved in this aspect. Aspects such as the number and quantity of windows in a room will also have an effect on the K parameter.

In addition to the expansion of a model, you could also fit the exponential graph that comes from the derivation of Newton's Law of Cooling. This does come with a number of additional challenges as the temperature of the outside and other rooms is not constant throughout the period. This would involve having to deal with the changing temperatures but may result in better results.

One of the limiting factors of this project was the number of homes in the IDEAL dataset. The IDEAL dataset is unique in its level of detail provided however if more homes were added it would unlock more research opportunities to help tackle the climate emergency. In the case of this work, it would be interesting to examine how the model performs on a wider set of homes as well as the development of more precise models that differentiate between different home kinds.

The final aspect that could provide interesting future work is to use of more complicated machine learning models. The intention of the project was to evaluate the potential metric developed from internal/external temperature thus much of the focus was placed on the development of the metric rather than the machine learning models used. This lack of a more advanced machine learning model could be a downfall in unlocking the metrics' full potential.

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Appendix A

Built Form

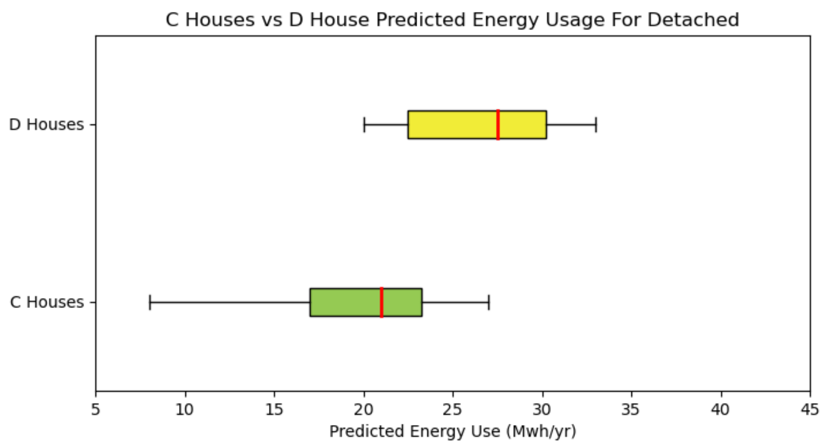

Figure A.1: Predicted Energy Use of Detached Homes

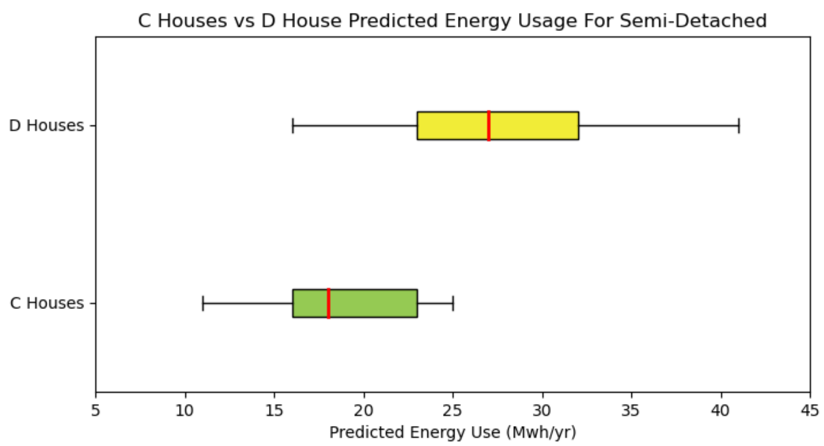

Figure A.2: Predicted Energy Use of Semi-Detached Homes

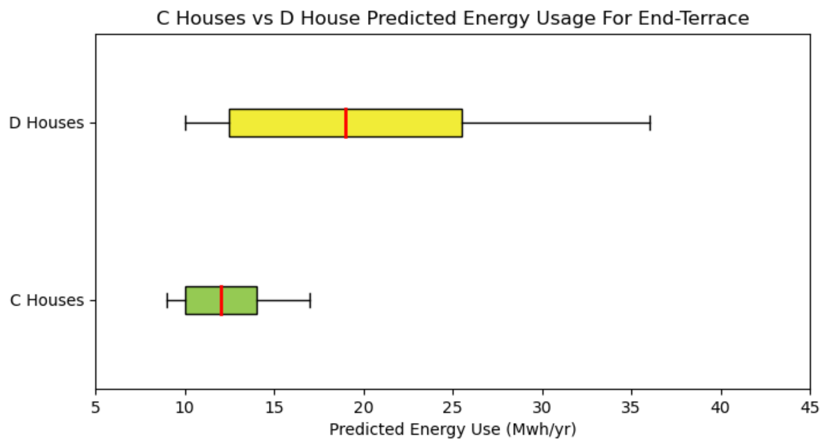

Figure A.3: Predicted Energy Use of End Terrace Homes

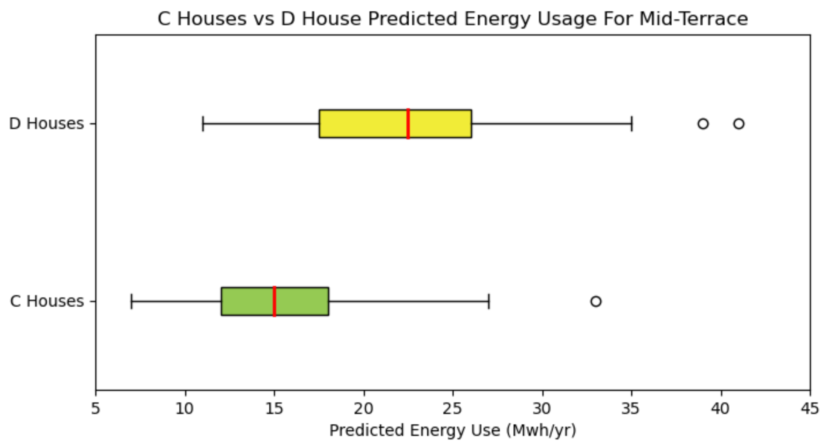

Figure A.4: Predicted Energy Use of Mid Terrace Homes

Appendix B

Additonal Rooms Type K Comparison

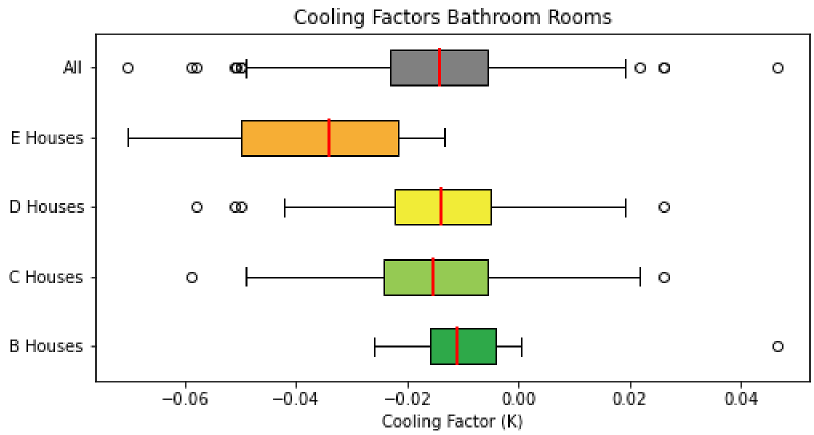

Figure B.1: Temperature Difference vs Rate of Temperature Change of Home 59's Living Room

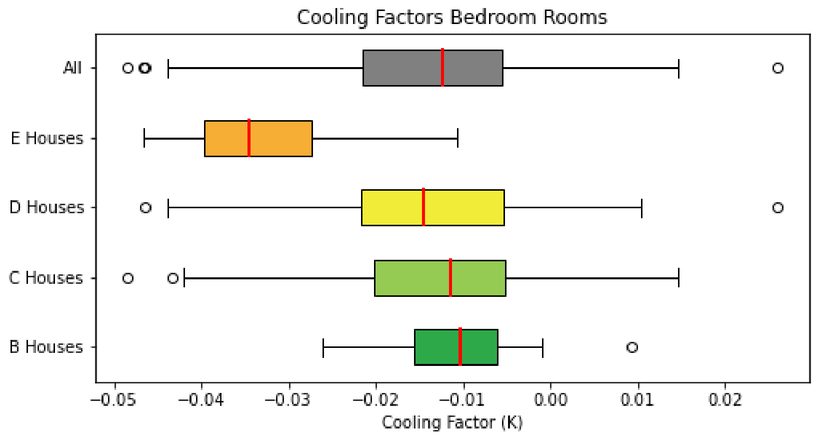

Figure B.2: Temperature Difference vs Rate of Temperature Change of Home 59's Living Room

