Modelling Non-Domestic Buildings Energy Performance Using Machine Learning Methods: A Case Study of the UK

By

Saleh Seyedzadeh

A thesis submitted to the University of Strathclyde
in fulfilment of the requirements for the degree of
Doctor of Philosophy

Department of Architecture

University of Strathclyde, Glasgow

July 2020

Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Name: Saleh Seyedzadeh

Signed:

Date: July 15, 2020

Abstract

In the UK, only 7% of non-domestic buildings are newly built, whilst this sector generates 20% of total gas emission. Consequently, the government has set regulations to decrease the amount of energy take-up by buildings. It is apparent from the seminal literature that deep energy retrofit is the primary solution to achieve that goal. Due to the size and complexity of non-domestic buildings, finding optimum plans is cumbersome. To that end, artificial intelligence has been employed to assist this decision-making procedure, yet limited to high time-complexity of energy simulations. Surrogate modelling seems a promising alternative for simulation software, developing accurate energy prediction models requires an understanding of the building physics and a vision on the use of data-driven models. This study evaluated the accuracy and time complexity of most popular Machine Learning (ML) methods in the buildings energy efficiency estimation. It established an approach based on evolutionary optimisation to reach the highest potential of MLs in predicting buildings energy performance. It then developed an energy performance prediction model for the UK non-domestic buildings with the aid of ML techniques. The ML model amid at supporting multi-objective optimisation of energy retrofit planning by accelerating energy performance computation. The study laid out the process of model development from the investigation of requirements and feature extraction to the application on a case study. It outlines a framework to represent the building records as a set of features in a

way that all alterations produced by applying retrofit technologies can be captured by the model to generate accurate energy ratings. The model provides a reliable tool to explore a large space of the available building materials and technologies for evaluating thousands of buildings going under retrofit to fulfil the energy policy targets and enables building analysts to explore the expanding solution space meaningfully.

Acknowledgements

The research presented here was supported by funding from The Data Lab (Edinburgh, UK) and arbnco Ltd (Glasgow, UK), through DataLab SFC Earmarked Grant Agreement: PO DL 00033. This work would not be feasible without the generous PhD funding which was co-funded by the Engineering The Future scheme from the University of Strathclyde and the Industry Funded Studentship Agreement with arbnco Ltd (Studentship Agreement Number: S170392-101). I wish to express my gratitude to the many people I have met during the course of this doctorate, including my colleagues and friends at Strathclyde. Only a few can be mentioned here.

Firstly, I would like to thank my supervisors, Dr Farzad Rahimian and Professor Ivan Glesk for all the help, support and guidance they offered. I am deeply grateful for them to give me the opportunity to do my PhD at the University of Strathclyde. Without their support and guidance, this research work could not have been possible. I sincerely appreciate their mentorship, guidance and cultivation, which makes my PhD study one of the most valuable experiences in my life. It was a pleasure to have Dr Marc Roper in the Advisory Committee. I thank him for the insightful discussion on different aspects of this research.

A special gratitude goes to arbnco Ltd for their invaluable financial and data support, without which this research would not have been possible. My gratitude also extends to Mr Simon West, Mrs Maureen Eisbrenner, Mr Alan Wegienka and Dr Parag Rastogi from arbnco.

I would like to special thank to my friend Mr Stephen Oliver for his valuable support during my PhD. He offered a great contribution to the technical part of data preparation.

I am indebted to my father and mother for being an incredible source of inspiration for me at every step of my personal and academic life. I am grateful to my in-laws for their love and moral support. I owe my deepest gratitude towards my wife, Parinaz, for her unending support and understanding of my goals and aspirations. Her unfailing love and support have always been my strength. Her patience and sacrifice will remain an inspiration throughout my life. My most profound acknowledgement also goes to my daughter, Aysou, the biggest blessings in my life that keeps me going. She has grown up with this thesis and unknowingly sacrificed for it.

Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Expansion
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEMS	Building Energy Management System
BER	Building Emission Rate
BPS	Building Performance Simulation
CIBSE	Chartered Institution of Building Services Engineers
CO_2	Carbon dioxide
CV	Cross-Validation
DEA	Data Envelopment Analysis
DEC	Display Energy Certificate
DHW	Domestic Hot Water
DM	Decision-Making
DSM	Dynamic Simulation Modelling
DT	Decision Trees
ECG	Energy Consumption Guide
EEM	Energy Efficiency Measure
EPBD	Energy Performance of Building Directive
EPC	Energy Performance Certificate
EPI	Energy Performance Indicator
EUI	Energy Use Intensity
FFN	Feed Forward Network

Abbreviation	Expansion
GA	Genetic Algorithm
GBRT	Gradient Boosting Regression Tree
GHG	Greenhouse Gas
GMM	Gaussian Mixture Model
GPR	Gaussian Process Regression
HVAC	Heating, Ventilation, and Air Conditioning
ISO	Organisation for Standardisation
L2B	Existing nondomestic building regulations
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MEES	Minimum Energy Efficiency Standards
ML	Machine Learning
MLR	Multiple linear regression
MOO	Multi-Objective Optimisation
MRM	Multivariate Regression Models
MSE	Mean Squared Error
MSPE	Mean Squared Percentage Error
NCM	National Calculation Methodology
nZEB	Nearly Zero-Energy Building
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
R^2	Coefficient of determination
PSO	Partial Swarm Optimisation
RF	Random Forest
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SBEM	Simplified Building Energy Model
SER	Standard Emission Rate
SFA	Stochastic Frontier Analysis
SVM	Support Vector Machine
USDOE	US Department of Energy
WWR	Window to Wall Ratio

List of Publications

UK Patent

1. Optimising building energy use, 2019, GB1906986.3 (Logged 17 May 2019)

CI/ISI Journal Articles

2. **Seyedzadeh, S.**, Pour Rahimian, F., Rastogi, P., Oliver, S., Rodriguez, S., and Glesk, I. (To Appear 2020) Modelling Energy Performance of Commercial Buildings for Optimal Retrofit Planning. Applied Energy, Accepted.

3. **Seyedzadeh, S.**, Rahimian, F. P., Oliver, S., & Glesk, I., Kumar, B. Data Driven Model Improved by Multi-Objective Optimisation for Prediction of Building Energy Loads. Automation in Construction, 116, 103188

4. Pilechiha, P., Mahdavinejad, M., Rahimian, F. P., Carnemolla, P., & **Seyedzadeh, S.** (2020). Multi-objective optimisation framework for designing office windows: quality of view, daylight and energy efficiency. Applied Energy, 261, 114356.

5. **Seyedzadeh, S.**, Rahimian, F. P., Rastogi, P., & Glesk, I. (2019). Tuning machine learning models for prediction of building energy loads. Sustainable Cities and Society, 47, 101484.

6. **Seyedzadeh, S.**, Rahimian, F. P., Glesk, I., & Roper, M. (2018). Machine Learning for Estimation of Building Energy Consumption and Performance: A Review. Visualization in Engineering, 6 (1), 5.

Conference papers in CI Proceedings

7. Oliver, S., Pour Rahimian, F., **Seyedzadeh, S.**, Rodriguez, S. and Dawood, N. (2020) Visualising simulation performance gaps using EnergyPlus and augmented reality, The 20th International Conference on Construction Applications of Virtual Reality.

8. **Seyedzadeh, S.**, Pour Rahimian, F., Rastogi, P., Oliver, S., Glesk, I., & Kumar, B. (2019, September). Multi-objective optimisation for tuning building heating and cooling loads forecasting models. In 36th CIB W78 2019 Conference.

9. Oliver, S., **Seyedzadeh, S.**, & Pour Rahimian, F. (2019, September). Using real occupancy in retrofit decision-making: Reducing the performance gap in low utilisation higher education buildings. In 36th CIB W78 2019 Conference.

10. Masood, M., Fouad, M. M., **Seyedzadeh, S.**, & Glesk, I. (2019). Energy efficient software defined networking algorithm for wireless sensor networks. In 13th International Scientific Conference on Sustainable, Modern and Safe Transport (TRANSCOM 2019).

Chapter 1

Introduction

1.1 Motivation and Background

In the UK, buildings are responsible for 46% of all carbon dioxide (CO_2) emissions [1]. This figure is 40% in the USA and 27% in Australia [2]. Accordingly, the enhancement of energy efficiency of buildings has become an essential matter in order to reduce the amount of gas emission as well as fossil fuel consumption. An annual saving of 60 billion Euro is estimated as a result of the improvement of EU buildings energy performance by 20% [3].

This issue has been addressed by the Energy Performance of Building Directive (EPBD) bounding EU countries to improve their building regulations. As a response to this request, the UK government set a series of regulations to abate its gas emission by 29% by 2020 and at least 80% by 2050. The UK has also targeted all new dwellings to be built on a zero-carbon basis by 2016 and non-domestic buildings by 2018. However, a great deal of the problem faced by the UK government and other countries is in existing buildings. In the UK as well as some European countries, the rate of replacing buildings is as low as 0.1% while the rate of constructing new buildings is over 1% [4]. It is expected 70% of existing buildings will be occupied at least until 2050 [5]. This estimation indicates that improving the energy performance of new buildings plays an important role. However, it is also crucial to establish strict rules in the refurbishment of existing buildings to make a significant contribution in reducing carbon emission.

The UK government has set a regulation that makes it illegal to lease out a building if it does not meet the Minimum Energy Efficiency Standards (MEES). The minimum Energy Performance Certificate (EPC) rating is 'E'. This came in to force on April 2018 for new leases and from April 2020 for existing leases [6].

In 2013, it was reported that 18% of the 427,814 non-domestic buildings assessed in the UK have EPC ratings 'F' or 'G' [7]. However, further research warns that the number of non-compliant properties could increase if EPCs are updated to take into account the changes that have been made to the calculation methodology in the last few years [8].

In the UK, energy assessments of non-domestic and public buildings are displayed as EPC and Display Energy Certificate (DEC), respectively. The bands show how efficient buildings are, in terms of energy consumption. By the end of 2019, over 1.3 million non-residential building have been evaluated with 15% receiving bands F and G. Figure 1.1 illustrates the energy performance statistics for non-domestic and public buildings in the UK. [9]. Details of EPC and DEC are presented in Section 6.3.

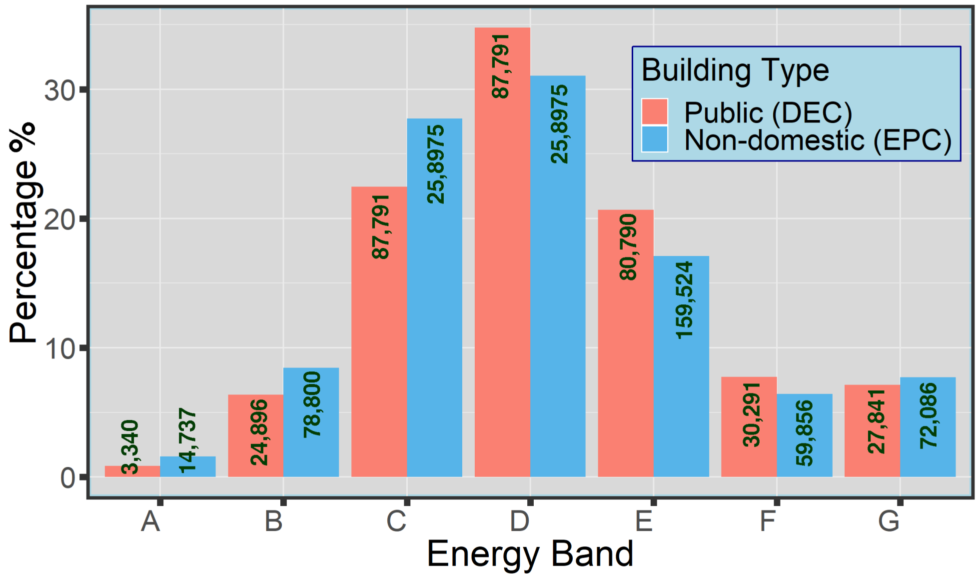


Figure 1.1: UK non-domestic and public buildings energy performance share per EPC and DEC bands.

Currently, there are many retrofitting technologies on the market. However, it is required to determine the most appropriate ones for a specific building taking into consideration the constraints, such as building characteristic, available budget, building usage, building fabric. In case of implementing non-optimised solutions, it is possible to alter a building at a subsequent attempt imposing however a much higher cost.

This process becomes more complicated for the non-domestic stock as the number of solutions is remarkably high and the building energy enhancement should fulfil the seven-year payback exemption test [10]. This rule allows commercial stockholders to be exempted from the Act if the payback of energy saving is less than the cost of the retrofit package. This legislation ensures improvements to be economically feasible, but on the other hand, it raises a challenge for building experts to find optimal solutions.

