An Investigation into Net Zero Energy Public Buildings with a Focus on Machine Learning Methods

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An Investigation into Net Zero Energy Public Buildings with a Focus on Machine Learning Methods

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Abstract

Global warming's negative effect on the environment necessitates the timely need to reduce CO_2 emissions. Commercial buildings are major contributors into such emissions in the UK that consume 277TWh from the Government's latest data collection and 89% of non-domestic energy consumption was from the grid. Therefore, government legislations worldwide are becoming increasingly stricter on carbon dioxide emissions from buildings. However, the buildings must continue to run, fully functioning, while still reducing emissions. While some building management systems (BMS) can manage the demands of the building and reduce energy waste, they rely on the current demand instead of planning for future demand. Moreover, some space heating methods are not fully understood such as with recently developed infrared technologies. Electric vehicle charging schedules are not previously optimised, and neither is energy management from on-site renewable generation.

In this research work, already existing machine learning algorithms (MLA) methods are applied to optimise energy efficiency of commercial buildings. Neural networks, random forests, support vector machines, and linear regression are developed to accurately forecast the buildings' energy characteristics for various resolutions and horizons to determine the best method and application to the BMS.

From the developed MLA's, the random forest has an accuracy as high as 96% and can forecast the energy demand in 15-minute resolutions on 24-hour horizons. One outcome of this research is a developed strategy that saves 64.7% on costs through using the energy capacity of electric vehicles. This allows energy to be purchased from the EV instead of from the grid at peak-times. Moreover, the heating consumption of a lecture hall is reduced by 75.97% through using infrared heating combined with MLA occupation density forecasting. Furthermore, neural networks, random forests, support vector machines, and linear regression to forecast the active solar panels are developed and critically analysed to determine data requirements and surrounding affecting factors. The MLA's used to forecast the energy consumption of the case study building are trained on a 16GB intel core i7, with a dataset of 97,185 samples of 11 features, with average training times of 172s (neural network), 61.9s (random forest), 270.3s(support vector machine), and 41.7s (linear regression) respectively.

Declaration

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

Copyright Statement

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It would not have been possible to write this doctoral thesis without the help and support of my friends and family, of which only certain individuals have been given a distinctive mention here.

I give thanks to my supervisor, Professor Alhussein Albarbar who firstly taught me as an undergraduate and maintained his efforts as I started a new role as his PhD student. Throughout my research, he has offered me wisdom and advice to push me in the right direction. Without his consistent work to help me with my research, I could not complete this thesis successfully. I would like to thank Dr. Mominul Ahsan who has worked with me throughout my research and has provided me with helpful knowledge for my thesis. Thanks go to Mr. Agomon Hossain Ferdaus for working with me in developing the infrared AUTOCAD research. After I discovered the research gap and developed product specifications for the entirety of the methodology for the research, he worked with me to bring the method to life as I instructed him, resulting in a research publication. Thanks to T. Kenan for her final checks of the infrared research to ensure smooth readability and cohesiveness.

Finally, I would like to dedicate this to my family for their love and support, and for providing me with motivation every day of my studies. Special thanks to my dad for his continued humour and inquisitive mind in pushing me towards my studies.

Nomenclature

Air Exchange	q^{i-j}
Alternating Current	AC
Amps per Hour	Ah
Association Between Variables	λ_{jk}
Biomass Energy Output	ΔE_{total}
Building Energy Storage	BES
Building Information Modelling	BIM
Building Management System	BMS
Carbon Trading Scheme	CTS
Decision Tree	DT
Direct Current	DC
Direct Irradiance from FIR Panel	DI
Display Energy Certificate	DEC
Dwelling Emission Rate	DER
Electric Vehicle	EV
Electrical Capacity of Charging Stations	SC
Energy Generated from a PV System	P_{PV}
Energy Management System	EMS
EV Battery Discharge	D_c
FAR Infrared	IR, FIR
Flywheel Energy Storage Capacity	E
Flywheel Energy Storage System	FESS
Gini Impurity	$Gini(D)$
Heating, Ventilation, and Air Conditioning	HVAC
Horizontal Axis Wind Turbine	HAWT
Hot Water System	HWS
HVAC Energy Consumption	E_{hr}
Hydrogen Energy Storage	HES
Illuminance of Lighting	$I(t)$

Kinetic Door Energy Output	E_{in}
Light Dependent Resistor	LDR
Light Emitting Diode	LED
Lighting Energy Consumption	E_{lr}
Linear Interpolation	y
Linear Regression	LR
Linear Regression	m
Machine Learning Algorithm	MLA
Manchester Metropolitan University	MMU
Maximum Relevance Minimum Redundance	MRMR
Maximum Relevance Minimum Redundance	Vs, Ws
Mean Actual Percentage Error	MAPE
Mean Actual Percentage Error	M
Mutual Information	$I(X,Z)$
Net Zero Energy	NZE
Neural Network	NN
Number of Batteries	Nb
Number of Full EV Charges	NF_c
Output Power from Electrolysis	$P_{EL,i}^{out}$
Parts Per Million	PPM
Passive Infrared	PIR
Phase Change Material	PCM
Photovoltaic Storage	PV, PVS
Power Required from IR Panels	RP
Probability of a Zone being Occupied	PDT
Proton Exchange Membrane	PEM
Random Forest	RF
Random Forest Out Of Bag	RF-OOB
Rate of Heat Exchange	q
Rate of Heat Transfer over Time	Q

Renewable Energy	RE
Required Power from FIR Panel	RP
Return On Investment	ROI
Rolling Average	μ
Root Mean Squared Error	RMSE
Simplified Building Energy Model	SBEM
Solar Energy Storage	SES
Standard Assessment Procedure	SAP
Standard Capacity of EV Battery	S_c
State of Charge	SOC
Support Vector Machine	SVM
Thermal Energy Storage System	TESS
Tonnes of Oil Equivalent	toe
V2G Profit	P
Variable Air Volume	VAV
Vehicle To Building	V2B
Vehicle To Grid	V2G
Vertical Axis Wind Turbine	VAWT
Wind Turbine Energy Output	P

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List of Publications and Contributions to Work

1. C. Scott, M. Ahsan, and A. Albarbar, "Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings," Sustainability, vol. 13, no. 7, 2021, doi: 10.3390/su13074003.
   [Q1 Sustainability, IP: 3.889, SNIP: 1.310].
2. C. Scott, A. H. Ferdaus, T. Kenan, and A. Albarbar, "Cost-effective occupation dependant infrared zonal heating system for operational university buildings," Energy and Buildings, vol. 272, p. 112362, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.enbuild.2022.112362.
   [Q1 Energy and Buildings, IP: 7.201, SNIP: 2.069]
3. C. Scott, A. Albarbar "Machine Learning Forecasting for Optimisation of Green Energy Generation in Non-Domestic Buildings," 3rd International Virtual Conference on Industry 4.0 (IVCI 4.0) 2022, 2022/01/01 2022.
4. C. Scott, M. Ahsan, and A. Albarbar, "Machine learning for forecasting a photovoltaic (PV) generation system," Energy, vol. 278, p. 127807, 2023/09/01/ 2023, doi: https://doi.org/10.1016/j.energy.2023.127807.

   [**Q1 Energy, IP: 8.857, SNIP: 2.038]**

1. "Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings".

C. Scott acted as the lead author as such he conducted the research survey, collected, and analysed the results. M. Ahsan provided initial review on the article, supported the codes development while A. Albarbar provided overall structure of the articles, supervised the research, and addressed the reviewers' comments alongside C. Scott.

2. "Cost-effective occupation dependant infrared zonal heating system for operational university buildings".

C. Scott conducted the research as part of his PhD, collected, and analysed the results, wrote the research article, and provided feedback for the peer reviewers of the journal. C. Scott and A. H. Ferdaus carried out the methodology on the software. T. Kenan reviewed the article. Albarbar contributed to the methodology and supervised the research.

3. "Machine Learning for Forecasting a Photovoltaic (PV) Generation System".

C. Scott acted as the lead author, conducted the research, wrote the literature review, developed, and carried out the methodology, collected and analysed the results, and wrote the research article. C. Scott and M. Ahsan provided feedback for the peer reviewers of the journal. A. Albarbar supervised the research.

4. "Machine Learning Forecasting for Optimisation of Green Energy Generation in Non-Domestic Buildings".

C. Scott carried out the research, found the novelty, developed, and carried out the methodology, collected and analysed the results, and wrote the research article, and provided feedback for the peer reviewers of the journal. A. Albarbar supervised the research

CHAPTER ONE: INTRODUCTION

This chapter serves as an introduction to non-domestic buildings' energy consumption and explains environmental, political, and financial reasoning for the energy reduction of non-domestic buildings. It critically analyses the energy generation and consumption of non-domestic buildings with an explanation of building management systems. Contributions to knowledge are outlined and finally, the aims, objectives, and structure of the thesis are explained.

1.1 Introduction to Non-Domestic Building Energy Consumption

Buildings in the UK use 34% of the total energy consumption as heating and cooling loads with gas and electricity using 78% and 12% respectively [1]. Non-domestic buildings consume 277TWh [2] or 38% of total electricity compared to industry (36%), transport (1%), and domestic (22%) sectors [3]. This is conveyed in Figure 1.1.

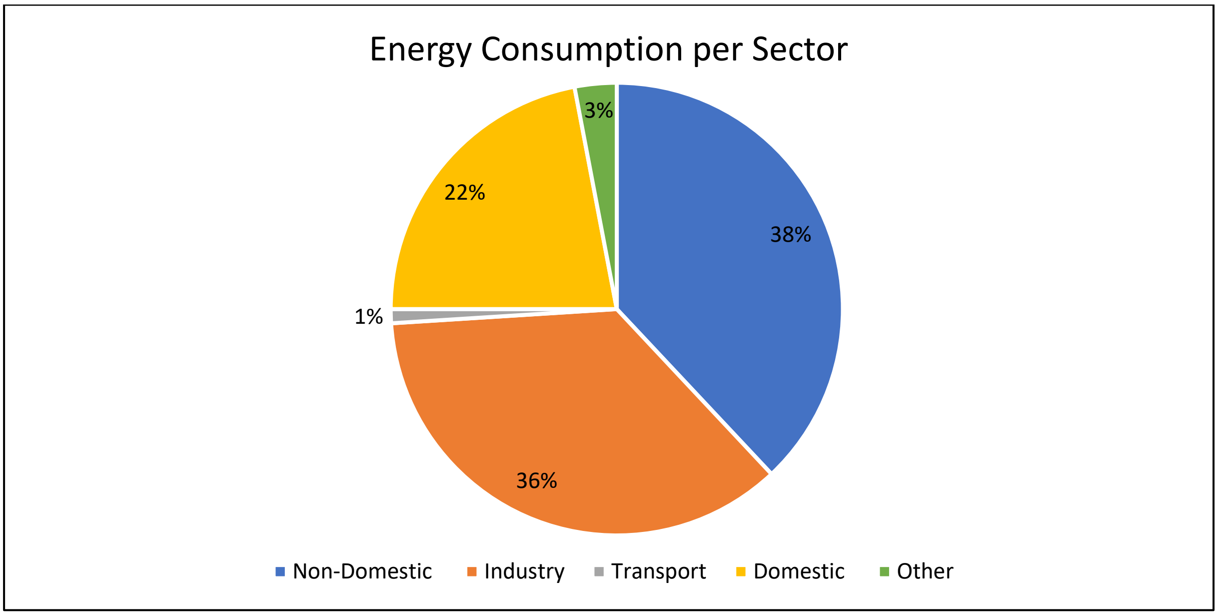

Figure 1.1. The energy consumption of the sectors that make up 100% of the total energy consumption in the UK.

Non-domestic buildings include:

- Offices.
- Restaurants.
- Hotels.
- Warehouses.
- Healthcare.
- Retail.

Industrial buildings include:

- Manufacturing plants.
- Power plants.
- Refineries.

- Storage and Distribution.
- Mills, dairies, and farming processing.

Transport includes any vehicles on the road, from lorries to busses to cars and domestic buildings include houses and flats.

An average UK temperature increase of 1.3ºC between 1961-2020 provides clear evidence that all CO_2 emissions produced must be reduced to stop the effects it is having on global warming [4]. To prevent further damage, the UK Government plan to eliminate greenhouse gas emissions from buildings by 2050 [5], stating that driving, manufacturing, heating, and electricity generation must emit as close to zero emissions as possible. Government regulations have a large effect on net zero energy (NZE) buildings as [6] climate, technology, and economic factors contribute widely. The transition to NZE is challenging when buildings rely on fossil fuels [7], but carbon trading schemes (CTS) [8] show some support for this transition. However, more supportive government policies are required for a wider adoption of NZE buildings. The UK energy mix from 2023 consists of coal (0.41%), petroleum (37.73%), natural gas (33.27%), bioenergy (11.36%), nuclear (9.41%), and renewable energy (7.79%) [9]. The UK only exports energy and heat at 0.65MWh at 7.45% and 0.08MWh at 1.29% respectively compared with Sweden, Denmark, Germany, and the Netherlands as a whole [10]. Overall net imports account for 35.2% of UK total energy use with energy generation of 1,652.63MWh [11]. Higher levels of renewable energy generation can decrease the amount of imported energy, but this can produce more unpredictability into the energy mix. Higher energy storage capacity within the national grid can reduce the amount of necessary imported energy. This can save costs for the UK through energy imports as well as reducing the CO_2 produced from conventional energy generation methods. The UK requires 43TWh of storage to enable 100% renewable energy generation which equates to 0.16% of the UK's total energy consumption in 2022 at 22,756Mtoe (265TWh). This would cost £165 billion, or 7% of the UK's GDP [12].

Energy consumption demand for heating is higher in colder climates such as the UK, making it a necessary focal point, but different climates will benefit from independent heating and cooling systems [13].

From all energy produced in the UK in 2022, 37.47% came from oil, 33.03% came from natural gas, and 0.45% came from coal, totalling 70.96%. The other 29.03% came from renewable sources and biowaste. Energy production is different from the energy mix as energy may be bought my neighbouring countries. The change in UK energy production is shown in Figure 1.2.

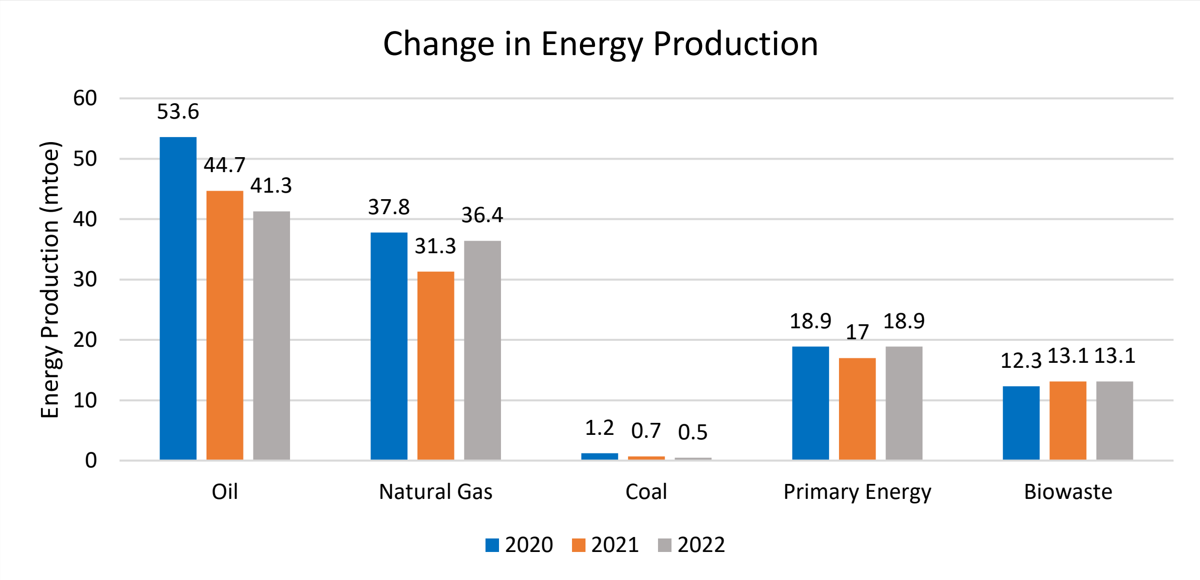

Figure 1.2. The change in energy production from 2020-2022[14] Oil and coal are steadily decreasing, natural gas is decreasing but with peaks and troughs, biowaste is steadily increasing, and primary energy (any fuels that can be found directly from a source without the need for conversion, including fossil fuels and renewables) is staying the same.

The average fossil fuel energy production over the three years is 72.62% of the total demand, with a demand decline of 13.6M tonnes of oil equivalent (toe) (12.36% of total 2022 energy demand). The renewable energy production has increased by 2.5% of the total generated energy from 2020-2022. The UK's national grid is reducing carbon emissions by using renewable energy sources, but this can be unreliable due to varied wind speeds, solar insolation, and tide ferocity. When these energy sources are lacking, instead of hitting energy production targets by fossil fuel methods, buildings can conform to the needs of the grid through demand side response, lessening load where necessary. This can ensure that fossil fuels are not necessary by reducing the load to match the generated renewable energy by the national grid. Better energy management and demand side response of buildings and other energy consumers can promote renewable generation, lowering CO_2 production.

The government regulations for the reduction of carbon emissions from all buildings within the UK require the effective use of energy generation and demand. To calculate the energy performance of the buildings, the government issue each building a personalised energy performance certificate (EPC) and a display energy certificate (DEC) [15]. An example of a DEC is shown in Figure 1.3.

Figure 1.3. The display energy certificate of 10-12 Downing Street.

The certificate is presented with a unique number, an expiration date, the location, and the operational rating. The rating scale is shown in Figure 1.4.

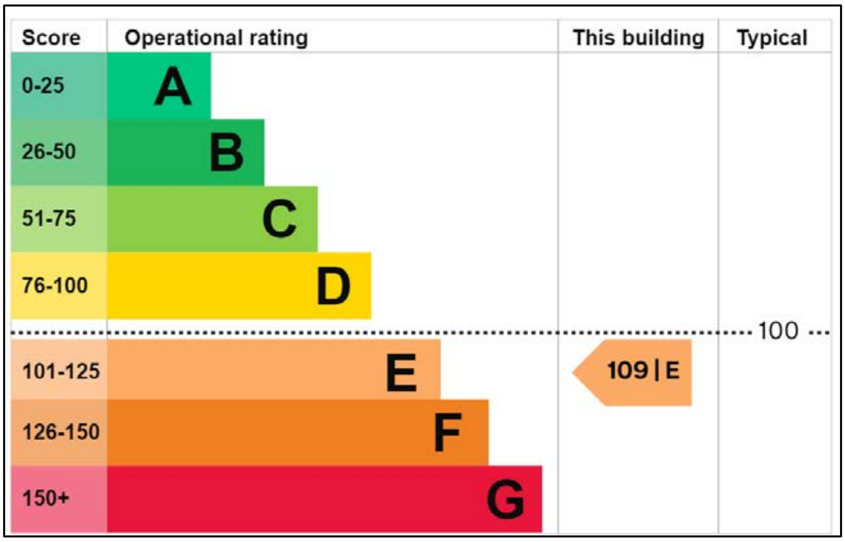

Figure 1.4. The operational rating scale from A-G.

The typical rating for a similar building is 100 whereas the selected building only has a rating of 109, meaning it is underperforming and must be improved to reduce carbon emissions. Previous rating for this building were 108, 136, and 109 for the years 2018, 2019, and 2020 respectively. This shows that the building isn't being improved through the years. The buildings' total energy use and fuels used, total usable floor area, and any renewable generation methods are also provided with the certificate.

A useful way of measuring the energy characteristics of a specific non-domestic building is for a government selected specialist to analyse the building. This analysis includes:

- The efficiency of the heating, if it is over/under working, and if the system is well equipped to handle the building or zone(s).
- The lighting systems, as they should be light emitting diodes (LED) instead of halogen bulbs. It is also important that they are never left on when the zone is unoccupied.
- The use of ventilation and if it is ventilating at the correct rate to match 2010 government building regulations [16].
- The efficiency of air conditioning, and if it is working harmoniously with the heating system instead of working against it.
- Insulation of the building materials, including walls and the glazing of windows.
- On site energy generation and storage.

After the main features of a building are assessed, a DEC is issued to the building which dictates how efficient the building is while in operation. Once this is issued, further improvements on the building may be simulated to determine an EPC, a theoretical performance on the building after improvements. This is done through a comparison of similar building types and functionalities to copy the energy performance of the similar, already functional building. This method, however, doesn't have any measurable accuracy and doesn't help the user to determine the correct steps to maximise the energy performance of the building.

To increase efficiency of energy generation and consumption, control methods are used to determine how the building will function. Occupants' control over systems often involves the use of heating and lighting when it is not necessary, so optimisation algorithms are able to reduce wasted energy. BMS's can control lighting, HVAC, fire alarms and smoke detection, motion detectors, CCTV, ICT systems, and elevators.

Smart lighting algorithms are designed to illuminate with dependence on the occupation of the zone. This allows the lighting demand to be reduced when there is no occupation such as on weekends or in educational buildings, during the summer holidays. The lighting can also be made dependent on the natural light coming in through the windows from outside. This can save more energy by not over illuminating the zones.

The HVAC system works through measurement of outdoor and indoor temperatures, and occupation. Real time analysis of outdoor air temperature is used to control the indoor heating and cooling. The systems' energy consumption is linear with the outdoor air temperature which means it is not considering internal lighting and occupation heat gains. For increased efficiency, the heating of zones can be determined through occupation, as unoccupied zones can be heated to a lower degree. When the zone is unoccupied or overheated, the heating can gradually reduce the temperature instead of turning it off to maintain a consistent heating system over time. Fire alarms, smoke detection, motion detectors, CCTV, and ICT systems are difficult to improve as they consume little energy already. Elevators energy consumption can be forecasted for the consideration of the buildings' total energy demand but again, they are efficient and aren't considered for improvement.

1.2 Energy Consumption, Management and Optimisation

The energy demand of buildings is often seen as a whole, like a black box, but this doesn't allow the improvement of the energy demands within. To better understand the energy characteristics of buildings, the internal demands must be analysed and understood. The internal energy consumers of non-domestic buildings are the lighting, heating, ventilation, and air conditioning (HVAC), major appliances (refrigerators, ovens, machinery, dryers), and minor consumers such as computers and wall sockets. This is shown in Figure 1.5.

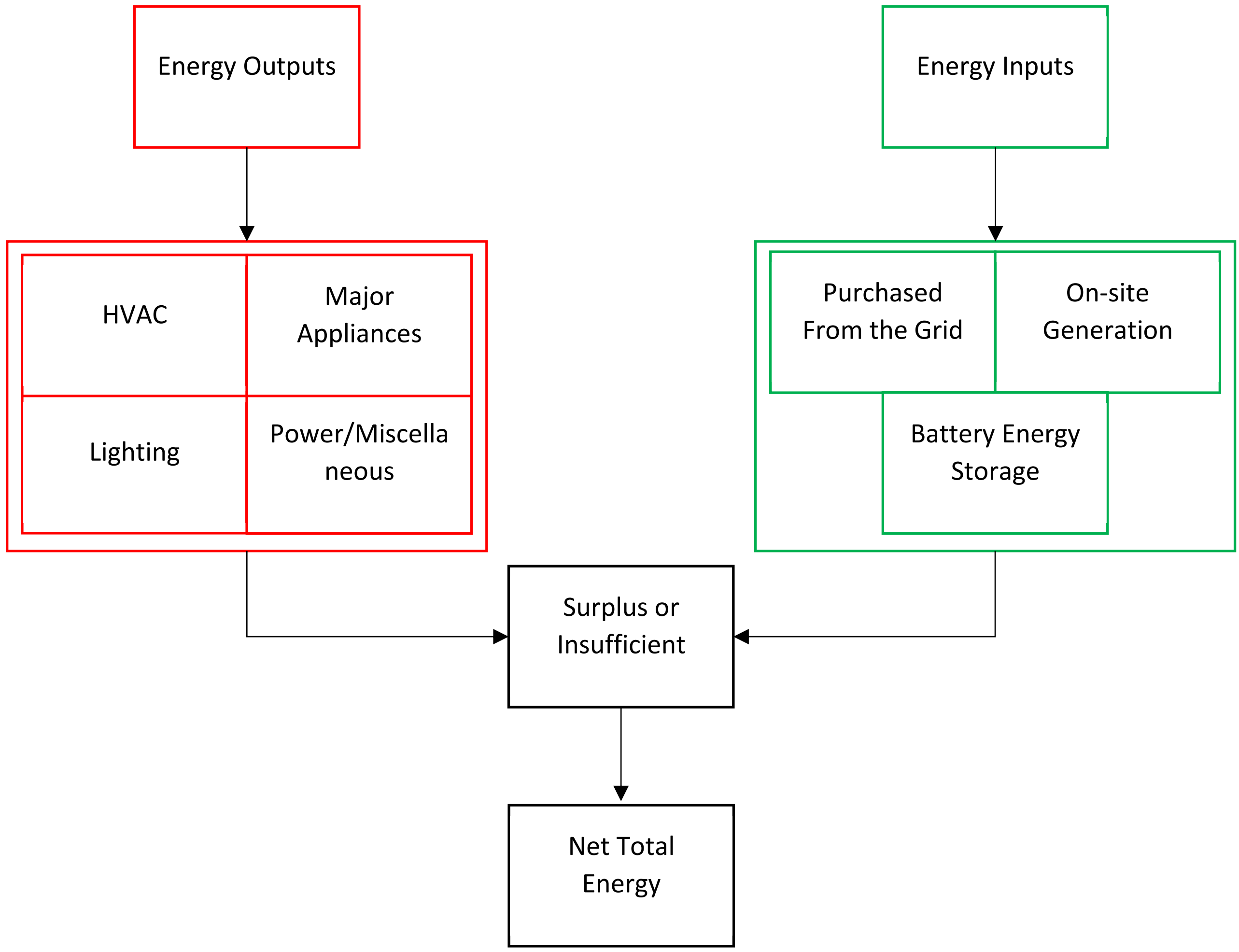

Figure 1.5. The inputs and outputs of energy within a building. The energy lack or surplus can be calculated.

The power and miscellaneous consumers represent plug sockets, computers, elevators, emergency lighting, automatic doors, and hand dryers.

The data described in Fig. 1.5 is collected through energy meters to provide information on the buildings' energy consumption systems such as the heating or lighting. To optimise the energy consumption of the energy consumers, an energy meter can be installed. This can provide information that allows the tracking of the energy consumption and thus, the management and improvement of the consumers' use.

To effectively manage the internal energy consumers of buildings, a BMS is installed. It can ensure there is no wasted energy through the building's features, such as the HVAC system. Common focus is on the main energy consumers within the building. For conventional HVAC systems, a desired temperature is maintained while under occupation. This ensures the user doesn't increase or decrease the heat as each occupant has different comfort requirements.

The lighting works the same as the room is lit until it is no longer occupied through CO_2 or passive infrared (PIR) sensors. For the kitchen, ventilation, and others, it is more complicated because of the high correlation with the occupation. The demand often increases with the occupation as more people use the kitchen, more CO_2 must be ventilated, and more energy is consumed through sockets and elevators.

The systems can present the collected data for management through a dashboard shown in Figure 1.6.

Figure 1.6. The dashboard of a typical building management system [17].

The system can present the data of system efficiency, consumption of fuels and energy, total savings, split into categories, CO_2 saved, and current load. Each part of the buildings' energy systems can be viewed through the collected data. The various systems that can be controlled by a BMS are shown in Figure 1.7.

Figure 1.7. The building management system's capabilities of management for a commercial or non-domestic building [18].

The systems include controllers, HVAC, security, fire, and hazard protection, building services, lighting, operational intelligence, and loss prevention (optimisation of the various systems), energy storage, and retail systems (any profit or required purchases).

BMS optimisation can be used to ensure there is no wasted energy by consuming, storing, and trading it where necessary. To optimise something is to ensure it is providing the maximum intended output it is capable of. Non-linear optimisation can be constrained, it can use continuous or discrete data, single and multi-objective, stochastic, and deterministic models. Constrained optimisation includes limitations such as lack of resources and data. Energy cost and times of consumption may be constraints within SEMS. The data in this research can be defined as continuous as it contains various collections of data such as cloud coverage (%), energy consumption (kWh), and air temperature (^{o}C). The optimisation models used for SEMS are multi-objective as considerable optimisation variables include times and intensity of energy consumption, energy generation and storage, and demand side response. Rule-based optimisation and reinforcement optimisation may be used. Rule-based is where there are defined parameters in which the system should operate to maintain optimum results, in this case, minimum energy consumption and maximum comfort. Reinforcement learning is where a target is set, such as the indoor air temperature, and a higher score is obtained from the algorithm when the temperature is closest to the target. Temperatures further from the target will provide a smaller score and therefore the algorithm would resist these occurrences. This can be multi-objective such as a combination between the air temperature and the lowest energy consumption possible. Optimisation of the MLA ensure it has reached the minimum error possible. This does not always occur though as the local minima can be reached instead of the global minima. In the case such as with gradient descent (GD), the error is finitely decreased until it reaches a minimum by changing the algorithms parameters. Once the error cannot be decreased instantly in either direction, the algorithm terminates. Often, the parameters that reach the local minima can be changed through an increase in error to reach a global error minimum which is the actual lowest error possible. To overcome this issue, the algorithm can be run for more iterations to determine which is the actual minimum error, but for algorithms with more finite parameters, the iterations must increase. Particle Swarm Optimisation (PSO) works through developing a selection of initial MLA models and evaluating the performance with a defined number of available MLA before the PSO algorithm selects an optimum MLA. The parameters of new models are close to the initial model with the highest performance, and this is repeated for a defined number of iterations. If the initial models do not find the global minima and instead the local minima, then all proceeding models will find the local minima too. Bayesian Optimisation (BO) can create MLA with all parameters to ensure it finds the global minima and not the local minima. This is often a slower algorithm, requiring more computational power, but providing an algorithm that can find the lowest error.

There are more than 39 BMS's commercially available for installation onto a non-domestic building with the ability to reduce energy emissions. A BMS is able to monitor equipment, occupancy, increase safety, and control the buildings' facilities remotely [19]. It has the ability to detect thermal leakage, it can integrate renewable energy sources into the functions of the BMS and can reduce energy consumption through more efficient power conversion and distribution [20]. Case studies of BMS applications include the Sydney Opera House, Eindhoven University of Technology, and Incheon International Airport [21]. These installations include automated HVAC and lighting, energy metering, video surveillance, elevator and parking control, and other safety features. These case studies are explained further in the literature review.

Eindhoven University of Technology has been improved through an 80% reduction in CO_2 emissions for the Helix building [22]. This was done through installing a BMS to automate the buildings' systems and to eliminate human error and energy waste. The main objective of the installation of the BMS was to reduce heating and cooling demands by having natural ventilation and by allowing maximum daylight and solar gains to enter the building. A curtain wall can insulate the building better to keep it cooler or warmer while using less energy from the HVAC systems. The windows can be automatically opened to provide natural ventilation and have triple solar-controlled glazing. The model couldn't eliminate carbon emissions even through the automated systems and thermal energy storage system (TESS). Future work includes eliminating the opening of windows at low temperatures or when it rains but no energy forecasting techniques are previously or planned to be employed. Forecasting of the buildings' energy parameters and forecasted climate conditions can be used for pre-heating and cooling or zonal heating if the occupation density and locations are forecasted. With the BESS, the Helix building could employ optimised energy trading and renewable generation actuation through forecasting of the energy characteristics [22].

The Sydney Opera House claims to be carbon neutral, although the building itself is still producing carbon. This is due to its carbon offset scheme where it is funding the planting of trees to make up for the carbon emissions the building produces [23]. The building's efficiency was improved through using LED's, using seawater to cool the building instead of only artificial air conditioning, and through an external company that uses the waste from the building to generate energy. These systems reduced the energy demand by 31% in total. To offset the carbon emissions of buildings, the cost is £14.82/tonneCO_2. This could cost £25,735 for the case study building in this research to offset gas and electricity per annum. The average carbon reduction per unit of crown cover of trees is 0.5kg/m^2/year [24], requiring an estimated 868m^2 of trees to offset the case studies' carbon emissions. This isn't a viable option for business's who don't have disposable income and there also needs to be enough land for the trees to be planted.

A BMS is able to automate HVAC, lighting, and security, but no previous BMS's are able to forecast and integrate the buildings' energy characteristics to eliminate carbon emissions

[25]. Applications for commercial buildings and university campuses are recommended [26]. Energy storage capabilities such as hydrogen provides more flexibility with energy trading and generation [27]. Hydrogen storage techniques do not degrade like chemical batteries do. This allows more financial savings over the same period from hydrogen energy storage than if a chemical battery is used.

As is described in this chapter, new methods of energy consumption and building parameter forecasting are necessary to optimise energy management within non-domestic buildings. MLA can be used to accurately forecast energy parameters and can therefore inform a BMS to improve energy management.

BMS's can automate the buildings' systems to reduce wasted energy and to improve comfort. They are tailored towards improved comfort and ease of use for the occupant through remote controlling of the systems parameters. They can improve security and data analysis so the BMS can manage the system's parameters. The CO_2 of various buildings aim to be eliminated with a fully decarbonised electricity supply by 2035 [28] but this has not been accomplished by any case studies in previous research. The accurate forecasting of a buildings' energy characteristics and application into the BMS's to eliminate CO_2 aren't accomplished in any previous work.

1.3 Research Aims

The aim of this research is to develop cost-effective methods to reduce energy consumption and CO_2 emissions of non-domestic buildings. This chapter concludes that non-domestic buildings consume 38% of the UK's total energy and that the government is reducing fossil fuel consumption. Government regulations are being used to push buildings into being more energy efficient, but previous case studies show that this is complex and financially expensive and laborious. More cost efficient and practical methods of reducing carbon emissions of heating and cooling, renewable generation, electric vehicle management, and energy management must be developed to hit government targets.

This will be achieved in three parts.

Firstly, reduce peak-time energy consumption of the case study building and increase grid stability. This will be achieved by developing an optimised charging and discharging schedule for an electric vehicle fleet, alleviating national grid peak-time demand while providing financial benefits for the building and for the EV owner.

Secondly, occupation density forecasting will be investigated and coupled with existing FAR infrared heating. This will be conducted through a computational fluid dynamics software and will improve attractiveness for infrared heating methods by reducing initial investment on occupation sensors and by giving a comprehensive study on a case study application.

Lastly, forecasting renewable generation management will allow the building management system to manage any generated energy optimally. This will be done by deriving accurate machine learning forecasting methods for the rooftop PV system on the case study building to determine requirements and benefits. This provides information on how data quality, varied inputs, and number of iterations affect the models accuracy.

1.4 Research Objectives

Research objectives are as follows:

- Conduct a thorough literature survey on previous work surrounding non-domestic buildings energy consumption to identify the research gap.
- Critically analyse existing design tools used to increase a buildings' energy efficiency. These include renewable energy generation, building energy storage systems, and various methods of reducing energy consumption.
- Assess the possibility of utilising electric vehicles available on site for better energy management and storage by developing an effective method of bi-directional charging.
- Search for more cost-effective heating methods such as through infrared applications.
- Develop MLA's capable of forecasting the energy characteristics of the case study building, and more precisely, the overall energy demand. Various MLA's will be developed to allow an accurate comparison between the models.
- Apply the MLA methods to the case study building to reduce the energy demand and to increase the energy generation with optimised storage and energy trading.
- Evaluate the MLA's through the forecasted energy demand compared to the actual energy demand of the case study building.

1.5 Structure of the Thesis

The thesis is constructed as is shown in Figure 1.8.

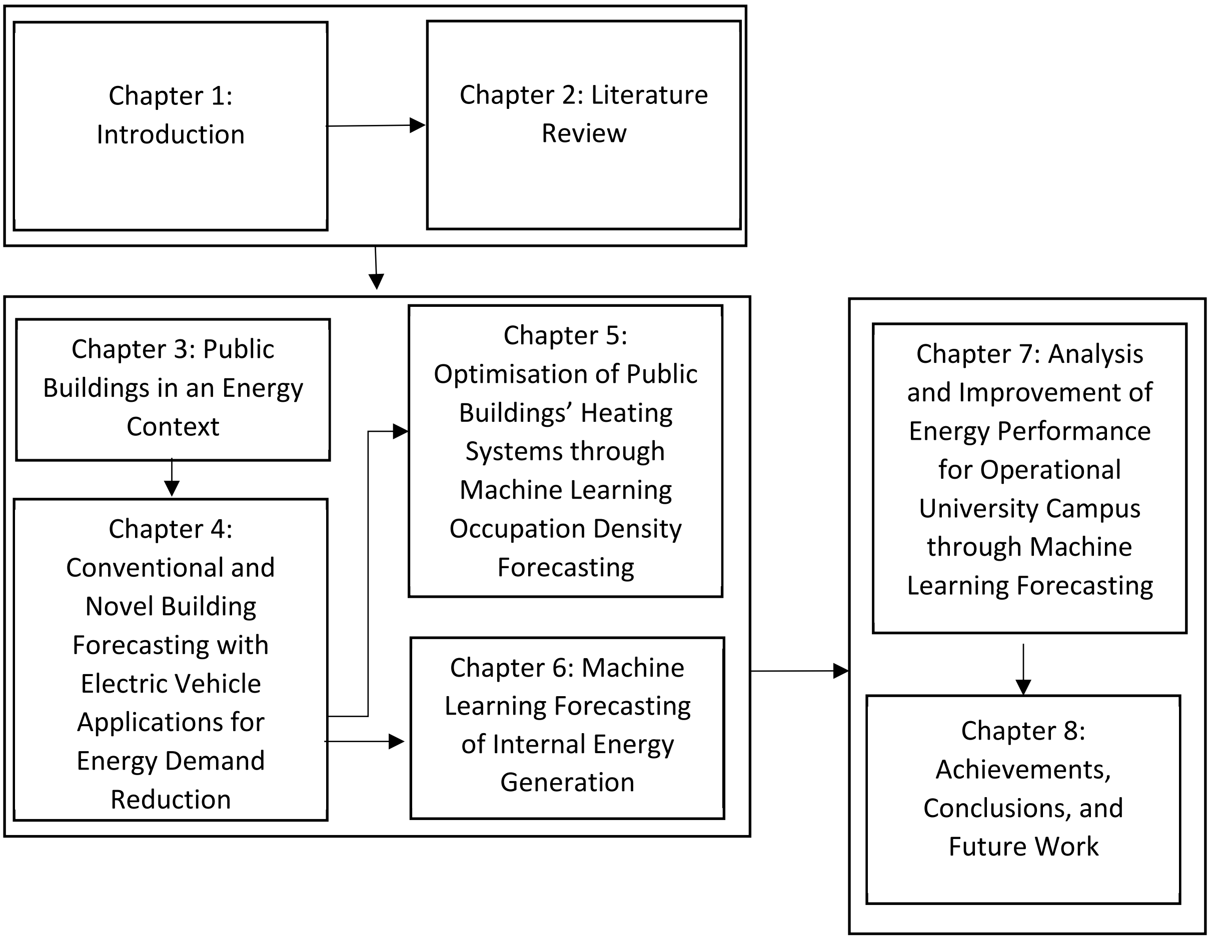

Figure 1.8. The structure of the thesis, showing the individual chapters of the introduction, the methods, and the outcomes of the research.

Chapter Two contains the literature review of previous works and the direction of the research.

Chapter Three shows the analysis of the energy characteristics of public buildings. The fundamental energy characteristics of an average public building and how the energy grades are determined by the UK government. The requirements for improving the energy grades are addressed.

Chapter Four compares conventional forecasting of a buildings' energy characteristics compared to novel methods such as AI ML methods. Current methods of forecasting, classification, and feature importance are explained.

Chapter Five shows the application of the MLA results into heating systems' for the purpose of optimisation. Occupation density and location can be forecasted and used to improve the buildings' heating efficiency.

Chapter Six develops MLA's capable of accurately forecasting the on-site energy generation of the Business Schools' photovoltaic (PV) system while analysing the potential of applying MLA's to other methods of renewable energy generation.

Chapter Seven explains the necessity of applying the developed MLA's to the case study building, how the building currently functions, and how the developed methods in this study can decrease the carbon emissions of the building. The impact that the MLA's have on the BMS is addressed through comparing the current BMS to a novel version with integrated MLA forecasting.

The thesis is summarised by the contribution to knowledge, conclusions of the work in the research, and assessment what work can be done to further the research in the future.

1.6 Contributions of this Study

The main contributions are as follows:

1. A developed occupancy forecasting method through machine learning methods, using CO_2 density data from the room as the input. This novel occupancy forecasting system is paired with already existing infrared heating to show how it may be applied, and to improve the energy efficiency of the heating within the case study by 75.97% [29].

C. Scott, A. H. Ferdaus, T. Kenan, and A. Albarbar, "Cost-effective occupation dependant infrared zonal heating system for operational university buildings," Energy and Buildings, vol. 272, p. 112362, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.enbuild.2022.112362.

[Q1 Energy and Buildings, IP: 7.201, SNIP: 2.069]

2. A method of using the energy capacity of electric vehicles is developed. Instead of purchasing batteries or selling all the energy surplus, the electric vehicles can be used to save non-domestic building costs by between 35%-65%, reducing required energy from the national grid [30].

C. Scott, M. Ahsan, and A. Albarbar, "Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings," Sustainability, vol. 13, no. 7, 2021, doi: 10.3390/su13074003.

[Q1 Sustainability, IP: 3.889, SNIP: 1.310].

3. A comparison of existing MLA's used for forecasting renewable energy generation of a local solar PV system installed on the roof of the case study, providing important knowledge on how each algorithm is affected by poorer quality data, less inputs, and less iterations to be trained and tested on. The solar PV system can be forecasted with 95% accuracy, allowing the application of optimised energy actuation from the on-site generation techniques [31, 32].

C. Scott, M. Ahsan, and A. Albarbar, "Machine learning for forecasting a photovoltaic (PV) generation system," Energy, vol. 278, p. 127807, 2023/09/01/ 2023, doi: https://doi.org/10.1016/j.energy.2023.127807.

[**Q1 Energy, IP: 8.857, SNIP: 2.038]**

C. Scott, A. Albarbar "Machine Learning Forecasting for Optimisation of Green Energy Generation in Non-Domestic Buildings," 3rd International Virtual Conference on Industry 4.0 (IVCI 4.0) 2022, 2022/01/01 2022.

4. An evaluation of feature selection and baseline machine learning algorithms for the forecasting of energy consumption of the case study building. Various sizes and quality datasets are used with four feature selection and four machine learning models. The outcome of this is a conclusion that the F-test and random forest is the 'best' combination in consideration for forecasting accuracy, development speed, and computational power. All combinations are analysed to stand as a framework for future applications of machine learning to non-domestic buildings with benchmark models.

C. Scott, M. Ahsan, A. Albarbar "Evaluation of Feature Selection and Machine Learning Algorithms for Energy Consumption Forecasting in Commercial Buildings". Submitted in the journal of Energy and Buildings 18/01/2024.

CHAPTER TWO: LITERATURE REVIEW

This chapter introduces previous and current works on low emission non-domestic buildings with emphasis on building management systems.

Renewable energy generation and building energy storage systems are explored with the integration of machine learning algorithms and artificial intelligence applications for energy characteristic forecasting. At the end of this chapter, a clear research gap has been identified to be addressed in the following chapters.

2.1 Introduction

Retrofitting of heating and building materials are analysed first to give context to the literature survey. Building management systems are analysed, machine learning algorithms are compared to building information modelling, the potential to incorporate the growing EV market into non-domestic buildings is contextualised, conventional and novel heating methods are compared, and renewable energy technologies are explained, all within the context of previous work and potential improvements for energy efficiency. It is finalised addressing the research gaps to be explored in this work.

The efficiency of a non-domestic building may be improved through the installation of new windows, doors, wall cavity and roof insulation, draft proofing openings, and through changing heating methods. Heat losses may be minimised through new windows and doors through double glazing or vacuum insulated windows and through thicker doors or materials with lower thermal conductance than typical wood such as polyvinyl chloride (PVC). Wall cavity and ceiling insulation may be improved through adding more insulation such as through reaction injection moulding (RIM) [33] which improves the thermal resistance of the walls and ceiling, keeping heat in during the winter and out during the summer. Draft proofing openings such as doors can ensure less heat is lost through gaps in the installation. This can be done with any material with a high thermal resistance and can be a cheaper alternative than a full replacement, saving an average of 3.2% on heating and cooling demand [34].

The heating methods used can be improved by replacing convection radiators with underfloor heating such that the heat must pass through more area before it is lost through the ceiling and windows. The replacement of a gas boiler with a heat pump, a pellet boiler, or electric boiler costs £2,400,000 £583,000 and £933,000 per MW. This translates to an initial investment for the Business School of £115,000, £27,950, £44,730 respectively, and an operating cost of £3,260, £1,965, and £383 per year. [35]. For an average energy price of 13.5p/kWh, these methods could save the Business School £21,968, £23,263, and £24,845 per year respectively if the only source of heating was a gas boiler. With an average lifetime of 25 years too, these methods can be a good investment, but it is dependent on how the building functions and on the shape and size of the rooms. The retrofitting of an office building with 1.2GW annual energy consumption reduces energy consumption by 39% with a return on investment (ROI) of over 5 years [36].

An energy simulation for 2- and 3-bedroom domestic houses with an average floor area of 195m^2 costs £27,614 to improve the thermal efficiency of a building with an insulation rating of 7-stars. In this previous research, it is rated from 5-stars to over 8-stars, and a higher star rating shows greater thermal insulation [37]. The physical characteristics of this simulation equate to a retrofitting cost of £1.7 million if the costs increase linearly for the Business Schools' floor area of 12.6km^2. This could save the Business School £180,987 per year, following the relationship between energy consumption and floor area, showing a ROI of 9.4 years.

The retrofitting of a building through improving the thermal resistivity of the materials can ensure there is limited heat gains and losses, and therefore the heating and cooling systems may require less energy for the same outputs. The absolute cost of retrofitting building materials and heating methods for the Business School cannot be defined, although it can be concluded that the retrofitting of heating systems can reduce costs of fuel and maintenance. Previous retrofitting methodologies can improve energy efficiency of the building, but they require initial investment, often much larger as the building size increases.

2.2 Building Management Systems

A building management system can optimise the energy management of the building through both software and hardware. Software's within the method include data storage, processing, and servers for monitoring and controlling the buildings' systems. The buildings' systems are often controlled with dependencies on collected data such as how the heating operation can be dependent on the outdoor air temperature. Hardware's within the method include automation controllers, smart meters, sensors, and manual room controllers. Automation controllers are used for management of the buildings' systems through data collected by smart meters and sensors. A level of occupation input can be considered through manual room controllers.

Main features in residential buildings include appliances, water and space heating [38]. A case study of an installed BMS to a domestic building is able to save between 34-57% of cost by implementation of HVAC and lighting models that optimise energy consumption [39]. Heat gains from surfaces, lights, building appliances, occupants, and insulation must be calculated. The energy management of residential buildings can be used in conjunction with PV and ESS to allow accurate and fair payments for selling generated energy to the national grid. The forecasting of energy parameters with a rolling average allows the battery to be charged/discharged, and for all energy to be managed optimally. [40]. This is on a communal scale and is for residential purposes, but it provides optimisation.

Influence factors of non-domestic buildings include cooling, thermal-energy, temperature, behaviour, comfort, climate, heat transfer, indoor air quality, heating, and ventilation, with other influencing factors included [41]. As there are various factors affecting the energy performance of non-domestic buildings, a BMS must be able to make real time decisions on what components to use (heating, cooling etc.). The heating is often controlled through measuring the current outdoor temperature to decide how much energy the internal heating needs and therefore how hot the inside of the building must be. Artificial variable ventilation is critical to maintain good air quality [42] which maintains health of occupants [43]. As the occupancy of a building may change at any moment, and as no ventilation system can have an instant effect on the zone(s), without any occupancy or temperature forecasting, artificial ventilation cannot be fully optimised. BMS's can involve building energy storage systems (BESS) such as a battery [44], TESS [45], flywheel energy storage system (FESS) [46], and hydrogen energy storage (HES) [47]. These storage systems can be controlled through the BMS to determine when they need to be charged and discharged. Currently, when the energy generation of the building is higher than the demand, with an installed BESS, the energy can be stored to use later when the demand is higher than generation. This surplus of energy can then be used or sold at peak-times to reduce energy costs. This is only valid when the building has more generation than consumption, which is very rare in the cases of non-domestic and public buildings. There are many commercially available BMS's with the capability to be installed on non-domestic and domestic buildings alike. They are all able to determine how to best control the buildings' energy features (HVAC etc.) but the application of MLA forecasting can optimise the control of these features [19, 21, 25-27].

Dwelling emission rate (DER) of a large residential building is measured with a BMS, and provides demand response to an aggregator, with overall demand response potential totalling 7.4MWh/y. Collected input data has 6 consumers all inside the apartments [48]. An energy management system (EMS) is proposed, considering outside environment such as orientation, automatic shading, and double façade. This allows more inputs for the BMS, requiring more computational power but by calculating variables that effect the energy consumption, automatic shading and other parameters can be controlled, producing a lower electricity cost by up to 97% when the EMS is used with inside and outside design tools [49]. The problem with more inputs towards the BMS and any AI that may be involved is not just computational power, but the importance of the selected features and how they affect the forecasts and decision-making progress. In previous work, only two inputs are needed for an accurate forecast of CO_2 density as the correlation between the inputs and output is high [42]. This can be an important factor as CO_2 density scales with occupation, and therefore, already installed CO_2 sensors may be used to forecast occupancy, but this is not covered in previous work.

A climate-independent EMS based on fuzzy logic is proposed to use on prosumers, integrating solar, wind, battery energy systems (BES), EV loads, and tariff rates into the system to reduce total energy bill [50]. This eliminates the need for the installation of sensors and thus the collection of indoor data while still being able to reduce the energy cost up to 429.9%. This method also heavily relies on the accurate forecasting of the surrounding climate for the input into the fuzzy logic algorithm. Multiple energy sources are crucial for a BMS [51, 52] where operation costs are reduced by up to 26% and an active distribution network (ADN) is researched. This is achieved through using dimmable lighting, HVAC, EV's, BESS, and PV generation. Reproducibility is a critical issue that must be considered [53] where data is becoming more accessible, and must be interoperable [54]. This mixture of rule-based control and reinforcement learning can save up to 80% on energy costs [55]. A HVAC system may be optimised through reinforced learning methods to reduce energy consumption by 13%. This is achieved through measuring the energy consumption against the indoor air temperature, ensuring it stays between 22^{o}C and 25^{o}C. The lower the energy consumption, and the closer the air temperature is to 23.5^{o}C, the higher the reward is for the system [56]. These optimisation methodologies for BMS can save energy and costs by reducing the amount of wasted energy.