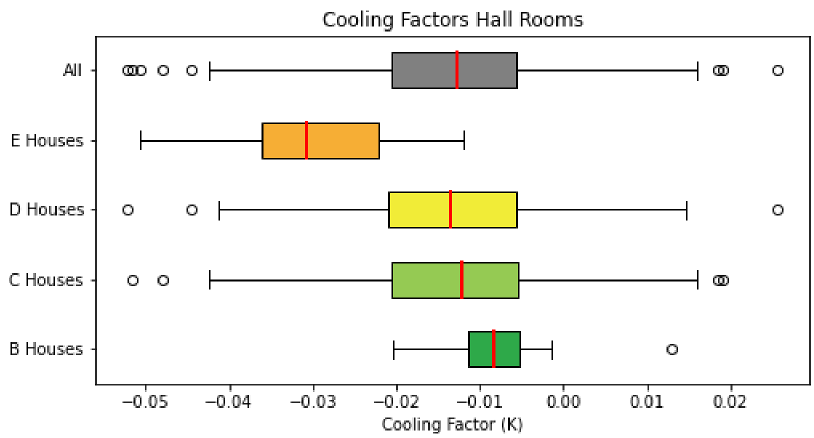

Figure B.3: Temperature Difference vs Rate of Temperature Change of Home 59's Living Room

Appendix C

Cooling Period Event Smoothing

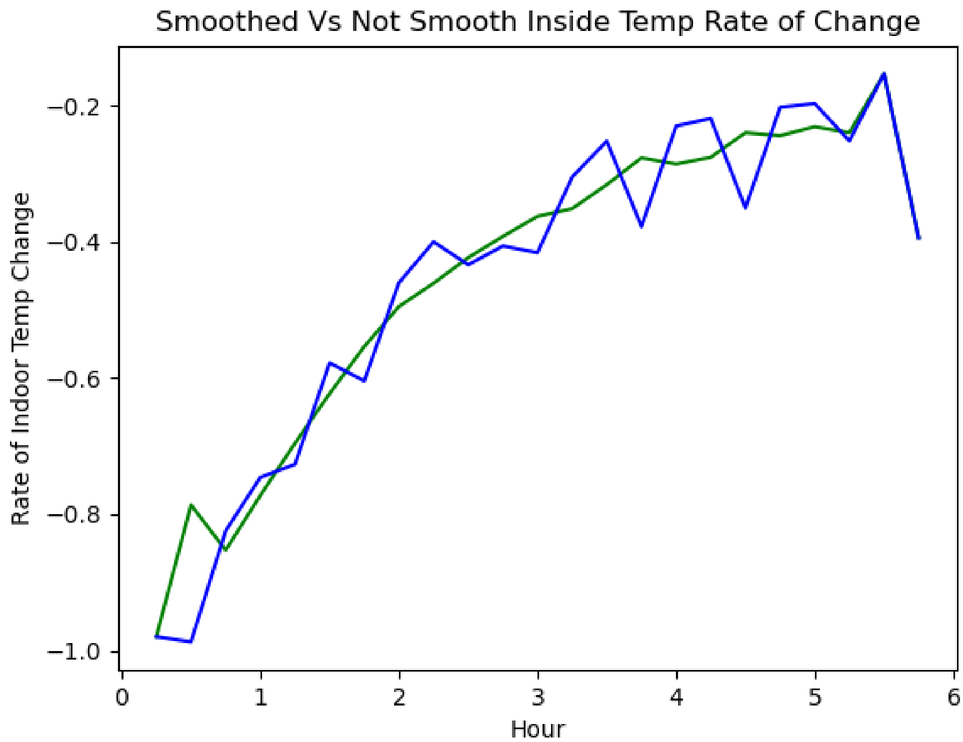

Figure C.1: Example of Smoothing that was later choosen not to explore further. Blue line is the unsmoothed rates of change while the green line is the smoothed rates of change.