Therefore, a decision-making (DM) tool is imperative to propose appropriate retrofit technology(ies) for each specific case. To facilitate decision making in selecting suitable solutions, where there is more than one objective, there are some methodologies which can be classified in priori, and multi-objective optimisation (MOO) approaches. Most of the developed methods are simulation-based optimisations in which the optimisation algorithm is implemented using a programming language, and the energy-related objectives (energy consumption or gas emission) are calculated employing a Building Performance Simulation (BPS) tool such as EnergyPlus [11], TRNSYS [12], ESP-r [13]. These approaches limit the computation complexity of the algorithm to BPS's calculation time, and when a large number of solutions are defined, the process may become extremely costly to handle.

In the UK, an EPC reflects the impact of buildings on the environment, and it is typically calculated using the Simplified Building Energy Model (SBEM) for non-domestic buildings. SBEM embeds the UK National Calculation Methodology (NCM) which has been developed in response to EPBD. A multi-criteria optimisation of CO_2 emission and retrofit cost by considering a few variables including insulation values, air tightness, lighting controls, system efficiencies and PV provision has been reported [14]. It has been pointed out that at least 9,000 simulations are required to obtain optimal solutions. By taking a large number of variables and their options, the number of obligatory simulations will be tremendously increased. Another research proposing an EnergyPlus-based optimisation for retrofitting office buildings has reported weeks of simulation for a single case [15]. There are multiple similar example studies which reported time-consuming procedures for optimising building energy performance and retrofit planning. [16–21].

This calculation time is the main reason why most studies, which focus on decision making for building energy improvement have investigated simple models or retrofitting only one or two construction parts of the envelope. Moreover most of the studies targeted residential houses [17, 22–26]. There are few reports about the optimisation of non-domestic estates [15, 19, 27, 28]. Although, a few retrofitting models have been developed to help decision making in the refurbishment of non-domestic buildings, human experience still plays a principal role in producing appropriate solutions. Therefore, the potential of Artificial Intelligence (AI) has been neglected in this area due to the lack of interdisciplinary research works.

Considering the problem with using BPS for optimisation, it is required to find an alternative method with accurate and fast forecasting of the target (e.g. building emission rate, energy consumption or efficiency) to lower the computational cost of optimisation processes. Otherwise, the means of generating optimal solutions for massive commercial buildings with the development of a MOO algorithm will be frustrating even for several sample cases.

On the other hand, the use of Machine Learning (ML) methods in the built environment and the prediction of building energy indicators to support such optimisation procedures are facing some challenges. Firstly, most seminal works have focused on modelling a single building or a group of similar buildings for the analysis of energy consumption or performance. Hence, the process of selecting relevant variables has been limited to elementary physical characteristics and climate features. Moreover, the use of proper ML model for such application has not been thoroughly investigated. In other words, ML for building energy performance is still in a premature level.

1.2 Research Problem and Hypothesis

Although AI optimisation has provided a useful solution for finding optimal packages for retrofitting buildings, it is restricted to case studies due to the time-consuming calculations required by the method. These algorithms consider various objectives rather than building energy performance, namely cost, number of applied recommendations and pay-back. However, the approach is highly bound to the calculation of energy efficiency as the most complex objective. BPS tools have been revolved in recent years, yet require substantial computational time. The reason is that these tools are based on engineering methods in which energy usage is derived for all energy-sub-systems using complex mathematics or building dynamics considering internal and external details as the inputs. Therefore, utilisation of BPS tools in the application of AI optimisation for retrofitting complex system as non-domestic buildings is not a practical approach.

It is hypothesised that developing a data-driven model for estimation of buildings energy performance by the utilisation of historical data and formulating building records as a set of numerical features will considerably reduce the time complexity of energy calculation and make multi-objective optimisation for deep energy retrofit of non-domestic buildings computationally practical.

1.3 Research Justification

The grounds considered in establishing the research questions and the corresponding objectives for this research are outlined in Figure 1.2. As addressed earlier in this chapter and concluded from Figure 1.2, although AI techniques have been advanced in the last decade, the optimisation of non-domestic, particularly large-scale buildings, faces several challenges towards meeting modern energy standards. These issues are raised from the lack of interdisciplinary research in this field. Furthermore, identification and preparation of meaningful and reliable data has been a primary concern. Due to the high costs of energy simulations in terms of computational complexity and human labour, neither the retrofit industry nor the stakeholders are willing to use costly optimisation methods. Thereby, those approaches are limited to academic case studies and partially optimisation of building characteristics. Hence, achieving a comprehensive retrofit planning considering all available technologies and energy policies is not practically possible without a fast and stable energy performance emulator.

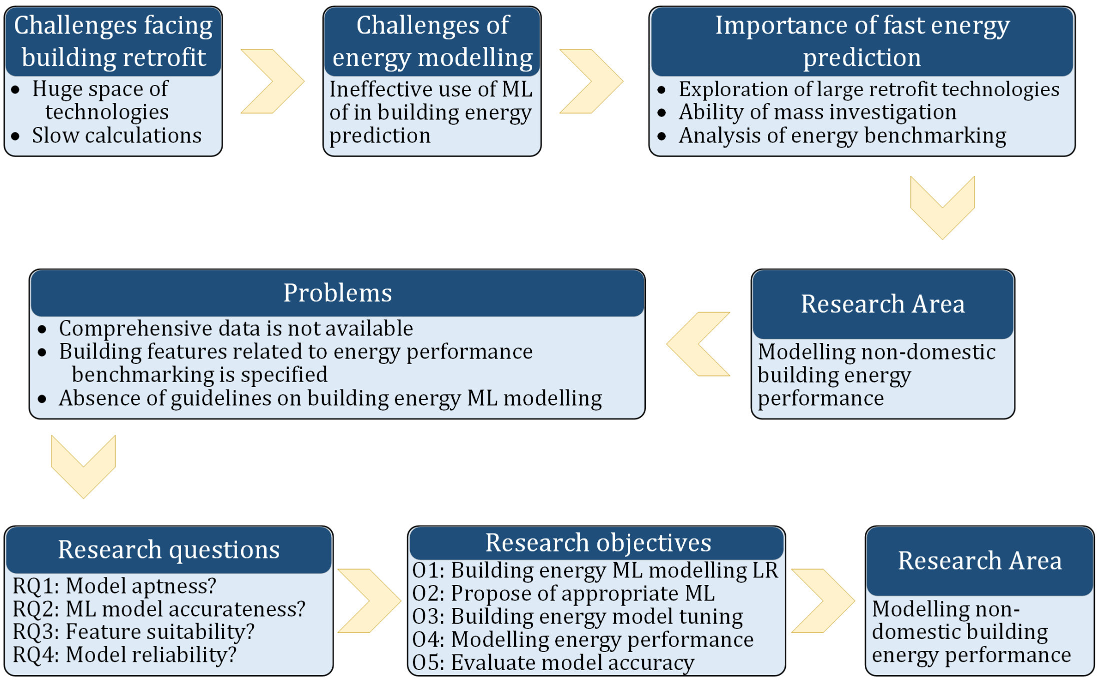


Figure 1.2: Summary of the study justification, questions and objectives.

This research provides benefits to both building owners to save and contractors/consultants by significantly improving the quality of knowledge on retrofit projects. This research highly contributes to the global attempt to conserve energy and to enhance the quality of human environment by paving the way to optimise building energy consumption and reduce gas emission.

Although ML has been widely used for modelling building energy indicators, this is the first of the kind study, providing detailed data-driven model is developed for supporting retrofit planning by considering available technologies which guarantees the accurateness of energy performance estimation and thereby reliability of the DM system.

1.4 Research Questions

As represented in Figure 1.2, it is necessary to advance the level of knowledge on the non-domestic building energy retrofit planning. This leads to the principal question of the present research as asserted below:

How to model non-domestic buildings to expedite accurate calculation of energy performance?

Funded on the main question, this study aims to answer the following research questions:

(RQ1): What are the model availabilities, and which is most proper for building energy performance modelling?

A broad review of research works in the area of building energy assessment, focusing on the energy retrofit is required to establish the basis of the study in the selection of methods, formulating the building records from raw data and achieving high accuracy. This question is addressed in Chapter 2 by providing an in-depth understanding of the gap, as mentioned in Section 1.1. The role of a specific application in the procedure of model development is also investigated. The seminal works on the use of ML models for building energy performance do not provide a complete evaluation of different non-linear models and do not provide sufficient guidance about model selection. Hence, there is a lack of guidance on how to optimise or 'tune' models to fit the problem at hand for the best predictive accuracy and consistency. This is addressed in Chapter 4 by investigating the accuracy of most popular ML methods in the forecasting building energy indicators, carrying out specific tuning for each ML model.

(**RQ2**): What are the methods to increase the model accuracy and to take full advantage of MLs?

Basic ML algorithms with few parameters provide simple modelling, but when dealing with a sophisticated ML algorithm, the utilisation of traditional method for improving model accuracy becomes cumbersome. That is why, traditionally, the researchers mostly relied on default values for those models parameters. This is one issue of the study because modelling complex systems as non-domestic buildings energy performance require the utilisation of those advanced algorithms. This is addressed in Chapter 5 by developing a precise method to optimise an ML model for prediction of one or more energy indicators.

(**RQ3**): What are the choices of model inputs to describe building energy behaviours? (i.e. key building and environment characteristics)

A few attempts that applied data-driven modelling for retrofit design focused on a building's general physical characteristics while disregarding all possible technologies and the energy policies.

Consequently, those models are not suitable for supporting deep energy retrofit planning. This main question of the study is addressed in Chapter 6, in which the recommendations from previous steps (Chapters 4 and 5) are considered in generating the features space for modelling non-domestic buildings energy performance, and by taking into account retrofit technologies and the energy policy in the UK. The feature set is used for generating big data and training an ML model for prediction of energy performance.

(**RQ4**): What would be the accuracy of the model on a new building retrofit evaluations?

The main concern in data-driven modelling is the accuracy and reliability of the developed model. As the centre point of this study is to model non-domestic buildings for accurate calculation of energy performance using ML techniques, this concern is addressed by evaluating the developed ML model through the assessment of thousands of variations of a case study building and comparison with the actual ratings.

1.5 Research Aim and Objectives

The aim of this thesis is to develop an accurate and fast prediction method to support decision-making for the optimal solution for retrofitting the existing non-domestic real-estate stock, using state-of-the-art AI methods. Contributions to carbon footprint reduction will be sought by decreasing the energy consumption, where both community and stockholders will be the beneficiaries of the provided service. To make MOO techniques computationally feasible, this thesis intends to propose a surrogate model for fast and precise evaluation of buildings energy performance.

To make it measurable and achievable, this aim is further divided into 5 objectives as follows:

Objective1: To investigate advances in building energy numerical modelling focusing on the use of ML methods

Objective2: To scrutinise ML techniques in building energy application and propose the ML selection framework

Objective3: To propose an intelligent method for the development of accurate energy forecasting ML models

Objective4: To develop a energy performance modelling for accelerated energy assessment of non-domestic buildings

Objective5: To evaluate the energy performance ML model by use of genetic algorithm and application on a case study

1.6 Contributions to Knowledge

The extent to which a study contributes to the body of knowledge has been a key criterion for assessing the quality of all research efforts in Architecture, Engineering and Construction (AEC) disciplines, including PhD studies [29]. As asserted by Glasziou *et al.* [29], a study's contribution at the PhD level is assessed with reference to two primary criteria, namely: (1) originality and (2) implications for practice.

Likewise, contribution to the knowledge in the field of building energy efficiency in the past 15 years has shifted from only creation of knowledge to be used by other academics to the creation of interdisciplinary knowledge which can be applied to problem-solving [30, 31].

Therefore, the contribution of a study in the building energy efficiency discipline lies in its originality in the development of knowledge as well as its impacts on practice [32].

Studies at the PhD level are expected to provide an original contribution to knowledge. In fact, PhD studies are defined as pieces of work that are designed to make an original contribution to knowledge [33]. Theoretical knowledge in construction research focuses on raising awareness of something factual about a concept of interest or on understanding how different realities associated with this concept are constituted [34]. Hence, the originality of any research study in this field is evaluated in terms of the creation of new theoretical knowledge. According to Handfield and Melnyk [35] in their seminal study, the creation of knowledge occurs through creating new theories, extending available theories and refuting theories (or some elements of theories) through exposure to empirical data. To establish the originality of this study, its contributions in different dimensions are next discussed. The research contributions of this research are summarised into three aspects as follows.