The real time management of energy systems is achieved in the reviewed BMS's with the ability of reducing wasted energy. Energy trading schemes are applied to allow any excess energy to be stored or sold. If there is no energy parameter forecasting, this energy cannot always be sold at the correct time to have maximum financial and CO_2 reduction benefits. Also, any stored energy then does not have to be sold and can be used later in the day, but it can only be guaranteed that this is necessary if the future energy demand is known. Although previous BMS's are capable of increasing energy efficiency, they still cannot optimise it due to the real time actuation instead of forecasting. They cannot know how much energy is needed to be purchased, sold, or stored, depending on renewable generation or energy demand. Instead, they manage the systems with dependencies on the building's current needs, ending with the building possibly purchasing the energy at a higher price or selling at a lower price.

Each method has applied case studies and recent research, proving they work under different circumstances.

2.3 Machine Learning Algorithms and Building Information Modelling

Building information modelling (BIM) software is used to model how the building will function through simulating air flow, HVAC, and power requirements [57]. BIM requires building data such as construction materials and orientation, all electricity users, installed HVAC system, and any other planned characteristics can be added into the software. A large difference between BIM and MLA's is that BIM's need much more data and time to develop, but they can also provide much more data than the MLA's. MLA can be used to accurately forecast the energy characteristics of a building without the need for generating a model through simulation software. MLA's mostly consist of supervised data, where historical data can be used to train the algorithm, and a specified output, such as the energy demand can be forecasted. BIM accuracy when forecasting energy characteristics can be more difficult than MLA due to BIM modelling all areas of the building, whereas an MLA can be trained through the energy data and less inputs.

BIM aggregated forecasting has 13.9% and 206.7% average error over 17 software's and 7 software's respectively [57, 58]. Single buildings' have 251.5% average error over 18 software's, giving an average error of 132.55% between 35 forecasts. BIM results include air flow, precise energy demand, heating parameters, and various other parameters. The error ranges from 0% to 665% between the previous case study and the BIM forecast. The BIM can produce necessary results for analysing buildings' systems but as is shown in previous research, the energy demand forecasting can often be inaccurate.

The forecasting of energy characteristic of domestic and non-domestic buildings can be achieved through MLA's. Two branches of machine learning exist: supervised and unsupervised. Unsupervised is where there is no previously collected data to train the algorithm with. Unsupervised algorithms are previously used to measure cultural homogeneity [59], data annotation in anatomic pathology [60], and various other previous research. The problem with unsupervised methods is that it can't accurately produce an energy demand forecast. Instead, it is capable of clustering or associating any data it is given. To forecast the energy demand, supervised learning techniques must be employed. A supervised MLA is an algorithm capable of forming mathematical bonds from inputs to outputs of a given dataset. When new input data is added, the bonds remain, and the outputs can be predicted [61]. Applications of ML are used in drug discovery and development [62], removal of contaminants on chemistry [63], and in transportation data analytics too [64], showing an application for almost every prediction and classification requirement. An abundance of previous applications of MLA's towards energy characteristic forecast can be seen in previous research. They can be optimised through Gradient Descent (GD), Bayesian Optimisation (BO), Particle Swarm Optimisation (PSO), and various others.

When forecast a buildings' energy demand, MLA's have an average error of 6.33% over 5 forecasts [65-69]. These forecasts range from 30-minutes to daily forecasts for single buildings to clusters. The various machine learning algorithms able to be implemented is due to each having advantages and disadvantages when forecasting certain characteristics, and when trained with certain characteristics and amount of data. The inputs for these algorithms include building and climate data such as outdoor air temperature, rainfall, humidity, cloud coverage, energy demand(s), indoor CO_2 density, and time of day. The MLA's require less data than the BIM's, but they can only produce information and forecasts that have a relationship with the training data.

Higher errors within energy consumption forecast result in a less informed and un-optimised BMS, and therefore more wasted energy due to inaccurate energy management. This may result in the heating system being pre-activated too early or too late, either wasting energy or reducing occupants comfort. It could result in generated on-site energy being sold to the grid because the energy consumption forecast is lower than the actual energy consumption, and therefore energy must be purchased back for a higher price than it was sold for, resulting in a loss for the building. If the energy consumption can be accurately forecasted, the BMS can be optimised, and energy waste can be reduced.

When forecasting a buildings' energy demand, Neural Network's (NN's) provide the highest performance [70], with 7 types of data processing, 30 types of feature selection, and 128 types of MLA's used for prediction of a buildings energy demand [71]. These include a few main types of algorithms, but each algorithm can be fine-tuned to the circumstance, creating a personalised algorithm each time. Various activation functions allow different amounts and types of data to be used, each using various computational power allowing for different accuracies [72]. A NN with GD is used for predicting cardiovascular disease with an error decrease of 3% and 6% compared to RF and NN without GD respectively [73]. A NN and BO is used to forecast the energy consumption of residential buildings with an error decrease of 25% and 67% for a SVM and a NN without BO respectively [74]. An energy saving of 8% can be found through employing PSO and a NN to optimise the use of a HVAC system by eliminating excess energy use [75].

Backpropagation involves working backwards through the created model to reduce the error of each input through altering the given weights. There are various ways of doing this with the Levenberg-Marquardt (LM) showing significant benefits over other types [76, 77]. This is a mixture of two previous methods of minimising the cost function, the Gauss Newton method, and the Steepest Descent method. The Steepest Descent can be explained through Equation 2.1.

$$\theta_{k+1} = \theta_k - \alpha \nabla f(\theta_k) \qquad \text{Eq. 2.1}$$

The value of 'θ_k' are the parameters at the current value of the cost function at iteration k, the 'θ_{k+1}' is the updated parameters at the next value of the cost function, 'α' is the learning rate, or the step size, and '$\nabla f(\theta_k)$' is the gradient vector of the function 'f' with respect to the parameters at the current iteration. A negative of the steepest descent is that it may have a small step size, and it identifies the local minima and not global.

This can be combined with the Gauss Newton method in Equation 2.2.

$$E(\theta) = \sum i \, (y_i - f(x_i; \theta))^2 \qquad \text{Eq. 2.2}$$

Where '$E(\theta)$' is the objective function which is defined as the sum of squared residuals, or the variance in error. 'x_i' and 'y_i' are the input and output variables, '$f(x_i;\theta)$' is the function between the value of 'x_i' and the internal parameters of the NN such as the weights. Due to the nature of the algorithm always seeking to move the cost function towards the negative gradient, the local minima may be found instead of the global minima.

The Levenberg-Marquardt method can be used to reach the global minima and faster than previous methods through using a damping factor to change the method between the Gauss Newton and the Steepest Descent. It often starts with the Gauss Newton approach for larger step sizes and as it approaches convergence, it switches to the Steepest Descent with a smaller step size to reach final convergence. The Levenberg-Marquardt can be explained through Eq. 2.3.

$$(H+\lambda I)\Delta\theta = J^T r \qquad \text{Eq. 2.3}$$

'H' is the Hessian matrix which is the sum of the Gauss Newton approximation $(J^T J)$ and 'λI' is the damping factor used to determine the method in which the algorithm uses (Gauss Newton or Steepest Descent). '$\Delta\theta$' is the parameter update vector such as the direction and amount of weight change, 'J' is the Jacobian matrix which contains the partial derivatives of the function with respect to each input, and 'r' is the vector of the residuals, which is the error of the

2.4.1 Decision Tree

A decision tree is a method of recursively splitting the data until it cannot be split to a better degree. The Gini method of node purity is used to decide whether the node is pure or not, meaning the data cannot be split any better. It is measured by the sum of all the probabilities of each class from a node subtracted from 1. This is shown in Equation 2.4. [78].

$$Gini(D) = 1 - \sum_{i=1}^{k} p_i^2 \qquad \text{Eq. 2.4.}$$

Where 'D' is the dataset that contains samples from 'k' classes. The probability of samples belonging to class 'i' at a given node is 'p_i'. Maximum impurity is given when the node has uniform distribution and minimum is given when all records belong to a single class. The tree splits the data so when new predictor features are added, it can split them the same way to give the target feature. This is a quick but often not very accurate algorithm due to the simplicity of it.

2.4.2 Random Forest

The Random Forest algorithm, also known as a bagged ensemble, is made from the aggregated results of decision trees. It is a more complex and slower algorithm than using single decision trees, but it often provides a much higher accuracy when forecasting. This is because it forms multiple decision trees and aggregates the results. The number of trees created can be selected so a compromise can be found between required computational power and accuracy. An example is shown in Figure 2.1.

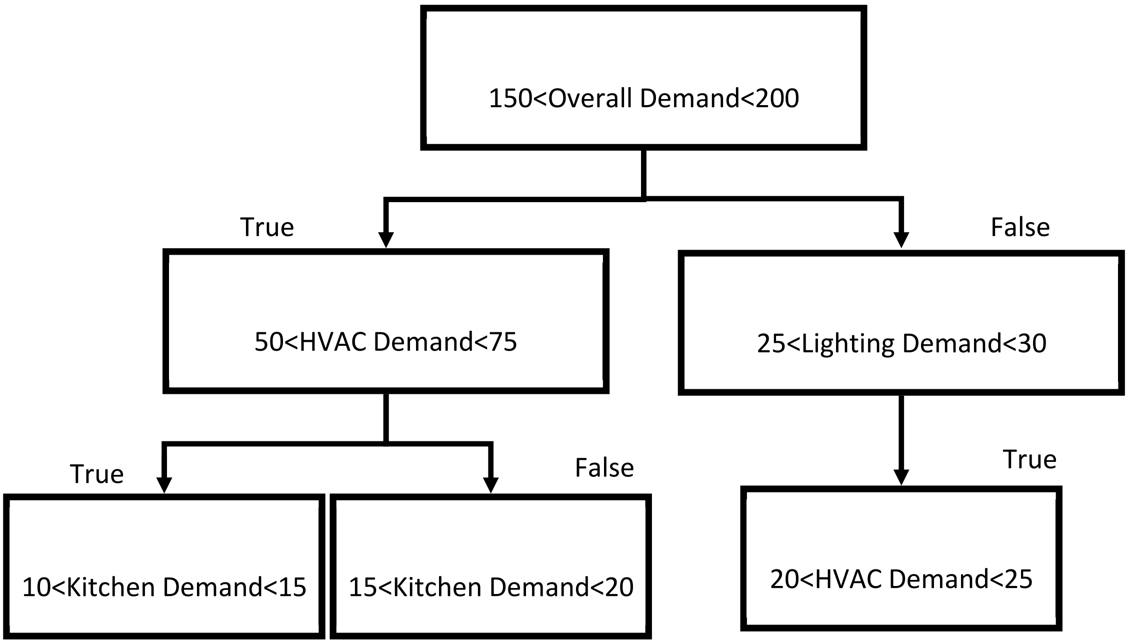

Figure 2.1. An example of how a random forest decision tree would look.

The data has been split here so that when the kitchen, HVAC, and lighting demand are in a given range, the energy demand (the target) is known. When new input data is given, the trees remain the same and the target data can be calculated. The final node on the right occurs when there is no better way of splitting the data. This process is repeated to split the data better, and the result from each tree is aggregated.

2.4.3 Neural Network

Neural networks are formed by four major parts: inputs, weights, bias, and summation functions. Weights are applied to the inputs to determine the importance of them towards accuracy of the output. A bias is used for shifting the summation or activation function to the left or right to match the output, and the activation function binds the weights and inputs together. It can consist of multiple layers which is necessary when there are more inputs. As a rule, there must be 3:2 input to layer ratio. The developed model uses a Levenberg-Marquardt method of error minimisation because it is able to reach minimum error quicker and more efficiently than other methods. The NN method works well with any number of inputs and sample data points, making it a robust model but prone to overfitting so it doesn't work well with poor quality data. This is where the algorithm learns the data too well and isn't able to work with new data but can be evaded through using less, better quality data from the dataset. A generic neural network is shown below in Figure 2.2.

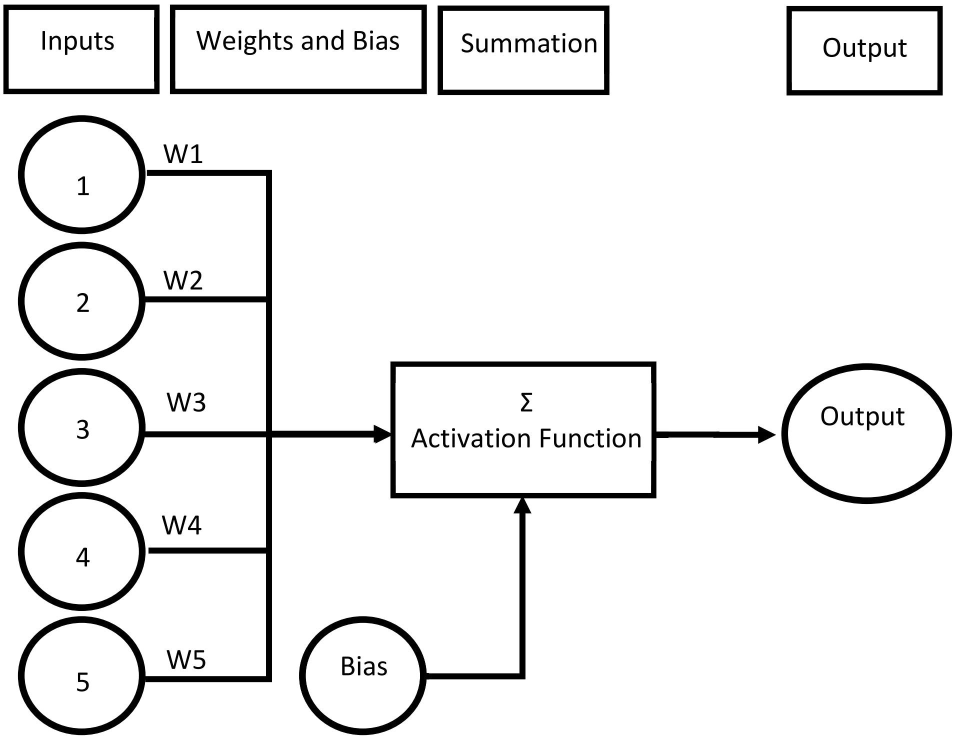

Figure 2.2. A single layer neural network. The inputs here could include HVAC, kitchen, CO_2, lighting and overall demand.

An input cannot also be an output in the same NN so wouldn't be included in the inputs if it is the target feature.

2.4.4 Linear Regression

Linear regression is one of the simplest methods of forecasting as a relationship between the inputs and the output is developed. This is calculated through Equation 2.5.

$$y = B_o + B_1X + \varepsilon \quad \text{Eq. 2.5.}$$

Where 'y' is the predicted output value when an input value is specified, 'B_o' is the predicted value of the output when the input is 0, 'B_1' is the relationship between the input and the output, 'X' is the input variable, and 'ε' is the error between the estimated value of the output and the actual value [79]. Once the slope is calculated with the training data the function remains the same with new data and is able to forecast the target data. It works well with data that is highly correlated. As this is such a simple method of forecasting, it is used for comparison towards other methods and whether they are worth the extra computational power.

2.4.5 Support Vector Machine

Support Vector Machines work by separating predictor and target variables through a hyperplane. The kernel functions used to separate the data are linear, polynomial, radial basis function, and sigmoid. The separation of two classes is shown in Figure 2.3.

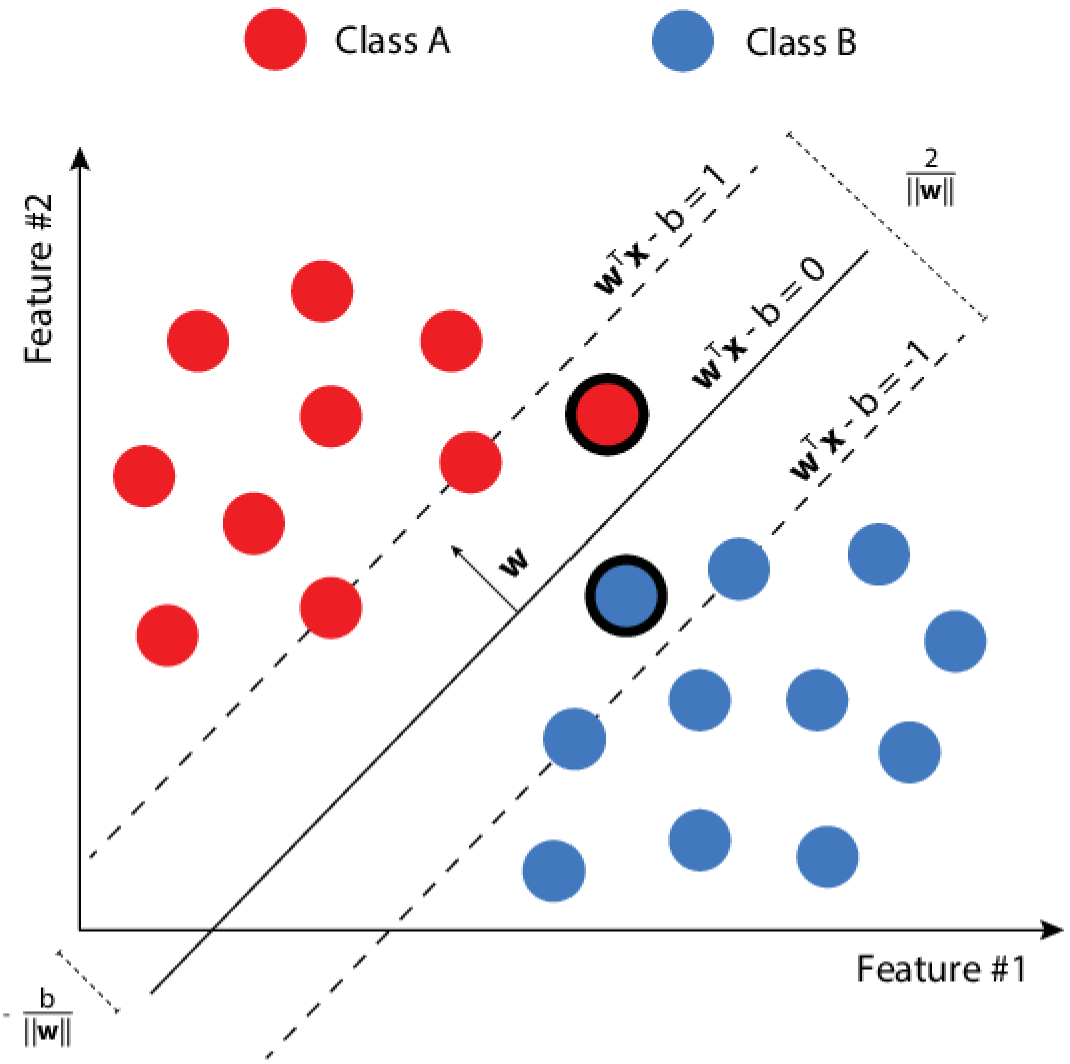

Figure 2.3. The linear separation of two classes in a support vector machine [80].

The margin that is ‘W’ can be determined to stop under or overfitting. A narrow margin results in overfitting and a wide margin result in underfitting. The kernel function has a regularisation function to optimise the size of the margin. The kernel function used to fit the hyperplane is used for regression as when a new input is added, it is fed through the function to give output data.

2.4.6 Feature Importance and Selection

The target features are the kitchen, heating, ventilation, and air conditioning (HVAC), lighting, and overall demand. The training features include these, but with additional features which are rainfall, outdoor temperature and air pressure, and the time of day/day of week. The algorithm chosen to determine feature importance is maximum relevance minimum redundance (MRMR). The various feature importance algorithms all gave similar results, but when MRMR was used, it provided more accurate forecasts when used with the algorithms. MRMR is calculated through Equations 2.6, 2.7, and 2.8.

The maximum relevance equation is shown below:

$$Vs = \frac{1}{|S|} \sum_{x \in S} I(x, y) \qquad \text{Eq. 2.6. [81]}$$

The importance of the feature with respect to the target is calculated. Where 'S' is the set of features, 'x' is the predictor, 'y' is the target, and 'I' is information gain. The information gain of the given feature to the target is summed for each iteration to give maximum relevance of the feature to the target.

The minimum redundance equation is shown below:

$$Ws = \frac{1}{|S|^2} \sum_{x,z \in S} I(x, z) \qquad \text{Eq. 2.7. [81]}$$

Where 'Z' symbolises another feature and not the target. It is calculated the same way as maximum relevance, but instead of with respect to the target, it is with respect to a different feature, giving minimum redundance of a feature. MRMR provides information on how important a feature is towards the forecasting of a target, while comparing it with other features, allowing the removal of features that are highly correlated. MRMR is effective and requires low computational power.

$$I(X, Z) = \sum_{i,j} P\left(X = x_j, Z = z_j\right) log \frac{P(X=x_j, Z=z_j)}{P(X=x_i)P(Z=z_i)} \qquad \text{Eq. 2.8. [81]}$$

Eq. 4.6 shows the mutual information between two variables, where the uncertainty of one variable can be reduced by knowing the other variable. 'I' is information gain, '(X, Z)' are variables and 'P' is the probability of that event occurring. It can be described as each variable's probability of occurring simultaneously divided by the probability of them occurring independently. The iterations are summed and it is multiplied by log to give an answer between 0 and 1, where the variables are independent at 0 and are completely dependent at 1 .[81]

An application of machine learning [82] provides a variety of results for predicting energy consumption of a building between 2.42% and 68.31% error depending on the ML method in use. MLA's can forecast a buildings' energy demand [65-67, 83-88]. These buildings are in various climates from Spain, Australia, China and more. Case study buildings include universities, commercial buildings, with domestic applications too. This shows that the energy characteristics of any building can be forecasted through MLA's. The accuracy though, is dependent on many variables.

Future environment trends are predicted using generalised corr-entropy assisted long short-term memory (GC-LSTM) to improve a BMS [89]. This domestic application is achieved through the forecasting of outdoor temperature, electricity price, and PV generation. No previous non-domestic applications of temperature forecasting and application to a BMS are available. Occupancy forecasting involves 78 ML methods, with 63% of them being used for heating, ventilation and air conditioning (HVAC) system optimisation with accurate data being of upmost importance [90]. This can be very important due to the high causation towards the energy demand of the building, providing an important input variable for training. Data collection must be of high accuracy, with a strong correlation between occupancy, wi-fi, and electricity consumption [91], and a higher spatial resolution of occupancy possibly results in poorer predictions [92].

Table 2.1. The summary some of MLA methods, accuracy, and applications used.

Citation	Main MLA method	Application	Accuracy
[65]	NN, CNN	University building	13.26, 9.38 MAPE
[66]	NN	University campus	4.31 MAPE
[67]	NN	University campus	3.46 MAPE
[83]	LSTM NN	University campus	0.36 MAE
[84]	LSTM NN	Sports centre	2.67 MAPE
[85]	NN	Cooling load of a shopping mall	0.8 MAPE
[86]	LSTM NN	HVAC system of a university building	5.31 RMSE
[87]	Gaussian process regression, DT, NN, and LR	Cooling load	0.4, 1.7, 2.5, and 13 MAPE respectively

[88]	NN	Business centre	2.14 MAPE
[93]	RNN	HVAC system of a simulated building	5.5 MAPE

From previous research analysed in this thesis, the main applications include a type of NN. Citations [65], [83], [84], and [86] use a LSTM, [66] uses an ELM, and [87] uses a mixture of DT, NN, LR, and gaussian process regression. Although Gaussian process regression has a higher accuracy, it is only forecasting the cooling load and therefore there are fewer affecting parameters than if it were to forecast the buildings' whole energy consumption. This is due to the cooling load affecting the entire energy consumption, and therefore, any affecting factors of the cooling load are added into the affecting factors of the entire energy consumption. Citation [65] uses a CNN which outperforms the NN with 38 inputs, showing that the standard NN could be overfitting, but this is not analysed within the previous research.

The ELM is forecasting a university campus, and not a single building, and does not compare this model with other MLA methods. It does state that the method may be better at forecasting larger-scale energy consumption such as from the power grid. The RNN used in [93] is applied to a HVAC system and not an entire building, and there is a similar theme when using RNN such as the application [94-96] into a power grid. There is not a comparison of a NN, RF, SVM, and LR in any previous studies for the energy consumption forecasting of a non-domestic building, apart from the work in chapter six of this thesis. In previous research, there can be a difficult comparison of MLA methods due to the variables involved such as quality and quantity of training data, volatility of the target data, and computational power available. The NN is most used to forecast the energy consumption of non-domestic buildings and for larger-scales, and although most previous research do not specify the reasoning for this,

There are 27 NN, 7 LR, 19 SVR, 8 RF, and 8 genetic algorithms reviewed in previous works [97] for the forecasting of a buildings' energy consumption. This previous research states that the NN, SVR, and RF is most used because: "This is mainly due to the difference in capabilities of the observed approaches in capturing useful information in time series data and for increasing the prediction accuracy." which is like the data and work in this thesis.

This mixture of rule-based control and reinforcement learning can save up to 80% on energy costs [55]. A HVAC system may be optimised through reinforced learning methods to reduce energy consumption by 13%. This is achieved through measuring the energy consumption against the indoor air temperature, ensuring it stays between 22°C and 25°C. The lower the energy consumption, and the closer the air temperature is to 23.5°C, the higher the reward is for the system [56]. These optimisation methodologies for BMS can save energy and costs by reducing the amount of wasted energy. The machine learning methods can be more accurate and less expensive to develop in the context of data collection and time. They give less data than building information modelling, but for the purpose of energy demand forecasting, they can be more practical.

2.4 Electric Vehicle Applications

Electric vehicles (EV) are becoming more popular with the aid of government incentives [98] and through domestic bi-directional charging to increase EV market share [99]. Global EV sales have increased by 444% from 2012 – 2021 [100] with an expected increase of 20.5 million new sales from 2022 – 2027 [101]. This will increase more strain on the national grid as they consume electricity instead of petrol or diesel which must be supplied by the grid. Better charging and discharging management is done through a vehicle-to-grid (V2G) and vehicle-to-building (V2B) method that charges the EV at night. Buildings' with higher demand require more EV's to maximum the method. This can be optimised with renewable generation for cost efficiency [102], grid flexibility [103], and number of connected EV's [104] with high dependency on electricity price variability and optimal charging and discharging times [105]. Battery degradation of the EV must be considered with these methods [106]. As EV's are becoming increasingly equipped with larger batteries and can be charged quicker, the method's cost and energy saving potential increases. They are not previously used with an optimised schedule to reduce the peak-time load of non-domestic buildings with consideration of battery degradation and business-as-usual for the EV owner. This could improve grid flexibility while promoting increase of research in the EV sector due to more applications and benefits.

2.5 Conventional and Novel Heating Methods

Conventional heat sources include furnaces, boilers, heat pumps, active solar heating, and electric heating. Furnaces use natural gas or electricity, where air can be heated and circulated around the building, with an efficiency of 64% [107]. Boilers heat hot water that can be circulated around the building into convection radiators with an efficiency of up to 95%. Fuel sources include natural gas, oil, coal, and wood [108]. Heat pumps can be sourced from the ground or the air with a potential efficiency of 63.4% which can vary for ground or air sourced [109]. Active solar heating works through absorbing the heat from the sun to heat circulating water to heat the building or for showers. Although the efficiency can vary greatly, solar collectors can generate 90% and 95% of hot water and space heating respectively [110]. Conventional distribution systems include variable air volume (VAV), wall or underfloor radiators, and hot water and electric baseboards.

VAV generates heat in the boilers which is distributed through a series of ducts throughout the building. This allows the building to be zoned and gives control over the volume of air in the room to regulate the ventilation. Outdoor air can be used for cooling. Conventional radiators heat water in the boilers and distribute it around the building into the specified radiators. They can be wall mounted but work better when underfloor due to convection. They are fuelled from heated water from the boiler, usually powered by natural gas.

Baseboards can be fuelled by either hot water or electricity. They can be placed in any room to achieve zonal heating, and while replacing traditional skirting boards, they are able to generate heat for the room. Due to the placement being at the bottom of the space, the convection heating they produce can heat more space and surfaces than if it were placed at the top of a space. Hot water baseboards are fuelled from water from a boiler or from an active solar heating system. Electric baseboards have the same potential as gas powered baseboards but due to them being fuelled by electricity, they can be powered from renewable energy sources.

Electric heating can be powered purely renewables. The problem with electric heaters and all previous conventional methods is that although conventional methods of heating can have high efficiencies towards 100%, the way the generated energy is used results in energy losses. Convection heat is not efficient as it heats the air which rises and results in losses through the ceiling or roof so even if the production is efficient, the execution is not. To eliminate convection losses, novel methods of heating are introduced. Infrared radiation can be considered a novel method of heating. It is a natural source of radiation produced by the sun with various applications for health benefits and food processing [111-116]. It can also be used for space heating as infrared doesn't target the air when it heats, and instead, infrared waves pass through air and heats the materials in its path. Due to this, FIR can have efficiencies upwards of 92% with an optimal response time of 1 second [117-119]. Currently available FIR heaters come in the form of panels and are powered through electricity. This gives an advantage over gas powered heating as gas fuels always produce carbon emissions whereas electricity can be generated through renewable energy techniques. Zonal heating is becoming more popular, allowing the heat to be controlled through the building better. The smaller the zones, the more degree of control the BMS has, and the less energy is wasted on heating unoccupied zones.

The methods of heating described are VAV, wall and underfloor radiators, baseboards, electric heating, and infrared heating. Previous applications and efficiencies are used to determine the importance and relevance of each method, providing insights into which methods may be used when designing a net zero energy building. VAV heating systems can provide heating and cooling demand through air handling units (AHU). The systems work through Figure 2.4.

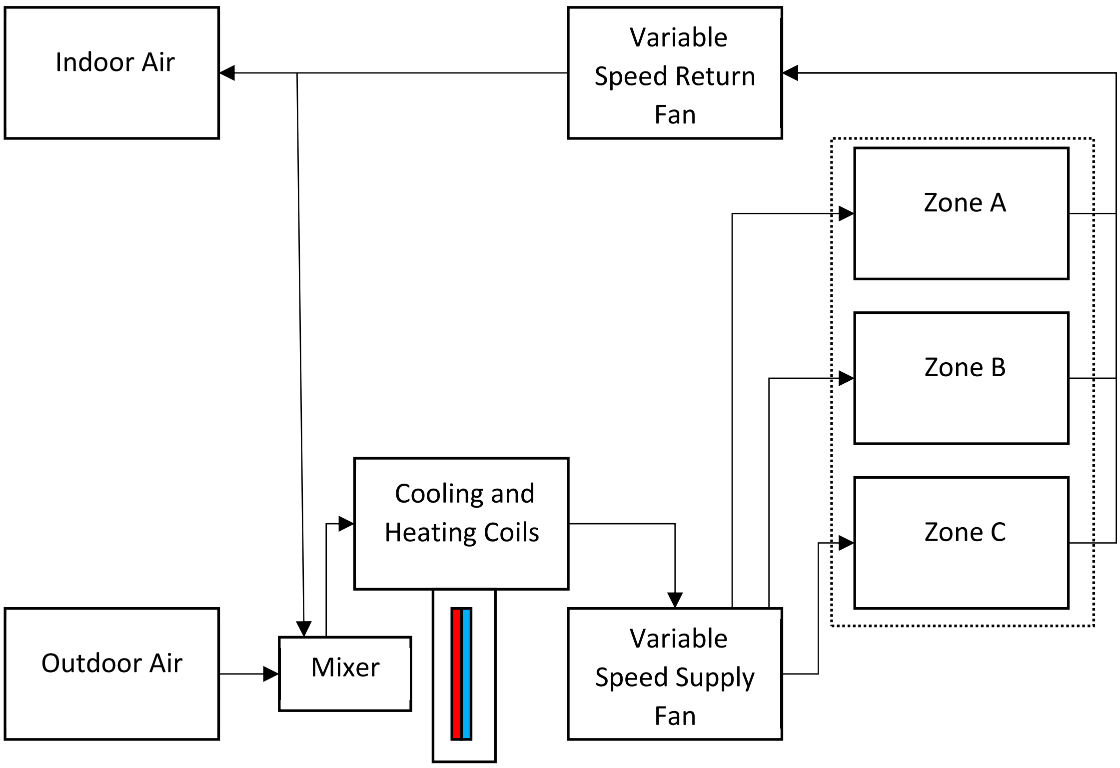

Figure 2.4. A typical variable air volume heating and cooling system for a public building.

Firstly, outdoor air is pulled into the building and is mixed with either the heated air or the cooled air in the mixer, depending on whether the system is intending to heat or cool the spaces. This is done due to ventilation recommendations in public spaces, requiring at least 10 litres/second/occupant [120]. Heated air must be removed from the spaces due to ventilation requirements so the energy from the heated air is mixed with cooler outdoor air to improve efficiency of the system. Cooling and heating coils are powered from electricity or from a boiler to manipulate the air to an optimum temperature for the spaces. The air is then passed into a variable speed supply fan, capable of maintaining a desired air pressure within the rooms through pumping the heated or cooled air into the rooms. Once the rooms are set to a desired temperature, the air within them can be maintained with less energy required, but the ventilation must still be maintained. The air is then passed through a variable speed return fan, capable of pulling the air out of a room and reducing the air pressure. The supply and return fans work together to maintain air pressure and ventilation rate. The return fan then pushes the air out of the spaces, through the mixer, and finally outside the building. This system works well due to the flexibility of the system as it can specify temperature, air pressure, and ventilation rate with ease while also conserving energy through the mixer.

Wall and underfloor radiators work through heating air or water from a boiler or ground source heat pump or an active solar heating system. The heated water is then distributed around the home from a pump into whichever room requires to be heated. The zoned system is explained in Figure 2.5.

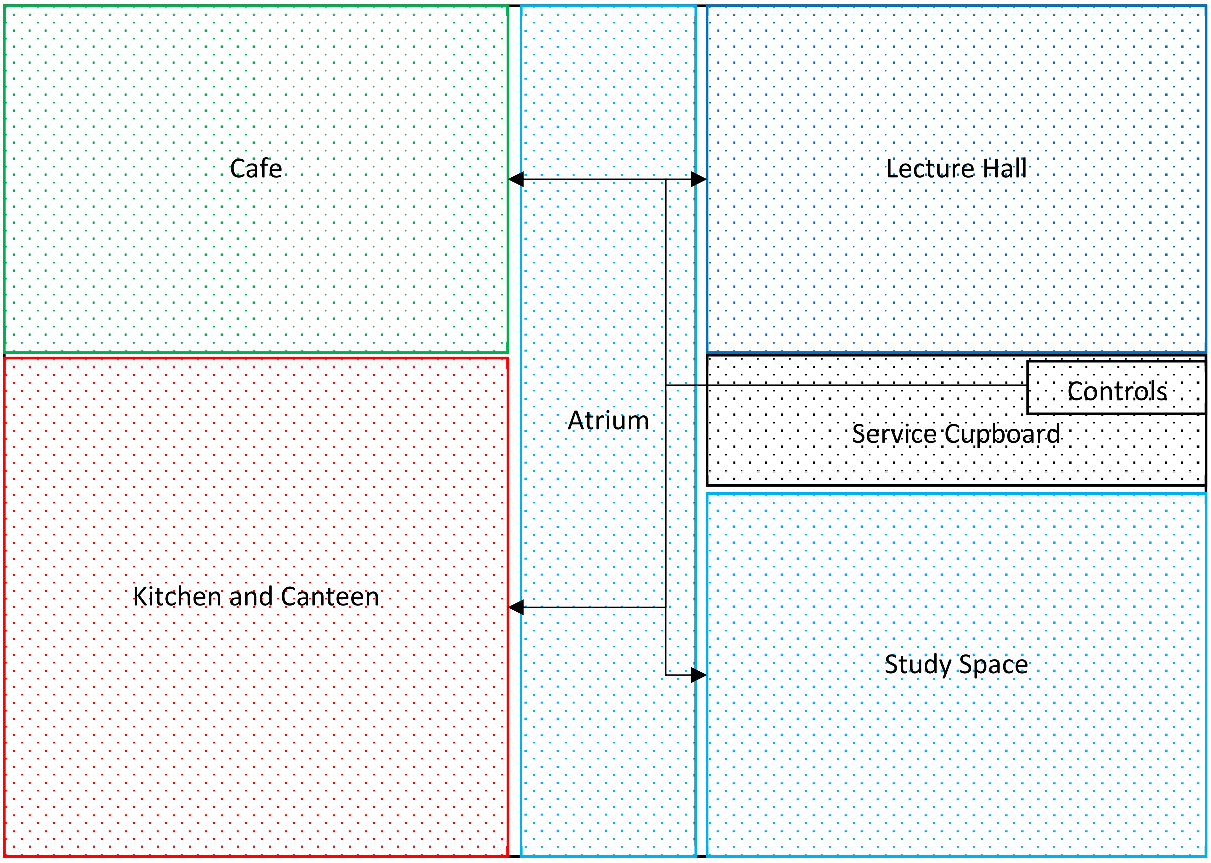

Figure 2.5. An underfloor water or air heating system distribution network.

Water or air can both be used to heat the spaces where water has a higher thermal resistance than air. This means that water is more difficult to heat but that it retains the heat better than air as it is distributed. The method that produces the least carbon emissions when providing heat to the system is a ground source heat pump. This allows hot or cool water to be stored underground and then pumped into the building when demand arises. The benefits of this system are that they can employ zonal heating due to multiple pipes coming from the controls and the heating source. The heated/cooled water can then be pumped into the room intended for heating/cooling. Although this system requires high upfront costs compared to other methods, due to the system being underfloor, it is the most efficient convection heating system. Wall mounted radiators work through the same system as underfloor heating systems except the convection heat is not able to pass through all objects in the room and instead often leaves through the ceiling or windows. This provides a system that is not as efficient as underfloor heating. Baseboards can be powered through electricity or hot water. Hot water can be pumped into the baseboards to heat them, or they can be supplied with electricity to heat metal fins within the equipment.

Table 2.2. A comparison of conventional and novel heating methods.

Name	Heating Method	Benefits
Variable-Air-Volume	Pushing conditioned air into an environment.	Can change the density of the air while heating and cooling with a highly efficient heat exchange plate.
Underfloor Radiators	Heats up the air through convection.	The heat passes through more space and materials and therefore can have greater heating effect.
Baseboards	Heats up the air through convection.	Has the same effect as underfloor radiators except it is simpler to install and can have greater losses due to it being closer to the building envelope.
Electric Heating	Uses electricity for convection heating.	This can be applied to any radiator and can therefore be used anywhere in a building.
Infrared Heating	Passes electricity through a material such as carbon fibre to generate infrared radiation.	Is more efficient than convection heating methods, can be applied anywhere in a building, and can be powered with renewably generated electricity instead of gas.

Each heating method has its own benefits, depending on the application. The most efficient method of heating for a large open space might not be the most efficient method for an enclosed space. Although infrared heating currently exists and are applied commercially, they are not previously applied with any MLA methods to improve their operation.

2.6 Renewable Energy Technologies

Renewable energy can be produced through solar, wind, kinetic, and from biomass on-site, allowing the building to become decentralised [121], as the source of energy has great effect on the buildings' CO_2 emissions [122]. The application of renewable energy generation to hotels in the Mediterranean show an energy demand reduction of 36-64% from the grid [123]. Ground source heat pumps (GSHP) are able to reduce CO_2 emissions by up to 5.9% [122]. This is dependent on the method that the renewables are applied to the building as the ground source heat pump (GSHP) also increased CO_2 emissions by 3.7%.

Solar photovoltaic energy generation is reviewed in 246 rooftop systems. These residential systems installed in the Netherlands have between 2-5 years of collected data from 2016-2020. Weather conditions effect the PV systems greatly, but without high correlation as the effect cloud coverage has on the systems vary greatly. PV generation is also able to be forecasted using weather conditions with a root mean square relative error (RMSRE) of between 6.43-12.2% [124]. These systems are for domestic use so the application towards commercial use would require an increase in scale, but if the correct data is collected, this method can scale. Larger scale PV systems that are installed on grid level are able to generate 273.75MWp which is able to reduce the national load by 200MW in a given month in Poland [125]. Various weather conditions make it difficult to calculate how much energy PV systems can generate. Commercial, rooftop PV systems in Vancouver are too expensive to be financially viable and require cost reductions of 50%. After this, the system is viable and can reduce the energy demand from the grid [126].

Kinetic floor tiles are capable of powering low consumption electrical devices, [127] producing 520mW per tile compression. There are 44 case studies including retail, education, transport hubs, sports stadiums, and smart city development where kinetic floor tiles are installed to generate energy from footfall [128]. The piezoelectric floor tiles are able to power low electric such as a wireless sensor. The tiles should be installed in a crowded place to ensure maximum generation [129]. This method has promising potential as the material of the tiles can be altered for improved energy generation and performance. The tiles can also produce important information on the volume of occupation for use in MLA's [130].

The rotational energy from manual rotating doors can be harvested to produce 40W per 180^o rotation, or 331W per minute of constant use [131]. A swing door can be used to generate energy through occupants. A damper can be used to control the speed of the door during closing through a generator. The energy generated through the action 'E_{in}' can be explained through Equation 2.9.

$$E_{in} = KE \times PE \times E_{go} \qquad \text{Eq. 2.9.}$$

Where 'KE', 'PE', and 'E_{go}' are kinetic energy of the door, potential energy stored in the torsional spring, and the energy absorbed by the generator, all measured in Joules (J), respectively. This method can be used for both the revolving door and the swing door.

This study is through a simulation, assuming optimum conditions. A case study develops a revolving door capable of generating 110W every two seconds, 0.61kWh per day. By increasing the mass of the three doors, the energy generated increases with the torque [132]. No rotating or swinging door energy harvesting has been applied to domestic or non-domestic buildings.

Wind energy can be produced in various ways such as turbine installation on a high ridge. A model is 13m long and produces between 4kW-12.5kW of energy depending on wind speed [133]. A conventional vertical wind turbine can be problematic as they produce too much noise and affect comfort conditions of the building [134]. The installation of a conventional wind turbine between two high buildings was able to generate more energy than usual due to the wind being focused between the buildings. Wind speed increases with heigh, meaning a ridge installed wind turbine will generate less energy the smaller the building is. No previous work has a case study where a wind turbine is installed on a ridge.

Biomass is a method that uses organic matter to produce energy which can be implemented into decentralised buildings [135]. The energy of combustion 'ΔE_{total}' (J) is explained in Equation 2.10.

$$\Delta E_{total} = C_s \times \Delta T \qquad \text{Eq. 2.10.}$$

Where 'C_s' is the heat capacity of the calorimeter and 'ΔT' is the temperature increase of the biomass material. To optimise the application of biorefinery, government policies must support further innovations into the method. There are 14 factors that affect the conversion from biomass to biofuel with 12 conversion methodologies [136]. Various fuels provide the system with various energy outputs as wetter fuels require more energy to dry, and some fuels don't have a high enough energy content [137].

Hydrogen technology shows high potential but can be costly, with green hydrogen providing the best potential for a low carbon footprint among simulations [138]. It is called green hydrogen when the electrolysis is achieved using renewable energy. Once the hydrogen is collected through electrolysis and stored, it can be passed into a proton exchange membrane (PEM) [139]. A hydrogen fuel cell is installed in a commercial building where it is able to reduce emissions by more than 50%, providing better results than the PV system [140].

The cost of carbon neutral grid connected residential communities in a hot climate show there are enough renewable sources for net zero buildings where initial cost has the biggest effect on overall effectiveness [141]. Each methods' energy generation can be forecasted to some degree of accuracy, resulting in viable options for the installation onto non-domestic and domestic buildings alike. The continued research into improvements for renewable generation make them almost a certainty for net zero energy (NZE) buildings.

An effective way for a building to reduce its carbon emissions is to match the energy consumption through RE generation. This can be done through a variety of ways. As sunlight is the most abundant source of energy, solar PV is the most common method of energy harvesting. Solar PV works through harvesting energy from the photons to excite electrons within semiconductor materials. The hourly power output 'P_{PV}' (W) generated from the PV array of a given area is shown in Equation 2.11.

$$P_{PV} = \eta_{PV} \times SI \times A_{PV}(1 - 0.005(t_o - 25)) \qquad \text{Eq. 2.11.}$$

Where 'η_{PV}', 'SI', and 'A_{PV}' are the efficiency of solar generation, solar irradiation (kWh/m^{-2}), and PV array area (m^2), respectively [142].

Solar thermal is a different method of harvesting energy from the sun. Instead of using the photons to charge a material, the heat from the sun can be focussed to heat a material such as salt or water. Solar thermal energy can either be used to reflect solar heat at a conductor to store for later use or for the heating of water or gas to pump round a building or to provide hot water. A solar thermal tower is common practise in countries with a high outdoor air temperature such as in Seville, Spain [143]. This is illustrated in Figure 2.6.

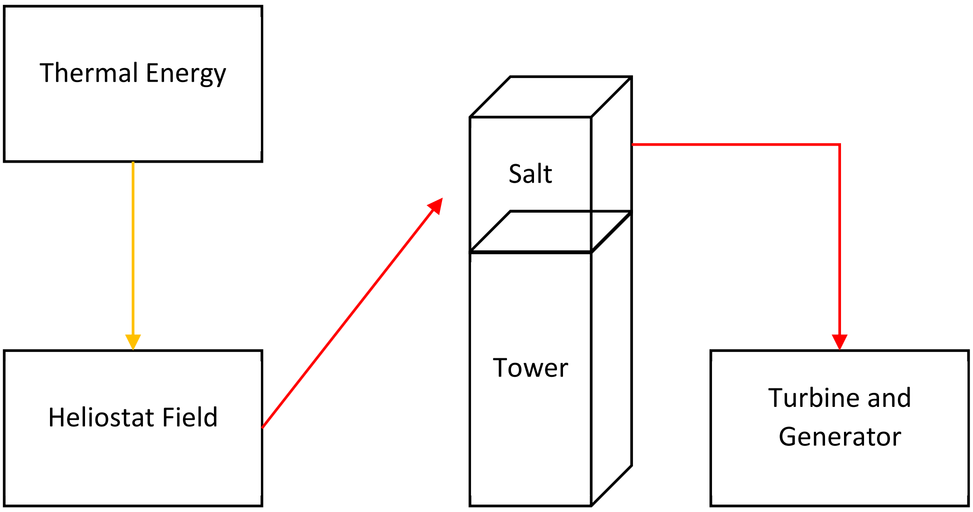

Figure 2.6. A solar thermal process through a conductive material on a tower. Heat from around the tower is directed to the conductive material where it can be used to heat water into steam to drive a turbine.

Incoming thermal energy from the sun is reflected from a heliostat field into the material at the top of a tower. This material is often salt due to it being an abundant resource capable of retaining the heat it has absorbed. The heat from the salt can be used at the time it is heated or later to heat water for a turbine and generator or to supply a building with hot water. A previous method of solar thermal collection has a 75km^2 heliostat field with 624 heliostats: 120m^2 each, and a 115m tall tower. The outlet temperature of the saturated steam ranges between 250^{o}C and 300^{o}C, has a pressure of 45 bar and can power a turbine with a nominal capacity of 11MW [144]. The efficiency of this system between the thermal energy hitting the heliostats to being converted into electrical energy is 15.4%. Solar thermal energy generation is previously forecasted for a 2MW system in Victoria, Australia. The algorithm had 4,464 input iterations with 10 inputs and 1 output, and has accuracies of up to 98.1% [145]. The input data is comprised of global horizontal irradiance, direct normal irradiance, ambient temperature, delta temperature, outlet temperature, inlet temperature, flow rate, time of day, day of week, and day of year. This system was used to supply a non-domestic building with energy, but it required 1.2km^2 of solar thermal reflectors.

The reasoning for using materials such as salt is due to the thermal capacity. This can be described as the quantity of heat necessary to produce a unit change of temperature in a unit mass of material [146]. Molten salts can have a thermal capacity below or close to 500 kWh/m^3 but can be combined with other materials to increase the thermal capacity [147]. Compared to another substance such as metal, with a thermal capacity of 220 kWh/m^3; molten salts can hold more heat, and therefore more energy to be used for turbine electricity generation [148]. As the figure shows, solar thermal requires large outdoor space and cannot be installed on rooftops, and therefore it cannot be used for the applications within this work. Solar PV is more practical in a cooler climate and in urban environments.

Geothermal energy can be gathered by collecting heated air or water from underground and can either be distributed around the building or used for hot water. This method vaguely relies on climate conditions but isn't affected as much as other renewable methods. Figure 2.7 shows an illustration on the method of collection geothermal energy.

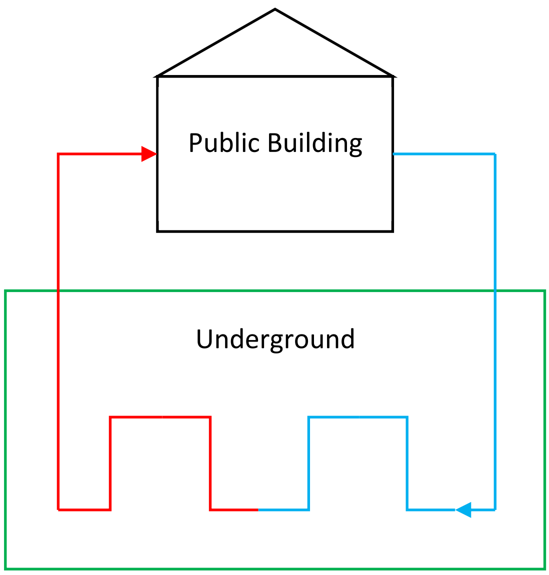

Figure 2.7. The method of geothermal heat exchange, either running cooler building air or water into a warmer underground environment, or vice versa, allowing it to heat or cool the building.