A contribution to the theoretical understanding of building energy permeance modelling: Proposing an integrative selection framework of ML model for diverse data

The work presented in this thesis makes a significant contribution to research and practice of energy management in buildings. In particular, the prediction of energy loads, which is mired with several challenges for practitioners, is going to be easier and more accurate using the approach outlined in this study. The application of ML techniques in the building energy load forecast is not widely used at the moment. Therefore, this research provided the practitioners with a novel approach to address the challenges they encounter in this important and key area of their routine activities. Although the potentials of ML techniques in predicting energy loads have been reported by several researchers, the credibility of results may be questionable without the tuning ML models. Tuning models not only increases the predictive accuracy, but also reduces model complexity, ease of use, and consistency of predictions. Particularly, when the solution space grows exponentially due to the large number of hyper-parameters, searching for the optimal solutions without tuning of models is a non-trivial task. This research addressed these issues and validated them on a substantial volume of realistic data drawn from both tertiary as well as residential buildings.

Generating an accurate model for calculation of the energy loads with fast and robust process paves the way for more informed and productive design decisions for built environments. Furthermore, the use of ML in the complex buildings goes beyond mere optimisation support matters by offering efficient retrofitting plans, without which it would be a rather cumbersome task for the engineers to carry out complicated calculations readily and make informed decisions.

The research highlights the potential of ML model-based techniques in modelling building energy indicators, which are sometimes laborious to simulate or calculate using engineering methods. It has been approximated that only three per cent of industrial data is currently being used in a meaningful way. This is why Industry 4.0 has put more emphasis on the utilisation of technologies that could take advantage of the ever-growing data.

A contribution to the theoretical understanding of model development for supporting retrofit DM

This study demonstrated that in the development of energy modelling for retrofit planning or other applications, such as building management, achieving a high accuracy is not the only concern. It is crucial to take into account all the variations and reflects the corresponding impacts in the model behaviour. For example, a proper energy modelling for supporting BMS should consider the occupational behaviour, as it can vary by different situations and cause model failure, whilst the model can accurately perform in the normal condition due to insufficient data collection.

This research investigated the retrofit recommendations prior to extracting features for ML modelling and explained how these technologies are affecting the model in prediction of building energy performance. The methods for sensitivity analysis described in this thesis provide powerful tools for such analysis.

A contribution to the development of MOO-based building design and retrofit optimisation

As policy tightens on inefficient energy consumption and our understanding of the limitations of BEM-led design decision-making, the necessity for more efficient and flexible models increases. Research over the last few years has been giving greater credence to designing buildings with consideration for medium-term climate change and any number of occupant presence or behaviour uncertainties. Every extension to the potential configurations exponentially inflates the problem space while likely reducing the conventional options solution space. Furthermore, these climate and utilisation properties are internal to BEMs, however, design and retrofit analysis is increasingly considering external and more challenging to integrate properties. The framework introduced in this study demonstrated that algorithmic decision-making capabilities are not nearing their limit and lays a foundation for more complex ML frameworks.

The study demonstrated a successful development of ML model capable of processing thousands of records in milliseconds, while generating accurate energy performance ratings.

The publishability of the work provides evidence of its originality [36]. As asserted by [33], "publishability is a way of measuring contribution to knowledge". The potential publishability of all or a number of parts of a thesis reflects the originality of the study in view of the rigour of the peer-review process that applies to publications. In particular, publishability is a reliable measure for assessing originality in disciplines associated with science, technology and engineering [36]. NB, there was an initial pause on the candidate's ability for publication of the main findings of this study, due to industry sensitivity and confidentiality aspects of the research carried out in collaboration with the industry partner. Therefore, most significant research outputs were only submitted to world flagship journals after securing the UK patent.

1.7 Overview of Methodology

In order to achieve the research objectives, this study is divided into four stages, each devoted to acquit one or more objective(s). The detailed method for the advancement of each stage of this research is explained in Chapters 3 to 6. Description of research methodology is as follows:

Firstly, an in-depth review of the state-of-the-art building energy performance benchmarking, employment of ML techniques in building energy evaluation and energy policies regarding non-domestic buildings was carried out. This identified other studies and the relevant research works in the area of investigation. Furthermore, it highlighted the gap between AI and human experts decision-making approaches as well as the most effective surrogate models dealing with building energy data. Second, different ML models were evaluated using established building energy datasets. This included the optimisation of prediction models using the traditional exhaustive search method. Next, using AI and MOO process, the model optimisation for prediction of building energy indicators was proposed and evaluated.

The next stage consisted of four main phases: Firstly, based on the findings from the literature review and the study of building physics, a set of relevant features for statistical modelling of UK non-domestic buildings was proposed. This procedure considered available retrofit technologies on the market in order to cover all alterations in energy performance estimation caused by the application of them. Secondly, a real raw data, which includes non-domestic building energy assessments from the industry, was processed and extended by mutating the records and evaluating the new versions using the simulation software. Thirdly, the processed data was translated to the ML space (i.e. the raw detail of building characteristics was converted to the numerical values of extracted features identified in the first step). Fourthly, the most appropriate ML model was trained over the generated data to create a model. Lastly, the importance of the proposed features was evaluated using sensitivity analysis. This approach also provided an overview of how well the retrofit technologies were covered by the building variables.

The final step was an evaluation of the developed model accuracy on a real case study by predicting retrofitted versions of the building generated in the process of optimisation.

1.8 Scope of Research

This thesis aims to develop a framework for improving the energy efficiency of non-domestic buildings by developing an energy performance emulator to support the optimisation of retrofit planning where the decision making is very complex and providing cost-effective solutions, which are not feasible by only relying on human capabilities. As in the refurbishment of dwellings, the computational time and calculation complexity hasn't been issues, this sector is out of the scope of this work. The enhancement of the energy efficiency of new stock is achieved in the design stage and is more flexible than for existing buildings as the structural limitations are far less. Hence, the energy modelling in this research work does not take into account the energy efficiency improvement of new non-domestic buildings.

This work focuses mainly on the UK non-domestic sector and uses related historical data for the development of energy estimation and modelling. However, the framework can be adapted for other markets where a reasonable amount of data is accessible or collectable. The data used in this thesis consists of five thousand original non-domestic building records evaluated using the SBEM energy simulation software which have been provided by a building energy consultancy company. Thereby, the case study is performed by selecting a complex commercial building in the UK.

1.9 Thesis Structure

This thesis is organised into seven chapters. This first chapter provides an introduction to intelligent decision making of building retrofitting and modelling building energy performance, presenting the motivation and background of the research. It discusses the research problem and defines the solutions proposed for tackling those challenges in building retrofit planning.

Chapter 2 continues with an overview of building energy benchmarking and provides a summary of related regulations focusing on the UK. It further justifies the need for rapid evaluation of energy consumption or efficiency and gives a broad review of developed models. The chapter provides a substantial report on four main ML approaches, including artificial neural network, support vector machine, Gaussian-based regressions and clustering, which have commonly been applied in the forecasting and improvement of building energy performance.

Chapter 3 presents an overview of the research methodology before describing in detail the methods in individual chapters (4 to 6). Details of the rationale behind the research plan are described, with a particular focus on the arrangement of processes to model non-domestic building energy performance effectively, outlined in sequential order. Moreover, the scope and objectives of the study are clearly defined, and the research activities presented in order to clarify the research methodology.

Chapter 4 presents the investigation the accuracy of most popular ML methods in the prediction of buildings heating and cooling loads by carrying out specific tuning for each ML model and comparing the results of two simulated building energy datasets generated by the use of EnergyPlus and Ecotect. The study uses a grid-search coupled with a cross-validation method to examine the combinations of model parameters. Furthermore, sensitivity analysis techniques are used to evaluate the importance of input variables on the performance of ML models. The accuracy and time complexity of models in predicting building energy loads are demonstrated.

The development of a MOO-based optimisation model for prediction of building energy indicators is presented in Chapter 5. This chapter proposes a method for optimising ML models for forecasting both heating and cooling loads. The technique employs the MOO technique with evolutionary algorithms to search the space of possible parameters. The proposed approach not only tunes single model to precisely predict building energy loads but also accelerates the process of model optimisation. It utilises simulated building energy data generated in EnergyPlus to validate the proposed method and compares the outcomes with a regular ML tuning procedure (i.e. grid search).

Chapter 6 describes the details of meta-model development for the estimation of non-domestic Building Emission Rate (BER). In this chapter, the original, available parameters and created synthetic data are elaborated. Then feature extraction and engineering procedures are described in detail. A machine learning model based on the decision tree algorithm is tuned and trained. The model fitting is followed by sensitivity analysis to demonstrate the importance of the input variables for final selection. Afterwards, the performance of the model in predicting energy performance of a non-domestic building and it's retrofitted suggested recommendations (reserved as test cases) is evaluated. The surrogate model detailed in this chapter could be used as an engine for feeding the primary retrofit optimisation target function (i.e. BER).

Finally, Chapter 7 summarises the thesis emphasising the significant contribution to knowledge and impact on the practice of this research work. Future works are also recommended.

Chapter 2

Literature Review

2.1 Introduction

The previous chapter defined the challenges of developing an intelligent decision-making system for retrofitting of non-domestic stock and explains the need for a fast energy performance emulator. To provide an in-depth understanding of the gap as mentioned in Section 1.1, this chapter provides a literature review of the current knowledge on building energy efficiency benchmarking followed by inspection of Machine Learning (ML) techniques used for prediction of energy consumption and performance of various building types. This chapter further highlights the necessity of attaining optimal solutions for retrofitting and rises the incompetency of AI in the building sector.

2.2 Drivers of Change

Global warming phenomena have been considered as one of the main threads for the human future. An average increase of 0.13 °C/decade is observed from 1956 to 2005. This value is almost twice of that over pas decade [37]. The primary cause of global warming is identified as anthropogenic greenhouse gas emissions (GHGs). The discharge of these gases including carbon dioxide (CO_2), methane (CH_4) and nitrogen dioxide (NO_2) in higher layers of the atmosphere is due to the human actions in excessive consumption of fuel and destruction of natural resources. Reports unveil that the effect of global warming will further be more intensified from current experiences such as extreme heatwaves, storms and violent floods to the extinction of species and human starvation [38].

It is approximated that nearly 50% of CO_2 emission, which has been recognised as the main contributor to change is related to fuel-burning for construction and energy use of municipal buildings [39]. The attempt to lower the amount of GHGs needs significant alteration in human behaviour in energy consumption, manufacturing of more environmental-friendly products, plus identifying and mitigating the causes of these undesirable gases [40]. Therefore, enhancement of techniques for the construction of more energy-efficient buildings and improvement of current buildings' energy usage seems excellent moves in the reduction of global warming menace.

In 1990, China showed a 30% drop in energy intake in building construction sector through the employment of some simple techniques in design and construction stages [2]. In Europe, enhancement of energy efficiency of buildings has been prioritised, which has led to the prologue of the Energy Performance of Buildings Directive (EPBD). EPBD requested EU member states to establish energy efficiency demands and begin an energy performance obligation scheme for existing and new buildings [41]. In 2010, EPBD recast was legislated introducing a new target for energy efficiency of buildings. The remoulding which came into force in 2013 amid at achieving Nearly Zero-Energy Building (nZEB).

The global attempt for cutting down GHGs by enacting related regulations forces stockholders to take action to improve the energy efficiency of their buildings. This enforcement indicates that retrofitting of buildings as well as improvement of the Building Energy Management System (BEMS) are the most essential solution in meeting the demanded decrease in carbon emission [42]. Although designers consider sustainability in new buildings to satisfy regulations, 99% of constructions are existent, and approximately 70% of these buildings will be utilised till 2050 [43].

The non-domestic building sector accounts for almost 20% of total gas emission [6]. However, due to the non-domestic sector's inattentive response to the sustainability program, governments mediation for improvement of energy efficiency for this sector has intensified significantly [44, 45]. The retrofitting of non-domestic buildings, particularly complex ones, has been a challenge for experts in obtaining cost-optimally solution [46]. The proposed optimisation solutions have proven to be an efficient tool for enhancing retrofit design employed on several case studies, however, some challenges hinder these methods to be practically applicable in industry and by authorities.

2.3 Building Energy Performance Assessment

Wang *et al.* [47] described that building energy assessment is an informative tool, which provides a comparative energy performance index to decision-makers for energy consumption improvements. Thus, the primary objective of energy assessment of buildings is energy classification and energy performance diagnosis, which connected to endeavours to enhance their efficiencies.

Energy classification apprises stockholders and public about the relative energy consumption and gas emission of buildings. The diagnosis provides a mean for identifying the defects in a building that induces the low energy efficiency, so aiming at the reform of the intended building.

Generally, the energy consumption of building during a definite period normalised by floor area is used to express the performance ($kWh/m^2/period$) known as Energy Performance Indicator (EPI) or Energy Use Intensity (EUI) [48, 49].

To achieve the aforementioned goal in building assessment, a comparison between calculated (through simulation or estimation) or actual measured efficiency (EPI or EUI) and a standard reference building is required [50]. Therefore, it is necessary to define a set of reference values for each category of buildings. To fulfil this aim, there are different approaches based on the performance assessment techniques as:

- Measurement of historical energy performance.
- Market survey of typical performance of similar buildings
- Building energy modelling at design stage to define expected energy performance.

- Building energy audits to delineate potential energy performance
- Regulatory method to get required standard

The energy performance for the non-domestic stock can also be calculated by normalising energy consumption by operational hours or both floor and hours. For calculation of this value generally, five factors are considered as climate, energy systems, occupant behaviour and maintenance [47].

Various methods for energy performance assessment, types of classification and the actual application of that, are described in the following sections.

There are mainly two methods for assessment of building energy efficiency namely performance-based and feature-specific. The former one is obtained by analysing the EUI or building emission rate (BER), and the given benchmark building is its category. The latter approach, the score is awarded by assessment of specific features (i.e. if these features are present) [51, 52]. Applying the feature-specific method is comparatively simple as it addresses the contents of the efficient envelope, Heating, Ventilation, Air Conditioning (HVAC), lighting, boiler and renewable energy systems [53]. The performance-based method is the most preferred, though the assessment of energy performance using this method is more challenging. The issues are because this approach is established based on quantifiable performance indicators which necessitate the development of quantification method and a standard for performance assessment [54].

Another category suggested by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) classifies energy assessment modelling in forward and data-driven modelling approaches. Forward modelling is mostly utilised in the design stage for optimisation of energy, and the latter focuses on the existing building and defining references [55, 56].

Burman *et al.* [57, 58] categorised energy performance assessment regarding engineering methods into a top-down and bottom-up approaches. In a top-down scheme, a system is first designed neglecting the information of sub-systems and calculates the incorporated energy or emission rates considering different general building materials. This approach can be implemented using simple or advanced statistical methods. In contrast, the bottom-up technique involves an accumulation of building system-level details through energy modelling. This information is then compared to actual building efficiency and used to create a more accurate summary [59].

Borgstein *et al.* [60] addressed a model-based and empirical benchmarking, characterised the leading strategies, and described in depth the application of benchmarks for the establishment of rating and classification methods. In this study, building energy assessment were separated into three main categories: engineering calculation, simulation model-based benchmarking and statistical modellings.

2.3.1 Engineering Calculation

The engineering methodologies employ physical laws for the derivation of building energy consumption in whole or sub-system levels. The most precise methods apply complex mathematics or building dynamics for the derivation of accurate energy usage for all components considering internal and external details as the inputs (e.g. climate information, construction fabric, HVAC system). Since input data gathering for engineering calculation is challenging, this method requires a great deal of time and effort [61].

In order to accelerate the calculations, several simplified models for estimating building energy efficiency has been developed [62–65]. These models intend to implement rapid optimisation in the design step; however, they can be beneficial in estimating energy efficiency and approximating the effect of preservation measures (e.g. for energy audit) [66]. The advantages of these models over simulation modelling are low computational time, obvious connection with physical parameters and being more comprehensible to use.

Typically, this computation implicates the development of mathematical equations and the methods in this class, in general, employ steady-state models that consider an average of variables for a duration (e.g. for a year) where other building features are constant. Quasi-steady-state (QSS) calculates the heat gain and loss on a monthly basis and explains the impact of transitory parameters (i.e. weather) [67]. QSS for estimating building energy performance connects the energy usage to those input features [64]. Software that exercise these simplified models generally do not consider all elaborate connections of a building; consequently, they do not simulate the energy behaviour of it. These tools are frequently mentioned as calculation tools [68].

The International Organisation for Standardisation (ISO) explains the procedure for computing method as a foundation for heating and cooling loads calculations before the simplified calculation of whole-building energy estimation [69, 70].

In the simplified calculation, building total energy usage can be estimated as the aggregate of the fair use of all systems [71]. This accumulation model has been referred as the most precise approach for estimating energy efficiency, which has the potentiality in the implementation of system-level benchmarks [57]. For benchmarking of existing buildings, these computations are compared to baseline buildings and provide advantageous detail and energy assessment. Figure 2.1 presents the axiom of end-use energy calculations [71].

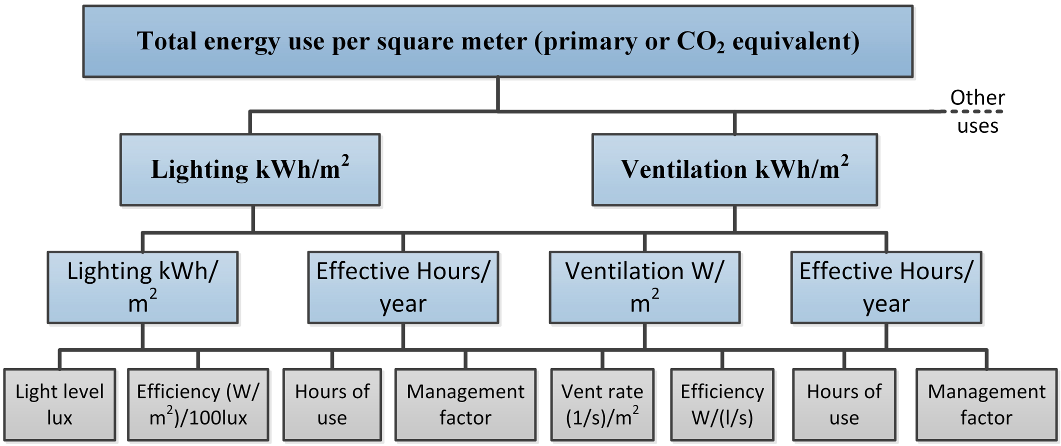


Figure 2.1: Demonstration of end-user energy analysis method.

Although the aggregated computation methods are obviously powerful tools for energy assessment and energy saving estimation, they have some specific restrictions in whole building calculations. Firstly, the HVAC heating and cooling loads must be individually computed, and secondly, these calculations are mostly beneficial along with system-level benchmark [58].

The method as mentioned above is established by the Energy Consumption Guide (ECG) for office building benchmark in the UK [72] and has been employed to expand the most of empirical benchmarks referenced in Chartered Institution of Building Services Engineers (CIBSE), which legislates benchmarks for non-domestic buildings in the UK [73].

2.3.2 Simulation Method

Building energy efficiency simulation includes software and computer models for simulation of performance with predefined status. Generally, computer simulation can be used for a variety of applications such as lighting and HVAC system design. A detailed method computes the energy usage with the first principle model and precise input detail.

In recent years, simulation software has provided an authentic tool to design low energy buildings. Optimisation of HVAC and other building parts using simulation tools have been reported by different researchers [22, 24, 46, 74, 75]. Building simulation tools are normally used for new buildings for acquiescence assessment [76]. Figure 2.2(a) and 2.2(b) illustrates the use of simulation models for energy evaluation of new and existing buildings, respectively [60].

Over the last three decades, many simulation tools for energy performance assessment have been developed, such as EnergyPlus [11], DOE-2 [77], ESP-r [13]. Table 2.1 summarises the commonly used simulation tools for energy performance assessment and shows the share of each tool in energy optimisation research. The application and developer of each software are also presented. As can be seen, EnergyPlus, DOE-2 and TRNSYS are three main tools, which are widely used in building energy optimisation. The former two are developed by the US Department of Energy, one for assessment of building energy performance and the other for hourly prediction of energy usage.

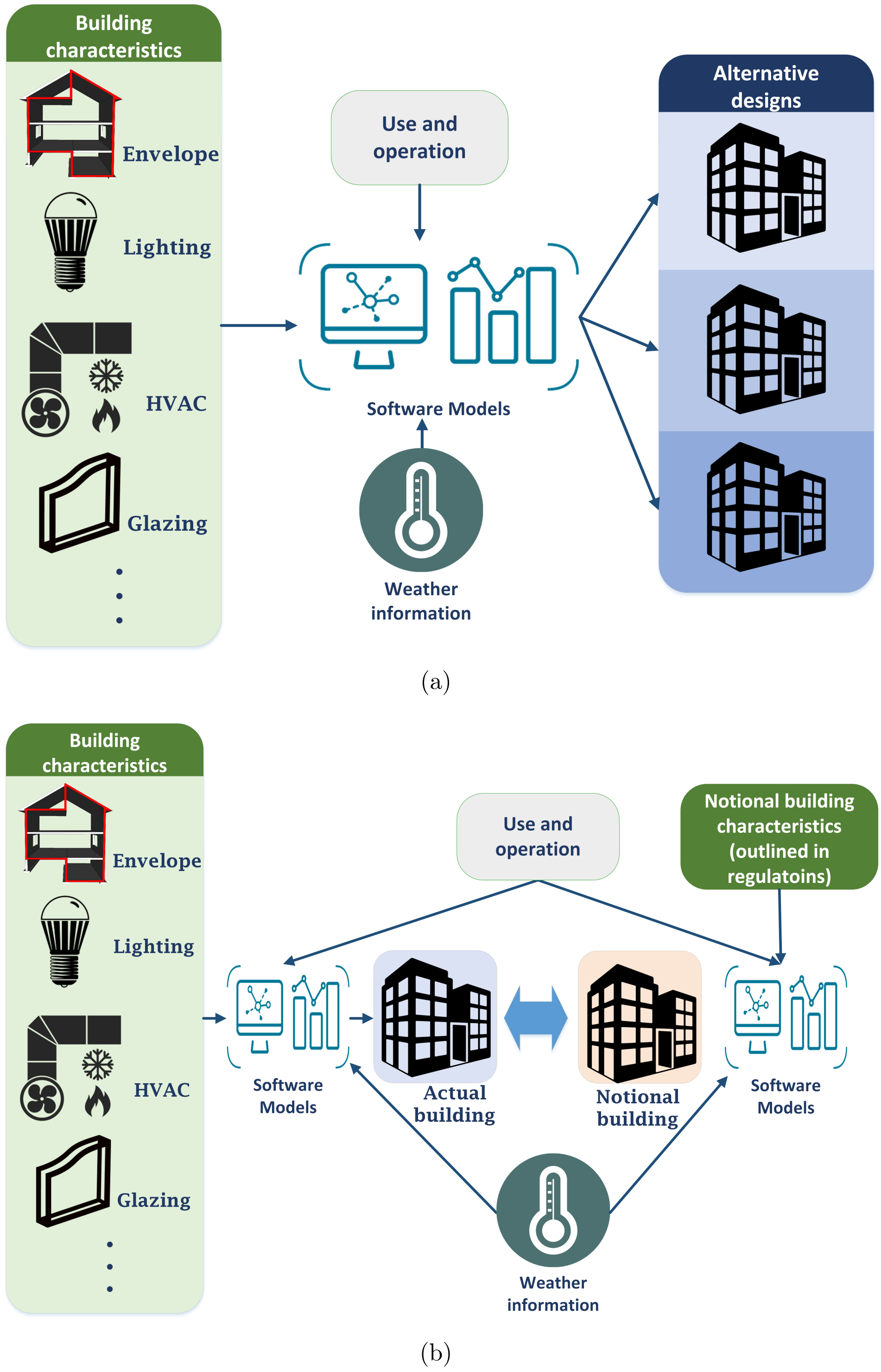


Figure 2.2: Illustration of energy performance assessment using simulation method for (a) new designs and (b) existing buildings.

Table 2.1: Common simulation tools for energy performance evaluation.

Software Name	Application	Developer	Share in energy opt.	Latest version	Ref
BLAST	Estimation of energy consumption, performance and cost for new and existing building	The US Army Construction Engineering Lab & University of Illinois	NA	V 3.0, Aug 1998	
BSim	Simulation tool for detailed and combined hydrothermal modelling of buildings	Danish Building Research Institute	Jointly 6.5%	V 6.13.9.24, Sep 2013	[78]
DeST	Analysis of building thermal processes and HVAC system performance		Jointly 6.5%	V2.0 2005	[79]
DOE-2	Prediction of the hourly energy use and cost of a building based on weather information, geometric and HVAC description	The US Department of Energy and Lawrence Berkeley Laboratory	10%	DOE-2.3 version 50e, Aug 2017	[77]
ECOTECT	Simulation of building performance from the earliest stages of conceptual design	Square One Research (until 2005) & Autodesk (until 2015)	2.7%	March 2015	[80]
Energy-10	Simulation of building energy design in early stage, integrates daylighting, solar heating and low-energy cooling strategies	The Sustainable Buildings Industry Council	Jointly 6.5%	V 1.8, Jun 2005	[81]

Table 2.1 (cont.): Common simulation tools for energy performance evaluation.