The depth and heat of the system increases linearly, as a deeper system provides a hotter water system for the building. This is due to the system having more ground above it, acting as insulation. Cool water is pumped out of the building and into the underground system where water has already been heating. This heated water is pumped out of the system and into the building where it can be used. Common practise is for the heated water to either be distributed around the building as heating, or to be used as hot water for in bathrooms and kitchens etc. Deeper systems provide hotter water but require more initial investment than smaller systems. This system requires there to be space for the geothermal system to be built, in which case, many public buildings do not have. Previous research shows that the thermal conductivity and type of ground affects the way the systems work. Dry sand and wet ground have a specific extraction rate of 10-15W/m^2 and 30-35W/m^2 respectively, and hard rock can be up to 70W/m^2 which can provide a yield of 100-120kWh/m^2 [149]. This is used for district heating due to the amount of energy that can be extracted from the sub-terrain, so it is practical for urban environment. Geothermal energy generation techniques are affected by the size of the system for depth and width, the global location, as hotter temperatures yield hotter extracted water or air, and the material of the ground, as they have different insulations.

MLA's are used to forecast exploration, seismicity, drilling, petrophysics, reservoir characterisation and engineering, and production [150]. The production of thermal power from geothermal systems can be forecasted with an average MAPE of 0.28% through a NN [151]. This system was trained with 4 inputs for 3 case studies with temperatures of 190^{o}C, 160^{o}C, and 140^{o}C, showing that MLA's can be utilised for accurately forecasting geothermal energy generation.

Wind energy can be harvested through 2 types of wind turbines. These are most commonly large-scale and part of a wind farm where the energy can be distributed through the national grid. The 2 types of wind turbine are horizontal-axis wind turbine (HAWT) and the vertical-axis wind turbine (VAWT). These are illustrated in Figures 2.8 and 2.9 respectively.

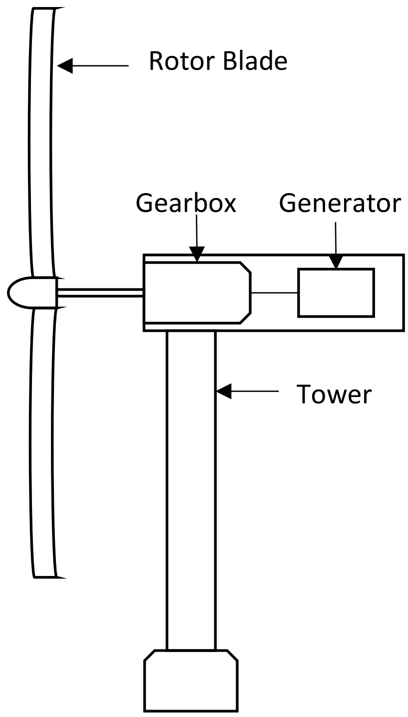

Figure 2.8. A horizontal-axis wind turbine.

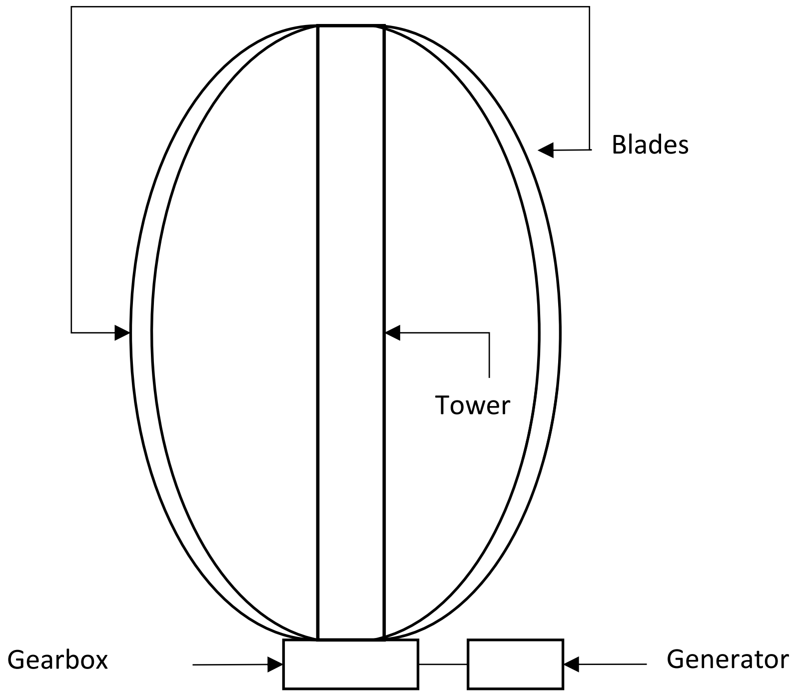

Figure 2.9. A vertical-axis wind turbine.

Both turbines are capable of generating output power from wind 'P' (W). This is explained in Equation 2.12.

$$P = 0.5 \times \rho \times A \times V^3 \times C_p \quad \text{Eq. 2.12.}$$

Where 'ρ', 'A', 'V', and 'C_p' are air density (kg/m^3), swept area of blades (m^2), the velocity of the air (m/s), and the power coefficient respectively [152]. In a previous study, a HAWT wind turbine generated 55% more energy than a VAWT. This is due to the HAWT turbine not being affected by backtracking; the reduction in energy due to the wind turbine having to push against the wind for a small period of time due to the turbine rotating [153]. Although HAWT can produce more energy, they can be difficult to install in an urban environment due to the amount of space they require to move. Larger turbine blades provide a larger surface area and thus more generated energy, but there is not always enough space for this. As VAWT turbines don't require as much vertical space and can be increased in height to provide a larger blade area, they can be the preferred model to use in an urban environment. They can also be repaired easier due to the gearbox and the generator being at the bottom of the turbine, allowing the maintenance to be conducted from the ground.

In previous research, wind data comprises of wind speed (m/s), dry bulb temperature (°C), rainfall (mm/h), snowfall (mm/h), snow mass (kg/m$\hat{A}^2$), surface radiation (W/ m$\hat{A}^2$), radiation at the top of the earths' atmosphere (W/ m$\hat{A}^2$), cloud cover (%), previous days' and weeks' wind speed (kW), air density (kg/ m$\hat{A}^2$), and total wind power production (kW). Solar PV data comprises of direct irradiance (kW/ m$\hat{A}^2$), diffuse irradiance (kW/ m$\hat{A}^2$), outdoor dry bulb temperature, rainfall, snow fall and mass, surface and top of atmosphere radiation, cloud cover, ambient temperature, and total solar power production (kW) [154].

Through both conventional methods of wind generation, there cannot be a unanimous decision on which turbine will provide the most benefits. A VAWT is more practical for an urban environment, but it may generate less energy and there may be no rooftop space if there is an installed solar PV system.

A novel method of generating wind energy is through a horizontal turbine installed on the highest ridge of a roof allowing them to be fitted in an urban environment. They work through channelling the wind up the roof and into the turbine as is show in Figure 2.10.

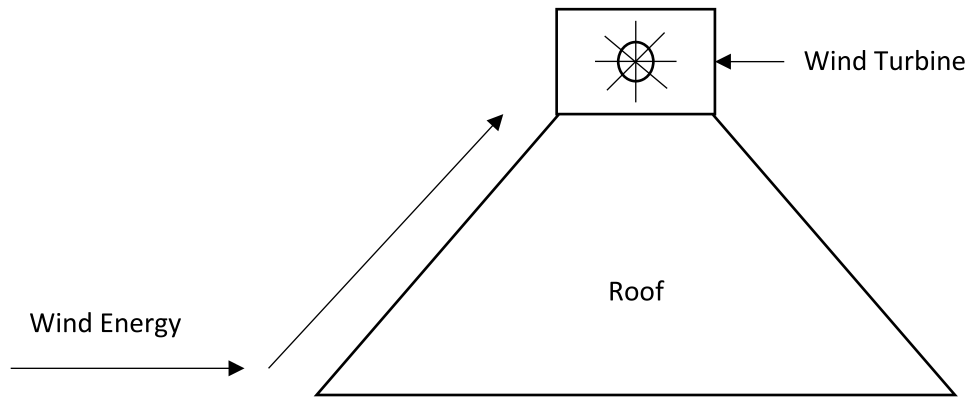

Figure 2.10. An appropriate wind energy generation system for an urban environment.

The system has the same parameters as a typical wind turbine, except it is able to be installed on a rooftop without the need for a tower like HAWT and VAWT wind turbines.

The energy generation of a wind turbine can be calculated through wind speed forecasting through a NN with an average error of 30.55%. The most accurate forecast contains 14 inputs with an error of 2.7% [155]. The inputs include humidity, temperature, wind speed, and direction, allowing the energy generation of the wind turbine to be calculated through Equation 6.2. The energy generation of a wind turbine can also be forecasted through ML methods in 8 wind farms. The algorithms are trained with 43 input and an average total of 11,382 datapoints for training and 11,383 for testing. The MLA's could forecast the wind energy generation with 29.55% more accuracy than when forecasted with a baseline method which is a reference curve [156]. The application of MLA's for forecasting the energy generation of wind turbines can be applied to any wind energy systems that may be installed in an urban or non-urban environment.

The RE generation techniques covered are very heavily weather dependent. Solar PV relies on cloud coverage and total amount of solar hitting the panels' surface. Solar thermal relies on the heat of the solar gains hitting the heliostats. Wind turbines generate energy linearly to how consistently and quickly the wind is travelling into the area of the blades. Geothermal energy is dependent on the climate due to the below ground temperature changing with the temperature of the above ground air and surfaces. Other methods of energy generation that do not depend on the climate or cannot be employed for an urban environment are kinetic, hydropower, and hydrogen.

The literature review shows the importance of renewable energy generation [122, 123, 125, 127, 131, 133, 135, 138], building management systems [39, 42, 49, 51, 52], building energy storage systems [44-47], the application of machine learning algorithms to forecast buildings' energy demands [70, 71, 82], and the importance of variables to optimise electric vehicle charging and discharging schedules [102-105]. From previous literature on the subjects, the following statements can be made:

1. The research and application of the above-mentioned energy storage, generation, and utilisation methods provide undeniable benefits towards the building. This includes through saving costs and reducing the buildings' carbon emissions. Further energy improvements though, require more investment and helpful government schemes such as a higher selling electricity price from the building to the grid or cheaper renewable energy installation etc.
2. Building management systems that use renewables in conjunction with electric vehicle bi-directional charging, especially green hydrogen, can reduce carbon emissions the most. The systems can save energy while working on a real-time schedule, but no previous works are able to produce net zero energy non-domestic buildings.
3. The DEC produced by the government do not provide enough information for the improvement of the building, requiring further work to determine the energy performance of the building if the energy efficiency was improved.
4. The MLA's can accurately forecast a buildings' energy demand more accurately and more easily than BIM software's and use less computational power, but they require initial data. They also cannot produce as much information as BIM's such as air flow and physical parameters.
5. Occupation density and behaviour can be difficult to predict due to different behaviours. Occupation has high correlation to the energy demand of buildings so by optimising comfort to the buildings' occupants, the BMS can automate without the need for the occupants to interfere. This allows the BMS to optimise other energy characteristics to reduce waste and carbon emissions.

2.7 Summary and Research Gap Identification

The UK Government regulations aim to have a fully decarbonised electricity supply by 2035 [28]. This requires both increased renewable energy generation and energy efficiency of buildings. Non-domestic buildings are among the highest energy consumers worldwide and in the UK, requiring improvement to meet government targets.

The application of MLA's for energy demand forecasting of various case studies prove that they can forecast the energy characteristics more accurately with less initial data and computational power than BIM software's. These techniques are previously applied to non-domestic building's BMS. Novel methods of MLA applications for energy consumption, management, and storage aren't exploited enough which can have large benefits for the reduction of carbon emissions.

The techniques used for forecasting the energy characteristics and for generating and consuming the energy within non-domestic buildings are reviewed. Various commercially available BMS's can reduce carbon emissions but are not able to apply MLA energy demand forecasting. It can be concluded that the BMS's require further improvement to eliminate carbon emissions from buildings. Building's energy demand forecasting is accomplished for the purpose of improving and fine tuning the MLA's. These forecasts range from 30-minutes to daily forecasts for single buildings and clusters [65-69, 157, 158]. This allows the building to optimise energy trading through purchasing at off peak for storage and selling or using at peak time, pre-heating and cooling only forecasted occupied zones, and lighting through LED's and LDR lighting.

In the aforementioned work, the application of machine learning forecasting to non-domestic buildings and installed BMS is under-explored. The aim of this research is to reduce non-domestic buildings' energy consumption through more efficient methods of energy management.

There are three major research gaps to be explored in this work. One research gap is within the field of EV's. They carry large energy capacity and are left plugged into the building for the majority of the workday, when their energy capacity can be used. This research target is a method that utilises the energy capacity of EV's by discharging the EV's at peak-time to save energy consumption from the building. The cars can be charged at off-peak times and the EV owners can be paid so that all parties find this solution profitable.

Another research gap is the application of MLA occupation density to infrared heating. As infrared heating's popularity is increasing, the forecasting of occupation can reduce wasted energy by only being in use while the room is occupied. The room can be split into zones and the heating can be occupation dependant, providing more control over the heat and reducing wasted heat by only using it when the room is occupied.

A third research gap is the exploration of MLA applications for local PV systems. Previously, there has not been a comprehensive analysis of benchmark models. This exploration would provide information on which models can be used, with respect to what type and amount of data there is to train the models.

CHAPTER THREE: PUBLIC BUILDINGS IN AN ENERGY CONTEXT

This chapter presents a general background on non-domestic buildings in the UK, the energy grades of non-domestic buildings', and how they are graded. Government recommended improvements and how the energy grades and improvements are calculated are also explained.

University buildings have a high carbon footprint so are actively seeking to reduce the carbon emissions. Manchester Metropolitan University is ranked the number two sustainability University in the UK and has had a top 3 finish for the past 11 years, providing validity for it to be used as the case study. This work is an endeavour to improve the CO_2 *print of the MMU Business School. The MMU Business School building's energy characteristics, operations and recommended improvements are described with the MMU Business School's building management system.*

3.1 Introduction

The UK contains over 1,755,000 non-domestic buildings [159]. Each building has its own function, physical parameters, occupants, and location, and some building's energy consumption is easier to reduce. Although lower energy consumption results in reduced carbon emissions, this does not always translate to a better energy grade by the UK Government. Instead, the energy performance of the building is also compared against other similar buildings to provide comparisons, so this is explored further in this chapter. UK building trends are analysed, showing the progress-to-date of how often non-domestic buildings are built, how their energy consumption changes through time, and in what industry this is occurring.

To determine how best to improve the energy performance of non-domestic buildings, the energy grades must be analysed. This includes exploring how building's data collected by the UK Government can be compared against average UK buildings for context, and how energy grades can be improved considering the function and other parameters of the building.

The main objectives of this chapter are to:

- Analyse how energy grades are obtained and how they can be used to reduce carbon emissions.
- Determine what an average UK public building looks like in an energy context.
- Explain how energy grades can improve and how these factors look when applied to the MMU Business School.
- Describe what types of public buildings exist and their functions.

3.2 Display Energy Certificates and Energy Grades

For non-domestic building's, among the highest energy consumers are offices, shops, and educational buildings, which are given a display energy certificate (DEC) by the UK government. This is a scale from A-G with 'A' being most efficient, and is evaluated through characteristics including location, size, age, and condition. This shows how much CO_2 the building produces. If the floor area is more than $1km^2$ then the DEC is only valid for one year whereas if the floor area is under $1km^2$, the DEC lasts for ten years [160]. As UK buildings' energy efficiencies are improved and carbon emissions are lowered, a better energy grade is also more difficult to obtain. 'D' or 100 is the average rating for a building of the same size and function, and the lower the number score, the more efficient the building is. This allows larger buildings with larger energy consumptions to be compared to smaller buildings with smaller energy consumptions fairly. The energy consumption does not always convey the energy efficiency of the building. Systems such as lighting or the HVAC demand will naturally be lower for a building with less occupants than for a building with more occupants due to the systems operating less. This does not mean that the systems themselves are efficient; just that they don't need to operate as much. Larger buildings whose systems are dependent on the occupancy can be considered more efficient, but again, this does not correlate to highly efficient systems just because they are being operated efficiently. Systems must be operated efficiently, such as not over or under working, and while operating, the systems should not be wasting energy such as by using LED's lighting instead of halogen lighting.

As energy grades of similar buildings are improved, the average energy grade becomes more difficult to obtain due to the requirement of reduced carbon emissions for the same grade. If all other similar buildings reduce their carbon emissions and a single building does not, even though it has not changed functionality, the energy grade will decrease. This ensures that all buildings are improving and are investing in more energy efficient methods of operations.

Table 3.1. The building objects that put together the energy system of the building and the key parameters defining them [161].

Building Object	Key Parameters	Linked Objects
Zones	Dimensions, activity type, lighting, heating, and ventilation	HVAC and HWS
Envelope Elements	Wall, floor, or roof, area, orientation, construction type, thermal bridges, perimeter length, and condition of adjoining space	Zones
Windows	Dimensions, glazing type, thermal bridges, shading system, frame factor, and aspect ratio	Envelope
Doors	Area, construction type, thermal bridges, and type of door	Envelope
HVAC	System type, heat source, fuel type, efficiency, duct leakage, fan power, and controls	Zones
Hot Water System	Generator and fuel type, efficiency, and if it is a storage system	Zones
Solar Energy Storage	Dimensions, orientation, inclination, and storage	Hot Water System

Photovoltaic Energy Storage	Dimensions, orientation, inclination, and type	NA
Wind Generator	Terrain type, dimensions, and power	NA
Combined Heat and Power	Fuel type, efficiency, building heat and hot water supply, thermal and electrical efficiency	HVAC
Solar Collectors	Type, operation, control type, absorptivity, and design air flow	Zones and Envelope
Showers	Shower type, efficiency, and pump power	Hot Water System

The energy rating is adjusted for the floor are of the building, so it is independent of size and dependent on the function of the building. The energy grade is then estimated through the standard assessment procedure (SAP) which is a government owned software. The SAP calculates generated and consumed energy, building function, size of the building, and various other factors such as building materials and orientation. These calculations are derived from other buildings where the data is known, and with similar sizes and functions. The outcome from the SAP allows a comparison between the selected building's energy generation, consumption, insulation, and therefore the carbon emissions. Once the building's energy profile is better understood, improvements may be analysed and acted on. There are no measurements of energy management or internal storage, neglecting a crucial factor within improving a building's energy efficiency.

3.3 Public Buildings in an Energy Context

A simplified building energy model (SBEM) is a method of measuring the energy required for the various energy consumers within the building. It contributes to the DEC and is a measurement of how much energy the buildings use and generates. It is different from the SAP as it requires more data and can calculate the necessary information with a higher degree of accuracy. The building objects and key parameters of definition are described in Table 3.1.

The SBEM considers:

- The zones of the building, how it is split, and how many rooms it has. The energy consumers within the room are addressed to determine the lighting and HVAC consumption.

- The envelope of the zones need to be determined. This involves collecting data on the surface area, materials, and various other parameters on the envelope of the zone.
- The size, orientation, shading system, and insulation of the doors and windows must be determined.
- Hot water system (HWS) needs to be added such as if water is heated, what fuel, and if the water is stored is determined.
- Solar energy storage (SES) and a photovoltaic system (PVS) can be added if they are installed, where the PVS generates the energy and stores it in a SES. The dimensions and orientation of the PVS and the size of the SES must be defined.
- Solar collectors can be added into the system where the heat from the sun is concentrated and used to heat water.
- Any installed wind generation along with the size and power output of them.
- A CHP generator, the fuel type, efficiency, and output power.
- Showers are also added with information about them such as the system efficiency and power of the water pump.

The collected data can be explained using Figure 3.1.

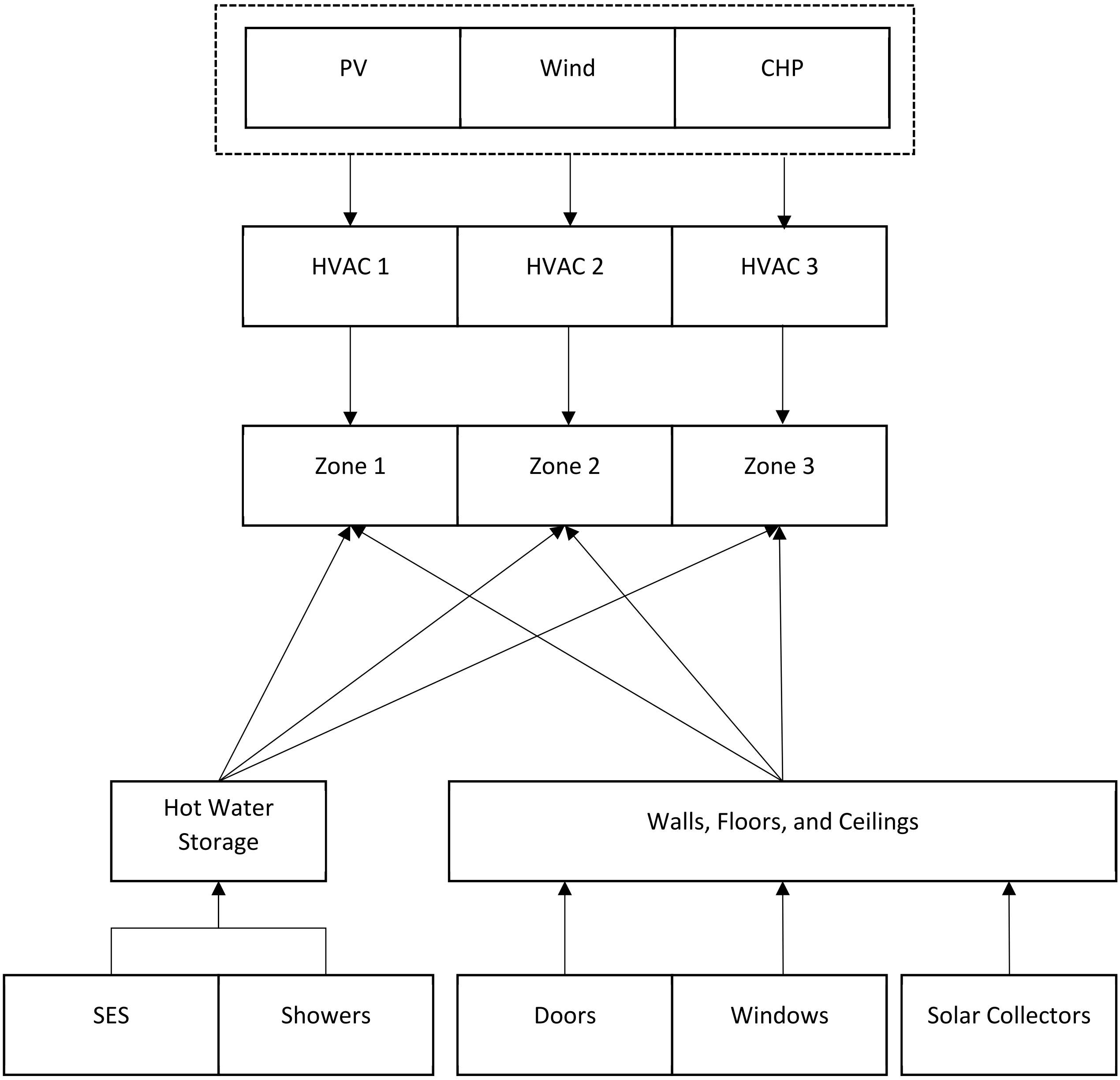

Figure 3.1. The buildings' systems and how they are connected from the generators to the storage, to physical parameters, to the consumers [161].

The SBEM must consider all categories from energy generators and storage, the buildings physical parameters of materials and size, to the buildings HVAC, lighting, and any other comfort systems it might have.

This method works well for buildings where all the physical parameters are known such as insulation and materials. For older buildings that are being retrofitted, this can be difficult to find, but overall, the data needed to complete the SBEM can be found with the buildings' blueprints. This is the currently preferred method that the UK Government uses to calculate the energy performance of a building, but it can become less accurate with more complex buildings as more data is required. To determine the energy and physical characteristics of buildings more accurately, BIM software's have been previously used. They are capable of generating a 3D model of the building with consideration of material, physical properties, and efficiencies of consumers, allowing more data to be collected. This is good in principle but due to simplifications in the calculations for carbon emissions and physical parameters etc., they are often not accurate enough for industry use. Previous case studies of BIM show a large error when forecasting the heating demand during the summer. When calculating the SBEM, some data is approximated, and some data cannot be used as inputs. There are no novel parameters such as energy storage methods (HESS) or kinetic energy generation additions to the models. The output is an energy report, showing various parameters such as CO_2 emissions target, and the actual emissions.

Energy trends of public buildings show an increase of 0.9% from 2020 to 2021 due to Covid-19 restrictions being eased in 2021 and cooler average temperatures in the first half of the year. For all building types, energy consumption increased by 1.8% from 2020 to 2021 [9]. The Business School's energy consumption has increased by 0.21% from 2020 to 2021.

Types of non-domestic buildings and the amount include education (39,000), commercial (476,000), offices (335,000), factories (227,000), hospitality (162,000), warehouses (204,000), and other (132,000). There were 1,656,000 non-domestic buildings in England and Wales in 2020 with education, offices, and hospitality consuming 32.48% of total energy consumption. Education includes all schools, colleges, and universities. The number of people in the UK between the ages of 3-22 are 14,272,979 (21.27%) [162]. This is the typical age where people would study and use educational buildings, but offices and hospitality make up the category of public buildings too. Historical energy consumption of non-domestic buildings is shown in Figure 3.2.

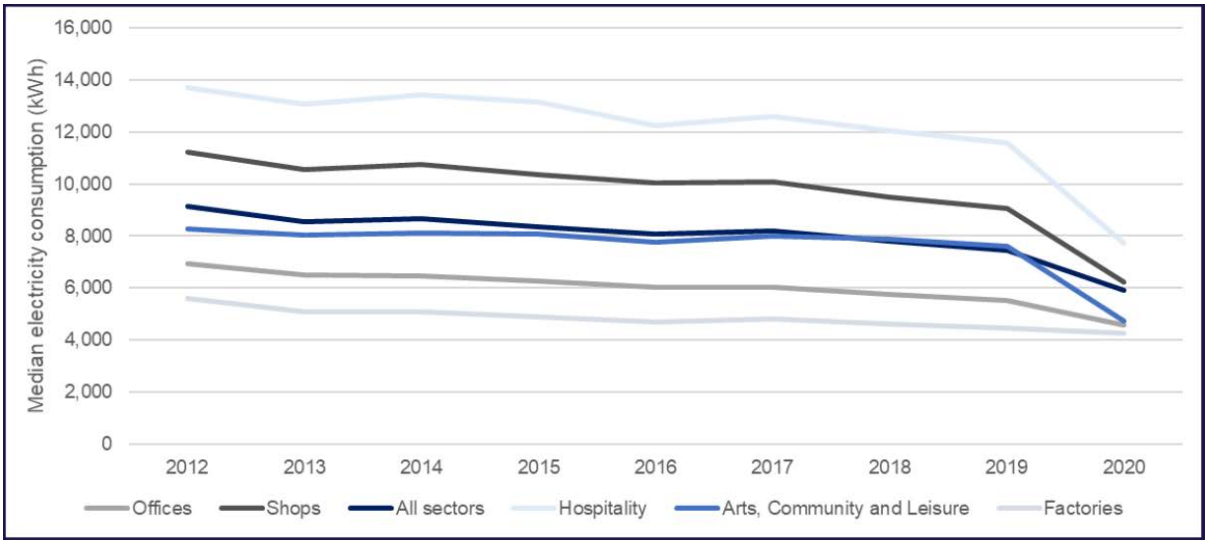

Figure 3.2. The median electricity consumption in non-domestic buildings in England and Wales [163].

The median electricity consumption has decreased as a whole for each sector of non-domestic buildings by 10.47% between 1998-2020 and 5.28% between 2018-2021. Commercial buildings' energy consumption are reduced by 18% between 2015-2021 with a record low of 62,761kW in 2020. This is accredited to the effects of the pandemic as footfall, sales, and occupation decreased among the sector. The historical energy consumption per sector are show in Figure 3.3.

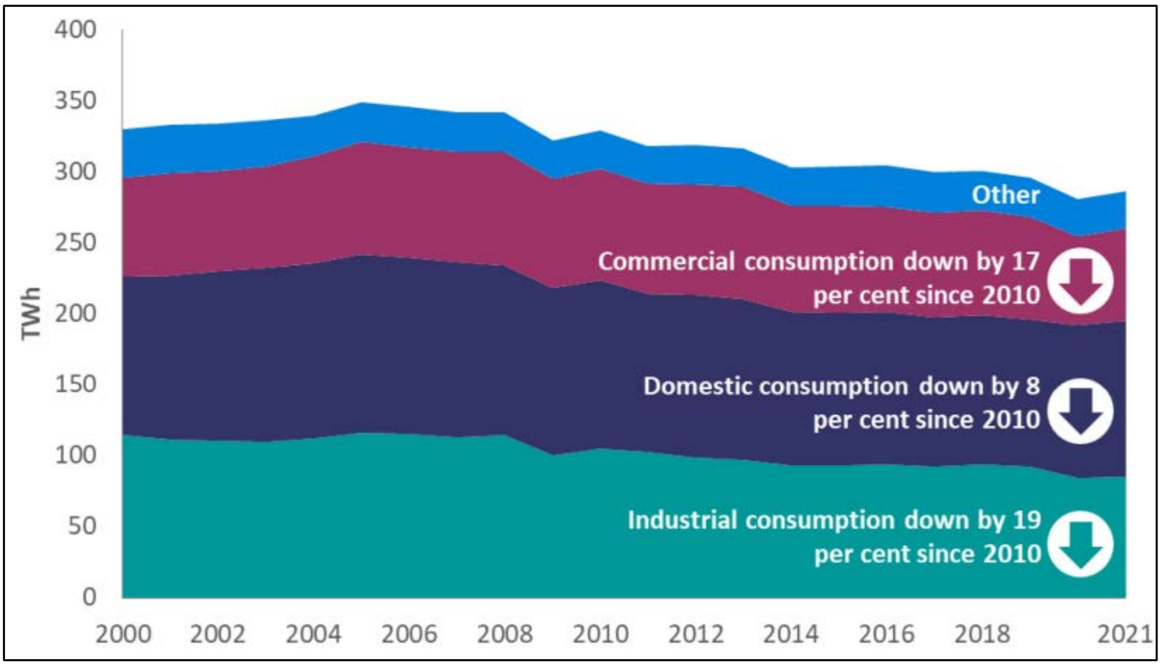

Figure 3.3. The energy consumption by sector from 2000-2021 [164].

The average energy demand has been reduced by 14.6% from 2000-2021.

Energy intensity of the sectors can be seen in Figure 3.4.

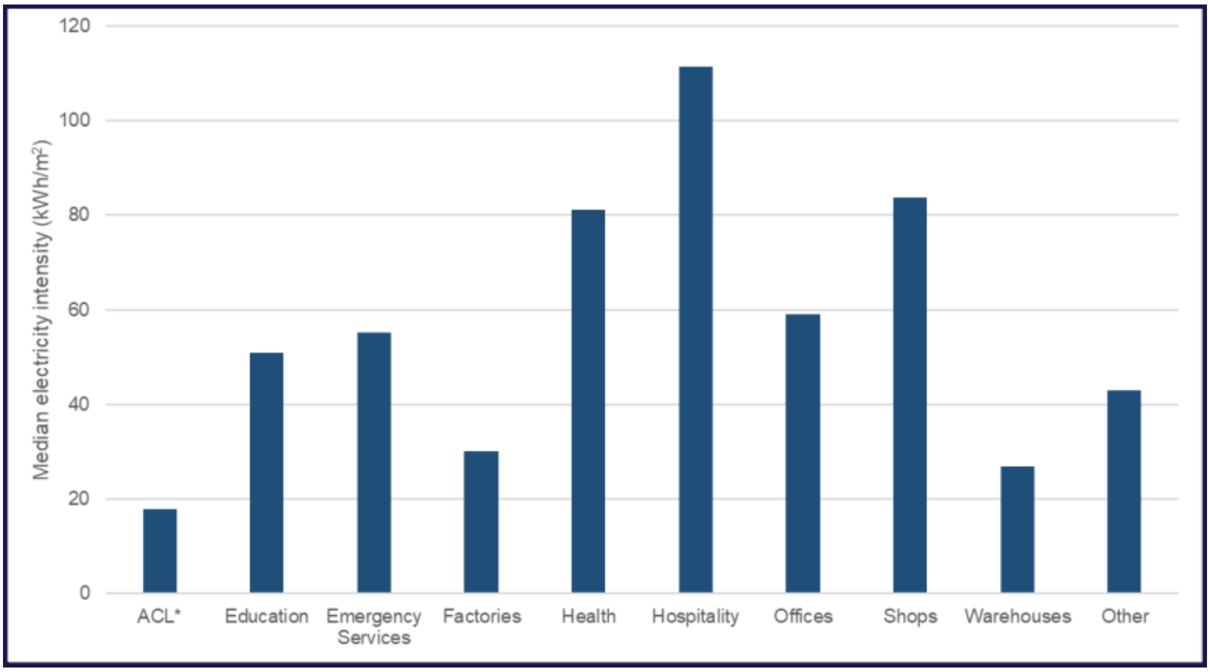

Figure. 3.4. The median electricity intensity of non-domestic buildings in England and Wales in 2020. ACL is arts, community, and leisure [163].

The energy intensity can be described as the amount of energy used per meter squared of a building. Hospitality has the highest energy intensity (111 kWh/m^2) due to operating in small premises but with activities such as catering which have high electricity demands. Energy not consumed from the public distribution system (national grid) can be determined to be generated from on-site generators. This has increased by 35% between 1998-2021 for all building sectors as a whole. Although this does not necessarily show an increase in on-site renewable generation, the growing necessity of renewable generation increases the probability that it is from renewables.

The energy efficiency of non-domestic buildings vary with insulation, function, and the efficiency of the internal consumers'. The insulation of the building is dependent on the materials and the thickness that they are made from. The age of the building can provide information on the heating and cooling requirements so the age of the building is important to determine the insulation.

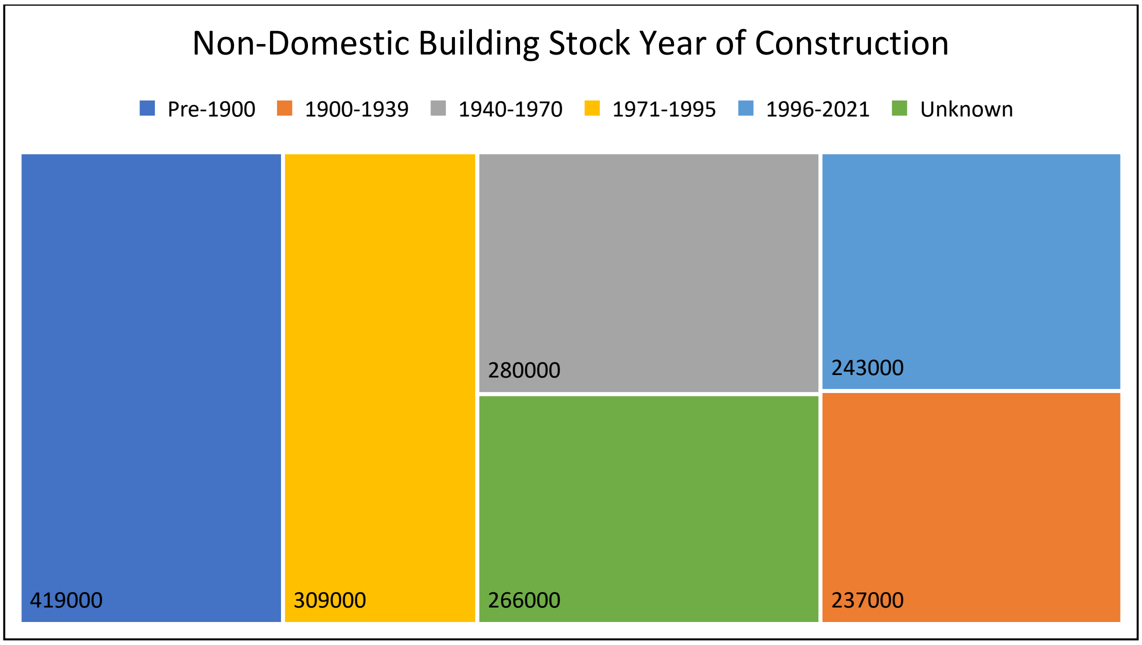

Figure 3.5. A breakdown of the non-domestic building stock in England and Wales by year of construction [164].

18.21% of buildings have been built before the 1900's with 89.43% of buildings being built before the year 1995, showing the need to be retrofitted with BMS's, smart energy measures, and better insulation to retain heat to increase energy efficiency and reduce carbon emissions.

The rate of non-domestic building construction is shown in Figure 3.6.

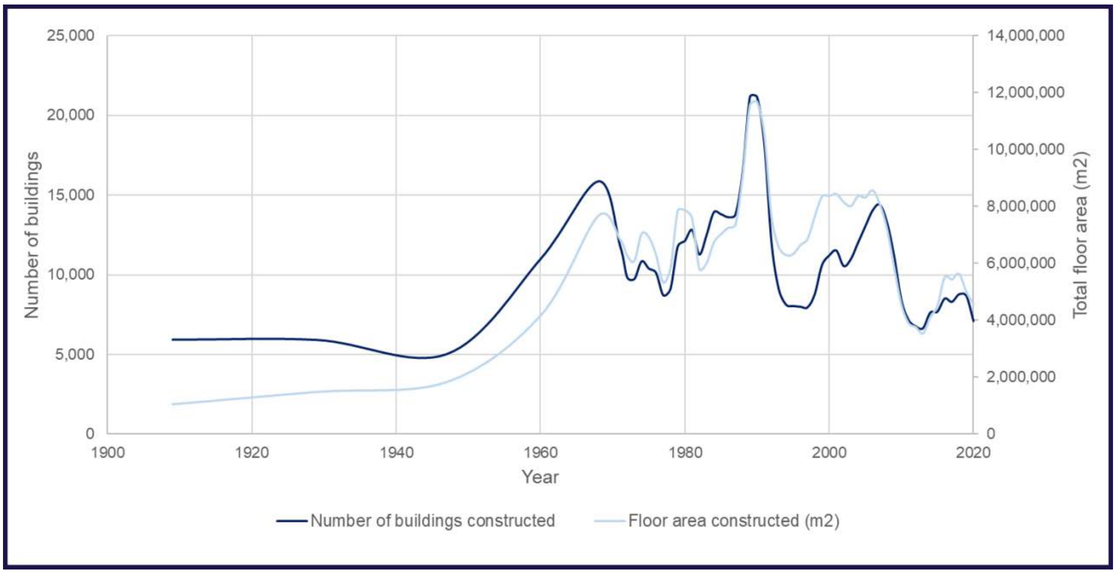

Figure 3.6. The number of buildings in the non-domestic building stock constructed between 1900 and 2020 in England and Wales by number and total floor area [164].

Originally, more buildings are built with a smaller floor area but due to lack of space and high rise buildings, the floor area has increased up to the current date. There is a decrease of new builds in the years 2019 and 2020 due to the pandemic.

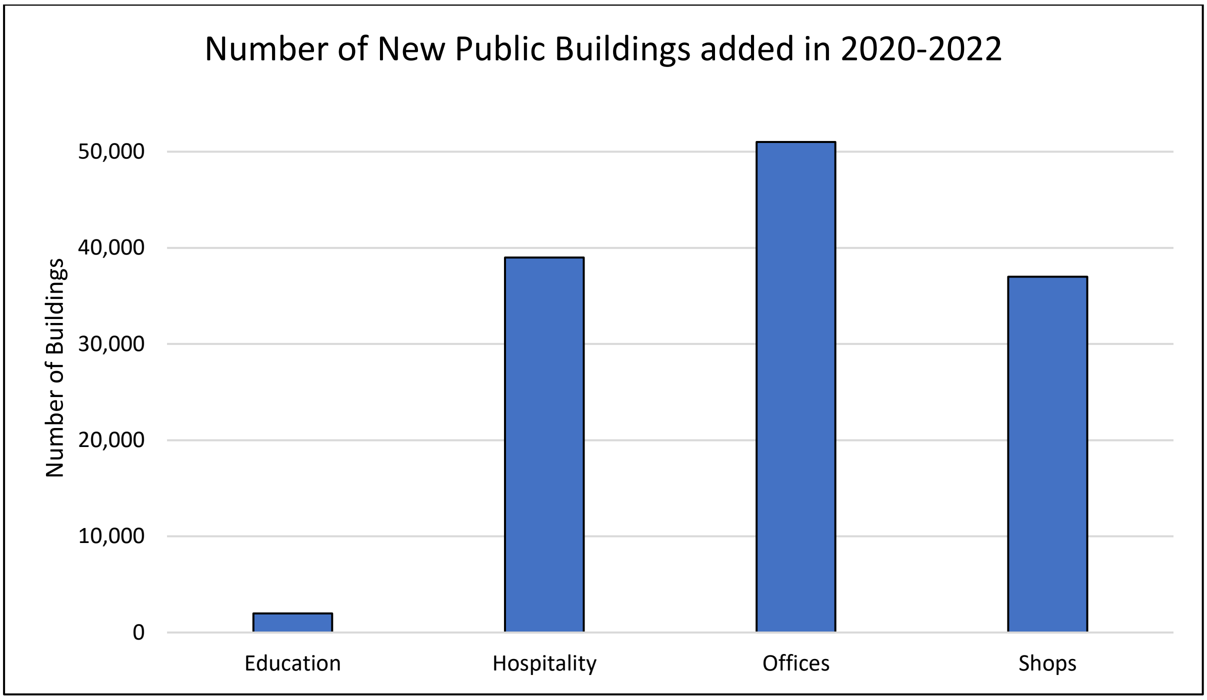

Figure 3.7. The number of new buildings in the non-domestic building stock constructed between 2020 and 2022 in England and Wales [163].

Education (1.12%), hospitality (21.91%), offices (28.65), and shops (12.35%) make up public buildings and 72.47% of new buildings between 2020 and 2022. The other buildings are factories (12.35%), health (0.56%), arts (1.12%), and warehouses (13.48%). As more public buildings are being built, the need for more efficient public buildings becomes more apparent.

In summary, the 10 sectors of buildings' that consume energy are currently reducing energy consumption and will continue to do so. As buildings' reduce energy consumption and increase energy renewable energy generation, the overall carbon emissions are gradually being reduced and more work needs to be done to increase improvement.

3.4 The Non-Domestic Building for the Case Study

Although the MMU Business School is an educational building, it has café's, offices, labs, and classrooms, being of use for all three sectors (education, hospitality, and offices). It is ranked the number two sustainability university in the UK in 2024 [165] and has had a top three finish for the past 13 years [166]. It is easily accessible to the public as there is no security to enter, and it is in use from 7am until 10pm. The functions of the building are varied due to the volume of people using the building. It is used for events, by students and teachers, for research, and for professional development and employment.

The Business School has a basic BMS but doesn't employ any form of MLA demand forecasting. If the results of the MLA's are used within the BMS, the BMS could optimise energy trade and actuation of the buildings' functions. The functions of the current BMS are automatic lighting, semi-automatic heating, PV generation, air conditioning, and there is no energy trade other than purchasing to meet the demand. The lighting is controlled by PIR sensors with a timer, so any unused space isn't being unnecessarily illuminated. The heating has a set temperature of 21°C but can be further controlled through a thermostat within each space. The PV generation does not generate enough energy to be in a surplus, and thus 100% of the generation is consumed within the building at the time of generation. The air conditioning is fully automated and works when the heating is no longer in use and when the buildings' internal temperature is consistently over 21°C. The B.S. is split into 3 parts to better manage the energy, blocks A, B, and C as is shown in Figure 3.8

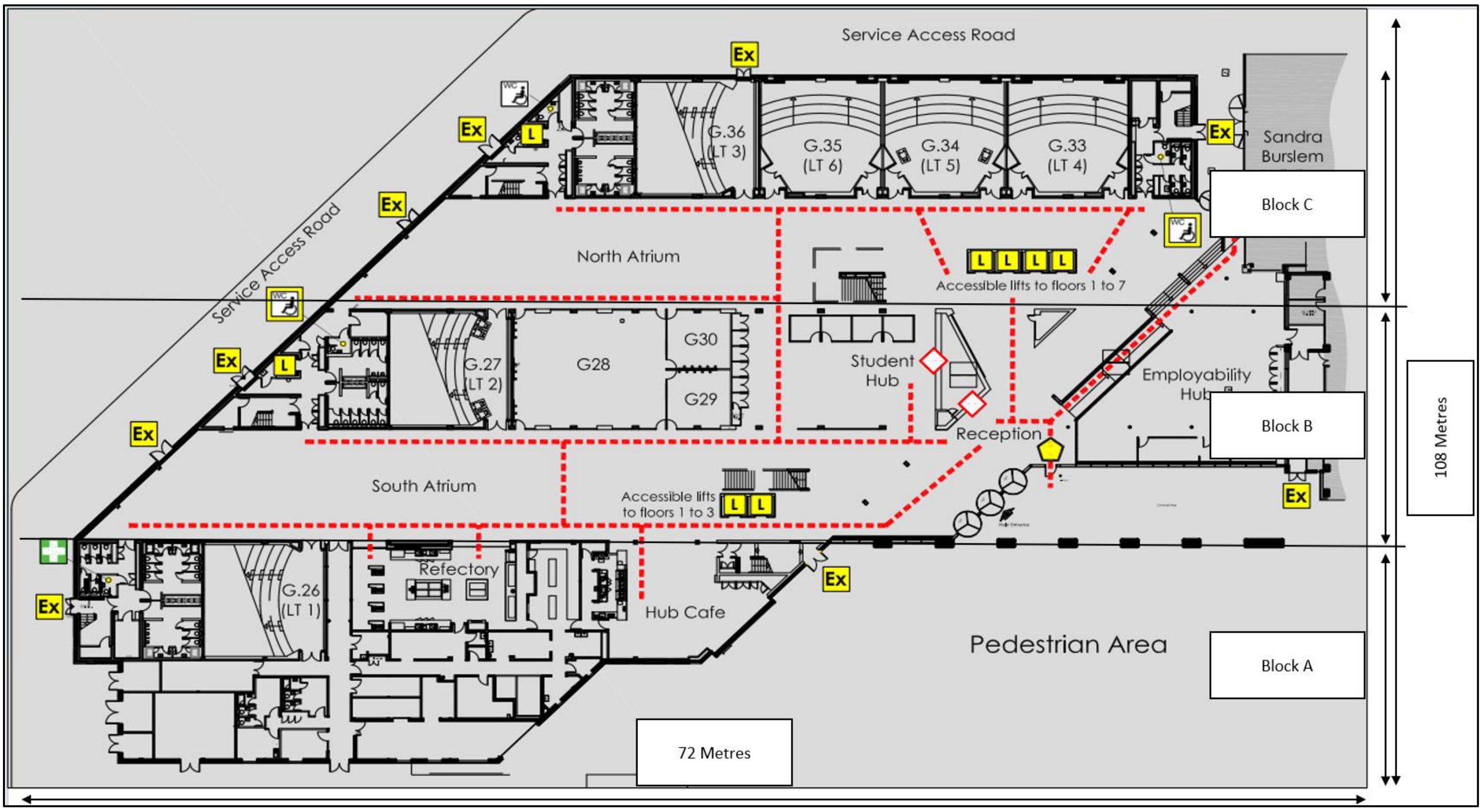

Figure 3.8 The layout of the ground floor of the Business School, showing where the blocks A, B, and C are separated.

Currently, only 14.2% of the electricity demand is being generated through on-site renewables. The use of other generation techniques such as kinetic floor tiles, a borehole, V2B EV trading, wind generation, and revolving doors can greatly reduce the amount of carbon the building is indirectly producing through purchasing from the national grid. The campus has space for all these techniques to be installed but the effectiveness of each method must be calculated and tailored for the specified building and purpose.

The building management system is designed to control every tool of the building to optimise comfort and energy efficiency. Targeted tools include heating, ventilation, and air conditioning (HVAC), on-site energy generation, energy storage, price of energy, lighting, olfactory, and acoustic optimisation. The heating and cooling system currently installed is a variable air volume system which uses 420.894MW per annum. On-site energy generation comes from the 150MW of annual power generated from PV panels installed on the roof. There is no energy storage for the Business School which limits the optimisation of the BMS. Price of energy has great effect on the effectiveness of the BMS as it fluctuates with energy demand. Peak time energy costs more than off peak energy, so for a BMS that aims to take pressure off the grid and to save money, storing energy to use at high demand will save money for the building and will take demand off the grid.

Internal energy consumers of the MMU Business School are explained through Figure 3.9.

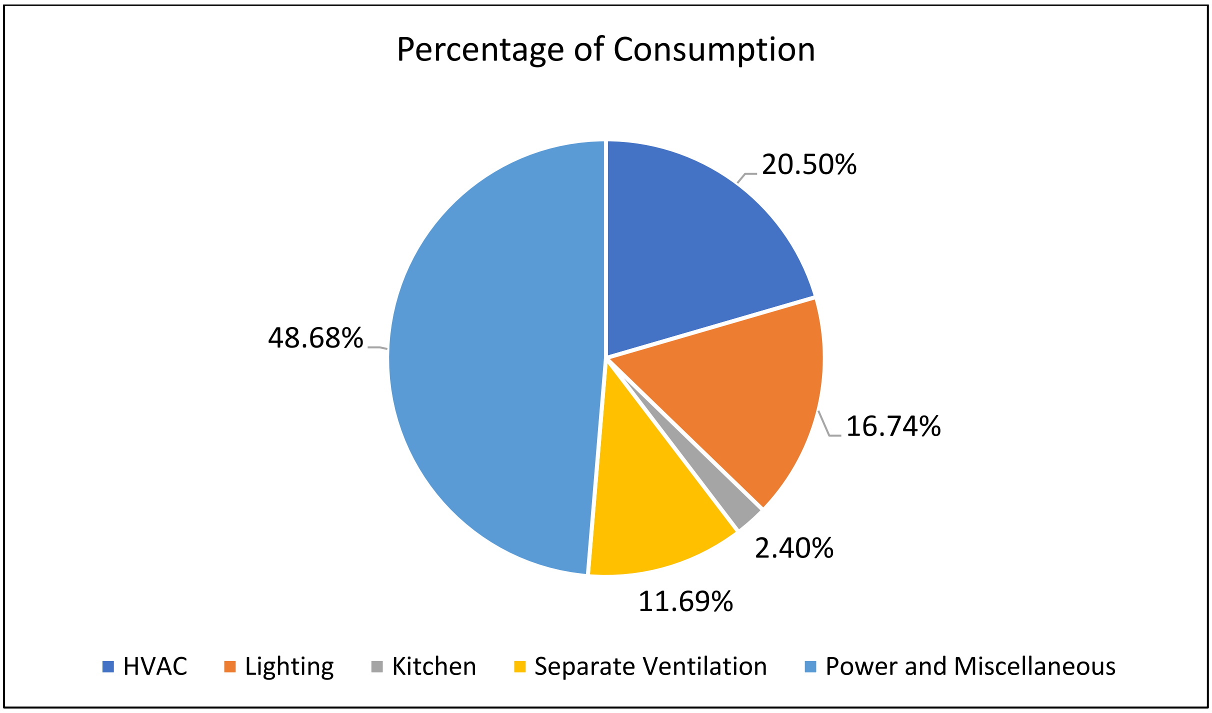

Figure 3.9. The split of energy consumers within the Business School.