Software Name	Application	Developer	Share in energy opt.	Latest version	Ref
EnergyPlus	A modular tool based on BLAST and DOE-2. The primary building energy simulation program supported by the US Department of Energy for calculation of building energy performance.	The U.S. Department of Energy	37%	V 8.8.0, Sep 2017	[11]
eQuest	Enhanced version of DOE-2 with GUI integration	National Renewable Energy Labratory	2.7%	V 3.65 build 7173, April 2016	[82]
ESP-r	Building performance assessment by modelling heat, air, moisture, light and electrical power flows and based on based on a finite volume approach	University of Strathclyde	5.6%	V 12.7, Jul 2017	[13]
HAP	Measurement of HVAC systems and simulating hourly building energy performance to calculate annual energy consumption and costs	Carrier Corporation	NA	V 4.20a, Feb 2004	[83]
SUNREL	Simulation tool for design of small energy efficient buildings	National Renewable Energy Laboratory	1.5%	V1.14, Nov 2004	[84]
TRNSYS	Simulation software for evaluation of thermal and electrical energy systems	Solar Energy Lab (University of Wisconsin & University of Colorado)	35%	V 18.0, Apr 2017	[12]

2.3.3 Statistical Models

Existing of building energy data has allowed usage of top-down methods for assessment of energy performance. The statistical techniques use building historical data and frequently apply regression to model the energy consumption/performance of buildings. These models are also called data-driven surrogate models as they take advantage of existing data instead of relying upon system complex detail.

Statistical models are utilised in benchmarking by introducing an anticipated value of energy usage for each building. In general, energy consumption is normalised and expressed as EUI. This method uses different building characteristics as input variables and EUI as target values for developing a linear or non-linear model to predict for EUI of other buildings.

The traditional statistical method that has widely used in the building sector is simple and Multivariate Regression Models (MRM). The general rules of using these models can be found in ASHRAE [85]. Another popular method is the ChangePoint Regression Model (CPRM), which imitates the non-linear behaviour of input features. CPRM is ideally suitable for prediction of energy loads of buildings have a temperature or other climate-dependent variable controlling [86].

Considering EE_b to represent the baseline energy efficiency, and U to denote the vector of input features (e.g. age of the building, energy system, roof type, floor area) throughout the monitoring stage, then EE_b can be calculated using:

$$EE_b = EE_0 + \sum_{i=1}^{n} c_i U_i \tag{2.1}$$

Here EE_0 is a constant value, c is a vector of coefficients that are calculated by training n number of input features. Then the problem of Ordinary Least Squares (OLS) can be expressed as [87]:

$$\underset{EE_0,a,\varepsilon_i^2}{Minmise}:\left\{\sum_{i=1}^{o} b\varepsilon_i^2|EE_b\right\} \tag{2.2}$$

where ob is the number of observations and ε is the stochastic error for ith observation.

Stochastic Frontier Analysis (SFA) which is a developed OLS regression, introduces a method for inefficiency calculation rather than only a simple error measurement [88]. SFA model creates an efficiency frontier as a function of determined features, and measure the inefficiency by calculating the distance from this frontier [89, 90]

Another mathematical method which has been recently received attention in building energy modelling is Data Envelopment Analysis (DEA). DEA is a non-parametric method and allows performing a multi-factor productivity analysis by introducing Decision-Making Unit (DMU) and efficiency expectation [91]. DEA in contrast with linear regression does not provide any information on the relation of building physical characteristics; hence, the interpretation of the model is difficult [92].

By increasing the vast amount of valid and attainable datasets of buildings, there is a great interest in the utilisation of Artificial Intelligent (AI) methods such as ML in the construction sector. The most applied ML techniques in this field are Artificial Neural Network (ANN), Support Vector Machine (SVM), Gaussian Process Regression (GPR) and ensemble models including Random Forest (RF). As the primary objective of this thesis is the development of a meta-model using state-of-the-art ML techniques for evaluation of energy performance for non-domestic buildings, these models will be discussed in detail, and thorough literature will be presented.

2.3.4 Classification of Energy Assessment

Classification of building energy is used to determine the efficiency of energy consumption in comparison with similar buildings, generally in the same region. Classification assigns a grade (e.g. a number from 1 to 100 or a letter from A to Z) indicating the performance of building energy usage, same as for electrical appliances.

The classification includes different processes as mentioned before, an informative tool to increase stockholders and public awareness of building energy efficiency. The report is presented as an explicit form such as grades (e.g. 1 to 100 & A to Z) or a satisfaction scale (i.e. poor to excellent). Various energy classification tools have been introduced as benchmarking, rating labelling and certification. Each type utilises unique classification procedure in categorising and presenting building energy performance; however, at some points, they have overlapping practices and can be supplanted [93].

2.3.4.1 Process of Benchmarking

Based on the Cambridge dictionary, benchmarking means "the act of measuring the quality of something by comparing it with something else of an accepted standard". Correspondingly, the benchmarking of a building denotes to the comparison of its energy efficiency with that of reference buildings defined by standards [87, 93].

The benchmarking energy indicators support the governmental and private sectors in regulating energy usage. In some countries, policy-makers use these models to set out rules for efficient energy consumption in buildings. The increasingly common metrics or indicators for benchmarking are EPI or EUI which mostly present whole building energy consumption.

The whole building benchmarking includes a method to provide decision-makers with a relative energy performance level by comparing the performance index of the desired building with the pre-defined benchmark building. Two famous examples of energy benchmarking are "Energy Star" and "Cal-Arch" in the USA and "Energy Smart Office Label" in Singapore [47].

2.3.4.2 Rating

European Standard EN 15603:2008 [10] has introduced two primary standards of energy rating, including calculated energy and the "measured energy ratings". The former is further divided into standard or asset rating and tailored rating, considering the calculation conditions (using standard data or actual data), and are devised to rate the building and not the occupant. The latter is based on real metering on-site.

Stein and Meier [94] presented the more accurate definition of energy rating: "a method for the assessment of predicted energy use under standard conditions and its potential for improvement" with standard output (i.e. energy usage foresight, score based on a comparison with a notional building and a list of energy improvement technologies).

The most common rating systems normalise energy consumption in relation to building size (dividing the annual usage by heated floor area or volume). An example of an energy rating system would be the Home Energy Rating System (HERS) developed by the US Green Building Council (USGBC).

2.3.4.3 Certification

Energy certification is a method to evaluate building energy performance and to provide an energy certificate by an authorised institution. This process includes three main parts: 1) an energy rating procedure to measure energy usage, 2) a licenced energy labelling scale to assign the correspondent presentation, and 3) a minimum requirement to reduce the unsatisfactory performance. Even though operational rating has been advised for existing building assessment, in reality, most methods for new and existing buildings utilise the asset rating based on standard practice. Building energy performance certification has become obligatory in Europ. The certificate should be available to new owners or tenants when buildings are sold or rent out.

The examples of EU mandatory certificate schemes are:

- Energy certification of large buildings or energy management (ELO) and for small buildings (EM) targeting new and existing buildings in Denmark,
- Energy Performance advice for existing houses (EPA-W) and for non-residential buildings (EPA-U) and Energy Performance Coefficient (EPC) for new buildings in the Netherlands
- Energy performance assessment for existing dwellings (EPA-ED) and for non-residential buildings (EPA-NR) approved by the European Commission and with engaging of European member states.

2.3.4.4 Labelling

EU proposed energy labelling with two main objectives 1) to inform consumers about the energy efficiency of devices consuming energy and 2) to increase energy savings. As a result of the achievement of its objective to domestic appliances, the scheme was extended to buildings after ten years (Directive 2002/91/EC 2002). Building energy labelling includes assigning an energy efficiency label or rank to the building and needs a scale related to a Labelling Index (LI) [93]. The decision of the comparison strategy is a crucial issue for the scale definition.

If the number of comparable buildings is high enough, labelling can be accomplished by assigning percentile intervals to energy bands through statistical analysis of the EPI. The labelling scale defines these percentile intervals (e.g. top 10 per cent for Lable A). This scale determines the way of displaying the evaluation results with distinguishing levels, in comparison with national performance.

Singapore's Building and Construction Authority (BCA) was launched in 2005 to motivate Singapore's construction industry for constructing more eco-friendly buildings. The scheme presents a complete frame for evaluating the overall environmental performance of buildings [28]. The existing non-domestic buildings owners and directors are inspired to satisfy the predefined sustainable operations goals and to decrease adverse consequences of their buildings on the environment. The National Australian Building Environmental Rating System (NABERS) scheme, proposed to originate Australia's rating system for existing, operational buildings. NABERS has been developed as a performance-based rating method scaling a building's actual environmental impact while operation, through real assessment instead of simulations, or forecasting [95].

2.3.5 Summary of Energy Performance Assessment

While benchmarking systems are developed by utilising the energy performance of a significant number of reference buildings, benchmarking outcomes can be used to encourage owners of the buildings which are poor in energy usage to enhance them. Benchmarking methods additionally operate as a public measure of energy-use performance in buildings; some governors release benchmarking information to the media. This communication demonstrates advantageous as it increases public pressure on owners/developers of poorly performing buildings. Accurately benchmarking energy efficiency of existing buildings is a key step towards the success of a building energy retrofitting strategy. Several building benchmarking systems have been developed based on one of the methods introduced in this section. The Energy Star scheme is based on actual energy usage data and a regression model and is considered the most reliable energy benchmarking. The Energy Star score is an estimation of the similar buildings nationwide with higher energy use intensities. Clustering which is discussed in Section 2.4.5 is also a promising alternative which seems to be considered in developing the future benchmarking systems.

2.4 Machine Learning for Building Energy Forecasting

Three main techniques that have widely used in the building sector for supervised learning are ANN, SVM and Gaussian distribution regression models. K-means and hierarchical clustering methods have also utilised for unsupervised learning purposes. Very recently, ensemble models have also been limitedly employed in this area. These methods are discussed in detail in the following sections, and a summary of other ML techniques is presented subsequently.

2.4.1 Artificial Neural Networks

In building sector, ANN models have been applied for fast estimation of heating and cooling loads [96–98], energy consumption [99–101], energy efficiency [102–104] and space heating [96, 105]. Several successful application of ANN for Automated Fault Detection and Diagnostics (AFDD) in building energy conservation [106], solar water heater [107, 108] and HVAC system [109] have been reported. ANN is also applied in building management systems to provide automatic energy consumption control [110, 111], optimisation of heating system [112, 113] and comfort management [114, 115].

In 1995, an early study on the application of ANN in prediction of energy consumption using simple Feed Forward Network (FFN) model was performed to forecast electric energy usage of a building in tropical climate based on the occupancy and temperature data. Mena *et al.* [116] used ANN for short-term estimation of building electricity demand. Targeting the bio-climatic stock, it was shown that outdoor temperature and solar radiation have a notable impact on electricity consumption. Mihalakakou *et al.* [105] used FFN and Recurrent Neural Network (RNN) for prediction of hourly electricity energy consumption in a residential building located in Athens. The models consider meteorological variables including air temperature and solar radiation using time series data gathered over six years. Gonzales & Zamarreno [117] estimated short-term electricity energy consumption using a feedback ANN. Effect of the number of neurons in hidden layers, the best size of data windows and the ANN parameters on the accuracy of the model is investigated. Li *et al.* [118] proposed an optimised ANN for prediction of hourly electricity consumption using partial swarm optimisation (PSO) algorithm. Principal Component Analysis (PCA) was used to remove unnecessary input variables obtained from two datasets: ASHRAE Shootout I and Hanzou library building.

Platon *et al.* [119] applied PCA to investigate the pre-input variables of ANN in the prediction of hourly electricity consumption of an institutional building. Results from comparison of ANN and case-based reasoning (CBR), revealed that the ANN is superior in term of accuracy. However, as CBR provides more transparency than the ANN and the capability to learn from small data, it can be an alternative approach for complex systems dependent on more variables. Li *et al.* [118] proposed an optimised ANN for prediction of hourly electricity consumption using PSO algorithm. PCA is used to remove unnecessary input variables obtained from two datasets: ASHRAE Shootout I and Hanzou library building.

Yalcintas [120, 121] used ANN for energy benchmarking in tropical climate contemplate weather and chiller data. The selected building included office, classroom, laboratory-type buildings, or mixed-use buildings. The accuracy of EUI prediction was compared with multiple linear regression methods showing a remarkable advantage over it. Hong [100] applied ANN and statistical analysis for energy performance assessment of primary and secondary schools located in the UK by estimating electrical and heating consumption. By comparison of results with DEC benchmarks, it was shown that the ANN is more accurate for the energy assessment. It was concluded that the statistic benchmarks required further advancement and considerations (e.g. number of students and density of the schools) to provide better evaluations in this sector. However, it has been shown that ANN prediction is not as precise as simulation and engineering calculations.

Wong *et al.* [122] used ANN for assessing the dynamic energy performance of a commercial building with day-lighting in Hong Kong. EnergyPlus software along with algorithms for calculation of interior reflection was applied to generate the building daily energy usage. Nash–Sutcliffe Efficiency Coefficient (NSEC) was used as the primary measurement to investigate ANN accuracy in predicting cooling, heating, electric lighting and total electricity consumption.

ANN can be used for determination of parameters for energy performance assessment of buildings. Lundin *et al.* [123] proposed a method for prediction of total heat loss coefficient, the total heat capacity and the gain factor that are key elements in the estimation of energy efficiency. Buratti *et al.* [124] employed ANN as a tool for evaluation of building energy certificates accuracy using 6500 energy labels in Italy. The study investigated a different combination of input variables to minimise the number of training features. Using the outcome of the ANN, a new index was proposed to check the accuracy of declared data for energy certificates with a low error of 3.6%.

Hong *et al.* [57] applied ANN for benchmarking of schools buildings in the UK and investigated the limitations of the assessment. An extensive database including 120000 DEC records was used for training and testing the model [100]. Reviewing outcomes of the research and comparison with bottom-up models, authors suggested the combinational use of top-down and bottom-up methods to achieve higher accuracy.

Khayatian *et al.* [125] predicted energy performance certificates for residential building using an ANN model and Italian CENED database as training records. A combination set of direct and calculated features was used as inputs and heat demand indicators (derived using CENED software) as the output target of ANN.

Ascinoe *et al.* [104] proposed an ANN for evaluation of energy consumption and inhabitants' thermal comfort to predict energy performance of the building. Energy assessment of the buildings was performed using EnergyPlus software, and a simulation-based sensitivity/ uncertainty analysis was proposed for further improvement of network parameters. New buildings and retrofitted stock in presence of energy retrofit measures was considered separately. For the latter case, ANN was employed for optimisation of retrofit parameters. For the first one, three single output ANN was developed to predict primary energy consumption of space heating and cooling and the ratio of yearly discomfort hours by setting whole-building parameters as network inputs (i.e. geometry, envelope, operation and HVAC). At the same time, Beccali *et al.* [126] proposed the use of ANN fast forecasting as a decision support tool for optimising the refurbishment actions of buildings located in Italy.

Kalogirou & Bojic [110, 127] applied RNN to predict hourly energy demand of a passive solar building. ZID software was employed to calculate the output target. Although results demonstrated high accuracy of estimation, the number of input features (season, insulation, wall thickness and time of the day) and total training records (forty simulated cases) was insufficient. Later in 2001, Kalogitrou [128] applies ANN for estimating the daily heat loads of model house buildings with different calumniations of the wall (single and double) and roof (different insulations) types using a typical meteorological data for Cyprus. In this study, TRNSYS software was used as an energy evaluation engine for all cases and the data validated by comparison of one building energy consumption with the actual measurement. Karatasou *et al.* [99] developed an FFN model for hourly prediction of energy loads in residential buildings. The impact of various parameters on the accuracy of a trained model was also investigated, and it was shown that parameters such as humidity and wind speed are less significant and can be eliminated from training features. Furthermore, the application of statistical analysis for enhancement of ANN model and 24 hours ahead prediction of energy consumption was demonstrated. These methods consist of hypothesis testing, information criteria and cross-validation in pre-processing and model development. However, there is less enlightenment about the main distinctions of applied FFN models. In 2010, Dombayci [129] used ANN to prediction hourly energy consumption of a simple model house based on Turkish standards. The degree-hour method was applied to derive the hourly energy consumption to be used in ANN training. The models are suitable for single building energy management of simple residential buildings as it does not take many characteristics into account.

Kialashaki & Reilsel [130] compared an ANN with Multiple linear regression (MLR) for estimation of the US domestic buildings energy demand. Seven independent variables (population, gross domestic product, house size, median household income, cost of residential electricity, natural gas and oil) was selected from different data sources (1984-2010) to represent the building characteristics. Antanasijevic *et al.* [131] compared ANN with multiple linear and polynomial regression models for forecasting the energy consumption and energy-related greenhouse gas emission using building data from 26 European countries. The results showed 4.5% improvement in term of ANN accuracy (mean absolute percentage error) in both cases.

Neto & Fiorelli [132] compared predicted energy demand of a building in Brazil using ANN model and simulation software, EnergyPlus. The research investigated the impact of using hidden layer showing an insignificant difference in accuracy of the models. Furthermore, it revealed that external temperature is more important than humidity and solar radiation in estimating energy consumption of the study case. The authors showed that ANN is more accurate that detailed simulation model, especially in short-term prediction. They concluded that improper assessment of lighting and occupancy would be the main reason for uncertainty in engineering models. Popesco *et al.* [133] developed an original simulation and ANN-based models for predicting hourly heating energy demand of buildings connected to district heating system. Climate and mass flow rate variables of prior 24h were used as inputs. Deb *et al.* [134] also used five previous day's data as ANN model inputs to forecast daily cooling demand of three institutional buildings in Singapore.

Olofsson & Anderson [135] predicated daily heating consumption of six building family in Sweden constructed in the 1970's. The building went through the retrofitting in the early 1990's, and the measurements were performed before and after the renovation procedure. ANN makes an accurate long-term prediction of energy demand based on short-term measured data. PCA was also applied to reduce the number of input features to four (i.e. construction year, number of floors, framework, floor area, number of inhabitants and ventilation system). Ekici & Aksoy [136] used back-propagation ANN to predict heating loads of three different buildings by taking climate information into account. Heating energy demand of the sample buildings was calculated using a finite difference approach of transient state one-dimensional heat conduction problem. Paudel *et al.* [137] used dynamic ANN to predict heating energy consumption focusing on building occupancy profile and operational short-term heating power level characteristics.

Ben-Nakhi [138] used a general RNN for prediction of public buildings profile of the next days using hourly energy consumption data, intending to optimise HVAC thermal energy storage. Data from a public office building in Kuwait constructed from 1997 to 2001 was used for training and testing the ANN model. Energy consumption value of buildings was calculated using ESP-r simulation software and considering climate information, various densities of occupancy and orientation characteristics. The results showed that ANN only needs external temperature for accurate prediction of cooling loads, whereas simulation software demand for intricate climate detail.

Hou *et al.* [139] predicted hourly cooling loads in an air-conditioned building integrating rough set theory and ANN. Input features of ANN were determined and optimised by analyses relevant parameters to cooling load using rough set theory. The proposed model with different combinations of input sets was compared with the autoregressive integrated moving-average model all showing better accuracy. Yokoyama *et al.* [140] used back-propagation ANN to predict cooling load demand by introducing a global optimisation method for the improvement of network parameters. The effect of the number of hidden layers and the number of neurons in each layer was investigated to optimise the accuracy of the proposed ANN.

Yan & Yao [141] has proposed an investigation of the climate information effect on energy consumption in various climate zones. Back-propagation ANN was used to predict heating and cooling load to assist new building designs. Later, Biswas *et al.* [142] applied the similar approach on residential sector and demonstration houses in the USA using Matlab toolbox.

Aydinalp *et al.* [143] modelled the Appliance, Lighting and space Cooling (ALC) in residential buildings located in Canada. ANN for prediction of energy consumption showed better accuracy in comparison with engineering calculation methods. Later, they used ANN to predict space heating and domestic hot water for the same buildings [96].

Azadeh *et al.* [144,145] demonstrated the application of ANN based electricity consumption prediction model in the manufacturing industry. The model was used to predict the annual long-term consumption of industries in Iran using a multilayer perception model. The results was compared with the traditional regression model using ANOVA and showed superiority for the application. Later in 2014, Kialashaki [146] foretasted energy demand of the industrial sector in the US considering gross domestic and national products and population.

2.4.2 Support Vector Machine

In building sector, SVM has been used for forecasting of cooling and heading loads [97, 147, 148], electricity consumption [149, 150], energy consumption [151–154], and classification of energy usage of buildings [3].

In 2005, at first in building sector SVM was applied for estimation monthly electricity usage for non-domestic building in tropical country of Singapore [149]. This study considered three input parameters including temperature, humidity and solar radiation and targets four different buildings. The data was collected over three years and used for training and testing the developed model. Results of using RBF kernel indicated that SVM model has excellent accuracy in predicting the electrical loads and the low error rate of 4%. The conclusion declared the superiority of SVM over previously derived ANN models in terms of selection of small model parameters and accuracy. This initial work was followed by Lai *et al.* [147] by applying SVM for forecasting monthly and short-term (i.e. daily) prediction of electricity consumption of a domestic building located in Japan. They used outdoor, living and bedroom temperature and humidity as well as water temperature as input parameters and collected electricity usage data over a year. Massana *et al.* [155] compared SVM, ANN and MLR in short-term prediction of non-domestic buildings' electricity demand and concluded that SVM provide higher accuracy and lower computational cost.

Later in 2010, Li *et al.* [152] used SVM for long-term prediction (yearly) of electricity consumption of domestic buildings. They considered fifteen building envelope parameters collected from 59 different cases along with the annual electricity consumption which is normalised by unit area. Besides, they compared the accuracy of the SVM model with three types of ANNs including propagation, RFB and general regression. Testing the trained model over 20% of study cases provided results that showed SVM outperforms ANNs for all samples. Solomon *et al.* [156] predicted weekly electricity consumption of a massive commercial building considering previous electricity usage, temperature data and wind velocity.

In addition, Li *et al.* [97] applied SVM to forecast hourly cooling leads of an office building located in China. They considered three similar input parameters which were used by Dong *et al.* [149] and collected from local climate database. The target samples were gathered during summer, and one month used for training and four months for testing the model. In the meantime, they presented a comparison with ANN models and indicate that SVM and general regression ANN have more potential to be used in the field. Hou & Lian [148] examined the accuracy of SVM with an autoregressive integrated moving average based model [157] and demonstrate the supremacy of SVM regarding maximum and minimum error values. Xuemei *et al.* [158] developed a model based on Least Square SVM (LS-SVM) and used the same input parameters. This approach contributes to learning correction for limited training sets and enhanced prediction time efficiency to traditional SVM model in load forecasting. Jinhu *et al.* [159] and Li *et al.* [160] applied improved PCA to find the significant parameters and show better accuracy. However, the information about original and selected features are missing. The further improvement of similar SVM based cooling load prediction has been demonstrated using a fuzzy C-mean algorithm for clustering samples [161], simulated annealing particle swarm optimisation to prevent premature convergence [162] and Markov chains to the farther forecast of the interval after primitive prediction [163]].

Zhao & Magoules [153] predicted energy consumption of office building using parallel implementation of SVM. They aimed at optimising the building characteristics of a model case. They utilised EnergyPlus software to calculate the energy demands. The results show a slight improvement regarding accuracy. Later in 2012, the authors applied gradient guided feature selection and the correlation coefficients methods to decrease the number of features for RBF and polynomial based SVM models [164].

In 2014, Jain *et al.* [165] used sensor-based data of multi-family domestic building located in New York City to develop an SVM model. The aim was to investigate the effect of a different time interval and building spaces of data collection on energy consumption forecasting. The authors pointed out that the optimum efficiency of the derived model was obtained when hourly intervals collected at floor level is utilised. Edwards *et al.* [166] presented a comparison of SVM, LS-SVM and ANN in forecasting hourly energy consumption of small residential buildings and find ANN as the least accurate model.

2.4.3 Gaussian Process and Mixture Models

Since early 2000, Gaussian process (GP) regression has been employed by researchers in different application [167–169]. In building energy field, GP has been recently utilised due to its potentiality in determining the uncertainty of predictions. In building energy modelling, there are usually uncertainties in the section of appropriate values for some characteristics (e.g. envelope insulation). Hence, evaluation of input uncertainty on foretasted results has made the GP as an alternative approach to model building energy rather than conventional and other ML regression models.

Heo [170, 171] applied GP model to calculate the building energy saving after retrofitting by forecasting the total energy consumption. The model used outside temperature, relative humidity, and occupancy count as an input variable and considers output measurement errors to approximate uncertainty levels. Later in 2013, Zhang *et al.* [172] used GP regression for predicting the energy demand of an office building cooling and heating in the post-retrofit phase. They showed that the accuracy of the GP model is very dependant on training and testing data range.

Noh & Rajagopal [173] proposed a long-term GP prediction model for total energy consumption of a campus building using smart meter measurements and weather data. Nghiem & Jones [174] proposed a GP based model for demand response service by predicting building energy consumption. Rastogi *et al.* [175] compared the accuracy of GP and linear regression in emulating of a building performance simulation and showed that the accuracy of GP is four times better than linear regression testing on EnergyPlus simulated case studies located in the US.

Burkhart *et al.* [176] integrated GP with a Monte Carlo expectation maximisation algorithm to train the model under data uncertainty. The aim was to optimise office building HVAC system performance by predicting its daily energy demand. Relative humidity and ambient temperature were considered as specific input variables and daily occupancy with two different scenarios (moderate and vigorous) as uncertain data. The results indicated that the models can be trained even with limited data or sparse measurements employing rough approximation and data range instead of sensor data.