The energy demand is distributed to the HVAC (20.5%), lighting (16.74%), kitchen (2.4%), and separate ventilation (11.69%). The other 48.64% is distributed among risers and power for widespread use such as computers and elevators.

The buildings' demand often increases with the occupation as more people use the kitchen, more CO_2 must be ventilated, and more energy is consumed through sockets and elevators. The correlation often provides valuable information on the direction of the energy demand when looking at a different variable such as the footfall. Correlation though does not equal causation. There can be a high correlation between the time of day and the volume of demand. This does not mean that the building is using more energy because of the time of day, but because the schedule and therefore increased volume of occupants are using more energy within the building.

The lighting within the case study building isn't entirely conventional as it is dependent on the occupation of the lighting zone. PIR sensors are equipped within zones to determine whether the lighting will activate, allowing the lighting demand to be reduced when it is not needed. The lighting energy demand through a year is shown in Figure 3.10

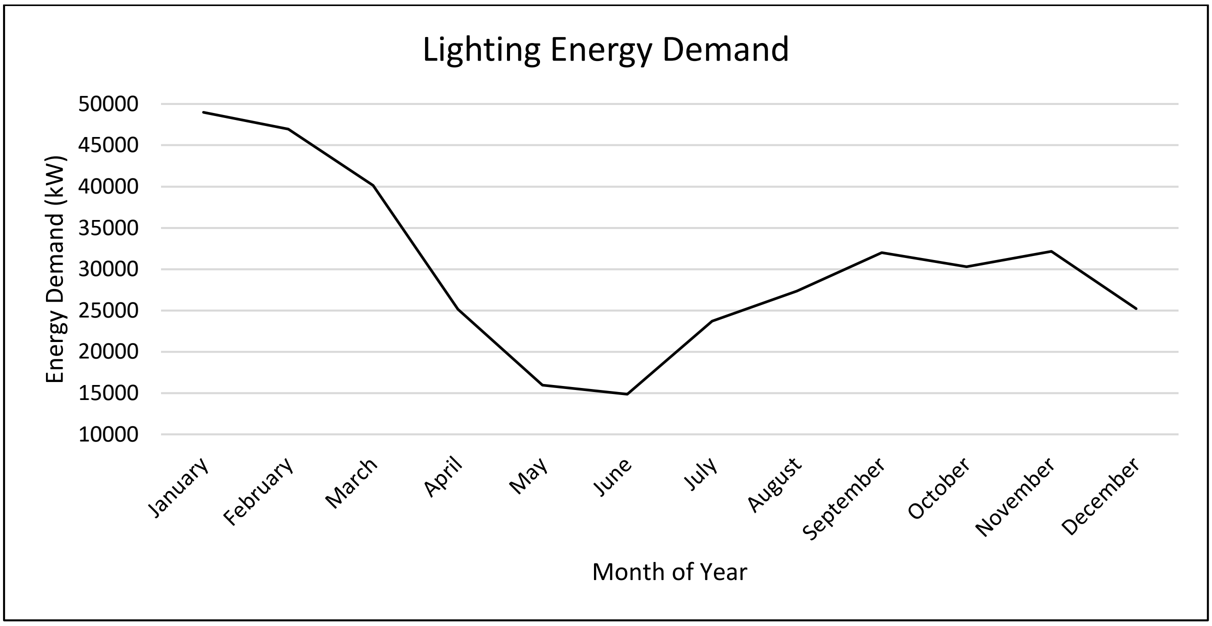

Figure 3.10. The monthly energy demand of the lighting system throughout a year.

The variation of the lighting looks as though it is correlated to the seasons of the year, but this is because the holidays are in the summer and December. During the holidays, the occupation decreases and due to the lights using PIR sensors, the demand decreases with the occupation. The ambient lighting for the Business School is shown in Figure 3.11.

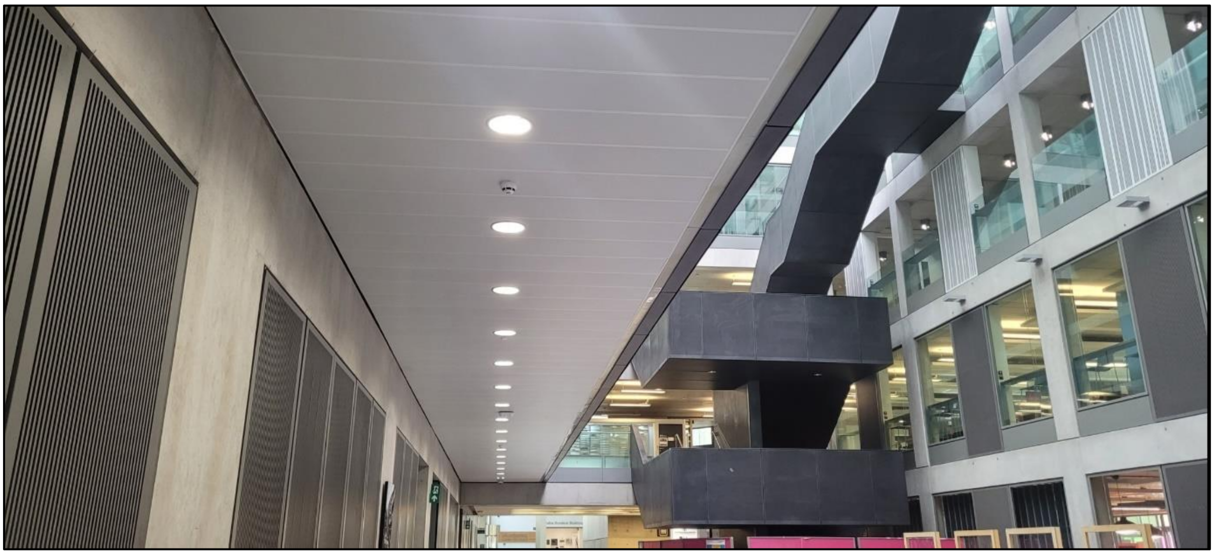

Figure 3.11. The lighting for the Business School. Daylight is used for the atriums and LED's are installed throughout the walkways and rooms with less natural light.

To increase efficiency further, light dependant dimmable lighting can be employed. For a building such as the Business School with a large WWR, the lighting system must consider sunlight bleeding into the building to optimise energy efficiency. If the outdoor light is sufficient to match the desired input and comfort level, then the lighting isn't needed at all.

The WWR is apparent in Figure 3.12

Figure 3.12 The façade of the MMU Business School, illustrating the high window to wall ratio.

Concrete supports are located on the ground floor and glass is the primary material for the walls. The building can use natural lighting to lower the energy demand of the lighting system.

The main entrance for the Business School is illustrated in Figure 3.13

Figure 3.13 The three revolving doors for the main entrance to the Business School.

These are the main entrances to the Business School, reducing heat losses and gains from a standard swing door. For research that requires occupation measurements of the building, these swing doors are useful as they can be fitted with PIR sensors.

The 20.5% and 11.69% of the main and additional HVAC system already uses an efficient method of convection heating for the building. As the heat is generated through a boiler and distributed among the building, the demand isn't instant, and the HVAC system often must adjust to over and under heating. This is illustrated in Figure 3.14.

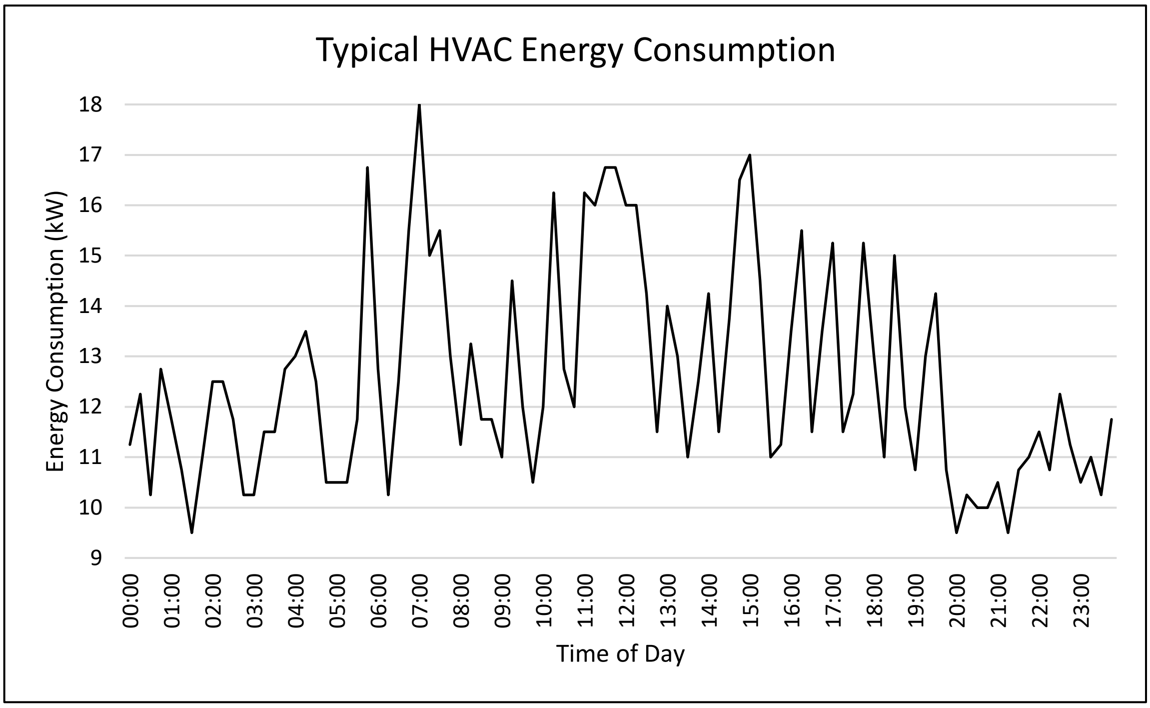

Figure 3.14. The HVAC energy demand over a typical day.

The date of the collected data is 09/09/2022, where the building is in standard operation during a weekday, and the HVAC systems' demand can be seen over the 24-hour period. The average variation over the 15-minute iterations for the day is 1.63kW or 13% of the daily average. This high variation can be attributed to the manual controls of the system and the time it takes for the zones to be conditioned. The energy is consumed to heat the zone(s) to a desired temperature, which is where the demand peaks. Once the zone(s) reach the desired temperature, the system can reduce the energy of heating the zone until the temperature needs to be adjusted again. Although the time taken for the zone to reach the desired temperature cannot be defined, it can be stated that this isn't instantaneous and that there is a delay between the zone being occupied and the reaching of the desired temperature. The application of MLA's has the capacity to forecast the occupancy and the heating demand for the day. If the HVAC demand and the occupation of the zone can be accurately forecasted, the HVAC system can be operated before the zones are occupied. This has the potential to increase comfort by pre-heating the zone, and it can stop excessive heating and cooling by eliminating manual controls.

The current VAV heating system for block 'C' of the Business School is described in Figure 3.15.

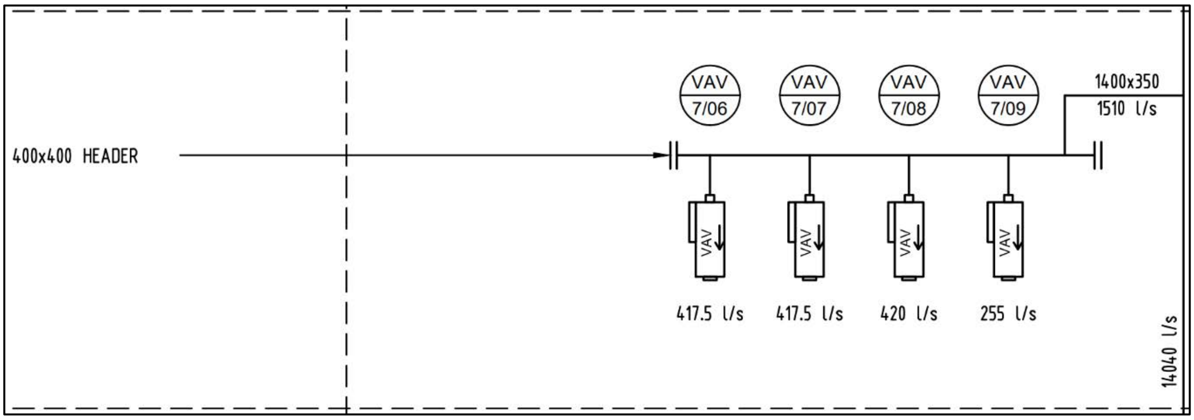

Figure 3.15. The current variable-air-volume heating system for the 7th floor of the Business School in block 'C'.

The systems' rate of ventilation and volume of space is 1,510 l/s and 1,400mx350m respectively. This covers spaces 6,7,8, and 9. Each VAV header is tailered for the space, allowing the system to condition and ventilate the spaces with limited energy waste. The VAV vents are located throughout all floors and zones of the building. This is shown in Figure 3.16.

Figure 3.16. The variable-air-volume system vents. They are located on the walls throughout the Business School.

The VAV system vents consider each zone and ensure it is climatised to the desired temperature. The vents are located from the bottom to the top of the atriums, where the ceiling is made of glass with a low thermal resistivity, allowing the heated air to escape, especially when emitted from vents near the ceiling.

Figure 3.17. The open plan of the atrium and canteen, illustating how thermal losses can be large due to nothing stopping the air flow.

This is showing how there is no physical materials seperating the spaces between the low ceiling of the canteen and the atrium, enabling thermal losses and requiring more energy for air conditioning.

As the ground floor consists of an open space, it is more complex to heat the zones efficiently. This can be improved through removing convection losses through using FIR heating or through seperating the zones with physical materials with high thermal resistivities. As occupation comfort is an important consideration within the function of commercial buildings, splitting zones up into smaller zones can be difficult due to the appearance of the interior of the building.

The Business School has an energy rating of C, or a score of 67 out of 150. This is an upgrade from previous energy ratings of 99 (D), 83 (D), and 71 (C), from 2019, 2020, and 2021 respectively. These improvements come from rooftop installed PV generation and a BMS, capable of automating the lighting and HVAC systems to some degree. The Business School has been assessed by a government appointed expert to determine the energy grade and to recommend some improvements. The recommendations for the MMU Business School from the government are as follows [167]:

- Higher energy efficient lamps with automatic PIR/daylight sensors to reduce heat produced by lighting, which can reduce cooling load.

- Examine heat loads from solar gains and investigate treatments to glazing or fitting blinds to reduce the cooling load.
- Fit zonal HVAC controls to reduce over and under heating.
- Implement a planned lighting and HVAC maintenance strategy to maintain efficiency.
- Fit secondary glazing or underglaze sky lights.
- Improve cavity wall insulation.
- Construct draught lobbies to reduce unwanted air infiltration.
- Implement biomass boilers.

Higher energy efficient lighting can be applied by ensuring all lighting systems within the building are light emitting diodes (LED). Daylight sensors are not novel techniques but show a reduced energy demand. The Business School has a large WWR, allowing large amounts of daylight in without the need for the lighting system to be on at all times. This application could reduce energy demands of the lighting system as they are working less, and energy demands from the HVAC system. This is due to the lighting system producing less heat, so the HVAC system doesn't need to use more energy as an increased cooling load. The energy consumption through the building can be explained through Figure 3.18.

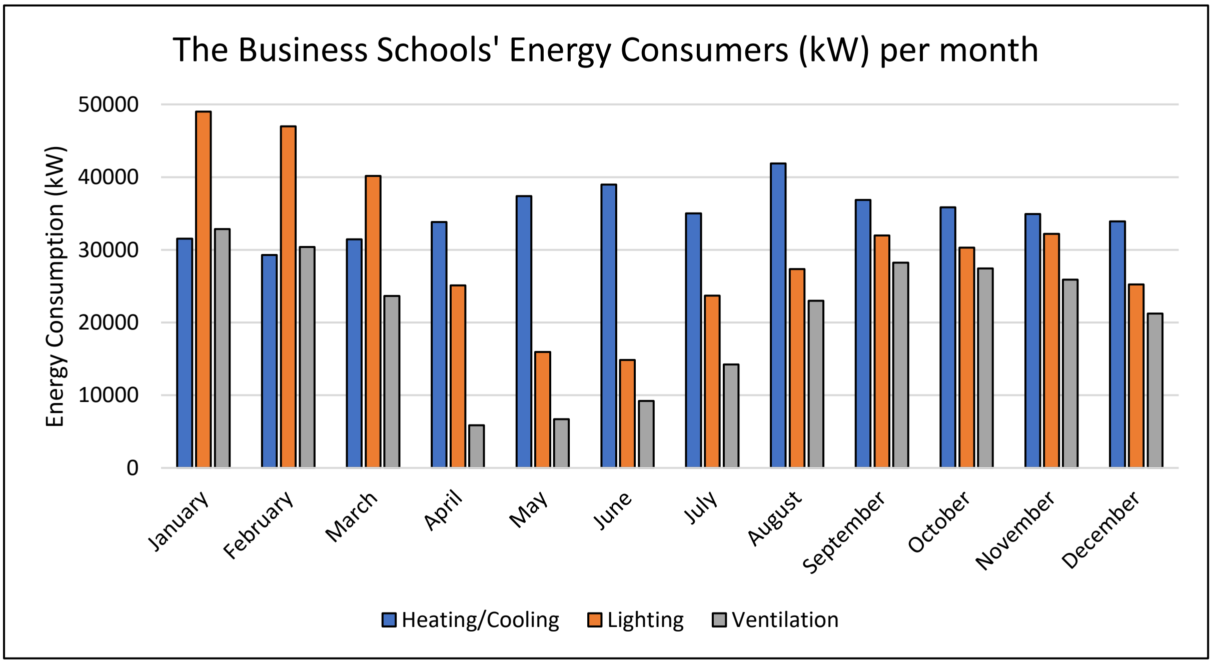

Figure 3.18. The Business Schools' energy consumers, showing heating and cooling, lighting, and ventilation demands over the year 2020.

The year 2020 is used because it is the last year with a full dataset and no errors in the data collection. The heating/cooling, lighting, and ventilation use account for 32%, 28%, and 18% respectively. The remaining 22% of the energy demand is through power such as computers and elevators etc. The lighting consumption is linear with the month of the year, the length of each day, and the occupation density of the building. No natural lighting measurement is used for the artificial lighting system, so it is not dependant on the length of the day. As it is an educational building, the summer holidays and December have the largest breaks in use. It is most likely that the occupation density is the reason for the change in lighting due to the automatic lighting system installed. Heating and cooling data is combined before collection and therefore the correlation cannot be calculated. The systems work oppositely as when one of the systems is in use, it is not efficient to be using the other system as they have opposing effects on the internal environment. It is unlikely that the building is at a desired temperature throughout without using one of the systems. The demand does increase during the summer months showing that cooling requires more energy than heating to keep the building at a desired temperature. The building has such large windows which can explain why it has large solar heat gains. This could be the reason for the increased cooling demand, or it could be due to the cooling systems efficiency, that it is less efficient than the heating system. If the heating system is activated, the cooling system shouldn't be used to conserve energy and vice versa. This is the reason for the energy consumption not varying throughout the year. The ventilation varies drastically throughout the year, with a peak in January and a trough in April. This is due to the ventilation being used in large lecture halls. The exam periods start in April through to September where the students will use the building again. When the students aren't in the lecture halls, they aren't used at all and the ventilation for them is not necessary.

The energy consumption of a building can easily be identified by how much they are taking from the national grid and the buildings' systems can be identified primarily as HVAC and lighting systems. To determine how much energy these systems use once they are broken down though can be difficult as each system requires an energy reader and there can be many systems within a building. There isn't a previous study providing a breakdown of the average public buildings' energy consumption into its systems in the UK. A comparison of the Business Schools', Australia and USA's average heating/cooling, ventilation, and lighting is shown in Figure 3.19.

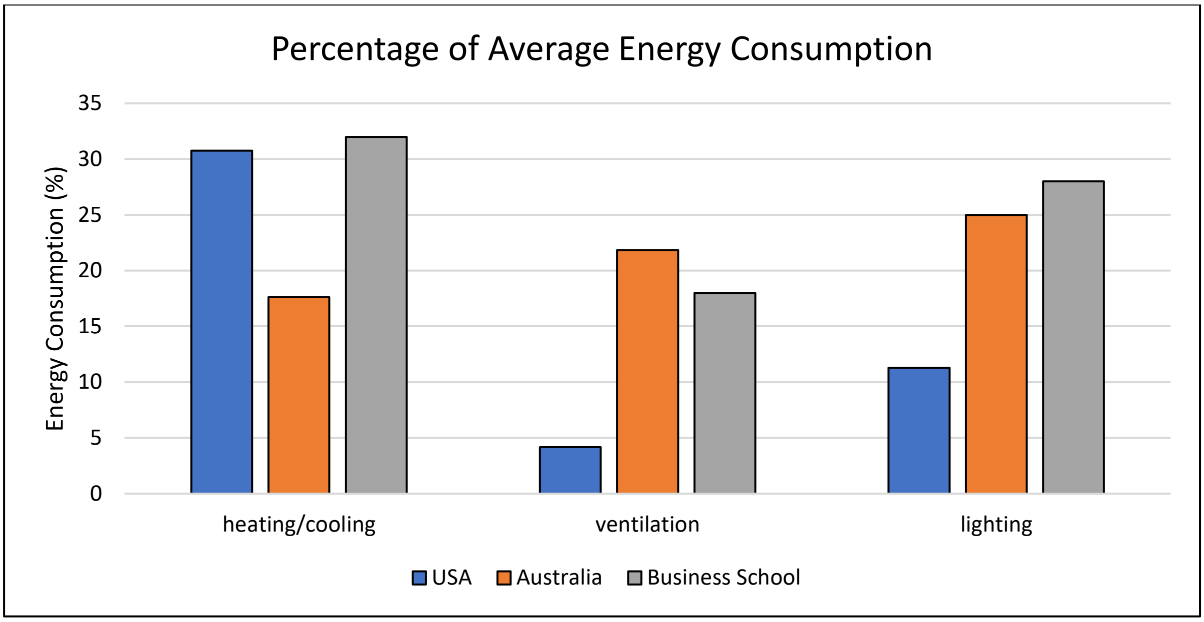

Figure 3.19. A breakdown of the energy consumption withing non-domestic buildings in the USA, Australia, and the MMU Business School by percentage of total energy consumption [168, 169].

Although the climate influences the heating and cooling systems, this can still be compared by stating that as an average, the Business School uses more energy for heating and cooling the building. The average temperatures in USA, Australia, and the UK are 24.6 °C, 18.08 °C, and 9.28 °C respectively. As Australia's temperature is in the middle of the two, it uses less energy on keeping the buildings hotter or cooler. It is most likely that the USA uses the cooling demand more due to the temperature being more than twice as hot as the UK on average, whereas the UK uses more energy on heating due to the low temperatures. The ventilation requirements in the UK, USA, and Australia vary significantly from 10 litres/second/person [120], 5L/s/p [170], and 25L/s/p [171] respectively. This explains the difference in energy consumption as the higher the ventilation requirements for the country, the higher the average energy consumption of the ventilation system. The lighting systems' energy consumption of the Business School is more than twice as high as for the average building in the USA. As there are no strict regulations on the required illuminance for the countries, this could be due to the USA providing dimmer indoor lighting than other countries. The Business School has a large WWR so it could employ a lighting system that is dependent on natural light. The lighting difference between USA and Australia can be explained by different lighting intensities due to there being no official regulations.

There is no collected data on the breakdown of energy consumption in non-domestic buildings in the UK, hence why it has been compared against other countries. The Business School is also compared against other buildings on the Manchester Metropolitan University campus in Figure 3.20.

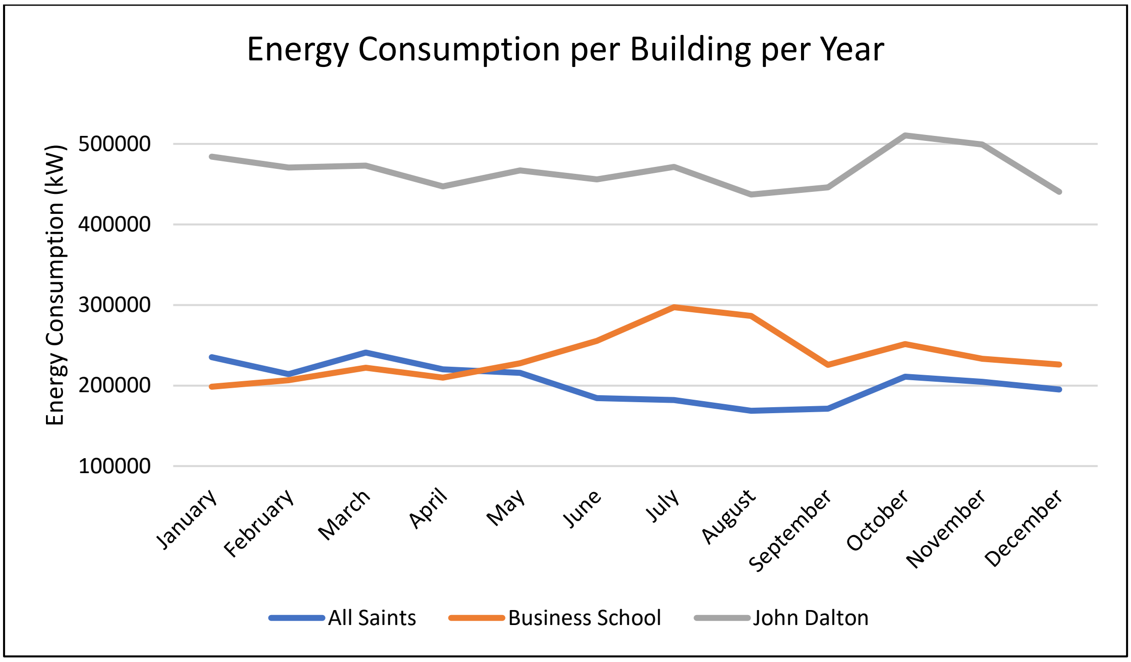

Figure 3.20. The energy consumption of the MMU Business School, the All Saints, and the John Dalton building in the year 2020.

The All-Saints building is student accommodation, whereas the Business School and John Dalton are used for academia. The All Saints and John Dalton buildings follow the same energy consumption trend of reduced in the summer holidays (June-September) and increased during term time (September-December and January-June). As the All-Saints building is used for accommodation, and with a 30% reduction from the March to August, this makes sense due to the students not occupying the building. The John Dalton building follows the same pattern with an increase of 14% August to October where the students are using the building again. There is less of an increase due to staff occupying the building during the summer. The Business School follows a different pattern of energy consumption with a peak during the summer. The building is used by students, teachers, and staff equally, but the cooling demand peaks during the summer by 33.2% compared to the heating demand in the winter. The large WWR can be used to explain the increase in cooling demand from the Business School due to solar heat gains through the windows. One of the government recommendations is to fit glazing and blinds to the windows to reduce these gains and reduce the cooling load.

Table 3.2. Five of the 24 buildings on the MMU campus.

Building	Energy Grade	Energy Consumption ($kWh/m^2/year$)	Useful Floor Area (km^2)
Business School	67 (C) [172]	123.87	24.441
All Saints Main Building	80 (D) [173]	186.14	11.148
Ormond Building	53 (C) [174]	157.25	3.116
Bell House	38 (B) [175]	113.35	0.332
Brooks Building	77 (D) [176]	215.83	23.852

The energy grade does not correlate with the energy consumption or useful floor area. This is because the display energy certificate compares the building with other buildings of the same function and size and these buildings have different functionalities and sizes. Although the Bell House may look like it functions better than the Business School, it is a renovated 19th century townhouse with only 1.35% of the Business Schools' floor area. Other buildings of the same functionality and age and do not have good thermal conductivity and therefore consume more energy than the Bell House, giving it a good energy grade.

Heat loads and solar gains have a large impact on the operation of buildings' HVAC systems. The better the buildings' insulation, the better the resistance to solar gains. Due to the Business School having such a large WWR, the buildings' HVAC system is highly correlated with the outdoor temperature and insolation. To prevent these heat gains the glass could be fitted with extra glazing or with reflective glass. The use of solar blinds can reduce incoming solar gains, but also require the building to provide artificial indoor lighting instead, requiring more power to do so. The trade-off is often beneficial towards reducing energy demand due to the high efficiency of LED PIR lighting.

The current HVAC system functions broadly throughout the building. There are three sections of the building, each able to be controlled separately. This works theoretically, but when one section is warmer than the other, due to large atriums within the building, the systems can end up indirectly heating and cooling the same zone. To negate this, the zones could be made smaller, and the HVAC system can be split further into each room for optimised energy efficiency.

Currently, there is no planned strategy for maintenance on the lighting and HVAC systems. When a system malfunctions or breaks they are repaired as soon as possible but this isn't always quick enough such as on the weekend or if multiple functions break simultaneously. LED's malfunctions are difficult to forecast, so often when one breaks, it is fixed but then soon after, another LED also needs replacing. A common way of saving costs on repairing the LED's is to wait for multiple to break and repair them at once. This leaves multiple systems down at once which isn't ideal as it can impede the occupant's comfort.

The skylights work the same way as the windows as they allow daylight in but also solar heat gains, requiring further work for the air conditioning. This works oppositely with the heating too as the windows' thermal resistivity isn't as good as the ceilings' solid materials, so more heat is lost during heating periods too. The recommendation from the government is to fit secondary glazing to the skylights which increases insulation. This reduces heating demand during cooler outdoor temperatures and cooling demand during warmer outdoor temperatures. Improved cavity wall insulation plays the same role as secondary glazing, saving energy on heating and cooling.

The Business School has three large revolving doors at to allow large volumes of footfall to enter the building with small time periods such as in the times 9am and 5pm. Although revolving doors help reduce heat transfer from indoors to outdoors, it does not eliminate it. On the inside of the building next to the revolving doors, the main lobby spans the entire eight floors. To better control the draught and HVAC systems, the size of open space can be reduced which will reduce heat loss.

Finally, the implementation of biomass boilers could have a large impact on the reduction of carbon emissions from the building. Biomass heating has the potential to generate energy from waste produced by the building or through imported local waste. The Business School has 108 toilets, and with 36,000 students enrolled on campus, the waste could be collected and processed for fuel with the biomass boilers. The volume of occupants using the building generate waste food too and the bins throughout the building have separate food collection to other rubbish types. This could also be collected to be used as fuel. Biomass boilers can be used to heat the building instead of using conventional techniques such as gas boilers.

To determine these recommendations, the building must be surveyed, and data must be collected. Building data needed to calculate the energy grades are [177]:

- Type of building.
- Age of building.
- Number of habitable rooms.
- Dimensions of the building and number of floors.
- Amount and type of window glazing.
- Material(s) used to build the property.
- Wall insulation.
- Roof construction (flat, pitched etc.) and insulation.
- Number of chimneys and open flutes.
- Heating system and type of fuel used.

The type of buildings denotes their function, such as commercial or educational. The age of the building often helps with understanding the building materials which are measured if possible. The building materials also produce CO_2 such as with concrete. Dimensions of the building and the materials used greatly affect the thermal insulation. The wall insulation, roof construction, and open flutes contribute to the thermal insulation of the building too. The heating system and type of fuel provides information on the amount of carbon emissions produced by the building. Number of habitable rooms have a high correlation with the footfall, affecting the buildings' functionality.

The MMU Business School has an installed BMS that automates the lighting, air quality and flow, and air conditioning. The heating is automated, or it can be manually controlled to some degree through thermostats in each room of the building. There is no trading of energy for profits or for alleviating demand from the grid. The energy is purchased to match the buildings' demand after the PV system has generated the 14.2% (157,753 kW) average generation of the whole demand. A borehole is installed on campus with the purpose of supplying the building with enough heat to match 100% of the heat demand but it has been out of service since 2019, providing no benefits. The heating is provided through electric boilers but there are back up gas boilers for if the electric boilers are out of service. The heating system is variable-air-volume, with a rotary wheel heat exchanger, providing a very efficient convection heating system. Although the heating system is very efficient and is suitable for the building, the cooling system is running at 100% and the building can become too hot in the summer due to the large window to wall ratio. One of the main improvements recommended by the government for the improvement of the Business School is that the heat from solar gains should be examined and considered when cooling.

3.4 Summary

This chapter demonstrates how non-domestic buildings can be graded and compared against other buildings of similar sizes, functions, and locations. The energy grading is then applied to the MMU Business School and government recommendations towards the carbon reduction is assessed. Historical analysis of total buildings shows that most non-domestic buildings are pre-1900 and therefore require energy saving methods and management. The energy consumption of on-campus buildings is compared and analysed for a year to decipher major causes and patterns of the energy consumers.

Although more efficient methods can be implemented into the building's energy functions such as FIR heating and a BESS, a BMS must be able to optimise the management of these for the benefit of energy conservation. If the future energy generation and demand of the building can be accurately forecasted, the BMS can optimise what to do with surplus energy, or how to optimise the operation of the buildings' functions. To determine the optimal method of forecasting the energy characteristics, novel techniques must be compared to conventional techniques. The comparison allows a clear understanding on how the techniques work and how they may be applied to a BMS.

An optimised BMS must be tailored to the building it is controlling, considering the functions, times of use, energy profile, location etc. To determine how to optimise the BMS, the building must first be analysed, and then the MLA can be developed and applied to the BMS to ensure it is controlling appropriate functions, with dependency on what data can be collected to be used for the MLA forecast. The theoretical application with real-data of the MLA-informed BMS to the MMU Business School encourages reproducibility of the novelties in this thesis due to the Business School not having any outstanding features, and it being multi-purpose.

Modern and conventional methods of energy forecasting are critically analysed and developed further into chapter 4 to determine optimal methods.

CHAPTER FOUR: CONVENTIONAL AND NOVEL BUILDING ENERGY FORECASTING TECHNIQUES WITH ELECTRIC VEHICLE APPLICATIONS FOR ENERGY DEMAND REDUCTION

This chapter explores the application of various AI and ML methods of energy forecasting. The comparison of MLA's and BIM software's provide an understanding on how they are used and in which context. The most popular methods of energy forecasting in previous research are employed for the forecasting of the MMU Business Schools' energy characteristics. Included are current methods of forecasting, classification, and the evaluation of algorithms' input features importance. The MLA processes and results are attained through the chapter.

An application of MLA energy consumption forecasting is introduced. A method of benefitting from the increasingly popular electric vehicle use is developed and validated to provide benefits for both the owners of the EV's and the buildings it is applied to. The energy capacity from the electric vehicles is used to reduce costs for the building and for the car owners through the implementation of ML methods onto the Business School.

4.1 Introduction

To employ an optimised BMS, the energy performance and buildings' functions must be accurately forecasted. As is described in chapter three, the government have their own method of forecasting a buildings' energy performance. The SAP algorithm is too vague to be used to improve the energy efficiency of buildings as it gives information on if the building is meeting carbon emission requirements but not exactly where or how it can be improved. It is a good guideline on how the building is performing but does not promote innovation or major improvement. A novel application of MLA methods for forecasting actions of EV's is proposed to benefit the Business Schools' energy costs while reducing peak load from the grid.

The aim of this chapter is to apply currently existing MLA models to a building's BMS to accurately forecast energy characteristics. This provides a framework to calculate optimised EV charging schedules.

The methods of energy and physical characteristic forecasting can be analysed and compared. Conventional techniques are compared against ML methods. MLA processes and models are developed for the specified problem.

4.2 Conventional and Machine Learning Energy Forecasting Methods

Before practical machine learning techniques, a new build's energy was forecasted through comparisons of other buildings energy performance with the same floor area and functions. This is still widely done today but through a software for more accurate forecasting. The energy forecasting software SBEM measures the geometry, heating, air conditioning, and installed renewables. The required data inputs for the SBEM algorithm include ten inputs mentioned in section 3.3. The collection of the data can also be invasive as the required inputs include building materials, dimensions, and number of habitable rooms, where the buildings' physical properties must be assessed.

From this data it can calculate the energy demand, insulation efficiency, and is able to analyse the energy used for space heating, water heating, electric showers, cooling, pumps and fans, lighting, and other features. Each of these calculations can be compared to the target result, providing information on where the building isn't meeting the target efficiency. This allows the building to be improved through adding renewables or upgrading the thermal insulation.

The results section is explained by Figure 4.1.

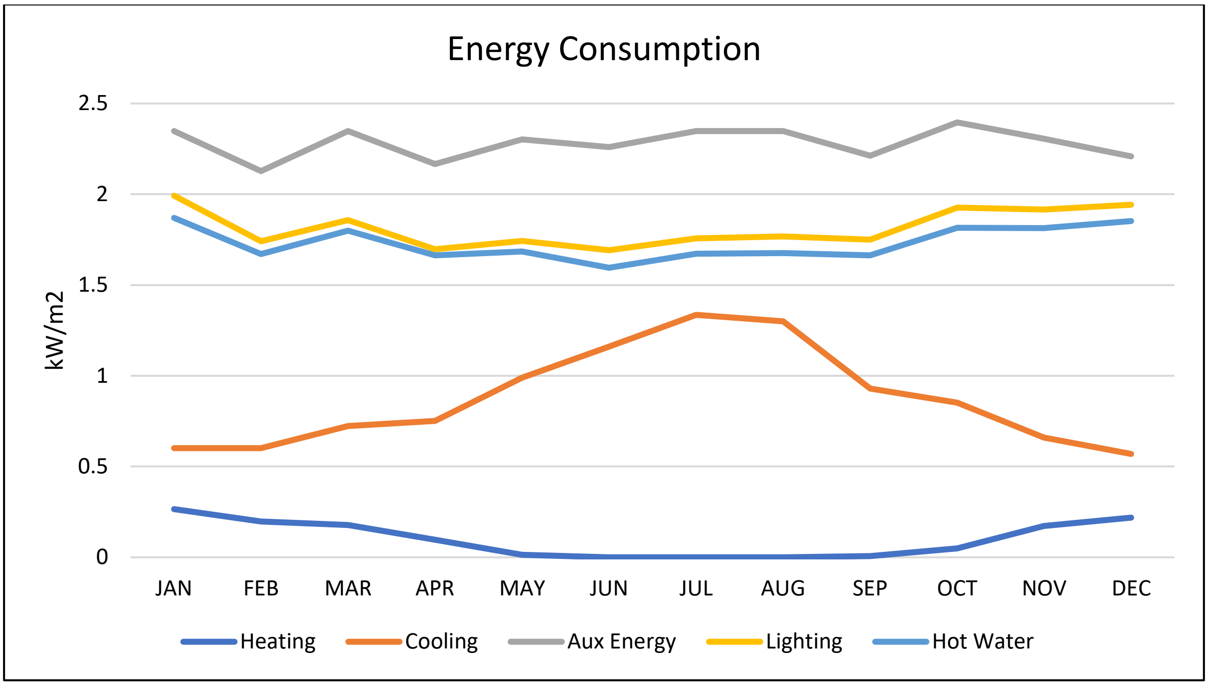

Figure 4.1. The results for an example generated building using the SBEM simplified building energy model.

The information needed to develop this model becomes vaster with larger buildings.

- General information includes the address, the area of foundation, the location to determine the weather, building rotation, and the number of floors.
- Envelope, door, and window construction include the external wall, ground floor, external doors, internal floors and ceilings, internal walls, and roof construction. These values require the U-value, thermal mass, solar transmittance, and light transmittance.
- A summary of the objects within the building includes number of windows and doors, hot water systems, shower types, PV systems, wind generators, CHP generators, solar collectors, SES, HVAC systems, number of zones, and number of building envelopes.

In total there are at least 41 values necessary for construction of materials, 77 values for the geometry, and 130 values for the buildings' services to make a total of 248. For the Business School, the measurements required are 15,745. The results from the SBEM software are shown in Figure 4.2.

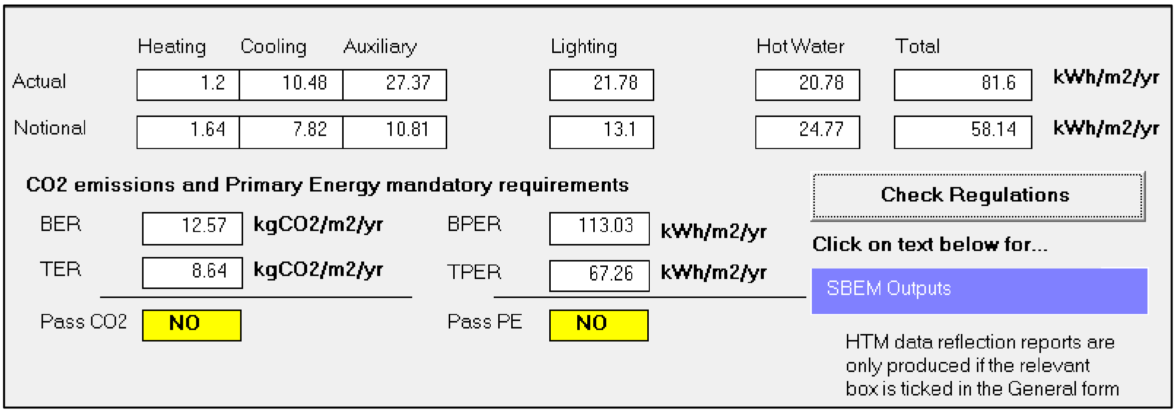

Figure 4.2. The results of the SBEM software, showing the energy consumption and carbon emissions.

The heating, cooling, auxiliary, lighting, and hot water energy consumptions are calculated with the building emission rate (BER) and the target emission rate (TER). This software must be used by the UK government but a demo can be downloaded to show how it works, which is what has been done here.

Unfortunately, the assessment is based on a standardised assumption of what the occupant behaviour is like, whereas the occupant behaviour clearly has great effect on the energy behaviour of building's [178, 179]. It also doesn't provide enough information for the application of an effective BMS into the building. The target energy efficiency for each building is different due to the operation and building variables but the target currently doesn't require the building to generate 100% of its energy consumption. This target must change to cater towards government plans for carbon neutrality [5].

The more novel machine learning energy consumption forecasting does not need the same inputs as the previously used SBEM software such as the address, and physical parameters, but instead needs data that has a relationship with the energy consumption. This data depends on the buildings functions and BMS management, but generally includes occupancy, local climate variables, and energy consumption. Other inputs may be added to increase the information gain further but can make the MLA more complex without adding value. Instead of simulating a model of the building and calculating air flow and through the software, the MLA strictly calculates patterns from the input data to the target data. MLA vary through the methods used, but they are all purposed towards calculating the relationships between datasets.

4.3 Data Collection and Processing

The collected data contains overall demand (kW), lighting demand (kW), HVAC demand (kW), kitchen demand (kW), outdoor temperature (^oC), rainfall (mm), cloud cover (%), outdoor air pressure (mb), and time of day. All data is collected in 15-minute resolutions so can be aggregated to form any large resolution (15-minutes to hourly, etc.). The data is collected from 03/09/2015 at 10:45 up to 31/12/2019 at 23:45, giving 36,935 samples and 332,415 datapoints in the set. It is collected through a total of 102 energy meters for lighting, power, risers, ventilation, and chillers for the kitchen, separated into blocks A, B, and C. Sensors are installed in each room to measure the CO_2 density. The lighting, power, risers, and ventilation are also aggregated from another energy meter to show the building use as a whole. The data is stored on an online database, which can be downloaded at any time through a CSV file onto excel and is extracted directly to the processing algorithm.

The collected data often contains incorrect values due to faults in the energy meters or in the storage database. Missing and outlying data points are included in the dataset which will negatively affect the performance of the algorithms. To eliminate this data, two algorithms are used. Firstly, any missing data points are addressed. In the original dataset there are 332,406 datapoints and an additional 112,959 missing datapoints. 110,688 of these are all missing in one section, meaning there are no energy readings at all and therefore there is no data to train, so these are removed from the set. The remaining 2,271 points are scattered across the dataset, meaning there is data for other building features at the same reading time as the missing data, so this data is useable if it can be corrected.

To do this, a moving mean is calculated, and the missing values are substituted with the mean of a selected number of surrounding values. This is chosen to be 5,000 in the 15-minute resolution dataset as this equates to about two months which allows the method to work if a month of data is missing. One month is the maximum amount of missing data after the 110,688 are removed. Linear interpolation is used for outliers that account for less than 2% of the dataset. Various methods of interpolation include linear, piecewise, shape preserving piecewise, Spline, Pchip, and modified Akima cubic Hermite. The difference between them being that linear interpolation plots a linear relationship between the points and piecewise plots a sine curve that often adds more curve than the actual data contains. Shape preserving piecewise plots often don't follow curves in peaks and troughs of the data. Makima is the most suitable algorithm for maintaining flow between empty data as it calculates weights to affect the rate at which the value changes and therefore how steep the curve is. This ensures the curve is flattened towards a local extreme, whereas other methods have a curve that is either too broad or too sharp, not representing the real data. The Makima interpolation is explained through Eq. 4.1

$$d_i = \frac{W_1}{W_1+W_2}\partial_i - 1 + \frac{W_2}{W_1+W_2}\partial_i \qquad \text{Eq. 4.1}$$

Where 'd_i' is the derivative and 'W_1' and 'W_2' are the calculated weights at the sample point, and '∂_i' is the slope of the line. Weight 1 and weight 2 are calculated through Equations 4.2 and 4.3 respectively.

$$W_1 = |\partial_{i+1} - \partial_i| + \frac{|\partial_{i+1}-\partial_i|}{2} \qquad \text{Eq. 4.2}$$

$$W_2 = |\partial_{i-1} - \partial_{i-2}| + \frac{|\partial_{i-1}-\partial_{i-2}|}{2} \qquad \text{Eq. 4.3}$$

The Makima algorithm produces fewer undulations compared to the Spline interpolation algorithm, allowing quick changes between flat regions with sharper curves. Although it is more aggressive than the Spline algorithm, it is less aggressive than the Pchip, meaning the curves are not flattened as aggressively and therefore the curve of the line is retained [180-182].

The problem with this though is that the actual data is volatile and often doesn't curve at a peak. The algorithm that best suits the given data is linear interpolation due to its simplicity and ability to follow peaks and troughs without adding a curve.

Methods of linear interpolation aren't used for missing values because the data often has large variance between two points, meaning it doesn't follow a straight line and has many peaks and troughs between the points which cannot be followed. Using a calculated average results in the data not having great effect on the output of the model while still being able to use the correct datapoints of other features within the set. Due to there being enough collected data, incorrect data can be removed, and the algorithm still has enough data to train for an accurate result. If there was not enough collected data for accurate forecasting, then linear interpolation is able to fill in missing data to a degree that benefits the algorithm more than having no training data at all. Linear interpolation 'y' can be explained by Equation 4.4.

$$y = y_1 + \left(\frac{(x - x_1)}{(x_2 - x_1) \times (y_2 - y_1)}\right) \quad \text{Eq. 4.4.}$$

Where 'y_1' and 'x_1' is the previous values of the input and the target, 'y_2' and 'x_2' is the next value of the input and the target, and 'x' is the input on the same iteration of the unknown variable 'y'.

To eliminate the 110,688 missing features, an algorithm is developed to find any data point within the features that don't contain any values between the specified points. The processed data can be exported to excel or can be directly used for the MLA. Historical overall electricity demand is fed into the processing algorithm in Figures 4.3, 4.4, and 4.5.

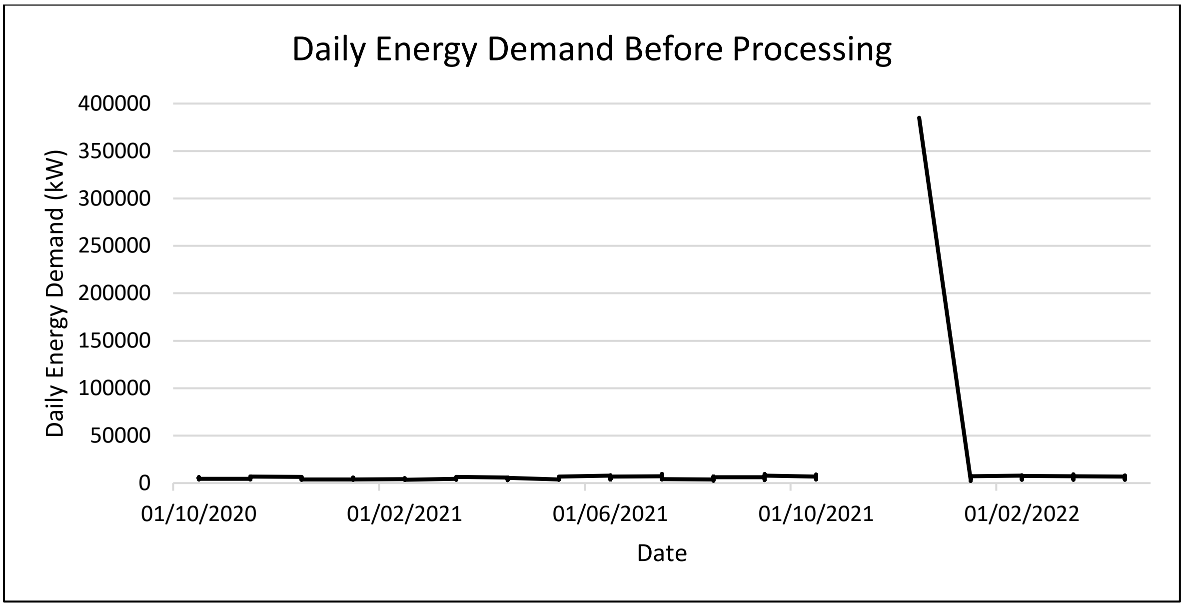

Figure 4.3. The Daily energy demand data collected from the smart meter before processing.