Manfren *et al.* [177] developed a method for calibration and uncertainty analysis of building energy simulation model. They used detailed simulation, GP with RFB kernel and MLR to predict monthly electricity and gas usage of heating and cooling systems. The results indicated that GP not only provides a tool for optimisation and uncertainty analysis of building energy models but also shows higher accuracy in comparison with a piece-wise regression model.

Sirvastav *et al.* [178] employed Gaussian mixture model (GMM) to predicts daily/hourly energy consumption of commercial buildings (a DOE reference model for supermarket and a retail store building). This parametrised model allows locally adaptive uncertainty quantification for building data.

Zhang *et al.* [103] compared change-point models, GP, GMM and FF-ANN models for prediction of an office building's HVAC system hot water energy usage considering weather data (ambient dry bulb temperature) as an input variable. The ANN utilised in this work has one hidden layer activated using tangent sigmoid transfer function. The results showed that the best performance is achieved using GMM and the worst by ANN. The authors concluded that as the ANN was not fed by adequate data, it was not a suitable model for the case study. Although the accuracy of GMM and GP is slightly better than the change-point regression, the later is recommended due to the simplicity of the approach. It should be noted that the Gaussian methods are the best choice for analysing uncertainty and capturing complex building behaviour.

2.4.4 Ensemble Models

The use of ensemble ML methods (e.g. RF and gradient boosted regression trees) in the building energy domain is restricted to recent years [179–182], despite an established track-record of utilisation in other disciplines. Li *et al.* [183] compared SVM, ANN and ensemble models on prediction of building energy performance by using trust metric to evaluate the reliability of the models. The superiority of SVM and ML over the ensemble and linear models was concluded. However, the authors did not optimise the models to generate the Pareto frontier. Papadopoulos *et al.* [184] also compared different ensemble models in estimation of the energy performance of residential buildings (including 768 variations of a model building) evaluated using Ecotect software.

2.4.5 Clustering Algorithms

Clustering is one of the well-known ML techniques that identifies implicit relations, patterns and distributions in data sets. Clustering is an unsupervised learning method that can describe the hidden structure in a collection of unlabeled data. In building energy, the primary application of this technique is to classify buildings using various features and characteristics instead of only use type or topology is very advantageous in building energy benchmarking. Clustering for such an application implicates four steps [185]: (a) data collections, (b) feature identification and selection, (c) adaptation of appropriate clustering algorithm and (d) benchmarking each building within classified groups. The most common clustering algorithm is k-means that iteratively seeks for a local maximum. The algorithm begins with a random selection of k centroids (centre of cluster), and each data is assigned to the nearest centre point. Then all centroids are recalculated using the mean of all data points in a group. This process continues until it satisfies a stopping criterion (e.g. a minimum aggregation of distances is reached).

Targeting 320 schools in Greece, Santamouris *et al.* [186] proposed a building energy classification method using fuzzy clustering [187]. Total energy consumption (heating and electricity) over three years along with information on operating hours, number of pupils, structure characteristics, etc., were collected. By applying a clustering algorithm, five building energy rating classes were determined. The clustering based classification was then compared to similar frequency rating process indicating that clustering offers more robust classes resolving the problem of low and unbalanced or very large class constitution. The authors applied outcomes to ten study cases to investigate the potential energy conservation. Gaitani *et al.* [188] used 1100 school samples for the development of a framework for heating energy consumption rating, aiming at evaluation of potential energy savings. A k-mean clustering incorporating PCA algorithm was utilised to form five rating classes and determine representative building of each cluster. Pieri *et al.* [189] proposed a cluster-based energy audit considering cooling and heating loads of hotels in Greece.

Gao & Malkawi [185] demonstrated that energy performance benchmarking using clustering algorithm is more accurate and robust than the US Energy Star scheme due to the ability in integrating all the building features that affect energy consumption. The feature extraction was made using ordinary least squares regression and clusters were generated using the k-means algorithm. Lara *et al.* [190] also applied k-means clustering to assess the energy performance of schools in Italy and characterise reference building for each group. First an MLR method, as a mean of correlation analysis, was used to identify the most appropriate quantities and variables for representation of energy demand and building properties. Then clustering algorithm clustered similar buildings regarding the defined variables. Finally, the building having the minimum distance from the centroid was selected as the representative for each cluster. These reference buildings are useful tools for optimising retrofit solutions.

Yu *et al.* [191] used clustering technique to demonstrate the impact of occupancy behaviour in building energy consumption. A similarity of building features unrelated to occupants behaviour was used for creating clusters, and the impact of users action in energy demand was investigated for each cluster. Petcharat *et al.* [192] proposed a clustering algorithm to asses potential energy saving regarded to the lighting system in Thailand non-domestic stock. The authors indicated that cluster-based analysis is more effective than the only comparison of target building power density with reference cases that are defined by the country's Energy Act.

Yang *et al.* [193] applied a k-shape (proposed for clustering time series) algorithm to identify energy usage patterns and then employ SVM for enhancing the accuracy of building energy demand prediction. Jalori & Reddy [194] proposed clustering of days based on daily/hourly energy consumptions to detect ad removed outlier data point. This process further improves data-driven energy forecasting models, and so increases the performance of BMS.

2.5 Summary of Building Energy Modelling Using ML

A summary of ML approaches based on the application is given in Table 2.2. The table provides information on prediction duration, the building study cases and data or energy usage collection and features used in model training. Column 'Target' presents the building energy indicator predicted by the ML model, which is specified in column 'ML'. The prediction term (i.e. the targeted period for energy predictions) is shown in column ' Pred. term'. Building study cases and the extracted features are presented in the other columns.

Table 2.2: Summary of machine learning techniques for prediction of building energy consumption and performance

Target	ML	Pred. term	Building case and data	Features	Ref
Energy Performance	ANN	Month	schools in England and Wales (120,253 DEC records)	Construction year, Phase of education, Number of pupils,Internal environmental conditioning, Site exposure, Orientation, North facade adjacency, South facade adjacency, East facade adjacency, West facade adjacency, Floor area, Building depth ratio, Compactness ratio, Surface exposure ratio, North glazing ratio, South glazing ratio, East glazing ratio, West glazing ratio, Glazing type, Roof shape, Roof glazing, Heating degree-days, Cooling degree-days	[100]
	ANN	-	Educational building (previous preliminary energy assessments (PEA) reports for over 60 buildings in Hawaii)	Operation hours, Age, Square feet area, Yearly electricity usage, percentage electricity used for lighting, air conditioning, plug loads	[121]
	ANN	Year	Office buildings in Italy (8800 building stock simulated using EnergyPlus)	geometry(9), envelope(30), operation (6) and HVAC (3)	[104]
	ANN	Year	Schools in UK (120,253 DEC records)	North glazing ratio, South glazing ratio, East glazing ratio, West glazing ratio, Glazing type, Roof shape, Roof glazing, Heating degree days, Cooling degree days	[57]
	ANN	-	Residential buildings (the online CENED database)	Degree days, Net volume, Net floor area, Dispersant surface, Opaque to glazed ratio, Year of construction, Thermal conductivity, Average floor height, Opaque surface area, Glazed surface area, Construction period, Non-linear features	[125]
	ANN	Day	An generic reference office building in Hong Kong (8760 hourly records calculated using EnergyPlus)	External weather conditions (daily average dry-bulb temperature, daily average wet-bulb tempera-ture, daily global solar radiation and daily average clearness index), Building envelope designs (solar aperture, daylight aperture, overhang and side-fins projections), Day type	[122]

Table 2.2 (cont.): Summary of machine learning techniques for prediction of building energy consumption and performance

Target	ML	Pred. term	Building case and data	Features	Ref
Energy Performance	Clustering	-	5215 commercial building samples (CBECS database)	Area, percent heated, percent cooled, Wall materials, Roof materials, Window materials, Window%, Shape, Number of floors, Construction year, Weekly operation hours, Occupants, Variable air volume, Heating unit, Cooling unit, Economizer, Refrigerators, Number of servers, Office equipment, Heating and cooling degree day	[185]
	Clustering	-	1100 school in Greece (data gathered over one)	Heated surfac, Age of the building, Insulation of the building, Number of classrooms, Number of students, School's operating hours per day, Age of the heating system, Energy consumption per unit	[188]
	Clustering	-	320 schools in Greece (Energy data have been collected for a three years)	Temperature, Solar radiation, Energy consumption per unit, Operational period, Number of students, Construction characteristics, Installed equipment	[186]
	Clustering	-	60 schools in Italy (data collected over 5 years)	Area of the floor in thermal contact with the ground, Opaque envelope area, Transparent envelope area, Windows tp vertical walls ratio, Windows to floor area ratio, Transparent to opaque envelope ratio, Envelope average thermal transmittance, Shape, Heating system Capacity	[190]
HVAC Loads	GPR	Day	An office building in Chicago (Loads calculated using simulation)	Weather, Occupancy count	[176]
	GPR, GMM, ANN	Day	Office building (three months data collected)	Outside dry bulb air temperature, Day	[103]

Table 2.2 (cont.): Summary of machine learning techniques for prediction of building energy consumption and performance

Target	ML	Pred. term	Building case and data	Features	Ref
Heating & Cooling Loads	ANN	Year	Model house with 9 combination of wall and roof type (loads are calculated using TRNSYS simulation)	Wall and Roof type, Maximum and mean daily direct and global radiation, Maximum and mean temperature of the day , Mean wind speed and direction (degrees)	[128]
	GPR	Hour	Office building in Philadelphia	Outdoor temperature	[172]
	GPR	Year	Typical buildings in the US (loads calculated using EnergyPlus)	Building characteristics, Climate data (28 features)	[175]
	GPR	Month	Retrofitted office building (Actual measurements and simulation)	Building envelope characteristics, Solar shading control system	[177]
Heating Loads	ANN	Hour	Simulation models (Data collected from a District Heating Company of the city of Iasi)	Solar radiation, Wind speed, Outside temperature of previous 24h, Mass flow rate of hot water of previous 24h, Hot water temperature exit from plant system	[133]
	ANN	Hour	Schools in UK (120,253 DEC records)	Glazing ratio in all cardinal directions, Roof shape and glazing, Heating and cooling degree days	[57]
	ANN	Day	Six single-family buildings, constructed in Stockholm	Construction year, Stories, Framework, Floor area, Number of inhabitants, Ventilation system	[135]
	ANN	Hour	An institutional building in Nantes (The data is taken from data acquisition system for 1.5 months)	Climate and heating energy data, Occupancy profile	[137]
	SVM	Day	Single-story mass-built buildings (Simulated using EnergyPlus)	Outdoor dry bulb and relative humidity, Wind speed, Direct solar, Ground temperature, Outdoor air density, Water mains temperature, Number of occupants, Total heat gain of lights, electric equipment and window, Heat loss for walls, Mean air temperature, Infiltration volume, Heating outlet temp	[164]
	ANN	Month	Three sample buildings	Transparency ratio, Insulation thickness, Building form factors	[136]

Table 2.2 (cont.): Summary of machine learning techniques for prediction of building energy consumption and performance

Target	ML	Pred. term	Building case and data	Features	Ref
Cooling Loads	ANN	Hour	Parking space (data gathers over 23 weekdays)	Temperature, Relative humidity	[140]
	ANN	Day	Public office building in Kuwait (data for three building types)	External temperature	[138]
	ANN, SVM	Hour	A model building in China (measurements from an existing HVAC system)	Temperature, Relative humidity	[139, 148, 158]
	ANN	Day	Three institutional buildings (The energy data is obtained through the facility management office)	Five previous day	[134]
	GPR	Hour	office building in Lemont city (data obtained from baselining and post-retrofit days)	Outdoor temperature	[170]
	GPR	Day	An School building in Stanford city (data obtained from baselining and post-retrofit days)	Outdoor temperature	[173]
Energy Demand	ANN	Hour	holiday home which is used only during weekends (forty cases generated by the program ZID)	Season, Insulation, Wall thickness, Time of day, Energy calculating function	[127]
	ANN	Hour	Two datasets (Great Building Energy Predictor Shootout I (5 months), office building located in Athens, Greece (one year))	Temperature, Solar radiation, Humidity ratio, Wind speed, Day	[99]
	ANN	Year	the US domestic buildings (energy consumption is taken from U.S. Energy Information Administration)	Population, Gross domestic product, House size, Median household income, Cost of residential electricity, Natural gas and oil	[130]
	ANN	Day	An office building in University of Sao Paulo	Daily maximum and minimum external dry-bulb temperatures	[132]
	SVM	Month	Four office buildings in Singapore (energy consumption is obtained from utility bills over 4 years)	Dry bulb temperature, Relative humidity, Global solar radiation	[149]
	SVM	Hour	Multi-family domestic building in New York City (data from the Great Energy Predictor Shootout)	Temperature, Humidity, Wind speed	[165]

Table 2.2 (cont.): Summary of machine learning techniques for prediction of building energy consumption and performance