The average energy demand without the missing data and the peak is 5,731kW but because the peak is so high, the data is difficult to comprehend. This peak is due to a fault in the smart meter. When the smart meters malfunction, they don't give any reading and once they are reset, the readings are aggregated into a large sum of the missing datapoints. This fault is corrected in Figure 4.4.

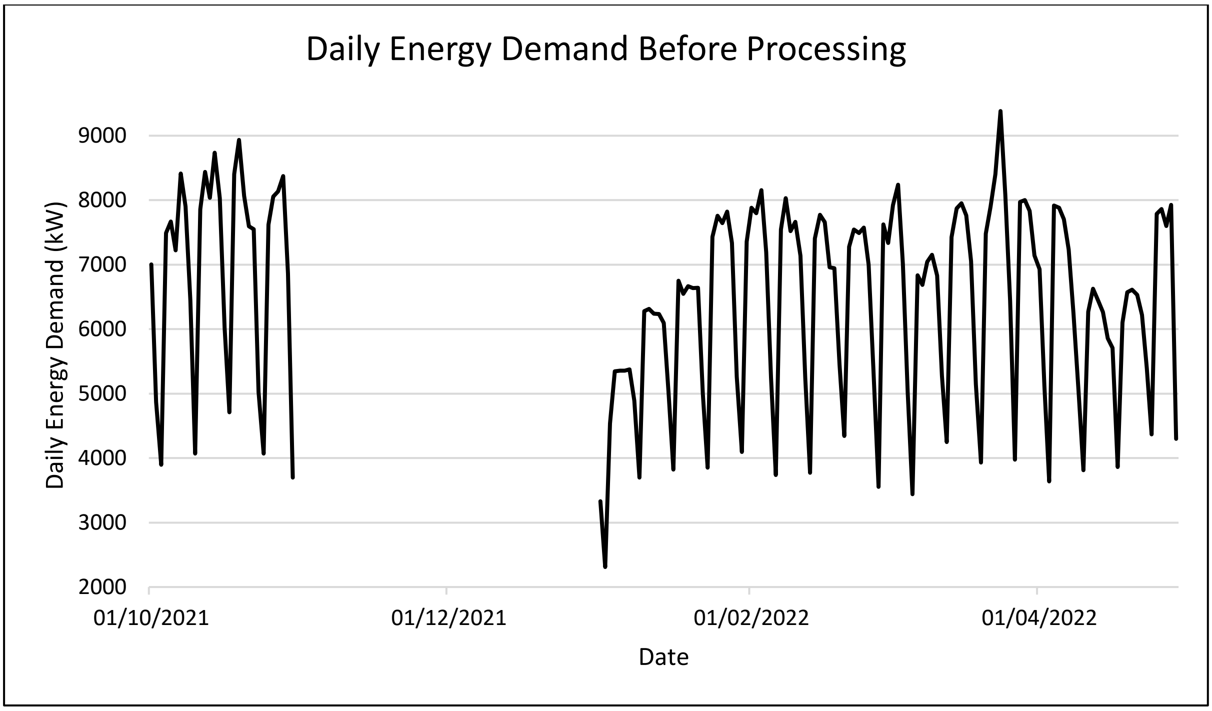

Figure 4.4. Daily energy demand before processing, after the peak is removed.

The peak is removed manually to maximise the quality of the training data. This can be done automatically through removing a set amount of outlying data such as the lowest 20% and highest 80%.

After the peak is removed, the raw data shows a large gap and multiple peaks and troughs throughout the dataset. This is removed through the next step of the processing algorithm in Figure 4.5.

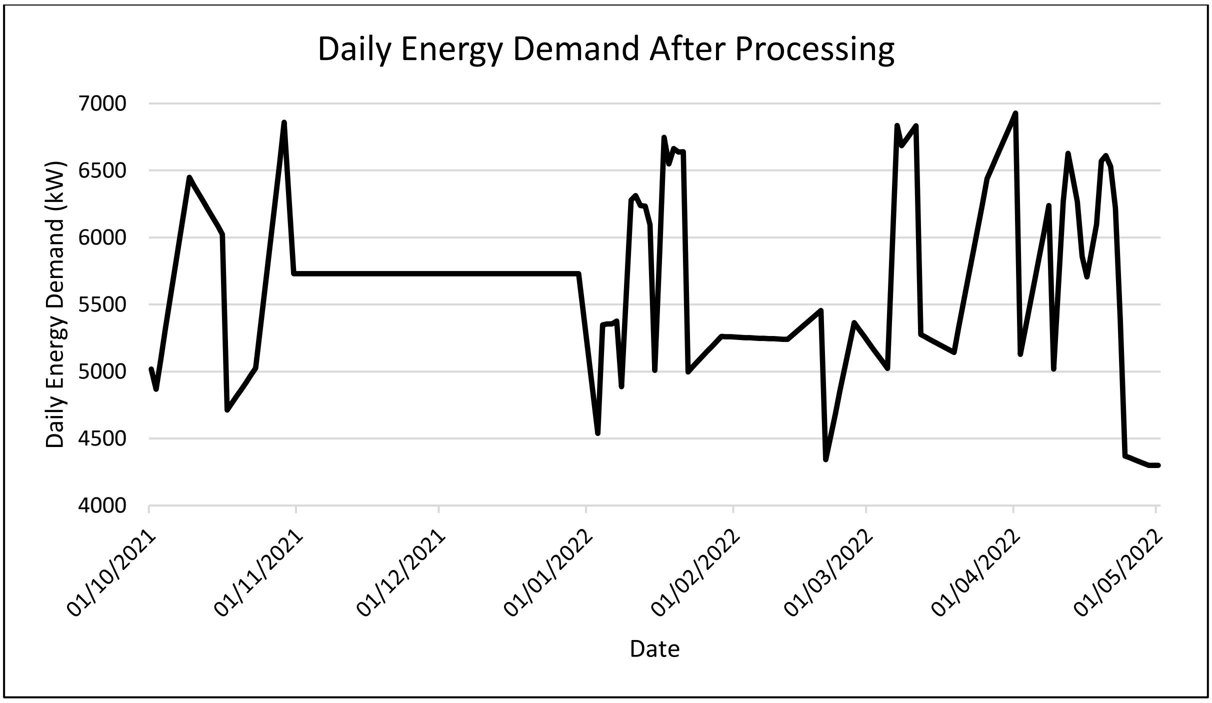

Figure 4.5. Daily energy demand data collected from the smart meter after processing.

Firstly, the malfunction with the sensors are addressed by removing the large peak, then the gap in the data is filled with linear interpolation. After the first two steps, the missing data is replaced by a rolling average of the dataset. This reduces the effect that the data has on the training of the algorithms. Outliers are filled with linear interpolation when they reside outside 20%-80% of the dataset.

Typically, throughout the many years of collected data, there isn't more than six months where there is collected data without any incorrect data points. Once the data is processed and there are no missing or outlying data points, it can be used to train the MLA's. This dataset is split into 80% for the training of the MLA and 20% for the testing of the forecast so the MLA can be validated against data it has not yet seen.

4.4 Machine Learning Application Forecasting and Accuracy Validation

The developed algorithms for energy characteristic forecasting include decision trees (DT), random forest (RF), neural networks (NN), linear regression (LR), and support vector machines (SVM). Figure 4.6 shows the method from data collection to feature forecasting and algorithm evaluation.

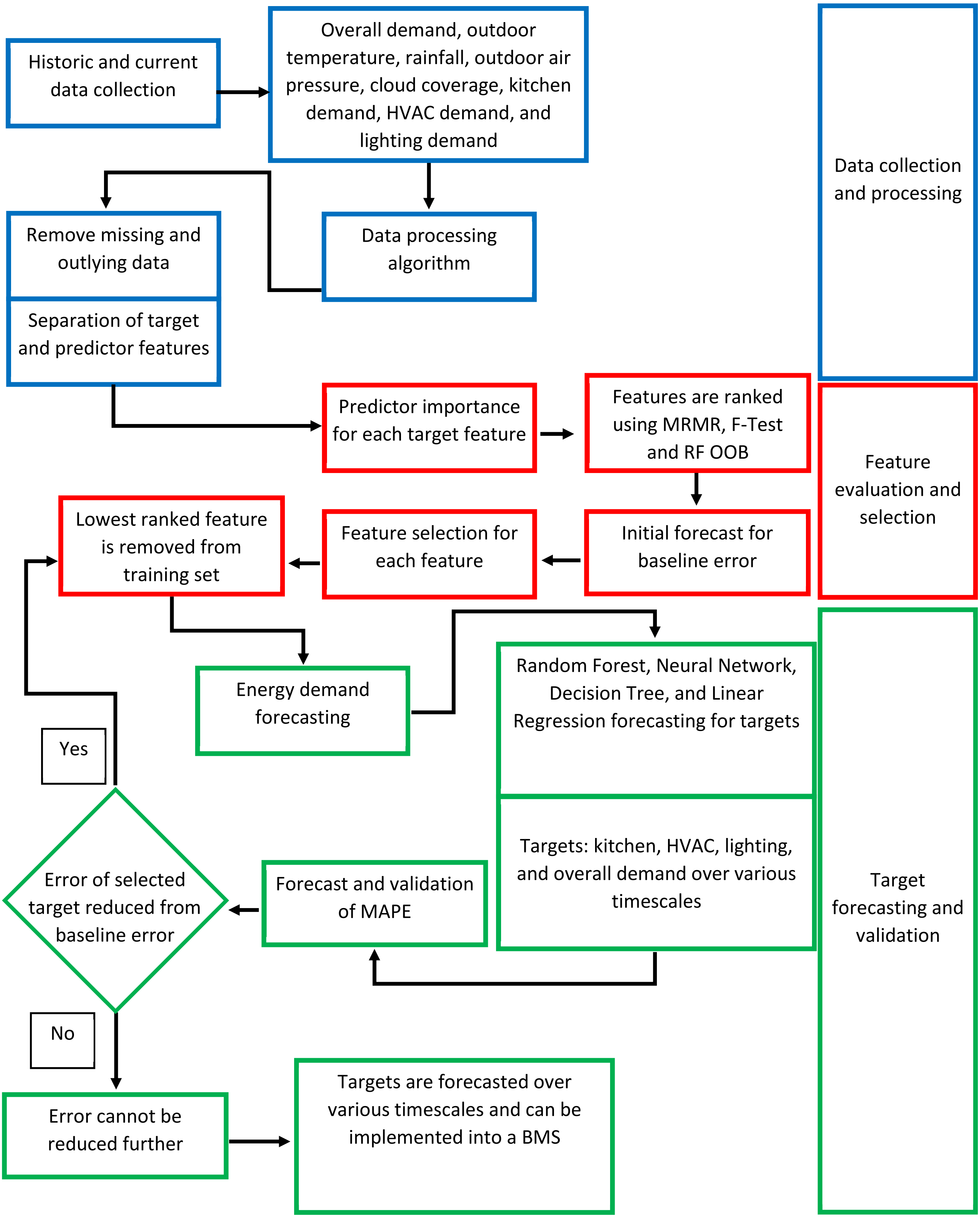
Historic and current data collection
Overall demand, outdoor temperature, rainfall, outdoor air pressure, cloud coverage, kitchen demand, HVAC demand, and lighting demand
Remove missing and outlying data
Data processing algorithm
Separation of target and predictor features
Data collection and processing
Predictor importance for each target feature
Features are ranked using MRMR, F-Test and RF OOB
Feature evaluation and selection
Lowest ranked feature is removed from training set
Feature selection for each feature
Initial forecast for baseline error
Energy demand forecasting
Random Forest, Neural Network, Decision Tree, and Linear Regression forecasting for targets
Yes
Targets: kitchen, HVAC, lighting, and overall demand over various timescales
Error of selected target reduced from baseline error
Forecast and validation of MAPE
Target forecasting and validation
No
Error cannot be reduced further
Targets are forecasted over various timescales and can be implemented into a BMS

Figure 4.6. The method of data collection and processing, feature evaluation and selection, and target forecasting and validation.

The methods used for characteristic forecasting vary as each algorithm provides different accuracies and have varied training times and dataset size requirements. Each MLA is personalised depending on available inputs and the desired forecasted output. This gives includes various methods and fine-tuning within those methods. As the BMS is designed to optimise every autonomous tool the building has equipped, for accurate results, each tool can have a different MLA with different inputs and predicted output. To validate the forecasted results, they are compared against collected energy readings from the building.

The performance of the algorithms is measured in mean actual percentage error (MAPE) which is explained below in Equation 4.5.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad \text{Eq. 4.5.}$$

Where 'n' is the number of iterations, 'A_t' is the actual value, and 'F_t' is the forecasted value. This method of validation is chosen because it gives a result that isn't affected by the type of data being forecasted because it is proportional. The overall demand is greater than the lighting demand so the lighting demand could have a high MAPE, but a lower root mean squared error (RMSE) which is a different method of validation.

The NN is most commonly the most complex algorithm requiring more computational power, but with the capacity to calculate more complex relationships between variables than other MLA. This means that it can have the highest accuracy but risks overfitting which must be considered. In the case of a building, if the energy consumption changes are volatile, but the collected data does not have a very high relationship with the energy consumption, then the NN would be the most suitable choice as it can calculate the relationships to a higher degree. It is a suitable choice to calculate the relationship between the energy consumption and the variety of input data such as the local climate and the occupancy of the building due to there being high-dimensional non-linear data.

The DT can be used for shallow data, in which one dataset is almost entirely reliant on another dataset. It is not prone to overfitting and would be suitable for the relationship such as between the lighting demand and the occupancy of a single room with light-dependant resistor lighting. This is because the lighting would be entirely reliant on the occupancy of the room to operate.

The RF is one step up from the DT as it is an accumulation of multiple DT’s. Instead of a single DT which can calculate the relationship between shallow data, the RF can aggregate the results of multiple DT’s allowing more splitting of input data with respect to the target data, and therefore a higher accuracy. Due to the capability of the RF to split small datasets up recursively, it can sometimes have higher forecasting accuracy than a NN as it can essentially generate multiple datasets from a single dataset. It is useful for if a building only a month of has collected data, but an accurate forecast is needed for the energy parameters.

The LR calculates the average relationship between an input and an output. In the LR developed in this work, it calculates the relationships between each input and the target, and then aggregates the calculated relationships. It ensures there is a little overfitting, and it can handle large datasets better than other MLA due to the simplicity of the method. It can be useful for forecasting any target data that has a high relationship with the input data, but it is also useful as a benchmark MLA to compare other methods to. For example, if the NN had an accuracy of 90% but the LR has an accuracy of 80%, then the NN is not calculating the relationship to a high enough degree, or vice versa.

The models are trained, validated, and tested with the same original dataset before the MRMR algorithm. They are validated against real data collected from the MMU Business School’s energy meters to determine the accuracy of the algorithms. They are evaluated for training and forecasting speed, required computational power, and accuracy.

4.5 The Application of developed Machine Learning Forecasting to Optimise On-Site Electric Vehicles

The use of energy consumption forecasting has importance for varied methods such as energy trading, energy storage, and a method of utilising the energy capacity from EV’s. The data described in chapter four is used to develop a MLA that can optimise the energy management of the on-site EV’s.

4.5.1. Methodology

As buildings reduce their carbon emissions, naturally, renewable energy systems are installed due to them supporting energy requirements while not increasing generated carbon. The major problem with these systems is that they generate power intermittently, depending completely on the weather conditions. This can result in more energy being drawn from the grid than previously anticipated such as if it is a cloudy day and the building is relying on solar PV generation.

The decrease of carbon emissions is not only prevalent in buildings, but in the transport sector too. The increasing popularity of EV's can be utilised for the benefit of the building that the owner is using. As EV's are charged in the building, they are often left on charge all day, until the owner has finished in the building, and in the case of the Business School, the staff are there 8am-5pm. This means that the EV's are connected to the building all day even though they can be fully charged within a few hours, depending on the initial charge. The proposed methodology of utilising the battery of the EV's is shown in Figure 4.7.

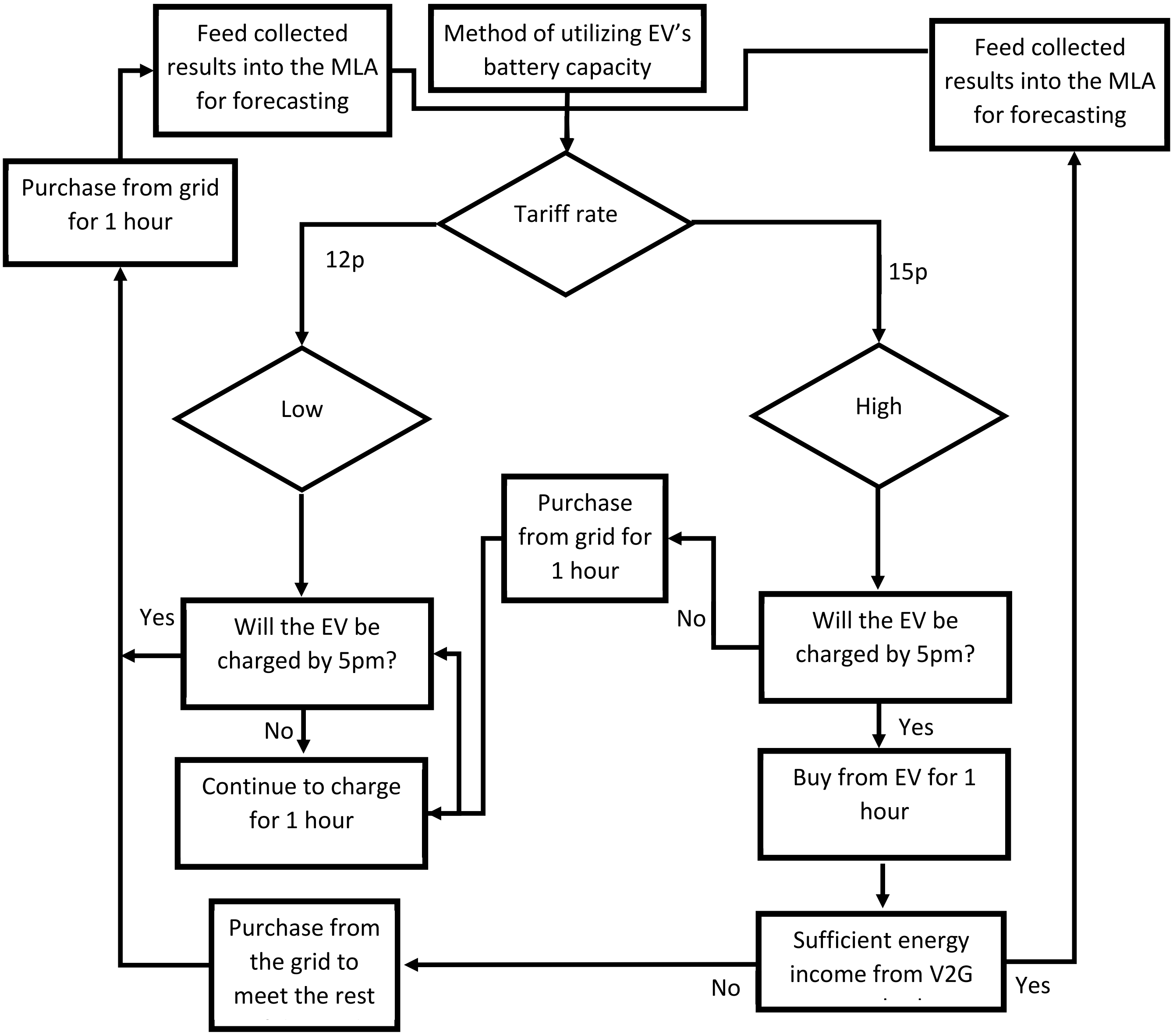

Figure 4.7. The method of utilising the EV's battery to alleviate peak time energy demand.

The method is split into hourly actuations, where the tariff rate is determined by how much the energy costs within the selected hour. It is assumed that the EV owners are arriving and leaving at 8am and 5pm respectively, and the EV's are fully charged by 5pm. If the tariff rate is high, the energy from the EV's can be used to supply the building for an hour. If the tariff rate is low, the EV's are charged for an hour. If the EV doesn't have enough charge that it will be full by 5pm, then the rest of the demand is purchased from the grid. To forecast the cost of energy for the EV owner's and the building, a NN is developed.

The major attraction from this method is the profit 'P' for both the building and the EV owners. This is calculated through Equation 4.6.

$$P = M - I \qquad \text{Eq. 4.6.}$$

Where 'M' and 'I' are generated income and installation costs. This is used to determine the ROI for the system by plotting generated income through time until the profit is no longer a loss.

4.5.2. Required Capacity and Battery Degradation

The energy consumption of the Business School on a selected day was 8256kW. The amps per hour 'Ah' and number of batteries 'Nb' can be calculated through Equations 4.10, and 4.11 respectively.

The number of batteries with a given size can be used to determine the capacity of 10 EV charging stations 'SC' connected to the Business School through Equation 4.7.

$$SC = C_r \times N_c \times N_h = 6.66 \times 10 \times 12 = 799kW/day \qquad \text{Eq. 4.7.}$$

Where the charging rate, number of charging stations, and number of hours they are required for are 'C_r', 'N_c', and 'N_h' respectively.

$$Ah = \frac{w}{t} = \frac{799.2kW}{12} = 66.6kA \qquad \text{Eq. 4.8.}$$

Where 'w' and 't' are Watts and the amount of time the batteries are filled for.

$$Nb = \frac{Ah}{C} = \frac{66.6kA}{4560A/h} = 14.6 = 15\ batteries \qquad \text{Eq. 4.9.}$$

Where 'C' is the battery capacity.

The price for this is estimated as £27,432.90 for 15 batteries, where the price of a battery can be affected by various factors including capacity, size, and the supplier. Two main methods are developed which either use the EV's energy at peak times or at all times of the day.

A pivotal observation in the research is the effect that charging/discharging has on the EV's battery degradation. Each time the battery is charged/discharged, the EV's battery degrades and the range of driving the car has from a full charge is reduced. Eventually, the battery must be replaced to maintain practicality for the owner. The number of full charges 'NF_c' and the standard capacity 'S_c' is calculated through Equations 4.10 and 4.11.

$$NF_c = \frac{DL}{DF_c} = \frac{152,000}{73} = 2,082 \qquad \text{Eq. 4.10.}$$

Where 'DL' and 'DF_c' are the distance travelled before 20% battery capacity loss, and the distance from a full charge, in miles. Assuming the EV is plugged in at 80% at 08:00 and is un-plugged at 100% at 17:00, the battery discharges by 25.3 kW/day, and charges 33.3 kW/day. The battery is discharged 63.25% per day. The standard capacity over 20 years is shown in Equation 4.11.

$$S_c = NF_c \times F_c = 2,082 \times 40kW = 83,280kW \qquad \text{Eq. 4.11.}$$

Where 'F_c' is the battery capacity when fully charged.

Due to the proposed method, a standard EV will be charged by an extra 52,674.6kW over 20 years. At a rate of being charged by 16,656kW/year, the battery capacity is reduced to 80% in 20 years. This equates to a battery capacity loss of 4.16%/year. The battery lifespan is calculated in Equation 4.12.

$$\frac{20Y}{4.16\%} = 4.81Y \qquad \text{Eq. 4.12.}$$

Where '$20Y$' and '4.16%' are the 20 years of operation and the battery capacity loss per year. When the EV is used in the proposed method, the battery is reduced to 80% of the total capacity in 20 years. For a battery with a cost of £4,265 every 4.81 years, the EV owner must make £0.825/hour from the Business School purchasing the energy from the EV.

A simulated day of charging and discharging, assuming the EV is plugged in at 80% at 8am and unplugged at 100% at 5pm, is described in Figure 4.8.

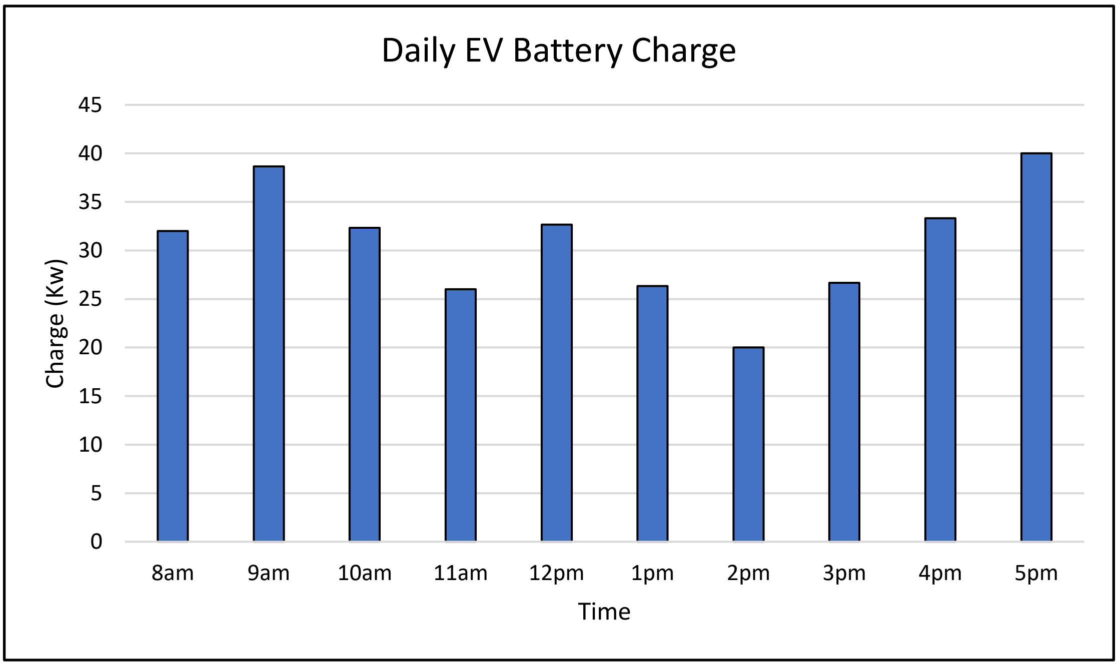

Figure 4.8. The times of peak and off peak while the battery is being charged or discharged.

The proposed method charges the battery as much as possible throughout off-peak times through Equation 4.13.

$$D_c = O_c + C_r - F_c = 32kW + 33.3kW - 40kW = 25.3kW \qquad \text{Eq. 4.13.}$$

Where 'D_c' is discharge/day, 'O_c' is original charge before the EV is plugged in, 'C_r' is how much the EV is charged during a cycle, and 'F_c' is the EV's capacity at full charge. This method allows the EV to be discharged as much as possible at peak times while still being fully charged by the end of the day.

4.5.3 Campus Profits

Using a 6.66kWh charger to while still charging the car to 100% is shown in Figure 4.12. As an incentive, the EV owner could earn £0.79/day from the campus. The campus takes a financial loss from this, but it would not have to pay for large battery installation for the energy storage. In the case of 10 charging stations, the approximate loss becomes £7.99/day for the Business School. Overall, if the campus installed ten 6.66kWh EV charging stations instead of purchasing a lithium-ion battery to match the required capacity of the charging stations, the university would save £79,856.29 every 10 years. The assumption is that the batteries have to be replaced every 2 years and the charging stations every 10 years.

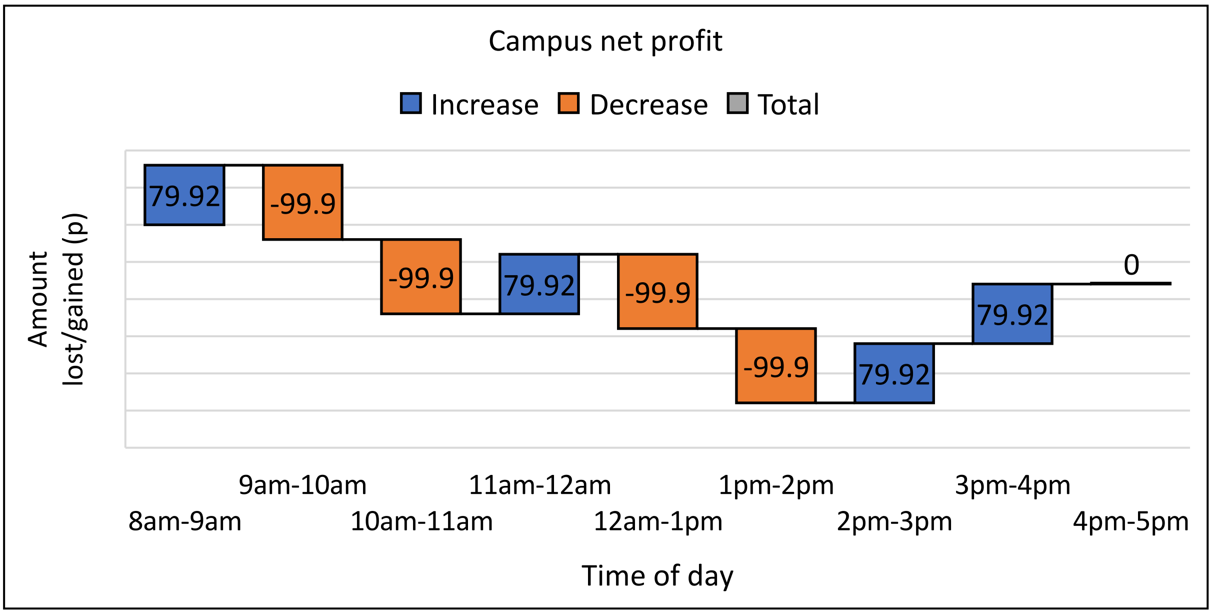

Figure 4.9. The Business Schools' net profit when while paying off peak prices throughout the day and purchasing energy from the EV's in peak times.

The campus must pay the EV owner £268.52/year and will save £1,749.45/year when only using energy from the EV's at peak times and charging them at off peak times. The benefit of this method is dependent on the energy demand of the building and the number of EV chargers available at a single time. If the battery storage is only for peak times, it would only need to have a capacity of 1916 kW over 4 h, which is equivalent to 72 charging stations. A 10-year simulation on the cost analysis and ROI of installing EV chargers on campus with storage equivalent of peak times of the day showing V2G storage is significantly less costly in Figure 4.10.

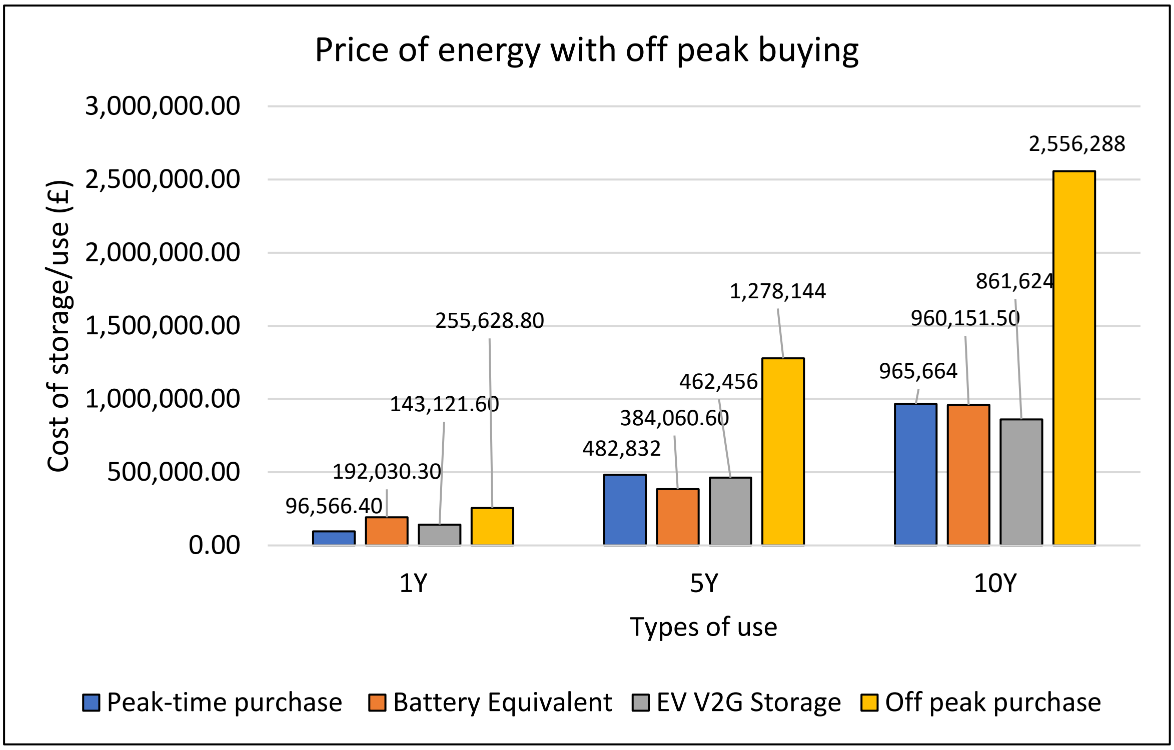

Figure 4.10. A 10-year simulation on the energy price when the simulation is used at peak times.

To show the benefits of the V2G method against a method where all of the energy is bought at off peak times, the simulation of Figure 4.13. is achieved. Installation of EV chargers are considered when evaluating the results. The V2G system shows a saving of £1,694,664 compared to purchasing the energy at off peak prices.

4.5.4 Machine Learning Forecasting of Energy Demand and V2G Cost

While most research and applications of machine learning and computational intelligence techniques relate to the energy consumption and price of electricity, the use of such technologies for enhancing future prediction is yet to be realised and demonstrated. A NN has been employed to predict the future energy demand and the future V2G cost for the years 2018 and 2019. The predictions for energy demand on each month in a year have been presented in Figure 4.11.

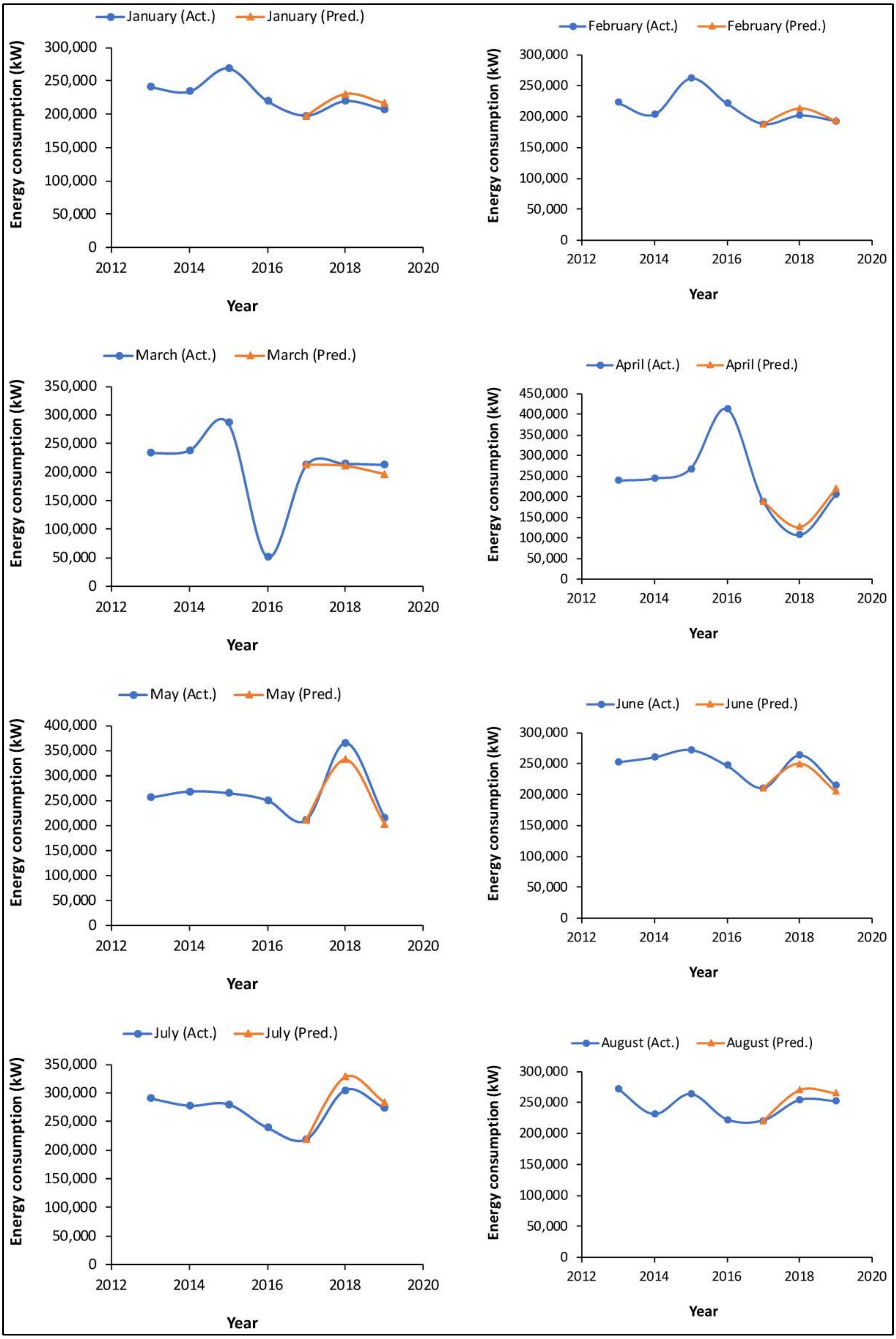

Figure 4.11. Monthly energy consumption forecast for the years 2018 and 2019.

In this case, higher variations of the energy consumption result in less accurate forecasts such as in May, June, July, and August. More complex algorithms with more data or data with more importance to the target can produce more accurate results when the data becomes more volatile. The accurate forecasting of the energy consumption of the building is necessary to the effectiveness of the V2G system with the charging rate and number of EV chargers. A larger energy consumption will benefit more from higher capacity and volume of EV chargers.

The price of electricity MLA error in MAPE over the years of 2018 and 2019 is displayed in Figure 4.12.

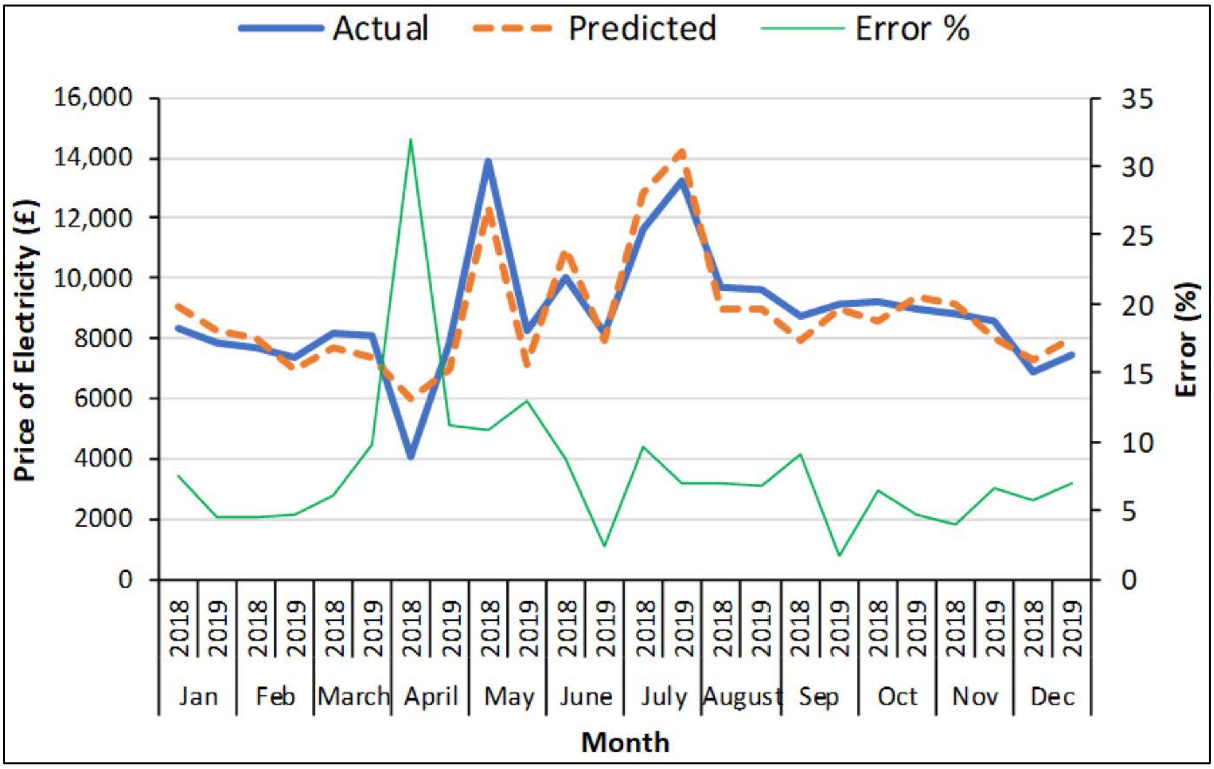

Figure 4.12. The NN forecasting errors of the price of electricity for the years of 2018 and 2019.

The NN has been trained with the years prior to 2018 to determine the years of 2018 and 2019. The largest error percentage was 32% in April 2018. The month with the lowest error was in September 2019 at 1.74%. The average error in prediction is 7.94% over 2018 and 2019. April is more varied through the years than the other months. It ranges from £15,662 to £4081 for the use of the V2G method between 2016 and 2019. This is a difference of £11,581. September is less varied. It ranges from £5711 to £9105. This is a difference of £3393. The average error across all months is 7.9%. The more varied the data is, the more data is necessary for an accurate prediction. Between 2017 and 2019, April's calculated V2G cost varied by £6822, whereas between 2017 and 2019, it varied by £5823. The cost of the V2G method is directly linked to energy consumption.

As conventional methods of energy characteristic forecast in previous research are unable to provide accurate forecasts, novel methods are developed. MLA's are developed to forecast the buildings' energy characteristics. The processes from data collection and processing, algorithm development, and validation are established. An application for MLA's forecasting is developed to save costs for the Business School through utilising the energy capacity of the EV's plugged into the ports at the building.

Due to the Business Schools' large peak time energy demand, 72 charging stations and EV's are required. For buildings with less or no parking, this can be a difficult method to implement. The buildings' features can be improved through changing the lighting from halogen to LED's or through changing the heating from convection heating to infrared. These methods decrease the buildings' energy demand by consuming less energy but still produce the same outputs (same illuminance and thermal output). By decreasing the energy consumption of the building, the developed V2G method doesn't need as many EV's, and thus, less car parking space, allowing a building with less space to still use the method.

4.6 Summary

Conventional and modern energy forecasting methods are compared and critically analysed to determine which methods are most viable. As the MLA's require historical data to train, the collected data is processed through an algorithm to remove any incorrect data. Each method of MLA forecasting is then explored, showing how they work. A NN is then developed to forecast the energy consumption of the Business School for the V2G method.

By exploring modern methods of energy characteristic forecasting, MLA's have the highest capability. The application of MLA's in chapter 4 aid in developing a generalised method of reducing peak-time energy demand for the Business School, with the capability to be applied to any non-domestic and domestic building alike. The management of the energy demand can be improved through methods explained in chapter 4, although the reduction of the energy demand also aids in the reduction of carbon emissions. This can be done through methods such as more efficient heating, cooling, ventilation, and lighting.

The monthly energy consumption forecasting is achieved in this chapter through MLA methods. Although this can be used to aid in calculating the energy price in this chapter, more finite data and complex MLA must be developed as in chapters 5 and 6 to provide more accurate forecasts for the energy parameters of a non-domestic building.

MLA's are developed to forecast the occupancy of a lecture hall to aid in the heating of the space. This is applied to an infrared heating system to reduce energy demands while producing the same comfort levels for chapter 5.

CHAPTER FIVE: OPTIMISATION OF PUBLIC BUILDINGS' HEATING SYSTEMS THROUGH MACHINE LEARNING OCCUPATION DENSITY FORECASTING

This chapter introduces methods of heating for a building. Fuel sources, generation methodologies and distribution techniques are analysed for the purpose of improving the energy efficiency of public buildings. A novel method of combining CO_2 – based occupancy forecasting and infrared heating to provide heat for a building is proposed to reduce energy consumption. The application of infrared heating to a lecture hall in the Business School can improve heating efficiency compared to conventional techniques. This is further improved through validated occupation density forecasting and a novel method of occupation location within the lecture hall. Both methods are forecasted through ML methods to provide forecasts on which areas within the room are occupied.

5.1. Introduction

Carbon emissions of heating systems are dependent on the fuel source, efficiency, and heating methods. Changing the fuel sources increases energy efficiency through powering the systems through electricity generated through renewable sources. The efficiency of systems varies greatly as the methods used to produce the heat from the fuel sources vary. The main type of heating includes convection heating, where the energy is used to heat the air within the building. Previous heating methods are still producing carbon emissions, accounting for almost 25% of all UK carbon emissions [183]. The UK governments' legislation targets for complete carbon neutrality from buildings by 2050, meaning all systems, including heating, must operate without producing any carbon emissions. This can be achieved by both:

- Reducing the energy consumption of the heating systems through both occupation dependent heating and through more efficient heating methods.
- Transitioning heating systems to electricity or biomass based instead of the conventional natural gas or wood.

As heating systems make the transition from natural gas to electricity-based methods, more efficient heating methods and fuel types must be developed to meet the UK governments' regulations on carbon emission reduction.

The aim of this chapter is to analyse previous methods of heating and how these can be improved for the reduction of carbon emissions. A general background of heating and a more novel method is proposed.

The application of currently available FIR heating techniques to a public building: the Business School, is achieved. A lecture hall is equipped with FIR panels to reduce the energy consumption of the heating system while forecasting the occupation density through MLA methods.

5.2. Infrared Heating Application Methodology

Current methods of heating include convection wall-mounted radiators, baseboards, underfloor heating, ground, and air-source-heat-pumps. Although each method can have benefits for various functions, they all use convection heating. As is analysed in this chapter, the convection heating method can have reduced efficiency compared to newer heating methods due to the way that heat is transferred throughout the air and materials in the room. This results in energy losses that can be avoided.

A heating method that already exists commercially but is newer than other methods is infrared heating. Instead of passing the heat through the air to the desired target, infrared heat can target a zone, such as an occupant, wasting less thermal energy on heating the air, so the target can be directly heated. This can require less energy to achieve the same result.

The process of retrofitting a generic room is explained through Figure 5.1 below and a description of the case study zone and method is described in this section.

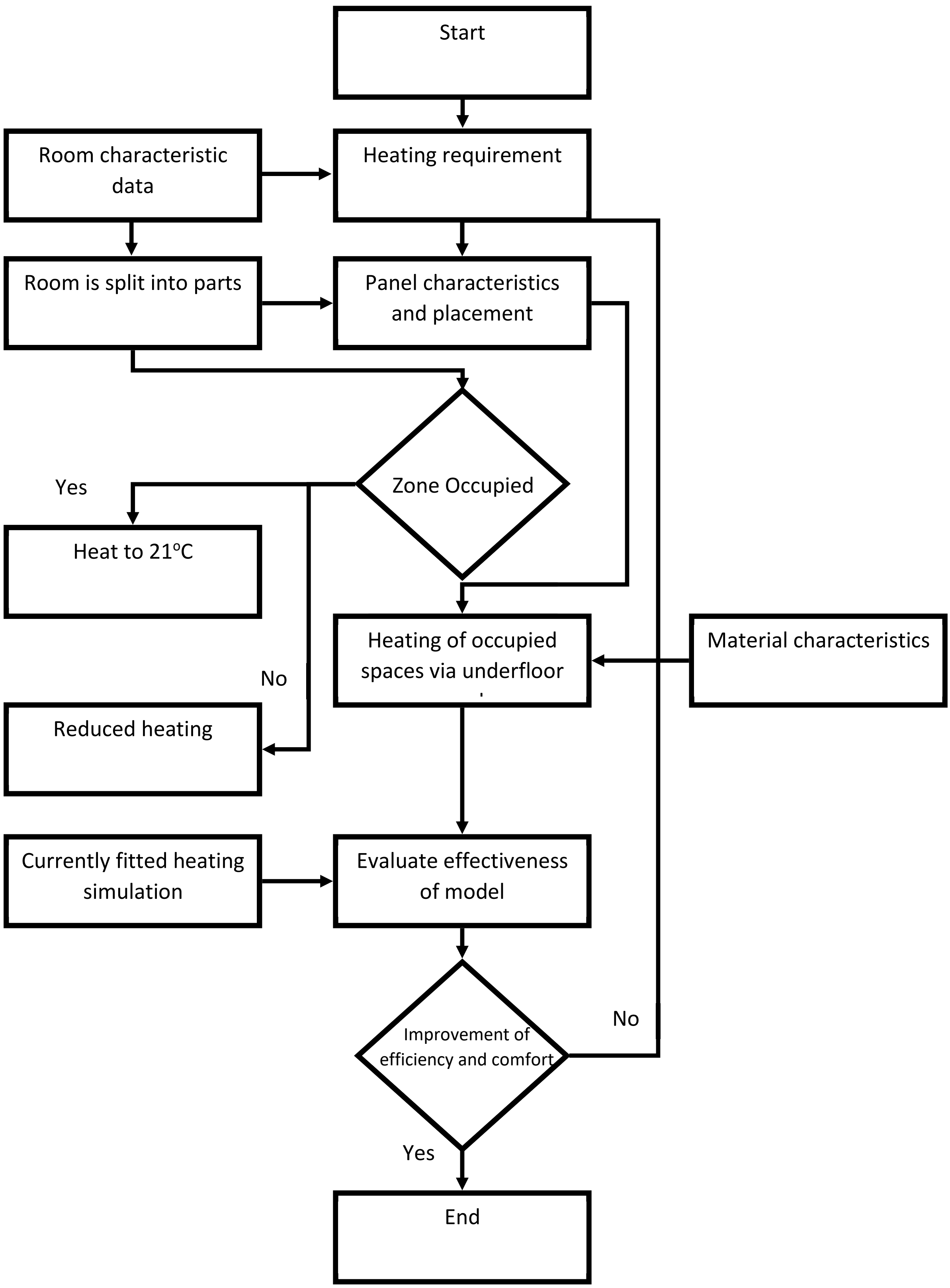

Figure 5.1. The process of retrofitting a generic room with FAR infrared heating.

Infrared heating can be applied to any space, where the IR panels are powered by mains electricity from the building. To determine how to optimise FIR panel applications details on the room and heating requirements must be considered. This is illustrated in Figure 5.1 above.

The case study building's lecture halls are all the same size, measuring 11m x 10.25m x 8.6m, with a maximum occupation of 118 people. The room characteristics are analysed such as the size and function. If only one zone of the room is usually occupied, the heating can be focussed in that zone and can often be disregarded in other zones of the room. The heating requirements of the room affect the required power output of the FIR panels, as does the placement. The panels shouldn't be facing a window or opening due to loss of heat. To eliminate any unnecessary heating, the developed system is dependent on the occupancy of the room. If the zone is occupied, the heating is activated, and if it is not, then the heating can be deactivated or reduced to a lower temperature. Material thermal characteristics have a large effect on the application of the FIR panels as materials that have a higher thermal conductance are easier to heat, but don't retain the heat well. Materials that have a lower thermal conductance require more heat to reach a desired temperature but retain that heat better. This allows the materials within the room to act as heaters themselves, once heated, as they radiate to the surrounding area. The novel FIR heating is compared to typical convection radiators, powered by gas or electric, to determine the advances in the novel heating system.

The FIR panels measure 60cm x 60cm and are designed to replicate a ceiling tile with a maximum rating of 350W and they can be installed with wireless communication to a thermostat. They are ceiling mounted and are targeting specific zones that are described in Figure 6.4. The wall mounted convection radiators are 1m x 2m with a maximum rating of 2kW. The room is split into 118 zones, with the capability of heating each zone and occupant independently.

5.2.1. Heating Power Requirements

All conventional heating methods, although they may vary in fuel sources and generation techniques, use convection heat for space heating. To determine this, Equation 5.1. can be used.

$$q = \alpha(t_s - t_f) \qquad \text{Eq. 5.1.}$$

Where 'q' is the heat exchanged, 't_s' and 't_f' are surface and fluid temperatures respectively, and 'α' is the convection coefficient [184]. Underfloor heating methods have the highest efficiencies due to the convection heat passing through more space, able to pass on more heat before it is lost through the buildings' envelope. Water and air can both be heated through electricity with the potential of being powered through 100% renewable sources, providing a carbon neutral heating system. This relies on the system not requiring more energy than can be gathered by renewable techniques. Infrared radiation though, can increase this efficiency further.

The average required power to heat an occupant is 712 W whereas to heat the epidermis it requires 0.0005 W/m^2.K [185]. The average surface area of an adult is 2.74 m^2 [186] so to heat the epidermis of an occupant from 0 °C to 21 °C the required direct energy output from the FIR panels is 0.02877W. It is assumed that each occupant is of the same dimensions and thermal conductivity, with nothing between them and the FIR panel to impede conductance, and direct FIR from the panel to the occupant. Tables and seats are made from wood with a thermal conductivity of 0.1664 W/m.K [187]. Infrared panels don't only provide direct heat, and instead evenly distribute the heat over 45° angles throughout the spectrum. Direct irradiance from the face of the panel 'DI' (W/m) and required power 'RP' (W/m) is explained below in Equations 5.2 and 5.3 respectively.

$$DI = \frac{P_{out}}{A_R} \qquad \text{Eq. 5.2.}$$

$$RP = K \times T \qquad \text{Eq. 5.3.}$$

Where 'P_{out}' is the output power of the panel, 'A_R' is the area of irradiance, 'K' is thermal conductivity of the occupant or material, and 'T' is the desired temperature of the occupant or material.

The rate of heat transfer over time can be expressed using Stefan Boltzmann's constant 'σ' in Equation 5.4.

$$Q = \varepsilon\sigma A(T_1^4 - T_2^4) \qquad \text{Eq. 5.4.}$$

Where 'Q' is the rate of heat transfer over time, 'ε' is emissivity of the receiving body, 'A' is the surface area of the receiving body (m^2), and 'T' is the emitting and receiving temperatures respectively.

5.2.2. Occupation Probability and Prediction

Rolling data of occupation is used to develop occupation prediction used for pre-heating. Previous data of occupation is analysed and added into the prediction to evaluate whether the heater will activate for pre-heating. Each zone has its own occupation prediction which is calculated using Equation 5.5.

$$PDT = \frac{\sum_{Zx1}^{Zxn} PDT}{PDTZxn} \qquad \text{Eq. 5.5.}$$

Where 'PDT' is the probability of occupation on a certain day at a certain time such as Monday at 9am. 'Z' is the unique occupation zone which is shown as 'x', 'x1' and 'xn' that show all of the collected data between the first and the last record. The Equation develops as more data is added where there are more points between 'x1' and 'xn'. For the case study, each room has a timetable when it will be occupied as lectures are held there. This method is useful only for when only occupation data is accessible but can accurately calculate the probability that a given zone within the room is occupied.

The occupation density can also be forecasted through ML techniques. Actual collected data included in the two occupation prediction simulations are rain (mm), wind (mph), temperature (°C)(K), time of day (15-minutes), cloud coverage (%), and indoor CO2 density (PPM). The developed NN algorithm is made from an input layer, two hidden layers, and an output layer, with a sigmoid symmetric transfer function. Inputs for training the algorithm are outdoor temperature, rain, cloud coverage, air pressure, time of the day and day of the week, with CO2 data used for targeting using only 10 days of data for training. The RF algorithm contains the same data set as the NN with 50 decision trees for feature selection and regression. New input data can be fed into the NN while it retains the same weights, bias, and functions, which allows it to make a prediction for the target. For the RF, when new data is added, the importance of each feature is saved from the training stage which allows an accurate output. Classification of input variables is part of pre-processing where each variable is replaced with random selections and the output error is measured. This eliminates correlation results and produces causation results instead, allowing any unwanted data to be removed from the training set. This is done through 50 decision trees too.

5.3. Simulation Specifications

To determine how to heat the room, it is split into occupation zones. In the case study lecture hall, the zoned areas are the student seating area which is in the middle of the room separated by the steps, the professor area which is the grid at the front, and the balcony area at the back of the hall which in this case acts as an overflow if there aren't enough seats. This is shown below in Figure 5.2.

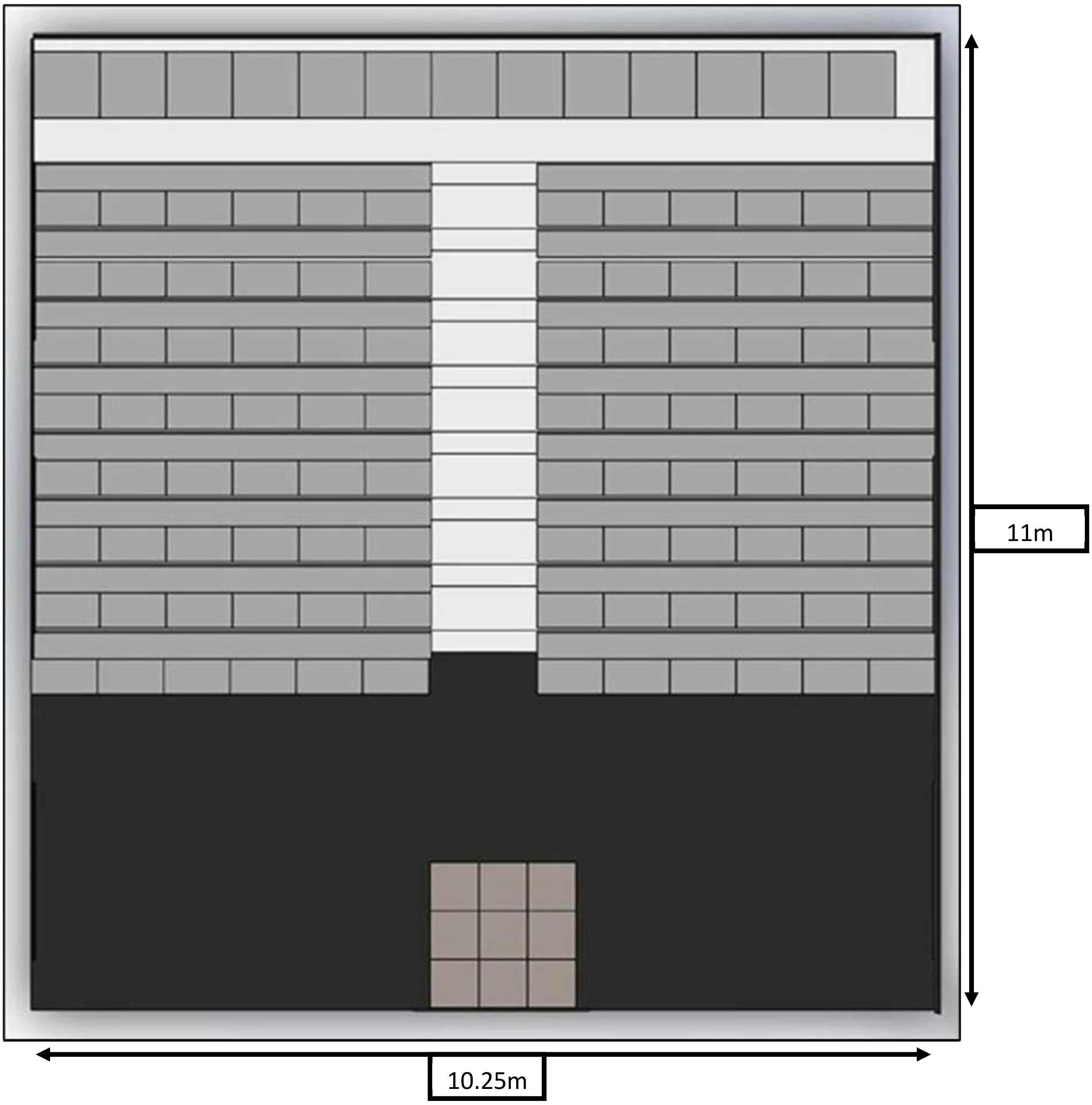

Figure 5.2. Division of the lecture hall into occupation zones.

Each zone is a different size and so are the panels for them can be too. Each heated zone for the 96-seat student area is 0.75 m wide by 0.4 m high, for the standing balcony area it is 0.75

m by 0.75 m, containing 13 zones, and for the professor zone they are 0.55 m by 0.55 m for 9 zones. The professor area could have one large panel but for a seating professor, smaller zones give more control. This allows for independent zones to be heated depending on occupancy. Each FIR heater is equipped with a smart thermostat allowing it to control the temperature depending on the occupancy or expected occupancy for pre-heating of the zones. The zones are independent from each other as they are occupied but to maximise energy efficiency in convection heating when there are multiple occupied zones that are connected, the zones have various energy requirements to maintain the same heat. This is determined by heating of the first zone to be occupied, and then the surrounding zones will be heated using less energy as they are occupied.

To simulate the occupiers of the room, two variations are implemented: standing and sitting. Both occupier types are cylinders with an emissivity of 0.98. The standing occupier has a height of 1.75 m, and the sitting occupier has a height of 1.55 m.

Table 5.1. The physical specifications of the simulation.

Object	**Specification (length x width x height)**
Wall-mounted convection radiator	$2m^2$ x $0.02m^2$ x $1m^2$
Infrared panel heater	$0.75m^2$ x $0.75m^2$ x $0.02m^2$
Professor heating zone	$1.65m^2$ x $1.65m^2$
Floor thickness	$0.01m^2$ concrete and $0.005m^2$ rubber
Wall thickness	$0.006m^2$ concrete and $0.01m^2$ fibre glass insulation
Ceiling thickness	$0.01m^2$ concrete and $0.005m^2$ rubber
Seating bench and desks	$4.5m^2$ x $1m^2$
Standing occupants	$1.75m^2$ x $0.5m^2$ x $0.5m^2$
Sitting occupants	$1.55m^2$ x $0.5m^2$ x $0.5m^2$
Air pressure	101,325 Pa
Humidity	55%

Table 5.2. The thermal specifications of the simulation.

Object	Material	Thermal Conductivity $W/(m2 \times K)$
Infrared and convection heaters	Aluminium	30
Floor, wall, and ceiling	Concrete	0.55
Wall	Fibreglass	0.045
Floor	Rubber	0.14
Occupants	Water	0.6

The composition of the wall and floor of the lecture hall are described through Figures 5.3 and 5.4 below.

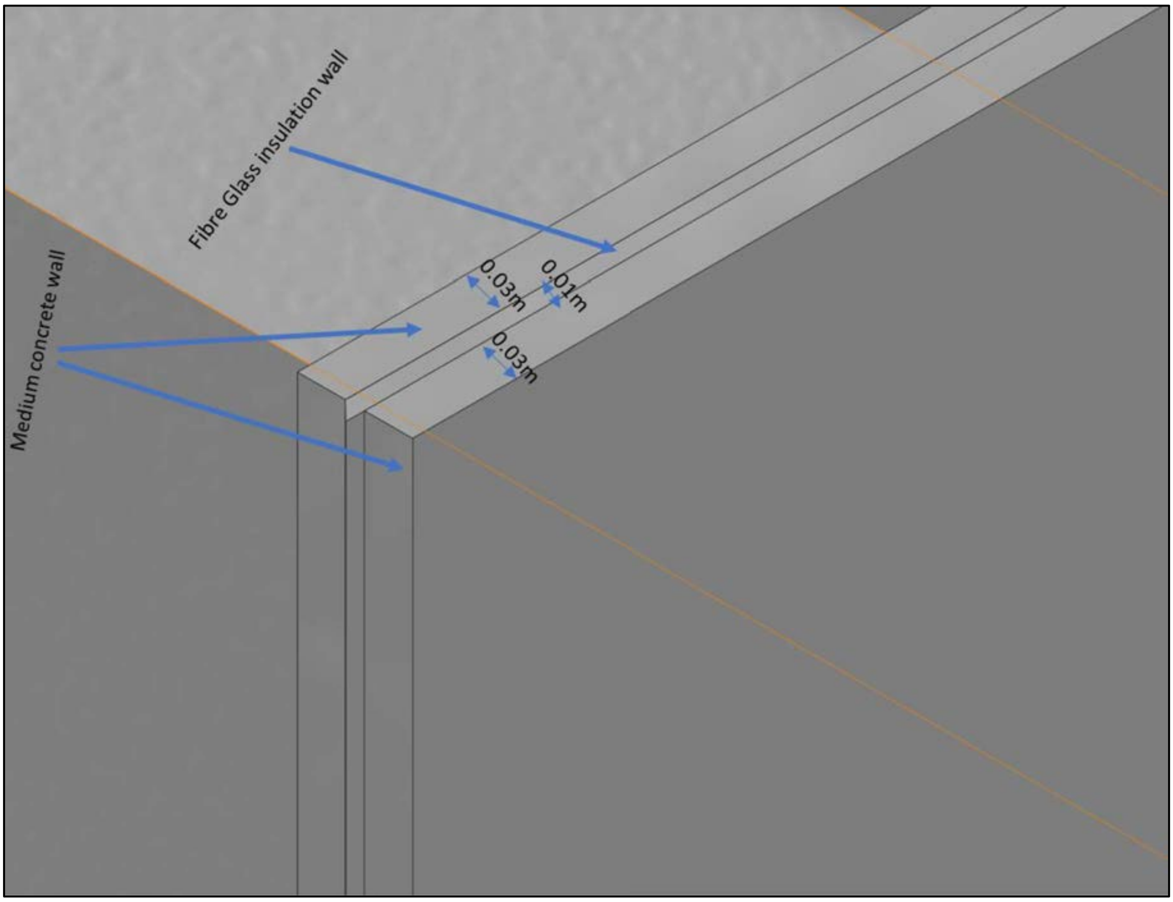

Figure 5.3. The material composition of the wall within the simulation.

The materials consist of two layers of concrete, containing a layer of fibreglass. The fibreglass is used as insulation to improve the thermal resistivity of the wall and retain the heat within the room.

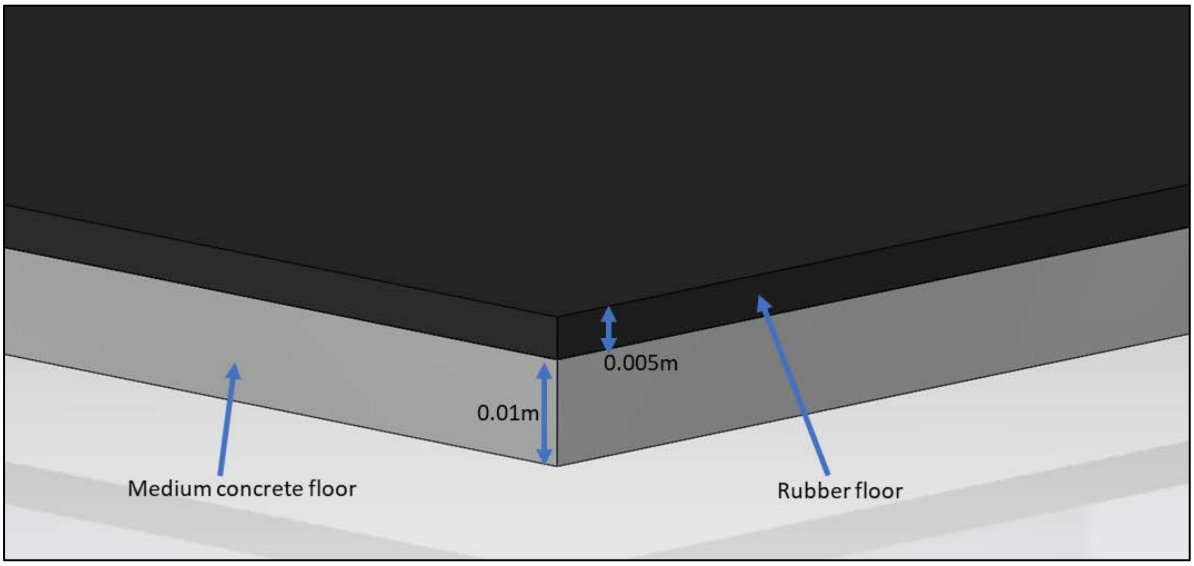

Figure 5.4. The material composition of the floor and ceilings of the lecture halls

The concrete is used for structural stability and the rubber is used for comfort, but it also has increased thermal insulation.

The computer-aided design (CAD) was designed through the Solidworks software, allowing the development of the methodology in this research. Solidworks uses computational fluid dynamics (CFD) to analyse the behaviour of the room's thermal and physical properties of solid material and air. The software was used with the help from A. H. Ferdaus. The use of CFD allows the simulation to provide accurate predictions of fluid-flow [188] with reduced costs compared to practical experiments. The solver used is the FFEPlus iterative due to the ability to solve non-linear problems while requiring less memory than the Direct Sparce Solvers [189]. The model is validated through a Mesh Convergence Study. This involves splitting the problem into smaller parts and measuring the changes in critical parameters such as thermal conductivity or air movement. As a more complex or smaller mesh requires more computational power, a larger mesh is beneficial, although a smaller mesh can also provide more accurate results within the simulation. To determine the trade-off between complexity and accuracy, the mesh is iteratively reduced in size such that there are more elements until the changes of critical parameters are minute within a defined parameter. This could be a percentage change in critical parameters such as the air flow or heat exchange, but this is calculated by the algorithm. The mesh convergence study is shown in Figure 5.5 below:

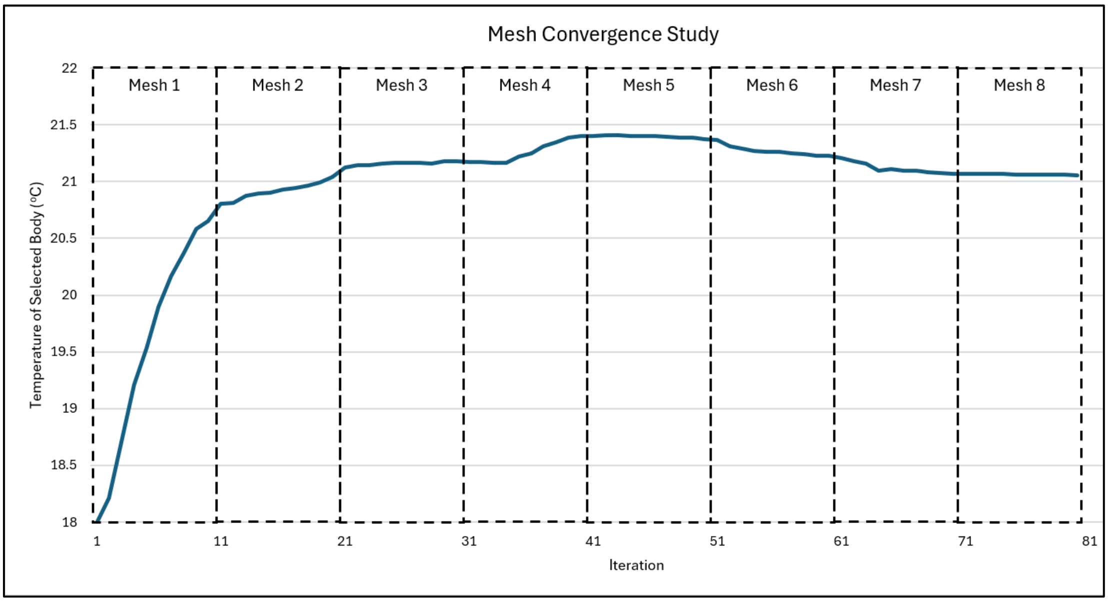

Figure 5.5. The results of the mesh convergence study, showing the plateau of the temperature of the selected body as the temperature increases from 18°C to 21°C.

The number of blocks within each mesh within the study is increased per mesh. The block size in mesh one is $0.1m^2$ and is decreased by $0.01m^2$ until mesh eight at $0.03m^2$.

The number of grid blocks in each mesh is described through Table 5.3 below.

Table 5.3. The number of grid blocks in each mesh. Each mesh contains more blocks, and therefore splits the room into smaller portions, allowing more accurate results to be obtained.

Mesh	1	2	3	4	5	6	7	8
Total Blocks	4848	5386	6060	6926	8080	9696	12120	16160

A more complex mesh could give more accurate results from mesh eight, but this would require more computational power and time, in which it becomes impractical, so there is a trade-off between how accurate the results must be. A more powerful machine could generate a more accurate study with a more in-depth mesh, but in this study, the above descriptions have been used for the mesh, and mesh number eight plateaus, showing that out of all of them, it has the highest accuracy.

5.4. Comparison of Convection and Infrared Heating Systems

The results from six convection heating simulations are shown in the results section. Occupation density is varied from minimum, medium, and maximum. This is tested with both the convection system and FIR heating. Minimum occupation is assumed to have 10 occupants, medium has 27, and maximum has 98 occupants.

5.4.1. Energy Consumption

The FIR heating method is done through zones that are activated when under occupation, enabling concentrated heated parts of the room.

The FIR panels can be placed at any point in the room so long as they provide heat to the required zone. In this case, the occupant is heated from above, so it is important that they are heated evenly from top to bottom. Each occupant and zone have a corresponding ceiling fitted FIR panel. The temperature of the bottom and the top of the professor is 21.19 °C (294.34 K) and 20.6 °C (293.75 K) respectively, giving a difference of 0.59 K. The seating area heating varies between 0 W and 320 W to heat the occupiers with a variance of 0.05 K from the top to the bottom of the occupier in the best case. The highest variance results are 2.17 K between the bottom and the top of the occupier. The simulated heat distribution for connection radiators and the proposed FIR heating system is illustrated in Figure 5.6. and 5.7. respectively.

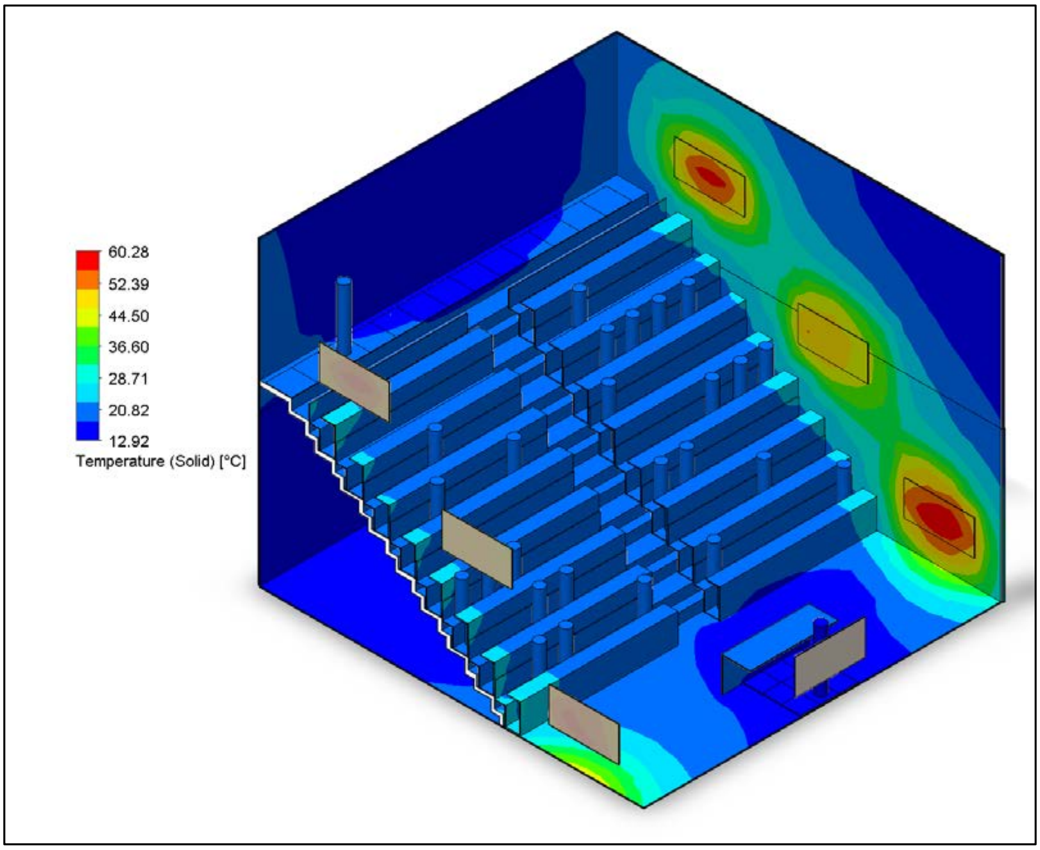

Figure 5.6. The current fitted radiator system.

The convection method heats the room from the radiators installed at the sides under medium occupation.

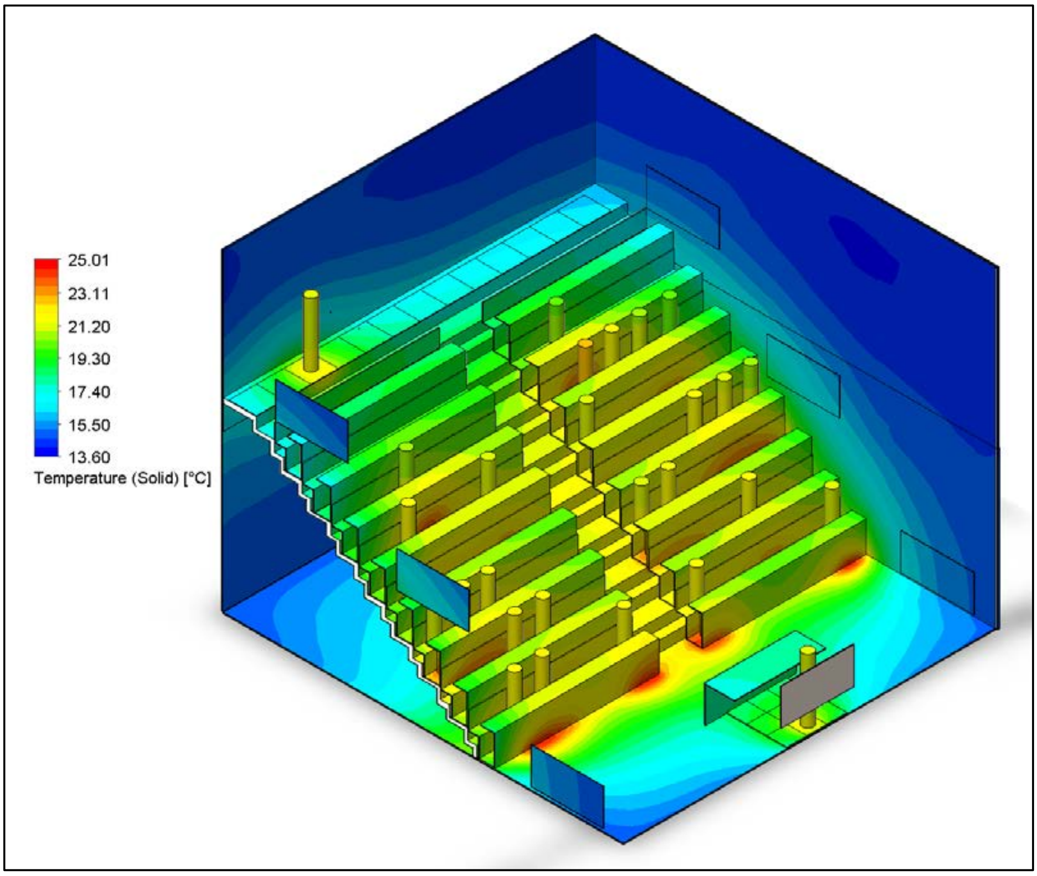

Figure 5.7. The FIR zonal heating system for medium occupation.

Both heating systems can heat the occupiers to the desired temperature of 21 ^{o}C but the heat distribution for FIR is more precise.

The FIR heaters vary in power, depending on the time of occupation for each zone. When all heaters are activated in the seating area, the heat is too high, so some of the heaters operate at a lower wattage or in the case of medium occupation, they don't operate at all.

To heat the room using occupation dependant heating with medium occupation, the FIR heating uses 3.46 kW. For the same occupation, the wall mounted radiators used 14.4 kW to heat the occupiers to the same temperature as the occupation dependant method. The energy needed to heat the professor per zone is 130 W. There are 9 panels/zones in the area allowing room for movement.

When in medium occupation, the energy requirements for each panel are shown in Figure 5.8.

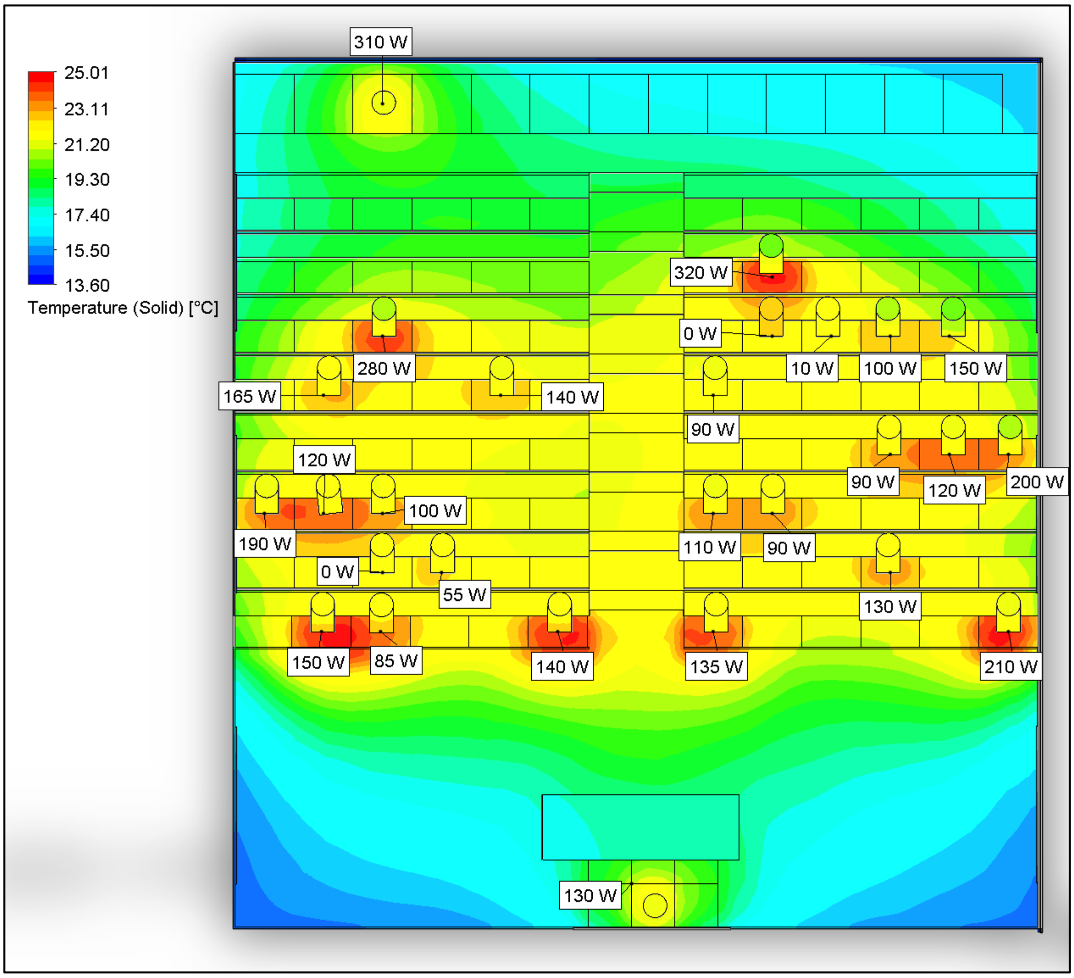

Figure 5.8. The varied energy requirements of the FIR heating zones to maintain the same heat.

The highest energy demand is 320 W and the lowest is 0 W. To heat just one occupied space, it requires 320 W and when all spaces around an occupied space is heated, that space doesn't require any, or as much heat. This method maintains the required heat for each zone while saving 5.2 kW compared to heating all the zones with 320 W.

Minimum and maximum occupations for both FIR and convection heating are simulated to show how the effectiveness of the method vary depending on occupation.

The energy demand, material, and air temperature variance simulation results for minimum and maximum occupations using FIR and convection methods show that FIR has a much lower demand for both minimum and maximum occupations. FIR also has lower material and air temperature variance. The energy demand for the methods are illustrated in Figure 5.9.

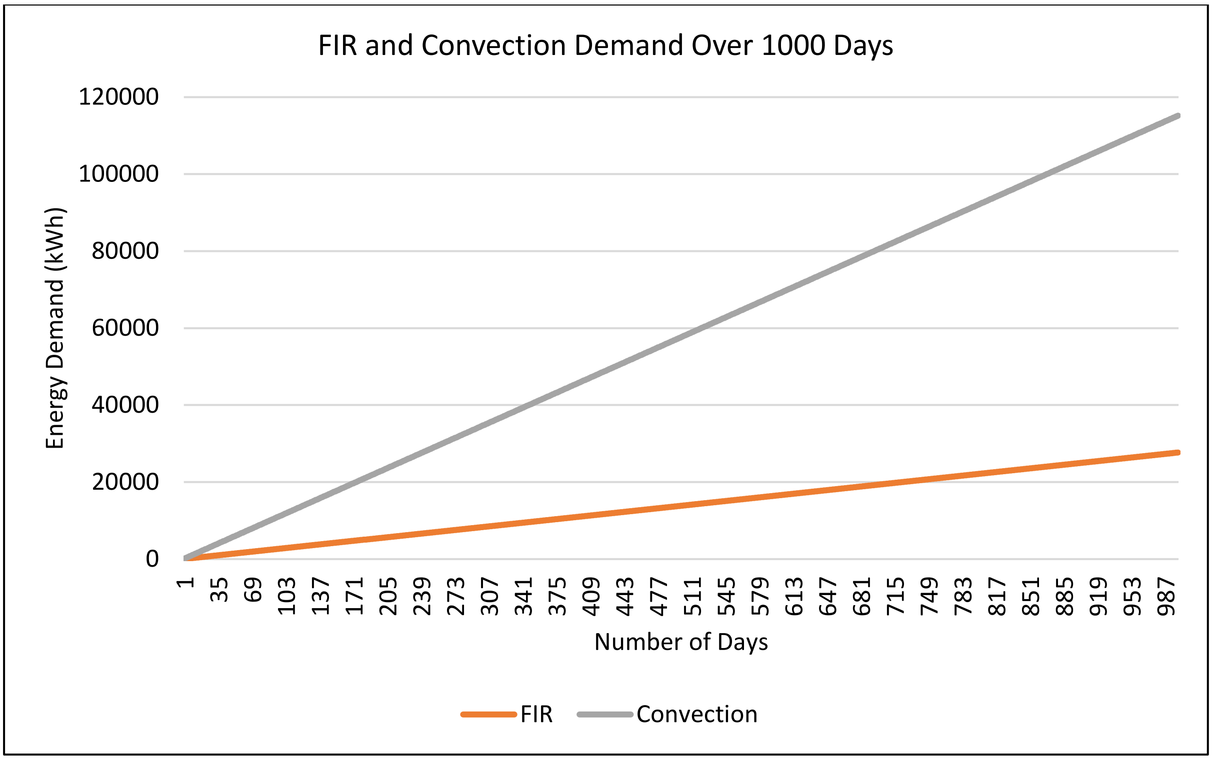

Figure 5.9. The energy demand (kWh) for the convection wall mounted radiators and the FIR heating system's energy demands over 1000 days under medium occupation.

The continued increase of savings from the FIR method compared to conventional methods show a larger gap in savings as time passes. The FIR occupation dependant heating system used 75.9 % less energy than the convection wall mounted radiators. These results occur when all methods are in medium occupation with 25 seated and 2 standing occupiers out of the possible 118 zones.

5.4.2. Air Flow

Air quality and flow provide important information on how the health of occupants is affected. The air flow for medium occupation for the FIR occupation dependant heating is simulated in Figure 5.10.

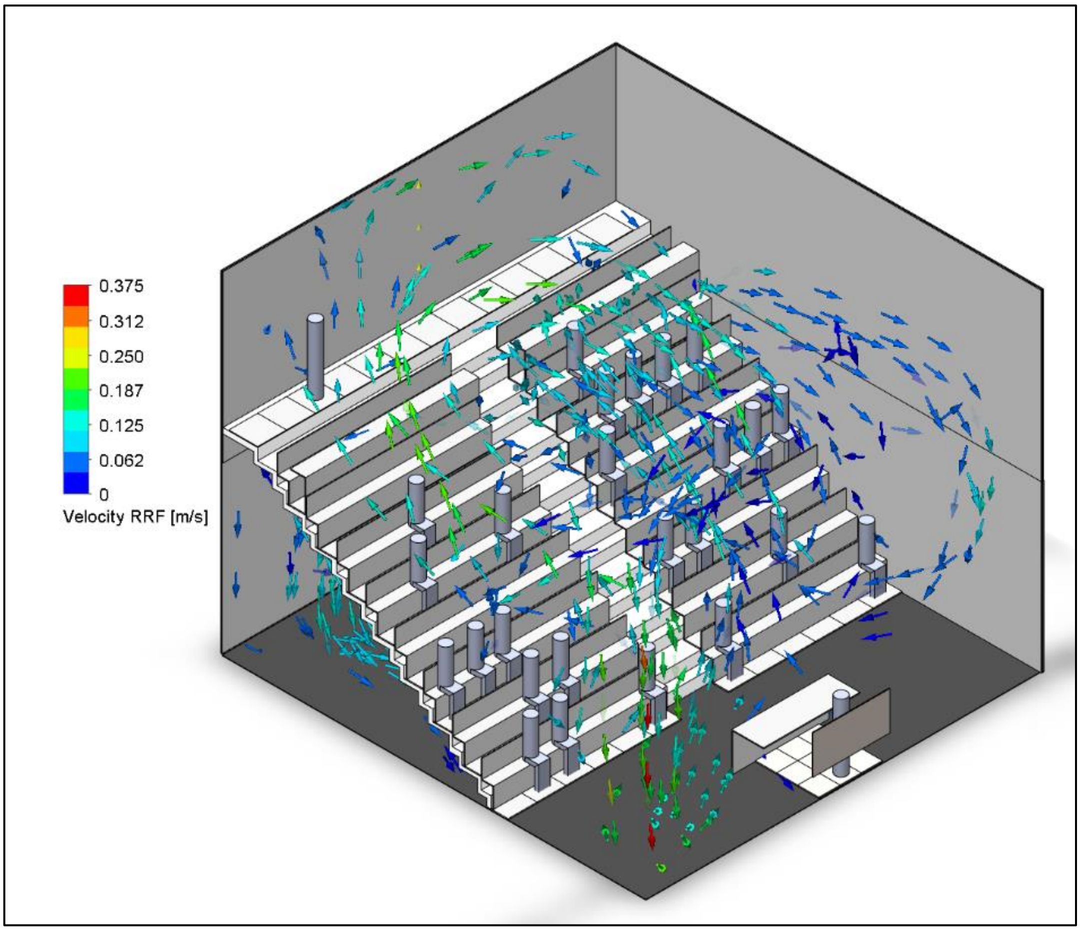

Figure 5.10. The FIR occupation dependant air flow and speed when heated to 21 °C (294.15 K) in medium occupation.

The colour blue shows slower air movement and as the air velocity increases, the colour changes through green, yellow, and then to red. The air flow has a range of 0.375 m/s all through the room, as heated air moves up the steps to the back of the room, then cools as it falls and moves towards the front of the room to be recycled. The temperature of the air has a range of 13.39 K.

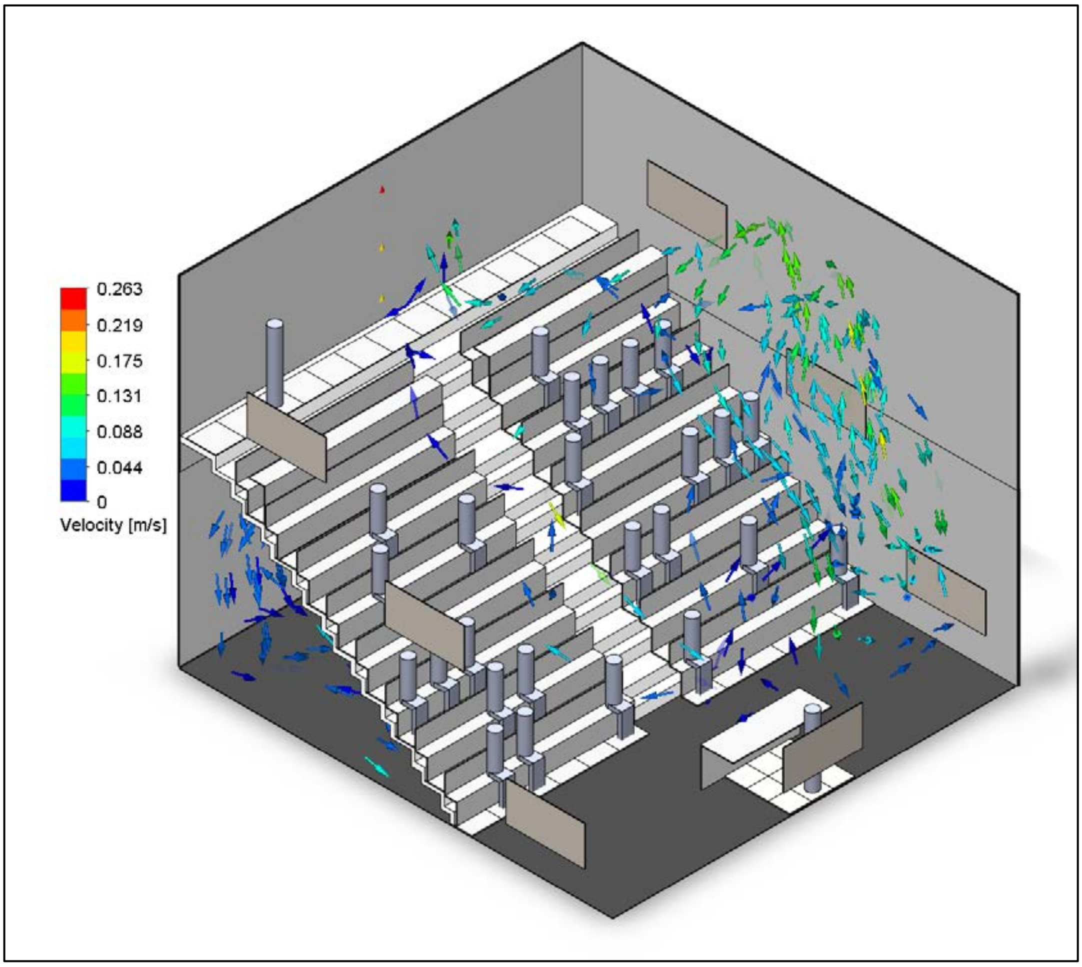

Figure 5.11. The air flow of the convection system when occupants are heated to 21°C.

The air flow has a speed range of 0.263 m/s through the room but has most of the movement at the front of the room where the air is cooling while also being heated by the radiators as a whole room. The SOLIDWORKS simulation is used to compare air temperatures of the hottest and coldest air temperature between FIR and convection heating methods.

For the medium FIR heating, the air flow has a maximum speed of 0.375 m/s whereas the convection heating has a maximum air flow of 0.263 m/s. Minimum and maximum occupation air flow speed and temperature for occupational and convection heating are shown below in Table 5.4.

Table 5.4. *Showing air speed and air temperature variance for FIR and convection heating for varied capacities.*

	Minimum FIR	Maximum FIR	Minimum Convection	Maximum Convection
Maximum Air Speed (m/s)	0.322	0.278	0.350	0.856
Air Temperature Variance (K)	10.64	12.37	25.22	39.85

Air Temperature variance is the difference between maximum and minimum temperatures throughout the air in the room at the same time. This is simulated through SOLIDWORKS. Convection heating has a higher temperature variance from materials in the room to the occupant compared to FIR, showing lower efficiency.

5.4.3. Cost Analysis

The retrofitting space for the heating is 28.8 m^2 for the student area, 7.3 m^2 for the balcony area and 2.75 m^2 for the professor area equalling 38.85 m^2 of heating overall. A quotation for wall mounted radiators and installation from a supplier costs £4,613, whereas the ceiling mounted FIR panels and installation costs £6,138. For medium occupation, the simulated methods are shown below in Figure 5.12.

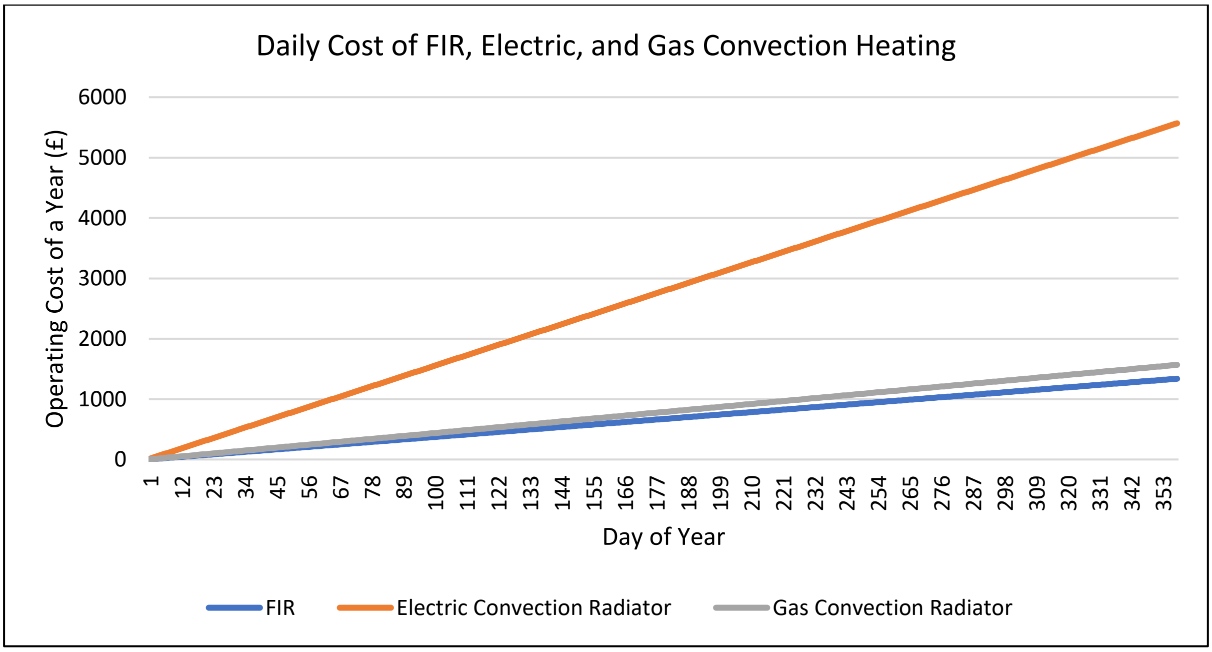

Figure 5.12. The cost to run FIR, electric convection, and gas convection heating over 1 year.

The FIR and convection heating systems installation costs £6,138.30 and £4,613 respectively. The average cost of energy is 13.5p/kW, meaning daily FIR and convection cost £3.73 and

£15.52 respectively. The FIR operation costs 42% less than convection heating, giving an ROI of 520 days and an annual saving of £4,312.

5.4.4. Occupation Prediction

A random forest and a feed forward neural network MLA are created with collected data surrounding the case study and added occupation data to show the results of the models. The CO2 data is collected through 2 installed CO2 sensors in the ceiling. Data points are predicted in 15-minute increments from midnight to 15:45 for both methods, with results in Figure 5.13.

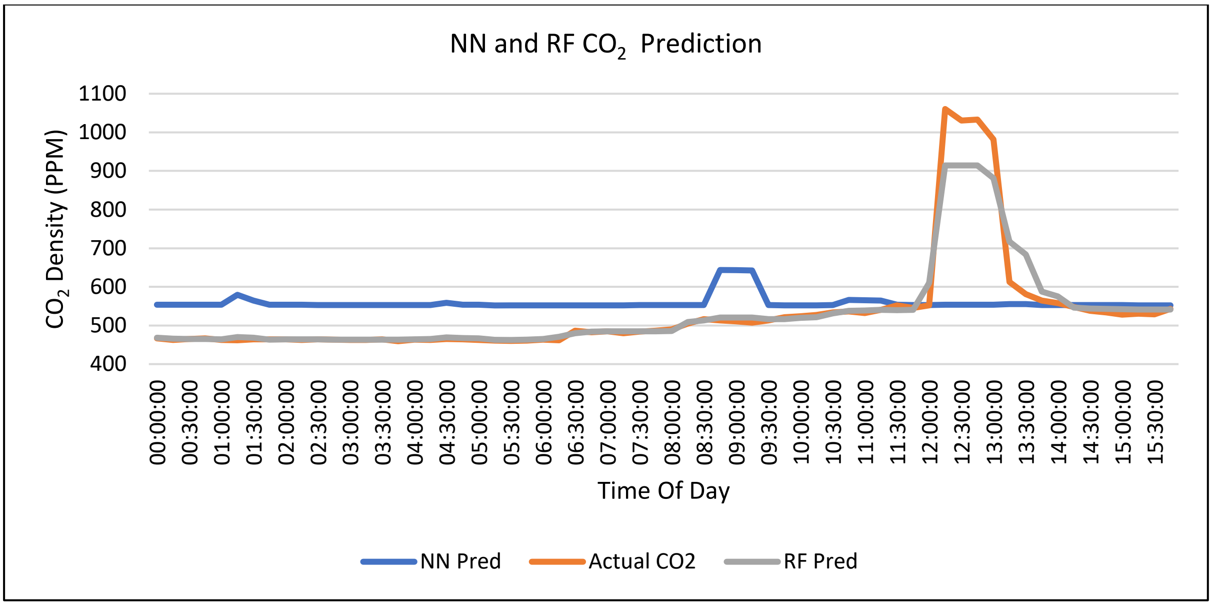

Figure 5.13. Showing forecast results from NN and RF algorithms for CO2 density.

The NN had an average error of 15 % with a high of 47.76 % and a low of 0.22 %. The RF method had an average error of 2.24 % with a high of 17.72 % and a low of 0.0187 %. There is a large peak between 12:00 and 13:00 which is followed by the RF but not the NN. This CO2 peak produces the highest error for both algorithms. The high peak between 12pm and 2pm is due to the lecture hall being fully occupied over a 2-hour period. This can happen at any time of the day, independent of many training variables such as the weather or other characteristics of the building. Due to it being independent from many training variables, the algorithms' accuracy decreases when the room is heavily occupied quickly. To overcome this issue, the schedule of the zone can be implemented into the training data for the algorithm. Average variance between data points is 6.8PPM which is 13.6 % of average PPM for the training set. The average PPM for the peak is 1026 which is 2051 % compared to the average of the rest of the data set. The RF produced results in 6.9s whereas the NN took less than 1s.

Classification of input data shows time of day, outdoor air temperature and pressure are the most important variables. Rain, cloud coverage, and the day of week don't affect the levels of CO2 as much as the other input variables, although they still aid the algorithm to an accurate prediction.

The occupation densities are split into minimum, medium, and maximum, with minimum CO2 density from 490PPM to 550PPM, medium is from 550PPM to 580PPM, and maximum is from 580PPM to 1060PPM or higher. Any lower than 490PPM and the room is deemed to be out of use until sensors are activated or the room is heated manually.

5.5. Achievements and Importance

This chapter focusses on the types of heating from conventional to more energy efficient techniques and how ML methods can be applied to improve them further. Convection heating is previously used and although fuels, methods of generation and distribution can improve efficiency of the system, the method of convection heat still produces more losses than FIR. The retrofitting of a single non-domestic lecture theatre with a FIR occupation dependant heating system to improve energy efficiency, thermal comfort, and flow of air is achieved. This was done through occupation prediction for pre-heating of occupied spaces to improve thermal comfort.

Machine learning forecasting is implemented for occupation prediction in 15-minute segments over a day with comparisons between convection and FIR heating methods. Results show the FIR occupation heating was more energy efficient by 10.36kWh in maximum occupation, 10.94kWh in medium, and FIR heating required 11.99kWh less than convection heating in minimum occupation. Air velocity is higher for convection heating at 0.633 m/s compared to FIR heating at 0.379 m/s. Financial benefit calculations show a saving of 75.97 % or £11.79/day with a return on investment of 520 days, providing incentives. Occupation prediction from the RF MLA show an accuracy of 97.75 % for 15 min intervals which allows the preheating of rooms and zones for optimal comfort. Zonal FIR heating is more efficient than convection methods by 75.97 %.

5.6. Summary

The MLA application for occupation forecasting provides accurate results, capable of providing information on the occupation density of a room. This was achieved without the need for facial recognition or PIR sensors, and instead through already installed CO_2 sensors which are a requirement in public buildings already. This has been used to optimise a FIR heating system but can be used for HVAC controls, lighting, or for other methods that can be optimised through occupation density forecasting.

The development of an occupancy forecast through collection of CO_2 data is novel. For this application where the occupancy and CO_2 density have a high relationship, The CO_2 density can be used to forecast occupancy density. This can remove the need for installing passive infrared sensors, resulting in a more cost-effective outcome. This also saves time in waiting for enough data to be collected to start the method, as for public buildings, CO_2 sensors must be installed by law, and so that data already exists.

Reducing the energy consumption through more efficient heating methods can reduce CO_2 emissions, but producing more renewable energy and having more control over the produced energy can be used in parallel. Using the energy with more efficient heating methods is explored in this chapter, whereas optimisation of renewable energy generation is explored in the next chapter. The active PV generation system for the Business School has been forecasted through MLA methods in chapter 6, allowing the results to be implemented into the currently equipped BMS.

CHAPTER SIX: MACHINE LEARNING FORECASTING OF INTERNAL ENERGY GENERATION TECHNIQUES

This chapter investigates the various methods of energy generation within a public building with more attention towards the methods the generate less or no carbon emissions. The analysis addresses issues where renewable energy generation can be difficult to use due to the unpredictability of renewable sources. To overcome this problem, MLA forecasting techniques are applied to the Business Schools' currently installed renewable generation to optimise management of storage, use, and trading of the generated energy.

6.1 Introduction

As buildings are reducing carbon emissions, both the efficiency of the energy consumers must increase as well as on site energy generation. The methods of generating energy without producing carbon emissions is through renewable energy (RE) sources. These include solar PV, solar and geothermal, wind, kinetic, biomass, hydropower, and hydrogen. Each method can have positive effects on public buildings with dependencies on the buildings' characteristics such as function and size. Although each method can be utilised to reduce the buildings' carbon emissions, it can be difficult to forecast how much energy they will produce due to the unpredictability of the weather and occupancy, and waste. When they do not produce enough energy to support the building, energy must be used from the national grid which is often from fossil fuels. To solve this problem, MLA's can be developed to accurately forecast how much energy will be produced at a specified forecast horizon.

The solar PV generation is partially dependent on insolation, geothermal is partially dependent on the depth of the pipeline and thermal conductance of the ground material, and the wind generation is partially dependent on the direction and speed of the wind. To optimise energy management within a building, the renewable energy generation techniques must be accurately forecasted to provide the BMS with enough information to make an informed decision.

This chapter aims to:

- Develop MLA's capable of accurately forecasting the energy generation of the currently installed solar PV system on the case study building.
- Compare and analyse the developed MLA's on necessary training data, training time, accuracy, and internal parameters.
- Analyse the application of MLA's for forecasting other renewable sources and how they would work.

There are currently 128 variations of MLA's used for prediction of a buildings' energy demand [71]. This statistic includes slight changes in a category of MLA such as a hyperparameter changed in a NN, showing that there are many variables to decide when developing appropriate MLA's. generation through RE cannot be considered a reliable source [190] but can provide a more reliable energy mix [191], with promotion of RE by world leaders improving application [192]. Energy generation in the UK connected at the distribution level accounts for 28% of all generation [193] which shows there is clear room for increasing decentralised RE. RE generation contributes 17.18GW which is 43% of the UK's total energy demand [194], with 4% solar and 31% wind due to the 6500 wind turbines installed across the country. This shows usability of various RE sources to contribute to the whole demand. Multiple MLA's can be applied to forecast PV generation [195] with different results of accuracy. Supervised machine learning relies on historical data of inputs and PV generation data to train the algorithm, but with various algorithms, it cannot be undisputed which algorithms provide the most accurate forecasts.

Once the developed MLA's are used to forecast the buildings' renewable energy generation, the MLA's can then be compared to decide which is the most suitable MLA and how they differ. The application of MLA's for other methods of energy generation other than solar PV provides information on the process of data collection, processing, MLA development, and validation.

6.2 Development and Validation of Machine Learning Algorithms

As is previously mentioned, there are 128 variations of MLA's used when forecasting a buildings' energy demand. Previous research shows the application of different types of MLA's used, as different sized buildings and datasets are used for training and validation. To fully optimise the actuation of the generated energy, it needs to be forecasted. To do this, the most common methods of MLA's are developed, trained, and validated against various datasets of collected campus data. The solar PV generation output is forecasted through 64 algorithms for the Business School to show the effectiveness of the developed algorithms. The developed methodology is illustrated in Figure 6.1.

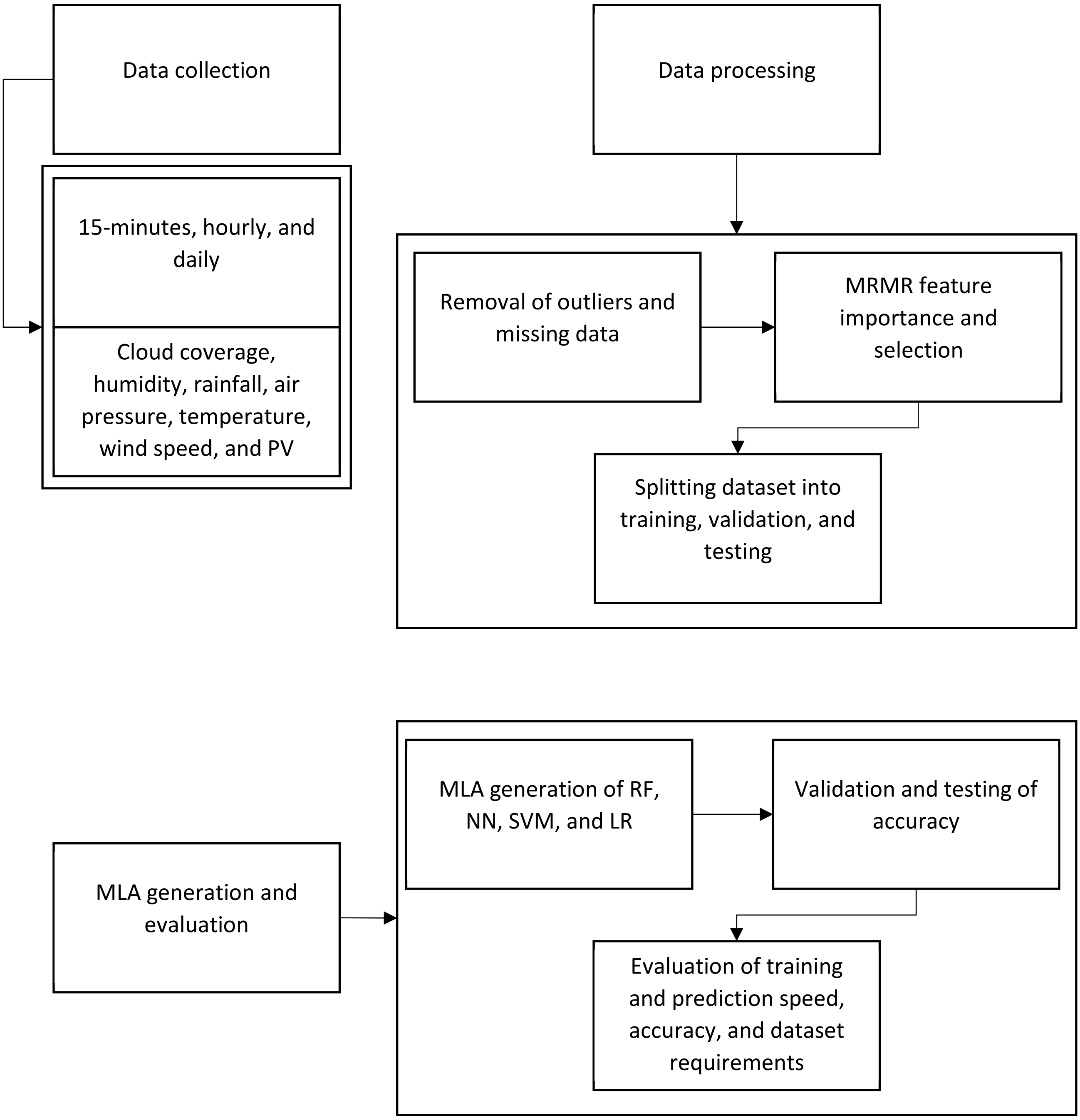

Figure 6.1. The methodology from data collection to PV forecasting for multiple algorithms and datasets.

The raw PV generation data contains 10 months of data and 30,842 iterations. The predictor variables are cloud coverage (%), humidity (%), rainfall (mm), air pressure (mb), temperature (^{o}C), and wind speed (mph). The entire original dataset contains 215,818 data points across the 6 inputs and the output (PV generation) for 10 months of data collection with 15-minute iterations.

The initial dataset is split into multiple smaller datasets for each algorithm to be trained and tested on. These are aggregated to include the original dataset of 15-minute iterations, hourly, and daily measurements. These can be used to train the algorithms with a varied time lag to forecast a specified horizon. The hourly dataset contains 7,281 iterations and the daily dataset contains 302 iterations. For each smaller dataset, another predictor variable is added for the time of day. This ranges from 1-96 for 15-minute iterations, 0-24 for hourly, and 0-7 for daily. Daily forecasting has larger errors when used with a 'time of day' input, so it isn't used as an input for training. The raw dataset is shown in Figure 6.8 and the processed dataset is shown in Figure 6.2 respectively.

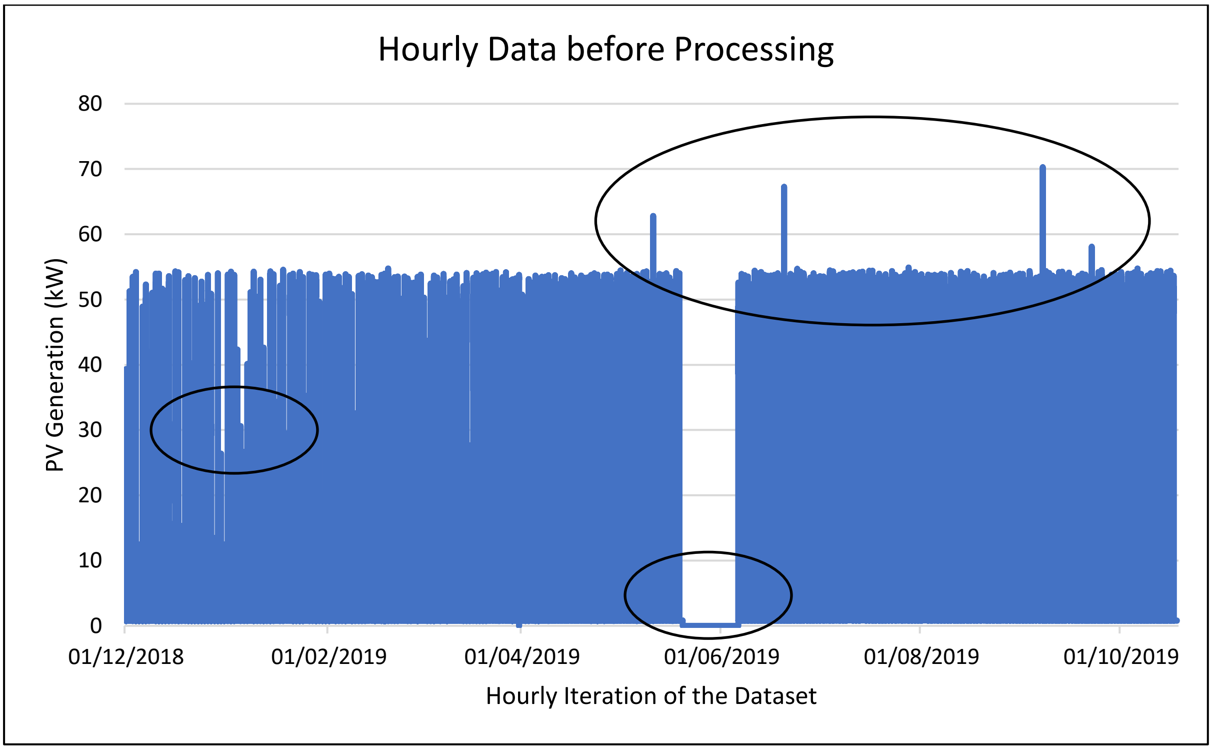

Figure 6.2. The hourly dataset, spanning 11 months; 10 months of training and 1 month of testing.

Major outliers and missing data are emphasised, where the data is much too high, too low, or completely missing. This is due to the sensors malfunctioning and restarting, which aggregates all of the missing data collected over a period of time into a high value at a single timescale.

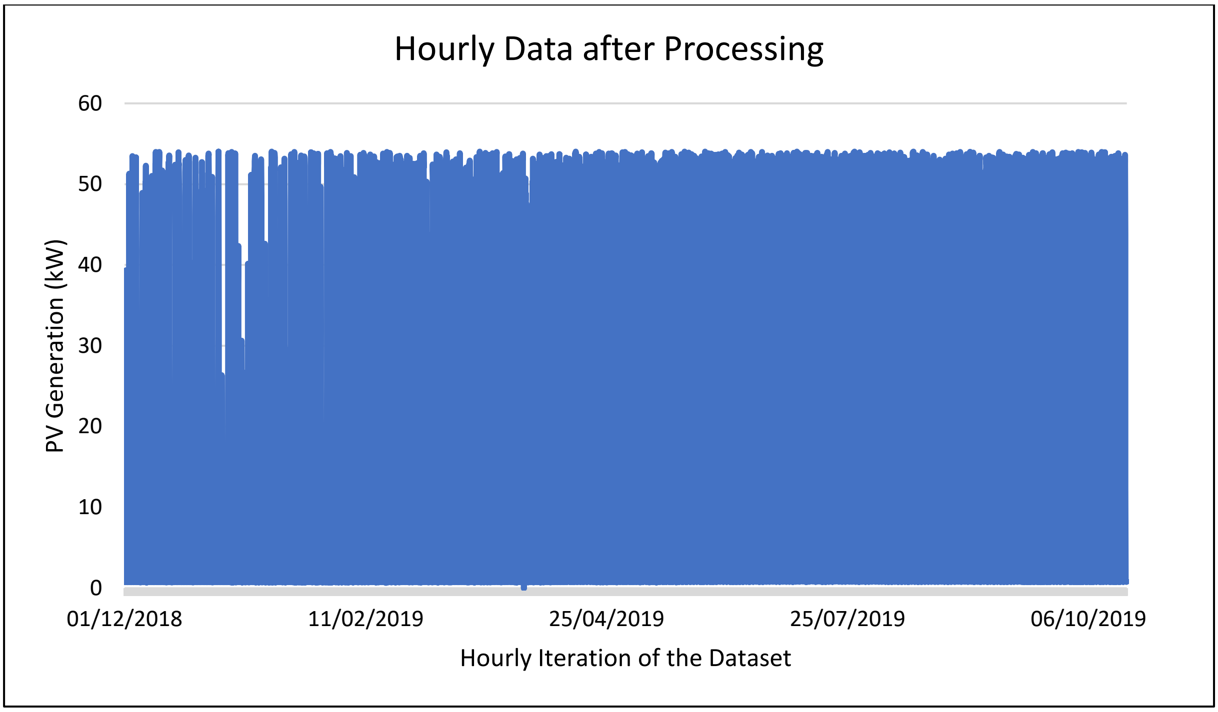

Figure 6.3. The hourly dataset after processing.

Major outliers and missing data are corrected and removed to provide the algorithms with higher quality training and testing data. The missing data points are filled through linear interpolation or removed, and outlying data points are corrected through a rolling average of the surrounding day, week, or month, depending on the size of iteration. The linear interpolation and rolling average methods are shown in Equations 4.4 and 6.1 respectively.

$$y = y_1 + \left(\frac{(x-x_1)}{(x_2-x_1)\times(y_2-y_1)}\right) \qquad \text{Eq. 4.4}$$

Where the previous and next points in the dataset are 'y_1', 'y_2', 'x_1', and 'x_2' respectively for each variable. Current points are represented with 'x' and 'y'.

$$\mu = \frac{1}{N}\sum_{-n}^{n} A_i \qquad \text{Eq. 6.1}$$

The rolling average is 'μ' and is the sum of the selected values, from '$-n$' to 'n' divided by thenumber of variables between those points 'N'.

Although outlying and missing data can be removed or interpolated, this does not consider incorrect data that isn't outlying and missing. This still results in errors within the training of the algorithm, but they can be reduced through data processing. The 3 datasets that the MLA's are trained with from 10 months of data are shown in Table 6.1.

Table 6.1. The average size of the datasets used for training when forecasting various horizons with 10 months of data.

Iteration	Inputs	Total Datapoints	Training Features
15 minutes	8	220,000	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, PV generation, and time of day
Hourly	8	58,228	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, PV generation, and time of day
Daily	7	2,285	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, and PV generation

The three iterations are used to train the models on 2 different horizons each. 15-minute iterations are forecasted for 15-minutes in advance and a full day in advance. Hourly iterations are forecasted for 1-hour and 1-day horizons, and daily iterations are forecasted for 1-day and 1-week horizons, so each horizon has a different sized dataset. The total datapoints are the sum of iterations multiplied by the sum of the input variables. The 'time of day' input that is used for the 15-minute and hourly datasets are not included in the daily dataset due to there being no 'time of day' as it is an aggregated result of the whole day. The 3 datasets that the MLA's are trained with from 1 month of data are shown in Table 6.2.

Table 6.2. The average size of the datasets used for training when forecasting various horizons with 1 month of data.

Iteration	Inputs	Total Datapoints	Training Features
15 minutes	8	23,087	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, PV generation, and time of day
Hourly	8	5,764	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, PV generation, and time of day
Daily	7	2,045	Cloud coverage, humidity, rainfall, air pressure, temperature, wind speed, and PV generation

The algorithms trained from the above-mentioned processed data can be altered and possibly improved through the measurement of feature importance and the size of the training datasets. From the collected historical input data, the feature importance is calculated through the MRMR algorithm, regarding the PV systems' energy generation. This is shown in Figure 6.4.

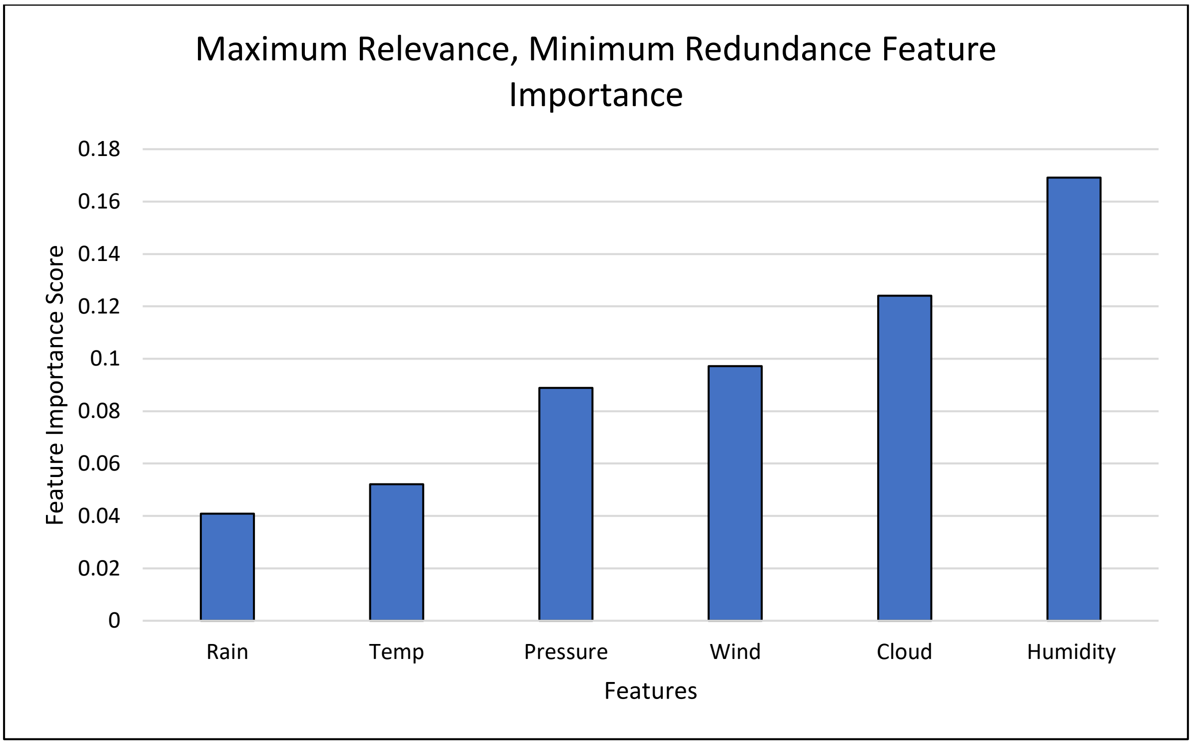

Figure 6.4. The Maximum relevance, minimum redundance feature importance algorithm, showing the optimal selection methodology. Humidity has greatest effect on PV generation whereas rainfall has the least effect.

This is an optimal selection methodology as the inputs with the highest importance can be added before the features with the lowest importance. There is a trade-off for the MLA between providing it with more data and providing it with data of importance. Due to the minimum redundance calculations of the feature selection algorithm, the selected input feature is compared against other inputs. The use of MRMR eliminates multiple similar relationships being calculated by the MLA to reduce training time and noise within the training dataset. This allows deeper MLA to be developed which can have higher accuracies than simpler MLA.

Importance of the collected input data towards the predicted data is both dependent on the quality of the data, and what data is collected. When forecasting the solar PV generation there are 6 inputs and 1 output. It can be difficult to distinguish whether the data has importance before it has been collected and evaluated through a feature importance algorithm. Data such as climate variables is logical that they have large effect on the energy generation of the PV system although rainfall had the least effect. Although rainfall and cloud coverage have a high correlation, it is not the rainfall that causes a change in the PV generation, but the cloud coverage, allowing less light to pass through onto the panels. Although this data can be used to train an accurate algorithm for forecasting the output of PV systems, other data might need to be collected to forecast other types RE generation.

There are 6 inputs and 1 output for the Business School compared to the previous study of 10 inputs and 1 output [154]. It is difficult to compare the results between the PV generation plant in China and the local PV system on the Business School due to the size difference of 199,970,000W and the location. After the data is processed and the feature importance is calculated, the algorithms can be developed and evaluated. This provides information on how they are functioning such as if they are being trained on too much data. After the MRMR algorithm calculates the importance of the input features, the algorithms can be evaluated through removing the features with less importance. This is shown in Figure 6.5.

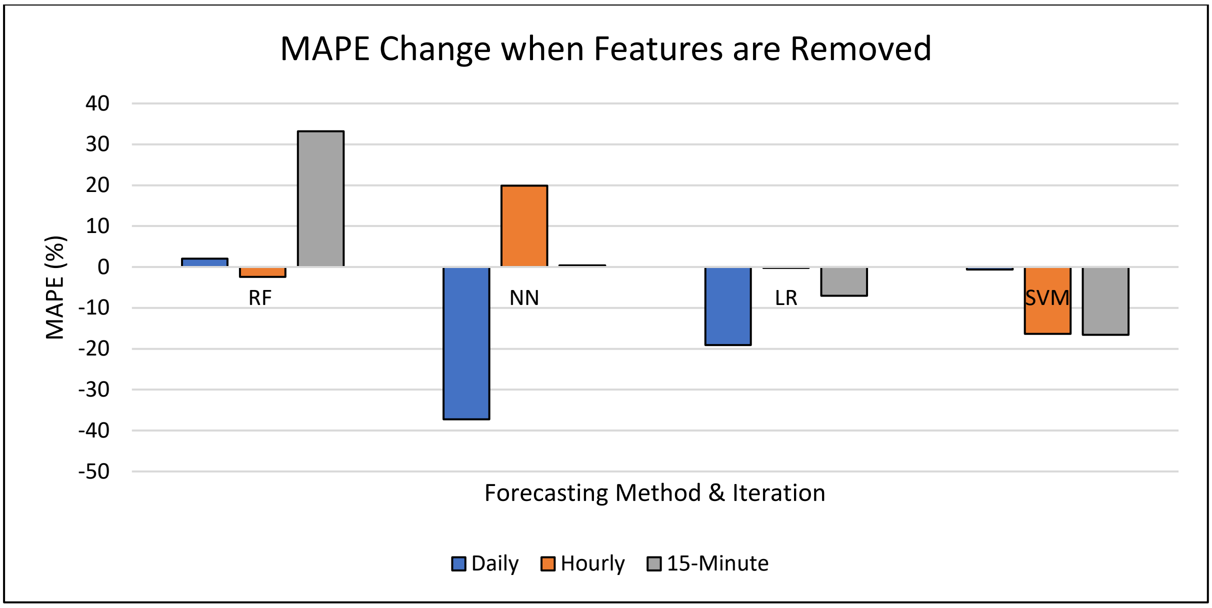

Figure 6.5. The change in MAPE when the three features with the lowest MRMR are removed, showing the results for daily, hourly, and 15-minute iteration averages for each method. These are trained with 1 month of data.

The average change for RF, NN, LR, and SVM are +10.94%, -5.65%, -8.77%, and -11.18% respectively. The largest decrease in error is for the NN during daily iterations at -37.25% and the largest increase in error is for the RF during 15-minute iterations at +33.19%. Of the developed algorithms, they are trained on daily, hourly, and in 15-minute iterations on various horizons. Larger iterations result in less data points due to aggregation.

One method of determining how the algorithms function is to measure the training and forecasting speeds across the developed algorithms. This is shown in Table 6.3.

Table 6.3. The average training and forecasting speeds across all tests.

Model	Training Speed	Forecasting Speed
RF	61.9 s	2368/s
NN	270.3 s	29821.9/s
LR	41.7 s	22802.4/s
SVM	172.4 s	8087.7/s

LR is the simplest and thus is the quickest to train, but NN is the quickest algorithm to use once it is trained. This is due to the way that the models function. Linear regression calculates the linear relationship through Equation 2.5.

$$y = B_o + B_1X + \varepsilon \qquad \text{Eq. 2.5.}$$

Where 'y' is the predicted output value when an input value is specified, 'B_o' is the predicted value of the output when the input is 0, 'B_1' is the relationship between the input and the output, 'X' is the input variable, and 'ε' is the error between the estimated value of the output and the actual value [79]. As this equation requires only one iteration to determine, it can be used to train a relatively simple algorithm. Although this can be used for one iteration, where multiple iterations are used for training, the calculated relationships between the inputs and outputs are aggregated. The NN's are more complex in the way the relationship is calculated. The NN's in this method use the Levenberg-Marquardt back propagation method of calculating the weights and thus importance of the input variables. Each input is given a weight that can be between -1 and 1, which specifies the effect it has on the prediction and if it is negative or positive. Due to the algorithm being supervised, predictor data is already known for the training dataset and thus, the algorithm can determine the optimum value of the weights to assign to the inputs. The weights are randomly altered and the error between the forecasted data and actual data is evaluated. The weights are then altered again and if the error increases they are altered oppositely. If the error decreases for this, the weights are continuously altered in the same direction until the error starts to increase again. Once the minimum error is reached, the weights for the inputs can stop being altered.

6.3 Forecasting Results of On-Site Renewable Energy Generation

Once the collected data is processed and used to develop an algorithm(s) for forecasting the RE generation, it can be tested. In this case, the algorithms are validated against actual collected PV generation data from the Business School. The validated algorithms comprise of NN, RF, NN, LR, and SVM.

Results for NN forecasting MAPE are illustrated in Figure 6.6.

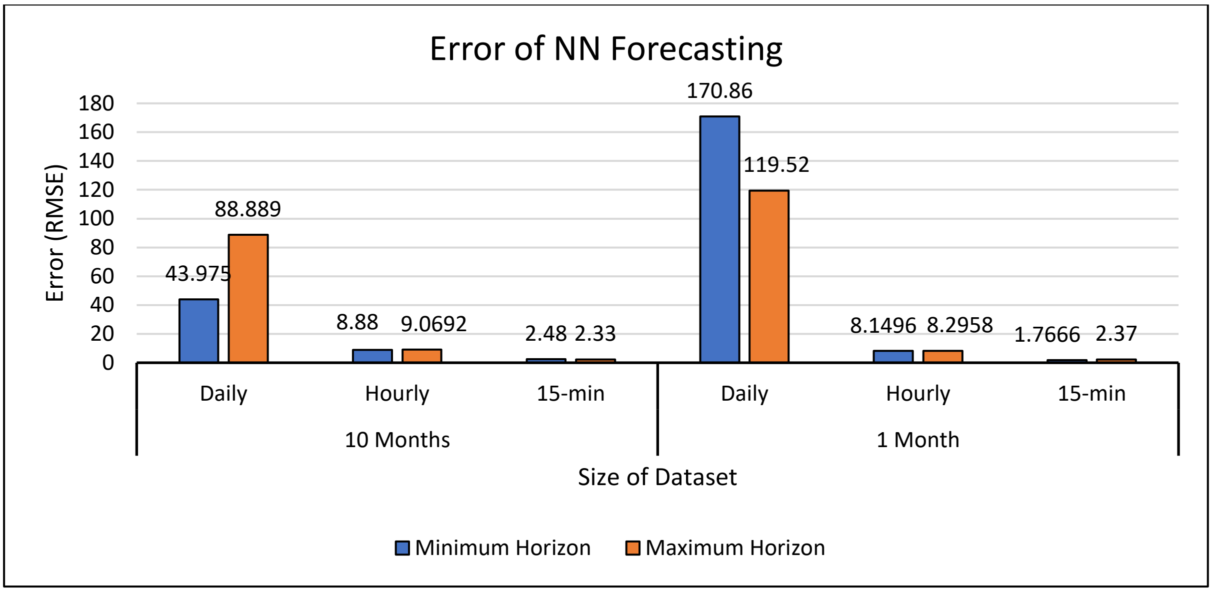

Figure 6.6. The NN forecasting results when trained with 1 month and 10 months of data.

The NN forecasting errors range from 170.86kW to 1.76kW RMSE. The maximum error is when the algorithm is trained with only 1 month of data and is forecasting daily PV generation with a 1-day horizon. In 4 out of 6 forecasts, the maximum horizon forecast provides a higher error than when the minimum horizon is forecasted. The NN algorithm has an average error of 38.88kW RMSE for all tests. It is more affected by lower quality data as in Figure 6.5 when the lowest importance data is removed, and the error is decreased.

Results for RF forecasting MAPE are illustrated in Figure 6.7.

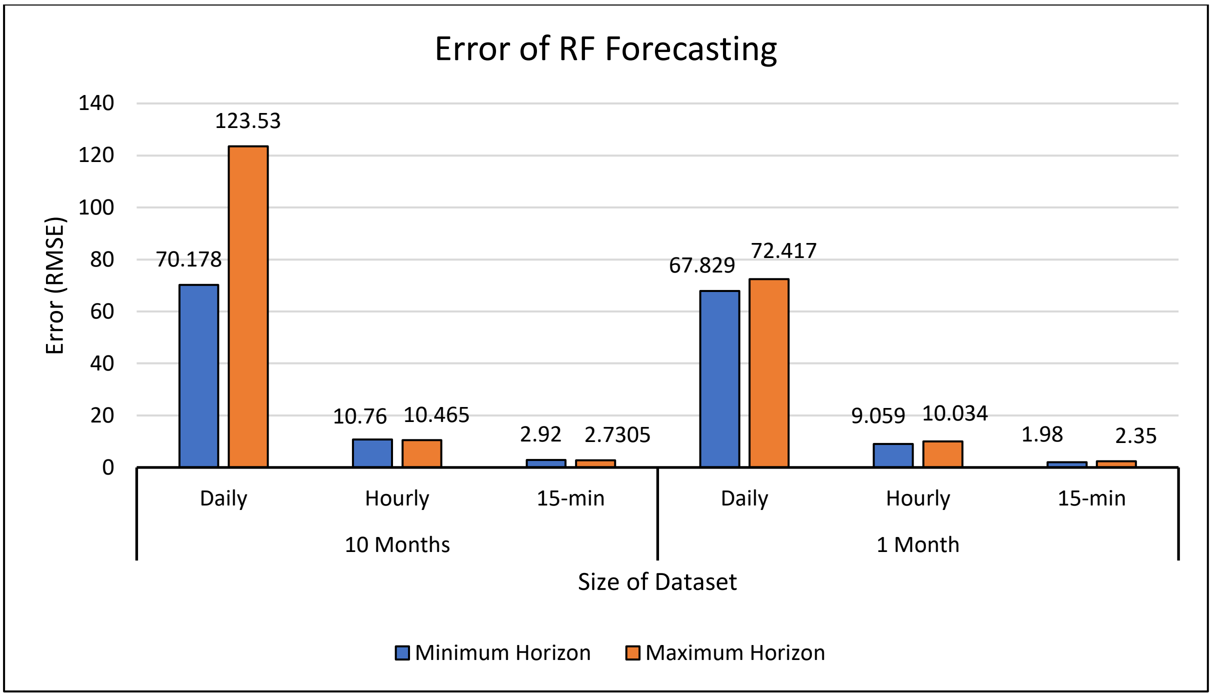

Figure 6.7. The RF forecasting results when trained with 1 month and 10 months of data.

The errors range from 123.53 RMSE to 1.98 RMSE, with smaller forecast horizons providing a higher accuracy. The RF algorithm has an average error of 32.02 RMSE throughout all tests. An RF algorithm is trained with 10 months and 1 month of data and is used to forecast daily, hourly, and 15-minute iterations. Each iteration is forecasted with a small time horizon into the future and also for a larger time horizon. Daily minimum and maximum forecasting horizons are 1 day and 1 week. Hourly minimum and maximum forecasting horizons are 1 hour and 1 day. 15-minute minimum and maximum forecasting horizons are 15-minutes and 1 day in advance. There are three time iterations each for when the algorithm is trained with 10 months and 1 month of data; daily, hourly, and 15-minutes. Each of these algorithms are then tested for minimum and maximum time iterations as is shown in Figure 6.3 These variables are the same for each MLA methodology. The daily error is much higher when trained with 10 months of data for the RF algorithm compared to just 1 month of training. This involves much less data for training, for 1 month, but the RF algorithm still only creates the same number of decision tress, regardless of how much data it is given. In this case, it is creating 50 decision trees when given 1 month of data and 50 decision trees when given 10 months of data. Due to this, it would be expected that the errors would be similar for any training set but with 10 months of data there is more chance of incorrect data that the processing algorithm cannot remove due it not being an outlier or missing. The input data doesn't have great importance as is evaluated by the MRMR feature importance algorithm. Less data with a higher importance value would improve the algorithm rather than adding more data of features with less importance. As the RF algorithm generates a certain number of decision trees per dataset, it doesn't necessarily use all of the data it is provided with for training. More trees within an algorithm provide a more stable prediction, but the computation time increases linearly [196]. 50 decision trees have been used as the accuracy increases from 0-50 trees and decreases slower from 50-100 and further. This is a trade-off between computational power and required accuracy.

Results for LR forecasting MAPE are illustrated in Figure 6.8.

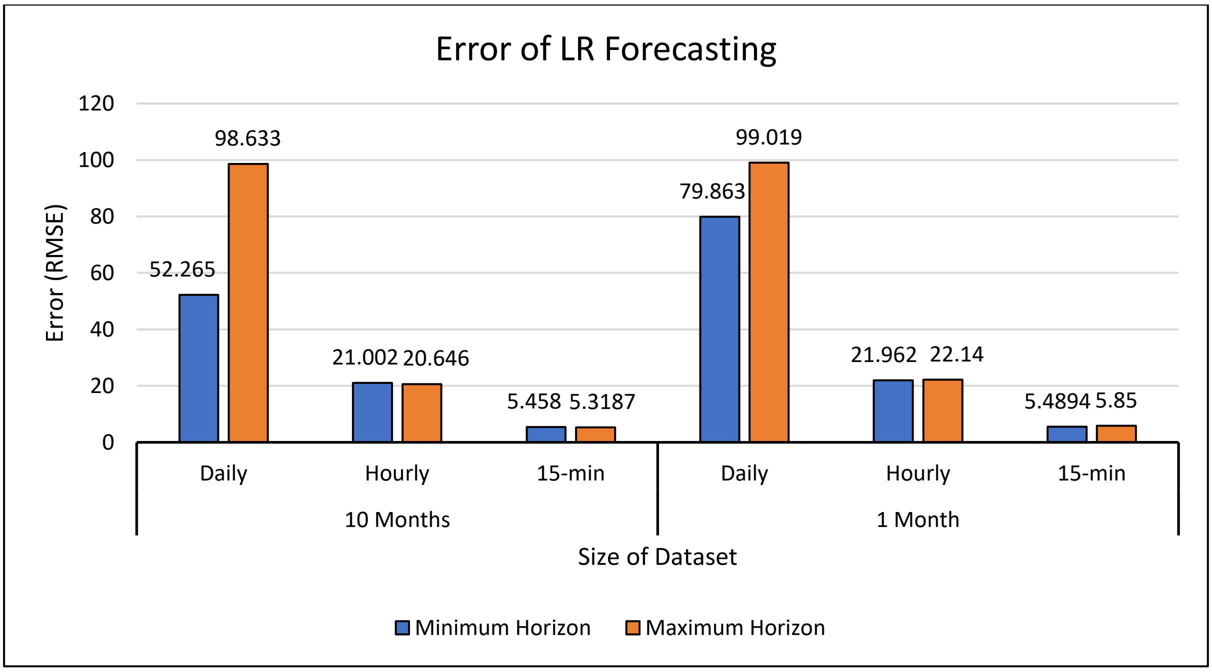

Figure 6.8. The LR forecasting results when trained with 1 month and 10 months of data.

The LR forecasting errors range from 99.019kW to 5.3187kW RMSE. Minimum horizon forecasting consistently provides lower errors except from when the algorithm is trained with 1 month of data for hourly and 15-minite forecasts. In this case, the maximum horizons provide a lower accuracy. The LR algorithm has an average error of 36.47kW RMSE for all tests.

Results for SVM forecasting MAPE are illustrated in Figure 6.9.

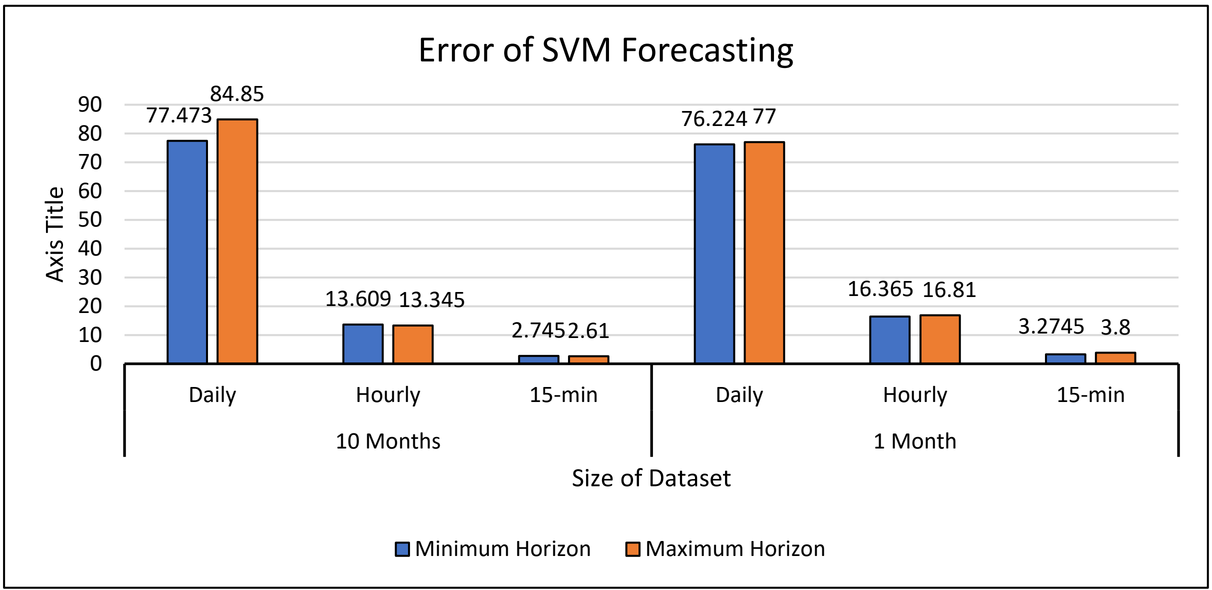

Figure 6.9. The SVM forecasting results when trained with 1 month and 10 months of data.

The SVM algorithm has a maximum and minimum error of 84.85kW and 2.61kW RMSE respectively. Maximum horizons have a higher error in 4 out of 6 tests but the RMSE error difference between the minimum and maximum horizons are much smaller than other algorithms. The average RMSE for the SVM algorithm across all tests is 32.34kW. A comparison of this work against other PV systems is shown in Table 6.4.

Table 6.4. The comparison of this research (first row) against previous MLA PV system forecasting [197-200].

Location and Average Outdoor Air Temperature °C	**System Size**	**Error**	**Method**
UK. 10.43	30kWh Peak	1.76kW	Neural Network
South Africa. 19.76	75MW Peak	4.56MW	Neural Network

America. 8.04	30MW Peak	4.1MW	Gaussian Regression
Belgium. 11.73	368kWh Peak	3.23kW	Neural Network
Italy. 15.04	327kWh Peak	1.04kW	Neural Network

This research's results are shown in the first row. The other results show that most research is done for forecasting a PV solar farm and not for localised systems. The accuracy of the forecasts are difficult to compare due to the different sized systems and climate they are in. The largest system is in South Africa with 75MW peak, and the smallest is in this research for the local PV system at 30kWh peak. The coolest climate is in America with a temperature of 8.04^{o}C and was still able to forecast with an error of 4.1MW of the peak output power. The warmest climate is in South Africa with 19.76^{o}C was able to forecast with an error of 4.56MW of the peak output power. There is low correlation between errors, system sizes, and air temperature, showing there is no optimal location or size for a PV system to be forecasted.

In this research, 64 models are developed and tested with a variety of sizes for training data and horizons. RF algorithms produced the lowest error with an average RMSE of 32kW and it required less data to successfully train the algorithms. This is due to the algorithm generating a set amount of decision trees and more data having more incorrect datapoints that the processing algorithm cannot remove. The NN's showed the highest RMSE at 38.8kW however it had a lower error on 7 of the 12 datasets it was trained and validated with compared to the RF with the lowest error on only 3 of the 12 datasets. The LR algorithms trained the fastest on average at 41.7 seconds per algorithm. Overall, RF provided the highest accuracy among the tested algorithms in this research work while requiring the least amount of training data. The collected data for each method of energy generation differs with data types. This includes weather variables and the design of the energy systems.

The Business School has no other on-site energy generation, although, the method of MLA applications for accurately forecasting the energy generation of on-site renewables covers all methods of energy generation. This is dependent on the volume and quality of the data, and the importance of the input data to the output data. As the occupancy, renewable energy generation, and energy consumption within the building can be forecasted, they can be applied to methods such as infrared heating and electric vehicle bi-directional charging. The accuracy of the developed MLA's and the improvement of energy efficiency and the reduction of carbon emissions must be evaluated to determine the effectiveness of applying MLA's to BMS's.

6.4 Summary

As renewables produce energy with no or reduced carbon emissions, they are imperative for improving the energy performance of non-domestic buildings. Their generation can be unpredictable though, so MLA's are developed to forecast the Business Schools' PV system. Various RE methods are analysed and compared to show the practicality and applications. The results from the MLA's can be used to aid the BMS in optimising the energy management.

The RF algorithm has the lowest error with 32kW RMSE and LR had the quickest training time with 41.7 seconds. The feature importance algorithm ranks the inputs in in order; humidity, cloud cover, wind speed, outdoor air pressure, outdoor temperature, and rainfall, concluding that if limited data is available, it should be collected in the specified order. The NN had the highest error among the selected MLA methods, so it is not recommended that it is used with this dataset, however, this does not mean that a NN would not work with different climate data and PV system. The RF forecasting accuracy increased the most when the three top features are removed by 33.19%, Showing that for the dataset used in this research, the RF algorithm provides the highest accuracy and LR has the quickest training speed.

The applications of the developed methods of energy characteristic, generation, and occupancy forecasting must be considered for a functioning non-domestic building. The application to the Business School shows how the methods can be applied and how they aid in the reduction of the buildings' carbon emissions. The novelty from this chapter is found in the data presentation. Previously, various applications, and therefore various datasets are used as inputs for RE forecasting machine learning models. The accuracy varies with different applications due to a number of variables such as quality and quantity of data, different inputs, location, and age of RE equipment. When deciding what data to collect and what ML models to develop, there is no defined conclusion due to there being too many variables.

The novelty in this chapter stems from using different sized datasets (10 months and 1 month), different forecasting resolutions (15-minutes, hourly, daily), different input features, and different algorithms. They are all forecasting the same variable, but they are all being controlled instead of comparing them based on completely different renewable energy system forecasting. Future applications can know that on average RF is faster to train among all datasets and is more accurate with less input features, but a NN has higher accuracy when provided with more data iterations. This gives a reference for future applications of MLA forecasting to PV systems. This could be improved further by adding more RE systems in different locations into the method in this chapter, providing a more generalised conclusion.

The combination of energy generation and consumption forecasting can be used to optimise a BMS. This chapter shows the applications of MLA's for RE systems and chapter 7 shows how MLA's can be developed and applied to a functioning non-domestic building to forecast energy consumption and characteristics.

CHAPTER SEVEN: ANALYSIS AND IMPROVEMENT OF ENERGY PERFORMANCE FOR OPERATIONAL UNIVERSITY CAMPUS THROUGH MACHINE LEARNING FORECASTING

This chapters' focus is on the application of the developed machine learning algorithm's into the Business Schools' building management system to increase the energy efficiency of the building. The developed algorithms can forecast the energy demand and surrounding characteristics of the building. The forecasting accuracy and parameters that determine the ease-of-use for the various algorithms are evaluated with a focus on the effects that the MLA has on the BMS.

The application of renewables and energy trading schemes within the BMS are analysed to determine optimised management of the buildings' resources. The novel methods of CO_2 *density forecasting which can be applied to energy efficient heating, bi-direction electric vehicle charging, and renewable energy forecasting are explored. They have previously been explored independently, but this chapter is with regards to the application together in a multi-purpose operational university building.*

7.1 Introduction

The Manchester Metropolitan University Business School is a non-domestic building within the Manchester campus. As it is ranked the number two sustainability university in the UK, the Business School has many smart features to reduce the CO_2 emissions, but it is far from being a net zero building. As the government legislations have a target for a complete elimination of carbon emissions from buildings, the energy efficiency of the building must be optimised. The BMS controls the HVAC system, lighting, and PV generation where the systems' energy waste is reduced in comparison with no applied BMS. The previously developed novel methods of energy reduction in this thesis such as bi-direction EV charging and CO_2 occupation forecasting and the novel exploration of RE generation are applied with already existing methods of energy reduction such as FIR heating, kinetic floor tiles, and revolving doors. The application of energy forecasting allows optimisation of energy management and storage with regards to energy price and fluctuation in current and future energy demand.

This requires accurate forecasting of the buildings' energy requirements. Although MLA have been developed in chapter 4, they are used to forecast the monthly price of energy, whereas in this chapter, more finite data is collected, and more complex MLA are developed for an accurate forecast of the energy consumption. The application in chapter 4 provides information on the economic practicality of the V2G method whereas in this chapter the MLA allow the optimisation of the MMU Business Schools' BMS.

The MMU Business School has an energy consumption of 2.5GW for the year 2020 where the average commercial building in the UK used 62,761kW for the same year. This shows that the Business School is a large building due to it having many installed energy saving measures and it still using 97% more energy than the UK's average commercial building. Although it is not exactly classed as a commercial building, it has commercial qualities that can consider it in that category. The building has many functions including two cafes, offices, lecture halls, computer rooms, a canteen, elevators, and a kitchen. The cafés are open spaces, with no ceiling until the roof of the building, and occupancy peaking at 9am and 12pm. This requires air conditioning for the occupied time and invokes a peak in HVAC and common energy consumption through the use of the coffee machines. The offices are often regularly occupied, from 9am – 5pm with a break at 12 – 1, and with ceiling between 2.4m – 2.7m high.

This invokes a peak at 9am and requires maintained air conditioning throughout the day. The lecture halls often have high peaks as large capacities of occupants arrive according to the schedule which often changes, bringing unpredictable energy consumption into the building. The lecture halls require more HVAC and lighting energy than other rooms due to them having no windows, high ceilings, and the required air ventilation and heating or cooling for the room under occupation. Computer rooms act like normal offices for the HVAC system, with standard ceilings and maintained air conditioning throughout the day but as occupants come and go, this can provide more unpredictable energy consumption. The canteen is opened at 12pm and must condition the air for up to 50 occupants once open, with no regulations for how many can fit into the room, this could be a large energy consumer for the HVAC system. The elevators energy consumption peaks between 8:30am – 9am, at 12pm – 1pm, and again at 5pm. This is due to occupants entering the building, leaving for lunch, and then leaving again once the working day has finished. The 6 elevators being used constantly for up to an hour at a time can require large amounts of energy consumption but can be predictable with respect to time. The kitchen is in use for the morning until the canteen closes after lunch. It starts to consume energy at 8am when it opens and continues until between 2pm – 3pm. As it is scheduled, it can be easier to predict the consumption with respect to time.

The current case study building has various smart measures and a BMS capable of automating some resources. The problem with non-domestic buildings in an energy context is that they work through real-time management of their systems instead of through forecasting. The benefits of forecasting the energy characteristics help the system to respond to changes faster such as starting the heating before the buildings' temperature has dropped. Energy trading has the potential to reduce the buildings' carbon emissions and energy costs through the forecasting of the buildings' supply and demand. Potential renewable energy harvesting and trading applications are developed in this chapter. The aim of this chapter is to present the results collected from this thesis and the developed MLA's in this chapter and how they are applied to the BMS. The improved BMS is then analysed to show the improvement in energy efficiency and costs compared to the BMS without any MLA applications.

The aims of this chapter include analysis of:

- The buildings' volume and times of energy consumption and renewable energy generation.
- The buildings' physical parameters such as open space, floor space, number of floors and other parameters.
- Energy systems such as the HVAC and lighting in the context of the energy performance.
- The current BMS to determine the management response to the above variables and how it can be improved.
- How the application of machine learning algorithm forecasting of the energy parameters can improve already-existing methods when used in parallel with the novel methods proposed in this thesis.

7.2 Application of Smart Energy Consumption, Storage, Generation, and Trading to an Operational University Campus

Demand forecasting can be used instead of purchasing energy at the time it is needed. Instead, the energy can be purchased in advance at a cheaper rate. The demand is either peak-time or off-peak, with an electricity price of 15p/kW or 12p/kW respectively. This can only be done if the energy demand is accurately forecasted a day before. A smaller resolution and a larger horizon forecast provide the BMS with more information it can use to save costs and stabilise the grid. The average daily energy demand for the year 2022 is shown in Figure 7.1.

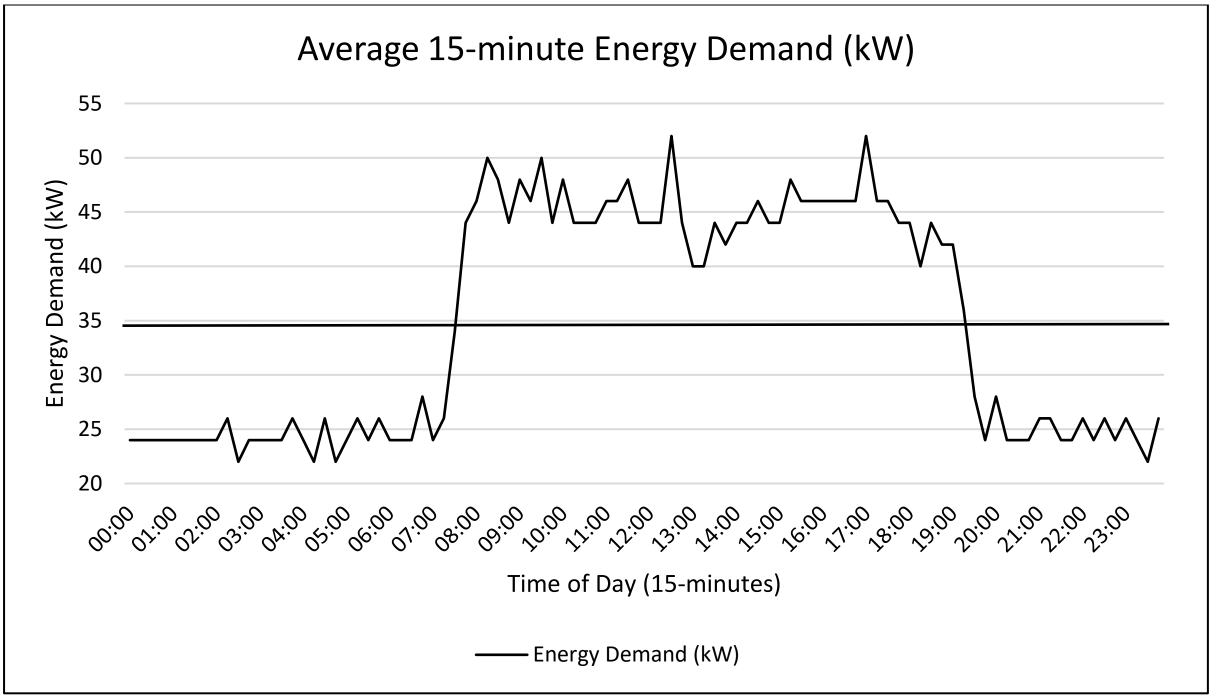

Figure 7.1. The average energy demand of the Business School in 2022 with 15-minute resolutions on the energy meter. This equates to 6.792kWh/day with 11.75 hours of peak time and 12.25 hours at off peak.

The average energy demand from peak to trough is 34.68kW/15-minutes and this is used to separate the energy rates. Above the average is peak time where the price is 15p/kW and below the average is off peak where the price is 12p/kW. For an average day, the buildings' energy tariff is £463.08 when purchasing the energy in real time for peak time and off-peak rates. Currently, the only energy generation for the building is from the PV system with no BESS. This is due to the BMS not using any energy storage or having any energy parameter decision making. Energy generation and storage within the building can be combined with the MLA energy characteristic forecasting to improve the energy performance of the building. The BMS can work many ways, but the main premise is that the BESS is filled through on-site renewable generation and the energy demand is met from purchasing from the grid at off peak times. When the buildings' energy demand increases to peak time, the energy from the BESS can be used instead of purchasing from the grid, saving costs. This can only be done if the MLA is able to accurately forecast the energy demand of the building, as this allows the BMS to calculate how much energy it needs to purchase and store and for how long.

The method of carbon emission reduction requires both the increase of renewable energy generation and the decrease in energy consumption from the buildings' various required systems. This involves heating, lighting, the use of EV's, building energy storage systems, and kinetic energy harvesting from the occupants' behaviours and movement.

It is necessary that the buildings' lighting consists of LED's as they can use 75% less energy and last 8 to 25 times longer than conventional halogen light bulbs [201]. The benefits of LED's within the Business School are apparent through the installation and measurement of CO_2 emission reduction over the course of 5 years. LED's and occupant dependent lighting started to be installed in 2013 under the supervision of Dr. Albarbar at the university, and between the years of 2013-2019, the yearly electricity demand and carbon emissions have been reduced by 124,690kW and 71,821kgCO_2 respectively. This is an electricity demand and carbon emission reduction of 6%. Currently, all lighting within the Business School are LED's and zones are controlled through PIR sensors, capable of detecting occupancy.

The Business School has a total of 12.6km of usable floor space throughout all 8 floors, with a total of 2.55km of corridor and door space for the use of kinetic floor tiles. There are over 40 parking spaces used by the buildings' staff, with the capability of using the V2B EV trading technique [30]. There are 4 revolving doors and 241 swing doors to generate electricity and 70m of roof edge for ridge installed wind turbines. The building already has a borehole installed but it is not yet in operation.

The application of MLA's for the forecasting of occupation allows the pre-heating of zones, and in particular, the application of FIR to improve the energy efficiency of the heating system. In previous work, IR sensors has to be installed to record occupation, but CO_2 can work if applied correctly to give the same results. Installed energy generation methods can involve kinetic floor tiles, revolving door generators, solar, wind, hydrogen fuel cells, and biomass.

The potential generation if kinetic tiles [127] are installed within the revolving doors of the building could be up to 360kW/day, saving between £43-£54/day, assuming maximum occupation. The revolving doors can be used to generate energy from the kinetic energy of the occupants opening the doors. This can generate 960kW/day, saving £129/day. The 241 swing doors can be used to generate energy from the occupants too, generating up to

1,090.5kW/day under the assumption that every door within the Business School is opened twice [131].

The current heating system could be replaced with an infrared heating system to improve efficiency by 76%, saving 280kW/day, with calculations taken from the CO_2 MLA forecasting algorithm from chapter five. The V2B method could save between 35%-65% on costs, which is between £145-£317/day. The ridge installed wind turbines could generate 508kW/day at peak power continuously, saving between £61-£76/day. PV generation currently accounts for 964.4kW/day, generating most of the energy at peak time when the insolation is most direct. These methods of energy generation and utilisation can improve the buildings' energy efficiency and costs. From the above-mentioned methods, 45% of energy generation and up to 100% of costs can be saved at peak power generation but only if the V2B method is applied at all times of the day and not only at peak-times.

The renewable generation isn't a constant supply, in which they will reach peak output at various times of the day. The relationship between the energy demand and the energy generation for the building is shown in Figure 7.2.

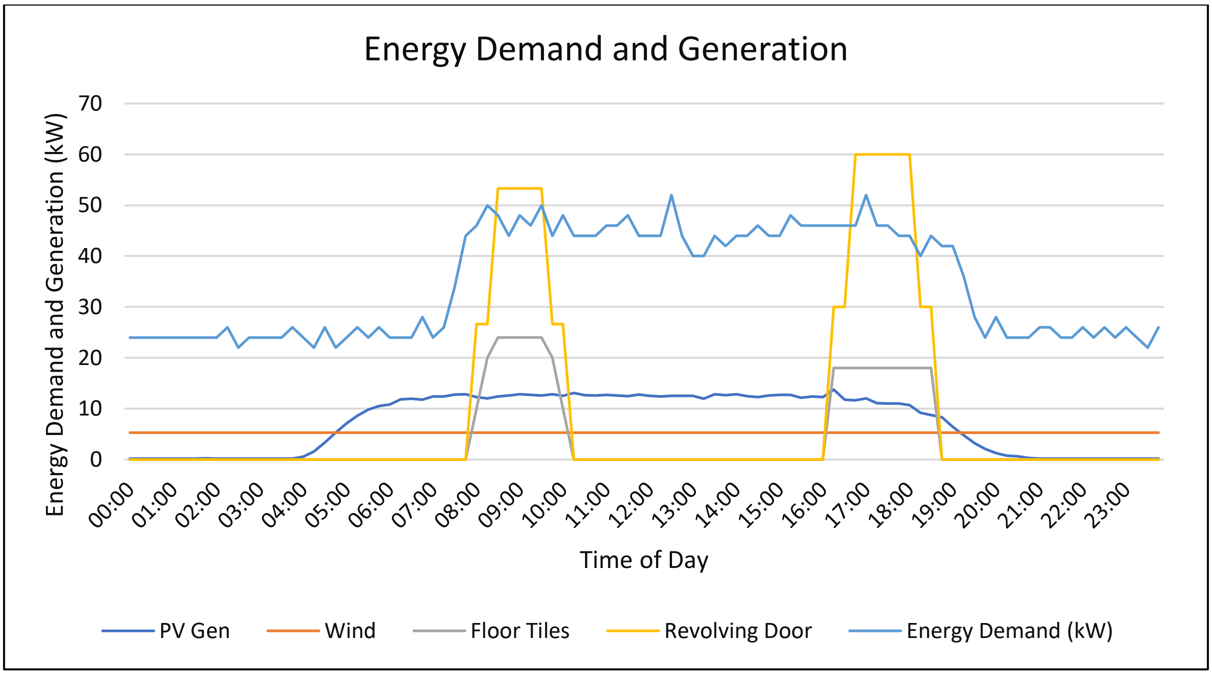

Figure 7.2. The energy demand and the renewable energy generation of the building.

Wind energy is constantly generating a low amount all day. In a real scenario, this energy generation would vary throughout the day but in this case study, there is no wind power installed. The MLA's can accurately forecast the wind speed and thus, the energy generation such as in previous research [156]. The wind turbine to be installed on a building with little dispensable space can be a turbine such as in previous research [133]. This allows the turbine to be installed on the highest ridge of the building, and due to the Business Schools' roof being sloped, the wind can be channelled up the roof and into the turbine.

The PV generation data isn't calculated and is instead taken from the actual data from the installed PV system on the Business School and aggregating the results of an average day. To determine the energy generation of a PV system, the developed method in chapter six can be replicated. This is where MLA's are employed and are given data surrounding the energy output of the system and climate data affecting the generation. The results from chapter six show that the energy generation from the PV system can be accurately forecasted with an error of 1.766kW when forecasting in 15-minute iterations over a 24-hour horizon when only being trained with 1 month of data.

The kinetic floor tiles are only able to generate energy when the occupation volume is high, and the placement of the tiles also affects the generation. For an optimum method of utilising kinetic floor tiles, they can be installed in the doorways that see the most footfall such as through the main revolving doors. This allows the tiles to see the most generation and from an economical viewpoint, it reduces wasted costs due to installing the floor tiles where they might not see occupation. From an economical viewpoint of using doors to generate energy, larger doors that see the most use are preferred as they provide the most energy. Like the kinetic floor tiles, if the doors are installed with energy generation methods and aren't used, such as in a boiler room that cannot be accessed by the public, then they won't generate as much energy but will require the same investment. The revolving door provide the best benefits, but to meet the requirements of a net zero building, all doors can be fitted with generation capabilities. Although no previous revolving door energy generation is forecasted, the developed method of forecasting the occupation volume in chapter five show an accuracy of 97.76%. This shows that the revolving door energy generation can be forecasted through MLA methods, as the occupancy directly affects the energy generation.

The energy surplus is illustrated in Figure 7.3.

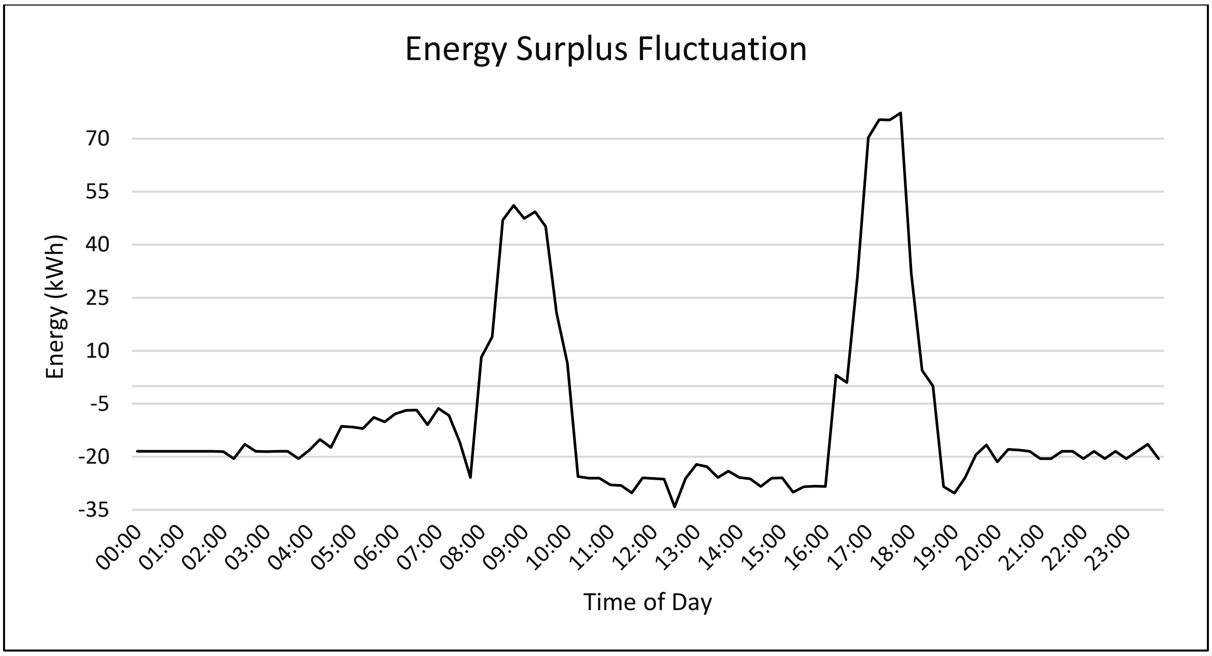

Figure 7.3. The energy surplus fluctuation throughout a day.

The energy surplus fluctuated greatly from -34.1kW/15 minutes to 77kW/15 minutes due to there being a peak demand at 12pm with not enough energy generation. Although there was a high demand 5pm-6pm, the footfall had large effect on the kinetic energy, generating a large amount of energy, leading to a surplus. To optimise the management for the energy fluctuation, the MLA results are applied to the BMS which is explained in the results section. If the future energy demands of the building are known, then the surplus can either be sold or stored, where the MLA's forecasted results are necessary to optimise the actuation of the generated and stored energy. Methods of storage where the energy can be generated and stored as renewable energy include hydrogen and biomass. The method of electrolysis and hydrogen storage is able to convert the energy from electrical energy into stored hydrogen that can be used within a hydrogen fuel cell to generate electrical energy. Biomass is less useful when dealing with excess energy due to it not only using energy to heat, but also combustible mass. The mass can be collected on-site through waste food, or it can be bought in from a supplier and can be stored until it is needed.

Hydrogen storage, hydrogen fuel cells, and biomass have not been calculated due to the large amounts of variability within the methods. Hydrogen that is generated from solar PV costs £4.35/kg to produce through electrolysis with an efficiency of 60% and contains 33.33kWh/kg [202]. The energy surplus of the Business School has two peaks at 289kW and 369kW which can either be stored, sold, or used for electrolysis, generating up to 395kW in total energy which can be stored. Hydrogen is a good method of managing the energy surplus, but due to the low efficiency of 60% and large energy losses, the method relies on the results of the MLA forecasting to optimise. If the forecasted results show that there will be a large increase in energy demand, then the hydrogen storage method can provide benefits for the building. This is due to the energy being stored instead of being sold and then potentially bought at a higher price. If the results of the MLA forecast a decrease in energy demand, the hydrogen storage isn't necessary, the energy can be sold, and no energy will be lost through the method of electrolysis. The trading of surplus energy isn't absolute, as some of the energy can be sold, and if the results from the MLA's are accurate enough, the energy can be stored for later use without selling or buying more than is necessary. The biomass energy generation can also provide different outputs, depending on the size of the system as a 7kW and a 20kW are previously tested [203].

For a scenario where there is no installed BESS, the energy can be traded for the advantage of the building but only if there is an energy surplus. The generated energy that has not been consumed within the building can be sold to the national grid which offsets the carbon emissions of the building. For larger buildings such as the Business School, it can be difficult to produce an energy surplus as on-site renewable energy generation requires initial investment, but once these generation methods are installed, the building can reduce the carbon emissions.

The bi-directional EV charging method developed in chapter four allows the EV's battery capacity to be used for the advantage of the building, meaning that the building doesn't have to purchase a BESS as large as it would without using the method. The CO_2 forecasting method developed in chapter five can be applied to the revolving doors and elevator consumption to forecast energy generation and consumption to a more accurate degree instead of for the building entirely. The RE forecasting analysis from chapter six can be used to develop a more accurate forecast, and thus more accurate energy management from the BMS.

7.3 Machine Learning Algorithm Energy Characteristic Forecasting

There are 25 developed algorithms, capable of generating the Business Schools' energy characteristics. The algorithms comprise of a neural network, decision tree, random forest, linear regression, and support vector machines. The energy characteristics comprise of the kitchen, lighting, HVAC, overall demand, and the CO_2 density. These are developed to produce results of multiple iterations and horizons, capable of being installed within any BMS for any type of building.

The data used in this chapter is collected from the 102 energy meters within the MMU Business School. The data consists of the overall energy demand (kW), the lighting demand (kW), HVAC demand (kW), kitchen demand (kW), outdoor temperature (^{o}C), rainfall (mm), cloud cover (%), outdoor air pressure (mb), and the time of day. The data is collected every 15-minutes from the meters, meaning the minimum resolution the data can be forecasted from the MLA is 15-minutes. This can be aggregated to form larger resolutions such as hourly. The start and end dates for the collected data is from 03/09/2015 at 10:45 until 31/12/2019 at 23:45, giving 36,935 samples and 332,415 datapoints across all the samples and the collected inputs. This data is stored into an online database and is downloaded locally to a CSV file that can be accessed by the machine learning software.

The models are trained by splitting the whole dataset into 20% for testing and 80% for training. The target data (energy consumption) is split from the rest of the inputs, and the rest of the data is used to train the MLA. Once the relationship is calculated by the MLA, the input test data is fed into the MLA. As it has not seen this data before, the forecast of the target data is compared against the actual collected data to show the difference between the datasets to show the error.

The models can be evaluated through measuring the error, in this case in mean-actual-percentage error. The MAPE is beneficial because it shows the error for multiple MLA, allowing a simpler comparison between them than with other error metrics.

The developed algorithms' forecasting accuracies for 15-minute iterations are shown in Table 7.1.

Table 7.1. The forecasting error of the developed algorithms when forecasting the various energy characteristics on a 24-hour horizon and a 15-minute resolution.

Method	**Demand %**	**Kitchen %**	**Lighting %**	**HVAC %**	**CO_2 %**
NN	11.11	35.39	41.96	12.46	3.21
DT	12.58	27.33	34.08	12.52	2.82

RF	10.9	24.76	36.39	13.02	2.76
LR	13.64	39.5	36.24	16.8	2.61
SVM	17.61	54	36.08	57.97	2.52

They are trained with 123 days, 11,798 iterations, or 106,182 data points. They are validated against 31 days of data in December 2019. The target data is trained 24 hours in advance so the algorithm can forecast for the next 24 hours. The CO_2 data is trained with 2 weeks, 1,283 iterations, or 7,698 data points. They are validated against 7 days of collected CO_2 data from a lecture hall in the Business School.

MLA's are also developed to forecast hourly and daily resolutions with the lowest errors of 6.6% and 4.07% for a decision tree and for a random forest respectively.

The correlation between the inputs and the target features has great effect on the accuracy of the various forecasts. The correlation's are displayed in the confusion matrix in Figure 7.4.

Temperature	1	0.228	0.206	0.184	0.215	0.259	0.136	0.096
Lighting	0.218	1	0.185	0.174	0.208	0.217	0.152	0.116
Cloud Cover	0.217	0.213	1	0.212	0.233	0.231	0.131	0.112
Rainfall	0.221	0.219	0.229	1	0.307	0.240	0.127	0.120
Air Pressure	0.213	0.209	0.216	0.253	1	0.230	0.126	0.133
HVAC	0.129	0.196	0.187	0.161	0.186	1	0.176	0.092
Kitchen	0.191	0.209	0.181	0.157	0.172	0.237	1	0.102
TOD	0.189	0.204	0.190	0.181	0.194	0.193	0.129	1
	Temper-ature	Lighting	Cloud Cover	Rainfall	Air Pres-sure	HVAC	Kitchen	TOD

Figure 7.4. The correlations between the collected input variables for the MLA's.

The vertical axis follows the same variables as the horizontal axis from top to bottom: outdoor air temperature, lighting demand, cloud coverage, rainfall, outdoor air pressure, HVAC demand, kitchen demand, and the time of day.

The correlations between the variables are measured through a DT algorithm. The calculations of associations between two variable splits 'λ_{jk}' can be explained through Equation 7.1 [204].

$$\lambda_{jk} = \frac{\min(PL,PR) - (1 - PL_jL_k - PR_jR_k)}{\min\,(PL,PR)} \qquad \text{Eq. 7.1.}$$

Where 'PL' is the proportion of observations in the left child node such that $x_j < u$. 'P' is the proportion of observations in the right child node such that $x_j \geq u$. The value of u is a threshold that is defined by how the data is best split. Where x_j and x_k are the predictor variables j and k respectively. 'PL_jL_k' is the proportion of observations at the node such that $x_j < u$ and $x_k < v$. 'PR_jR_k' is the proportion of observations at the node such that $x_j \geq u$ and $x_k \geq v$. This gives a value of between $-\infty$ and 1 where any value above zero provides an important variable. The DT is grown, and an optimal split is identified through how even the data is split, and it is used as a reference. Among all the other decision splits that are compared to the optimal split, the best surrogate decision split yields the maximum predictive measure of association. This method can distinguish the similarities between decision rules that split observations in a DT. Pearson's correlation is often used to measure the correlation between two variables, but it can only measure the linear relationship. As the data isn't linear, the method of predictive association provides a more accurate correlation. Correlation provides information on the relationship between two variables, but it does not show causation or explain the reasoning behind the change in the variables. This must be calculated through a method such as the MRMR algorithm.

The feature importance and selection method that provided the best results was MRMR when compared to the F-statistic and RF-OOB. The top three features are the lighting, time of day, and outdoor temperature. Removal of the three features with the lowest importance score provided an error improvement of 1.05%, from an original error of 11.08% to 10.03%. These are rainfall, outdoor air pressure, and cloud cover. This is due to the MRMR algorithm not just measuring the predictor against the target, but also against other predictors, so if two predictors are highly correlated, only one of them needs to be included in the target. This works well specifically with the RF because the same number of decision trees can still be created, but they can focus on predictors with a higher importance to the target.

Currently, RF provides the best results because the average Pearson correlation from the demand to the other features is 0.46, meaning there isn't a high linear relationship. NN's require more data for training compared to RF and as this method is using a limited number of inputs, other MLA performance is lower.

The features with the lowest importance are removed from the MLA's to measure the effect they have on the algorithms. To measure these, the MRMR algorithm is developed with the training data and the results are shown in Figure 7.5.

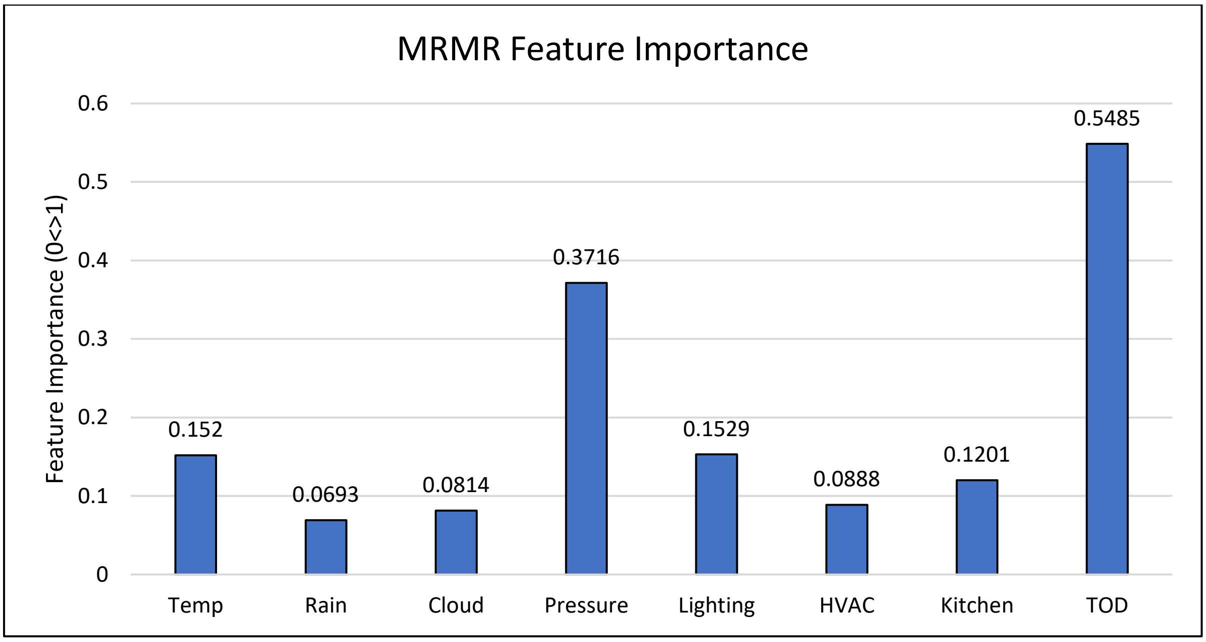

Figure 7.5. The MRMR feature importance scores for the input variables when forecasting the overall energy demand.

The time of day has the largest effect on the overall demand and the rainfall has the least effect on the demand. The buildings' main functions are the HVAC system and the lighting which are both somewhat dependent on the volume and behaviour of the occupants of the building. As the occupants enter the building and use the functions during the same times every day, the energy consumption follows a pattern as is shown in Figure 7.2. Due to the relationship between the time of day and the energy demand of the building, the MRMR results show that the time of day has a larger importance than the other inputs.

7.4 Summary

The developed energy generation and consumption improvement methods are applied to the Business School with already-existing methods of energy reduction. The current energy generation and consumption of the Business School is analysed. Applications of energy saving techniques such as LED's and FAR infrared heating are explained, showing the benefits for the Business School. Energy storage and trading are explored, showing that hydrogen can often be used to store excess energy with no carbon emissions, but with reduced efficiency.

Collection and critical analysis of training data for the MLA's is completed through an algorithm that removes outlying and missing data. Feature importance is calculated through the MRMR algorithm, and finally, the MLA's are developed.

The importance of accurate energy characteristic forecasting is demonstrated with various applications of MLA's being applied to the developed methods. For the building to be considered net-zero, it must generate more or equal energy than it is consuming. The energy can be reduced through methods such as FIR heating and more energy can be generated through methods such as kinetic tiles. The energy deficit and surplus vary throughout the day as does the demand. To ensure the energy management is optimised, the MLA's have been developed and employed to accurately forecast the specified variables to ensure the energy is stored, traded, and consumed with minimum waste. This can be more accurate than previous methods such as building information modelling and the Government standard assessment procedure tool to forecast energy characteristics with less intrusive data collection and can be an efficient and reliable tool to help reduce the carbon emissions of non-domestic buildings.

The novelties in this research are applied to a functioning non-domestic building with already-existing methods of energy reduction. These include combining the EV V2G method from chapter four with previous energy generation and storage techniques to reduce energy demand by up to 45% on the case study building. This requires accurate forecasting of the energy generation of kinetic tiles and revolving doors, and consumption of elevators, lighting, and HVAC. This requires occupancy forecasting. As the CO_2 forecasting from chapter five does not require PIR or facial recognition sensors to be installed, it is a cheaper option of occupancy forecasting, and it allows more management of generation and consumption. On top of this, the RE forecasting can be achieved through the analysis from the method in chapter 6 and can be combined with the above methods. This results in accurate forecasting of CO_2 (which can be used to determine occupancy) and renewable generation, and with more control over energy management through using the battery capacity of connected EV's. More control through MLA forecasting can reduce energy consumption by 45% for the case study building.

This chapter demonstrates that reducing energy consumption, increasing production, and optimising management through machine learning methods can be a necessary contributor to the reduction of carbon emissions for non-domestic buildings.

CHAPTER EIGHT: ACHIEVEMENTS AND FURTHER WORK

This chapter starts by outlining achievements as compared to the objectives set in section 1.4. After this, more precise conclusions are outlined and finally, recommendations for future works are stated.

8.1 Contributions to Knowledge and Significance of this Research

In this work, the application of machine learning to the building management system, electric vehicle fleet, heating system, and renewable energy system is achieved. This allows analysis of energy management optimisation through energy storage, trading, and consumption. The application of MLA forecasting can aid in better energy management, reducing energy consumption, and increasing energy generation.

The work achieved in this research include numerous novel aspects. These are summarised below:

1. A developed occupancy forecasting method through machine learning methods, using CO_2 density data from the room as the input. This is combined with a FAR infrared heating for a public building, showing an energy reduction of 75.97% compared to the existing heating system for the specific application. The applications of MLA forecasting were able to predict what times the lecture hall was occupied, allowing pre-conditioning of the zone.
2. A method of using the capacity of electric vehicles is developed. This is important not only because it can save the case study building and other public buildings costs, but because it reduces the energy demand from the national grid. The cost reduction from this method could total 64.7%.
3. A comparison of existing MLA's used for forecasting renewable energy generation of a local solar PV system, providing important knowledge on how each algorithm is affected by poorer quality data, less inputs, and less iterations to be trained and tested on. The solar PV system can be forecasted with 95% accuracy, allowing the application of optimised energy management from the on-site generation techniques.

The significance of this research is summarised below:

1. In the UK, prices of energy are increasingly difficult to afford for the average home and business owner, affecting profits for businesses and quality of life for homeowners. If the energy consumption of non-domestic buildings is decreased, there is less demand while maintaining the same supply for the national grid, and

there is more energy to be provided for domestic buildings, and therefore the price of energy is reduced.

2. Currently, the UK has a single coal power plant which produces CO_2 emissions and is activated to meet peak power loads for the national grid. Other countries rely on coal or other fossil fuels as their main source of energy, generating more CO_2 emissions than necessary. This proves there is a timely need for applying research such as this into all situations including non-domestic buildings.
3. In densely populated cities and places of production, more carbon emissions will be generated through transport, production of materials and products, and various other methods. By targeting electric vehicles and non-domestic buildings, these CO_2 emissions can be alleviated, providing better air quality for all living creatures.

8.2 Objectives, Achievements, and Discussions

The main achievements that are described in the introduction chapter and how they have been accomplished are explained.

Objective 1: Conduct a thorough literature survey on previous work surrounding non-domestic building's energy consumption to identify the research gap.

Achievement 1: A diverse range of sources are collected to show current methods of energy forecasting, carbon emission measurement, renewable energy generation, electric vehicle applications, and building management systems. These sources range from government documents, scientific review and journal publications, and websites from previous case study buildings. This provides a comprehensive analysis of previous work in this field, allowing the conclusion that current techniques of reducing carbon emissions are not good enough to meet government regulatory targets, and can be improved through machine learning applications.

Objective 2:

Critically analyse existing design tools used to increase a buildings' energy efficiency. These include renewable energy generation, building energy storage systems, and various methods of reducing energy consumption.

Achievement 2:

The analysis of previous design tools for increasing the energy efficiency of buildings' has been accomplished. Conventional energy generation techniques are evaluated, and the applications of novel techniques are explored. Chemical battery building energy storage is compared against hydrogen and the utilisation of the battery capacity of electric vehicles. Hydrogen has the potential to reduce carbon emissions and V2G applications can reduce stress from the national grid while reducing energy costs from the building. Energy reduction techniques are developed through applying infrared heating and machine learning to the Business School and comparing the results to a convection heating system.

Objective 3:

Assess the possibility of using already-existing electric vehicles to improve energy efficiency of the building and demand side flexibility for the national grid.

Achievement 3:

A novel method of optimised bi-directional scheduling is developed, using the already existing electric vehicle fleet. This saves up to 64.7% on costs and provides higher flexibility for the national grid.

Objective 4:

Search for more cost-effective heating methods such as through infrared applications.

Achievement 4:

Available heating methods are firstly evaluated through the comprehensive literature review and causes of inefficiency are reviewed. The already-existing method of infrared heating can be considered highly efficient and is further improved by the application of machine learning occupation density forecasting. Occupancy forecasting provides more accurate management, reduces wasted heat when use with infrared heating, and when compared to a conventional convection heating system, it can save up to 75.97% of energy consumption in the case study.

Objective 5:

Develop MLA’s capable of forecasting the energy characteristics of the case study building, and more precisely, the overall energy demand. Various MLA’s are developed to allow an accurate comparison between the models.

Achievement 5:

The MLA’s are developed with collected data from the Business School and the surrounding climate. With the data, they can be trained to forecast the energy demand, other energy parameters, and the CO_2 density of the building, providing vital information on the footfall and how the energy is being consumed. Various algorithms are developed using conclusions from analysis of previous research, allowing the comparison and evaluation between them for this application. This allows them to be applied to the BMS to reduce energy consumption for the case study building.

Objective 6:

Apply the MLA methods to the case study building to reduce the energy demand and to increase the energy generation with optimised storage and energy trading.

Achievement 6:

The collected data from the Business School is used to train the algorithms and the dataset is split into training and testing. The MLA’s are used to develop the V2G research by forecasting the costs and the FIR heating by forecasting the occupation of the lecture hall. The MLA’s are used to determine the management of the energy within the building by forecasting the energy demand and generation. This stops incorrect energy management such as over and under purchasing and selling.

As the surplus of energy fluctuates throughout the day from generation and consumption of the energy, the management has been optimised. This includes generation, storage, trading, and consumption. Generation techniques such as kinetic floor tiles and revolving doors have the capacity to power parts of the building. The storage of the generated energy can be done through techniques such as chemical battery storage, although if hydrogen energy storage becomes more accessible, it can be used while emitting no carbon emissions during operation and giving the building enough energy for when the demand increases. Energy trading can be achieved once the MLA’s have forecasted the buildings’ energy demand. This allows the BMS to control the on-site energy better, allowing the energy to be stored or sold, depending on the forecasts. Smarter consumption such as FIR heating increases the buildings' efficiency, making it easier for the generation techniques to match the energy demand. The Business Schools' carbon emissions could be eliminated through energy saving methods and the application of MLA's, allowing the BMS to purchase and store an optimal amount of energy, with dependence on the generation and consumption of the building.

Objective 7:

Evaluate the MLA's through the forecasted energy demand compared to the actual energy demand of the case study building.

Achievement 7:

The algorithms are tested by forecasting a certain variable for a set number of iterations, and then compared against the actual value of the variable for the number of iterations. This is then evaluated through mean actual percentage error.

The MLA can forecast the energy demand and parameters for 15-minute iterations and a 24-hour horizon with an average error of 10.9% over 31 days. The random forest algorithm is the most accurate algorithm with 89.1% accuracy for 15-minute resolutions and 24-hour horizons. The accuracy increases to 96% for the RF algorithm when forecasting the energy demand in daily iterations for a 1-week horizon. MLA's are applied to the Business School for CO_2 and cost forecasting for both the FIR heating and the V2G method. Both methods showed accurate forecasts of 97.76% and 92.1% respectively. The energy generation from the solar PV system is forecasted with an accuracy of 95% compared to the total energy generation. Overall, the RF provides the better results as the accuracy is often higher while it requires less data to train. The accuracy of the algorithms has great importance for the application towards a BMS, but this can be increased through more complex methods, such as more decision trees in a RF or through more layers in a NN. It can be concluded then that at the present, MLA's provide the best solution to forecasting energy characteristics of non-domestic buildings.

8.3 Conclusion

This thesis concludes that the application of machine learning techniques on smart energy measures and on non-domestic buildings' management systems can play a critical role in the reduction and elimination of carbon emissions.

This can require less initial investment than retrofitting and can be more effective, depending on a multitude of factors such as thermal envelope and other uses that have been explored in this work. The machine learning in this thesis has higher accuracies than previous methods of energy forecasting through AutoCAD software's.

The machine learning has an energy demand forecast accuracy high of 96% when forecasting a 1-week horizon, for every day of the week with the RF algorithm. The solar PV system, occupancy through CO_2 density, and cost forecasting of an electric vehicle to building bi-directional charging method, all providing information for the building management system, and increasing the energy efficiency of the case study building.

8.4 Further Work

This section is split into MLA's and data processing, occupancy data collection and forecasting, future buildings and how they may be designed, and novel technologies that can reduce carbon emissions.

As the development of MLA's are providing the capacity for less necessary data for training and more accurate forecasts, the applications for them become easier. Less training data means that the algorithms can be used on newer buildings, but the accuracy of the algorithms must be maintained to ensure the results can be used within BMS's. As newer buildings often have the aim of having a low carbon footprint, the applications of MLA's towards new builds and buildings with limited collected data must be explored. This could be completed by either using data from similar sized buildings and functions, such as in the case of how the government calculate the EPC, or through improving the MLA's. The improvement of MLA's includes more complex algorithms, requiring more computational power. As the government software's are often inaccurate when comparing the selected building with previous similar buildings, the MLA's are the preferred choice.

Data processing must be improved if MLA's are used in the industry. Incorrect data can negatively affect the performance of the algorithm but can be difficult to remove once the data has been collected and stored. Processing algorithms can remove outlying and missing data, but any incorrect data included in the dataset cannot be removed. This must be removed or noted by the sensors for the dataset to be considered fully clean. This is especially important if there is a new build or a recent renovation and there is not enough data to train the algorithm effectively.

Throughout previous research, occupancy forecasting can be viewed to be difficult to accurately forecast. This is shown where occupancy forecasting has 16.88% error [205]. In the future, tracking of occupancy through more PIR sensors throughout the building or through using the location on their smart phone can aid in the forecasting of occupancy density and behaviour. As behaviour is shown to affect the energy characteristics of buildings, this is an important factor to accurately predict and understand. This can be done through surveys, and in a piece of previous research, this was done through wrist bands that allow the occupants to show their comfort levels. The comfort and behaviour of occupants can be forecasted and the relationship between these variables and manual input on the building can be understood. This will allow the manual controls such as the lighting, HVAC, and window operation to be optimally controlled by the BMS, reducing the total energy demand of the selected building.

Future new builds and renovations will have to consider the carbon emissions generated through the initial build and though the function of the building. This is affected by the buildings' dimensions, type of heating, lighting, and ventilation systems, function, and global location. For a building with FIR heating, there can be larger open spaces such as in the Business Schools' atriums, due to there being less convection heat being lost. For a V-A-V heating system, more energy can be saved when the zones are smaller and easier to condition. The lighting system in a location with less cloud coverage can be optimised through more windows, assuming there are well insulated if it is a hot or cool location. Global warming needs to be considered when selecting the level of insulation. If a building needs to retain heat better now, it doesn't mean that it will need to retain heat better in the future. If the temperature rises, measures should be in place to reduce the insulation and allow better air flow to ventilate the spaces, even if it is not yet required. Research into how a renovation or a new build can be optimised to reduce energy consumption and to promote energy generation would greatly benefit the future building industry.

The FIR heating was applied to one of the lecture halls within the Business School. As each room has a particular function and physical parameters, the benefits of FIR applications can vary. To fully analyse the benefits of FIR heating, the application to many buildings and rooms must be executed. The real-life installation and analysis of the FIR heating system will reveal how the comfort of the occupants are affected and how practical the installation and maintenance of the system is. The developed methods of FIR applications and V2G for the improvement of a non-domestic buildings' energy consumption and costs is done theoretically. Although the FIR method is developed on a recognised computer aided design software, only when it is physically tested can unforeseen circumstances be acknowledged. Although IR heating is used in food processing and in saunas, showing it does not have any short-term health detriments, the long-term exposure from artificial IR has not been investigated. As novel methods of heating must be proved that they have no health detriments, such as with microwave ovens, the long-term investigation will make FIR more popular in the industry. Industry applications of FIR heating may be determined by Figure 8.1 below.

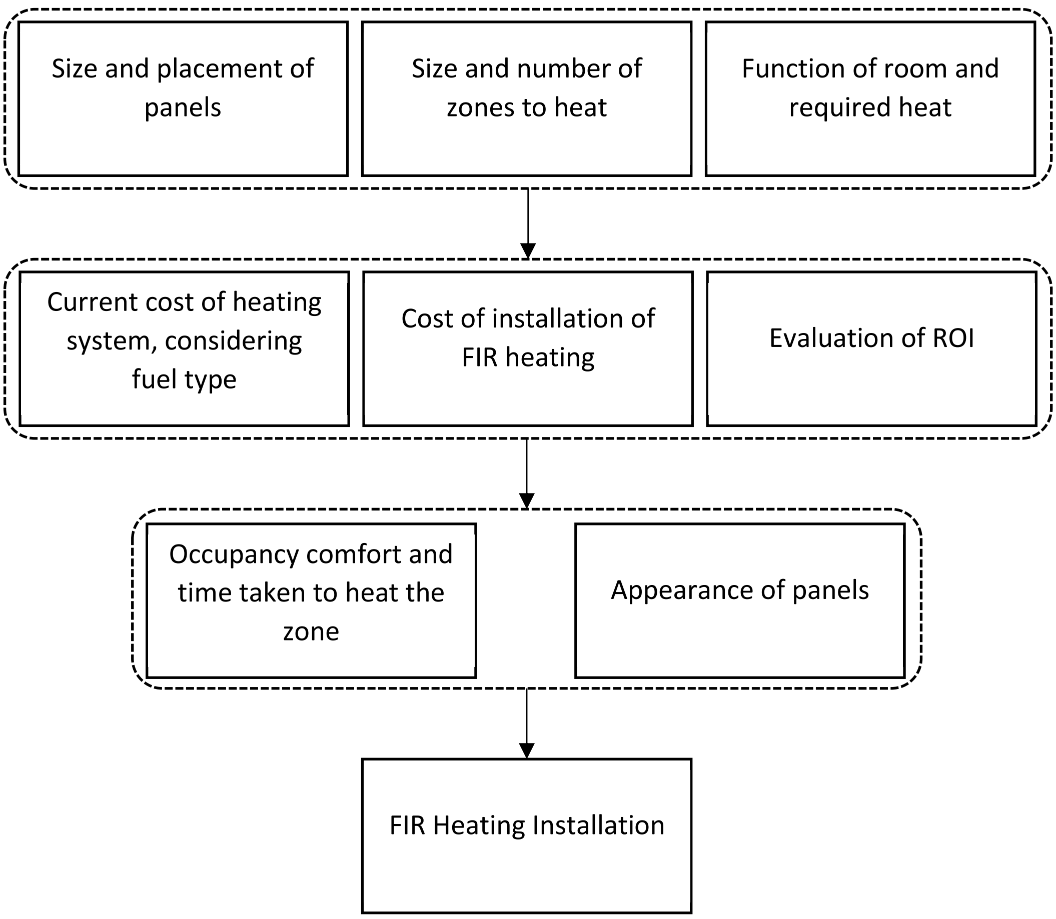

Figure 8.1. The consideration methodology when installing a FIR heating system towards a non-domestic building.

Firstly, the physical parameters of the systems' requirements need to be calculated. This involves the size of the panels and where they will be placed so that they can heat which zones are required. The functions of the zones affect the heating requirements as in an office it may be set to 21^{o}C whereas in a dance studio, it may be set to a lower temperature due to the movement of the occupants.

Secondly, the cost of the FIR heating system must be evaluated. This involves evaluating the current heating systems' cost by fuel type and energy consumption. Most heating systems' use natural gas and therefore FIR heating has the capacity to emit less CO_2 if the electricity is generated through clean methods. Cost of initial purchase and installation must be evaluated, and the ROI must be calculated. This will allow the investor to determine whether their finances are being invested wisely.

Finally, the comfort of the occupants must be evaluated. This can be affected by how long it takes to heat the zone if it is not pre-heated. FIR is the quickest method to heat solid mass, but the comfort of the occupants must still be considered. The appearance of the panels can be interchanged, and especially for modern buildings, the appearance often has high consideration.

These main steps provide the building with enough knowledge to accurately consider the benefits of a FIR system and to conclude on the replacement of a conventional heating method.

The V2G method is forecasted through MLA's and uses real-time data from the Business School, but it also requires the input from owners of the EV's. As the developed methods don't consider whether the owners want to save costs and the occupants' behaviour when using the method, this should be applied to a case study to evaluate the benefits. The real-life applications of the developed FIR and V2G methods should be achieved to determine how effective they are and to boost the utilisation in the industry. The energy capacity of the EV's batteries have a large effect on the benefits of the developed methods. If the capacity of the EV's are smaller, more EV's are required to match the same total capacity, or the system can only be applied to a building with less energy demand. As EV's are becoming more commercialised, one major attraction to a buyer is the range the EV can travel from a single charge, or the size of the battery capacity. As the battery capacities are increasing, the V2G method can provide larger savings for both the EV owners' and the building in which they are being supplied from.

Overall, newer buildings are being designed with consideration of the environmental impact, with the aim of emitting the least amount of carbon. As this is achieved by generating the buildings energy requirements from renewable sources and by minimising energy losses from the buildings' systems, both of these classifications must continue to be invested in and applied to the industry. Emerging technologies include biomass and hydrogen, able to produce zero carbon and with the capability of contributing towards non-domestic buildings' carbon reduction. Biomass has been used for practical domestic applications [206], generating more than 50% of the energy demand. This has not been applied to non-domestic buildings though. As they require more energy, the system must be larger and thus requires more investment. As this is shown to be practical for reducing the carbon emissions for domestic buildings, the application for non-domestic buildings must be investigated. Hydrogen energy generation and storage has been applied to Keele university in the UK by blending the hydrogen with natural gas to reduce carbon emissions. As natural gas deposits are depleting, it is necessary for HESS's to be applied to non-domestic buildings to further reduce carbon emissions.

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