Target	ML	Prediction term	Building case and data	Features	Ref
Electricity Demand	ANN	Hour	An institutional facility in Calgary (data collected over 15 month)	Outside temperature and relative humidity, Boiler outlet water temperature and flowrate, Chiller outlet water temperature and flowrate, Supply air temperatures for hot, cold duct, Supply and return control settings, Indoor air temperatures of 2 different zones	[119]
	ANN	Hour	A building in Athens (time series of hourly values are collected over 6 years)	Air temperature, Solar radiation	[105]
	SVM, ANN	Month, Day	A residential building in Japan (data is collected over one year)	Date, Outdoor temperature, Bedroom temperature, Living temperature, Living humidity, Bedroom humidity, Outdoor humidity, Water temperature	[147]
	SVM, ANN	Year	59 residential buildings in China	Mean heat transfer coefficient of building walls, Mean thermal inert index of building walls, Roof heat transfer coefficient, Building size coefficient, Absorption coefficient for solar radiation of exterior walls, Window to wall ratio in four directions, Mean window to wall ratio, Shading coefficient of window in four directions, Integrated shading coefficient	[152]
	SVM, ANN	Hour	A university office building (electrical load data is collected with a power meter)	Outdoor/indoor temperature and humidity, Indoor illumination, Solar radiation, Calendar nominal attributes	[155] [152]
	GMM	Day	DoE super market reference model (climate data from Chicago)	Outside dry-bulb air temperature and humidity ratio, Direct solar radiation	[178]

Based on the results from seminal works and proposed methods for different applications and considering some ML factors, this study proposes a framework for selecting the right method for building energy prediction and benchmarking as demonstrated in Figure 2.3

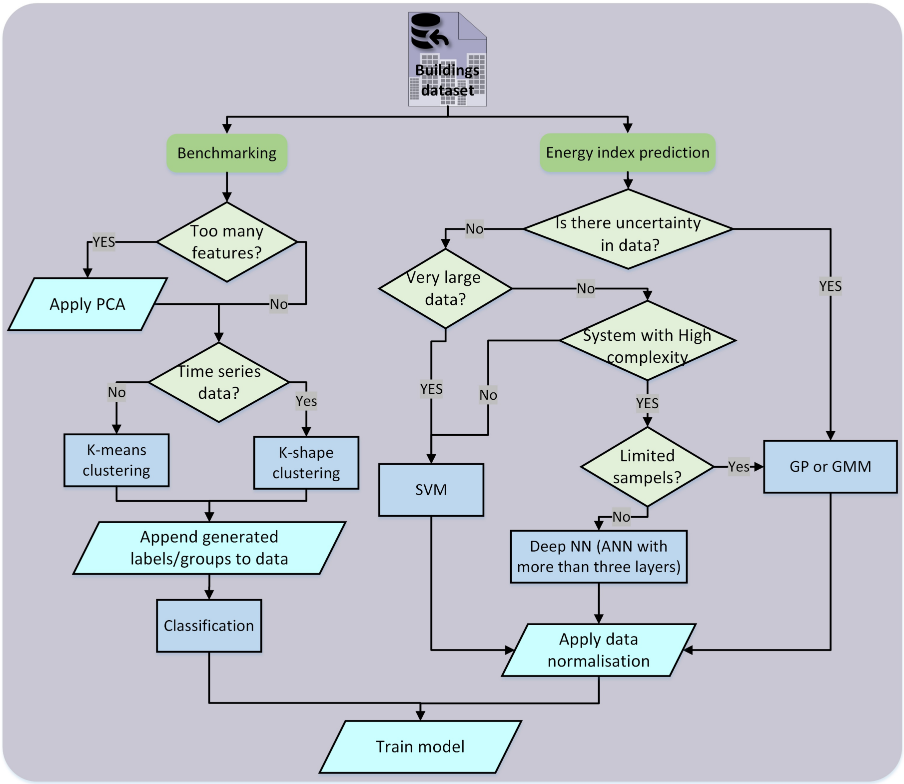


Figure 2.3: Proposed method of selecting ML for building energy data.

ANN has been broadly used in building energy forecasting since the first introduction in the sector at 1990's. ANNs provide a powerful tool for modelling building energy modelling and faithful prediction, however, they require proper choice of network structure and precise adjustment of its several hyper-parameters for training. The performance of the models are not guaranteed as ANN suffer from local minimum problem. Results from different researches indicates that ANN should be fed with adequate number of samples in order to obtain acceptable accuracy, otherwise it might be outperformed with simple MLR models. It could be concluded that ANN is much appropriate for engineers having a strong knowledge of deep learning and statistical modelling.

In contrast with ANN, SVM and GP are supervised using few parameters and provide satisfactory performance. It has been shown that SVM surpasses ANN in load forecasting and has the potential to build models from limited samples. Nevertheless, the ANNs used for comparison in the aforementioned studies, exploit simple structure and the hyper-parameters might not be well optimised due to the complexity. Among ML techniques and other black box methods, only GP is used for model training with uncertainty assessment, nevertheless, it is not the sole capable technique. Recently, uncertainty and sensitivity analysis for other ML techniques has been introduced and utilised. Hence, it worth to devote research attention to deploy these approaches for modelling building under uncertain data.

Im general, it is very difficult to conclude that which ML model is the best, as from literature it can be induced that all models provide reasonable accuracy by supplying large samples and optimising the hyper-parameters. Thereby, it is very important to thoroughly analyse the nature of available or collectable data and the application, in order to choose most suitable model. For example, ANN provide a fast and precise short-term load forecasting for EMSs where temperature and humidity data is collected using sensors, while GP is more beneficial for long-tern energy estimation when there is uncertainty in input variables. In fact, feature selection itself require an extensive investigation for each application as it is the preliminary requisite for implementation of any ML methods.

2.6 Building Retrofit Planning

This section provides the study of state-of-the-art literature on non-domestic retrofit planning and related developed decision-making methods.

2.6.1 Critical Factors of Efficient Retrofit Plan

Ma *et al.* [195] suggested a comprehensive study of the leading methods utilised for devising an effective energy retrofit, through distinguishing fundamental elements. These factors include policies and regulations, client resources and expectations, building specific information, human factors, retrofit technologies and other uncertainty factors as illustrated in Figure 2.4 [195].

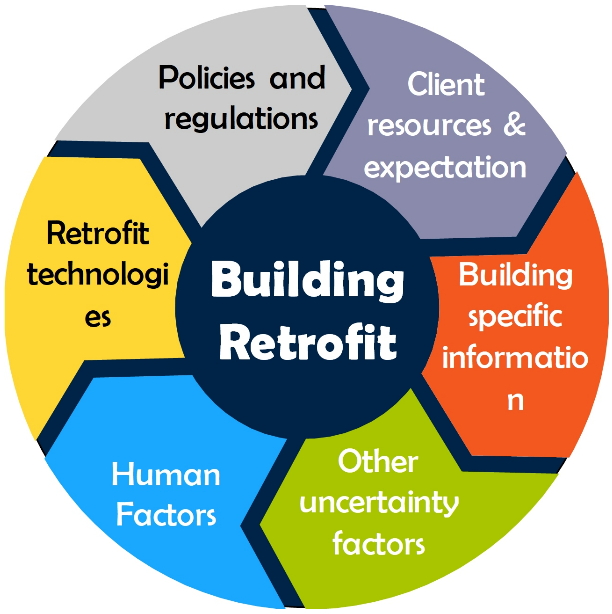


Figure 2.4: Factors effecting building retrofit decision-making process.

Building energy policies and regulations force a minimum level of energy efficiency to be obtained during the retrofit. Some governments offer financial packages to encourage building owners to take part in energy enhancement programmes. The Salix grant scheme funded by Department of Energy & Climate Change (DEEC) and Green Investment Bank (GIB) funding are examples of these governmental supports for energy efficiency improvement [196]. Tobias & Vavaroutsos [197] summarised public policies addressing building energy efficiency retrofit (BEER) and Pombo *et al.* [198] reviewed the practices and energy saving measures in renovations.

Client resources and expectations delimit the project objectives, available cost and the constraints in retrofit planning. This pieces of information are essential factors in MOO for searching the optimal solutions. Several elements affect the decision-making on investment in energy efficiency improvements, however, the one most important is the payback period [199].

Retrofit technologies are applied to improve building energy performance and categorised into supply-side management consisting electrical system enhancement and the application of renewable energy, demand-side management including the procedures to decrease heating and cooling loads, and the use of efficient equipment and low energy technologies, and alteration of consumption patterns [195].

Retrofit DM requires a precise measurement of building specific information including geographical location, class, dimensions, age, energy sources, operation and maintenance plan, fabric, etc. to alleviate the number of assumptions that need to be made [200].

An extra essential challenge for the achievement of a proper empirical risk minimisation regards to a stable and precise evaluation of the building energy and thermal performance. Different approaches of building performance evaluation are discussed in Section 2.3.

Building retrofit process is divided into different steps: In the first step the project targets are set by the owner and consulting with an Energy Service Company (ESCO) to manage the retrofit planning. In the second step, a professional assessor audits building energy characteristics which are then used for determining the building energy rating. Step three is the identification of the most appropriate retrofit options employing established energy assessment methods to confirm the energy saving achievement. The final step involves the implementation of chosen retrofit measures.

This study focused on the third step (decision-making) where there is a significant challenge on the selection of retrofit measures as it involves not only the available technologies, but also many other factors. These include policies which are different in countries, weather condition, owner constraints, etc.

2.6.2 Decision Making for Retrofit

Building energy efficiency enhancement consists of an optimisation method of determining a selection of technically advantageous and cost-effective measures. The traditional procedure of evaluating a broad variety of retrofit technologies is to investigate several potential solutions based on practician experience. The primary restriction of with this strategy is that only limited number of scenarios can be evaluated and the probability of obtaining an optimal solution is quite low. It has been indicated that implementing of non-optimised solutions, it is possible to alter the building at a subsequent attempt imposing much higher cost [201]. This issue causes investors to be unwilling to invest in their building energy efficiency improvement.

To consider all technologies and combinations, an evaluation of a considerable number of solutions is needed which make the decision-making process a complex work and challenging to manage [202]. Several methodologies have been proposed to facilitated DM in energy retrofits which generally are divided in two groups: priori or multi-criteria analysis (MCA) and multi-objective optimisation (MOO).

MCA still relies on users' experience by defining a set of alternative options and pre-evaluation of the solutions. As such achieving the most optimal retrofit packages is not guaranteed [203]. IN MCA,each criterion is weighted, and then total weights create a unique criterion. Gero *et al.* [204] were among the first to suggest an MCA method for design of an energy efficient building. This model examined the trade-off between the thermal efficiency and other factors which are not energy-related (e.g. building cost and available area). This approach was then followed by several researchers by applying in related problems [205–208]. Jaggs *et al.* [209] and Flourentzou *et al.* [210] suggested strategies for the assessment of retrofitting situations. Kaklauskas *et al.* [211] proposed a multivariate design and MCA approach for energy retrofit, defining the importance and advantages of building retrofit options and choosing the topmost preferred alternative. Another drawback MCA based methods is that the information about the sensitivity of each criterion to alteration of others is not provided [16].

The other method, which is based on MOO, allows considering a broad retrofit technology options limiting the search space and perceive the trade-offs among the objective functions assisting in attaining an optimal solution. Still, comparatively limited consideration has been given to tackling building retrofit DM support with MOO [23]. This is due to the fact that a large number of simulations are required to obtain a solution. These calculations are time-consuming and demand for heavy processing in case of using energy simulation tools. Diakaki *et al.* [22]

studied the usefulness of applying MOO methods for enhancing building energy efficiency, by use of a simplified model for thermal simulation. Asadi *et al.* [23] developed a MOO model to support the definition of retrofit scenarios intended to cost-effectively optimise energy consumption. Further to that, a MOO model coupled with TRNSYS was developed to optimise retrofit cost, energy savings, and thermal comfort in a residential building [24].

Ascione *et al.* [19] proposed a framework for the MOO to optimise building energy design considering the most extensive selection of objective functions and design variables. Genetic Algorithm (GA), combined with EnergyPlus, was used to generate the retrofit solution space for an office building. The same group previously was focused on the use of MOO for optimising residential buildings retrofit planning [25]. Gou *et al.* [212] used the MOO approach by coupling ANN and GA to optimise residential building comfort indoor and energy usage. Ferrara *et al.* [17] also focused on a residential building and used TRNSYS and GenOpt optimisation software to minimise energy demand and global cost. Bre and Fachinotti [20] focused on minimising energy consumptions for heating and cooling and maximising thermal comfort for occupants by coupling EnergyPlus and GA. Jafari and Valentin [26] also employed GA and eQuest and aimed at optimisation of life cycle cost of the retrofit strategies for a residential building. Carlucci *et al.* [213] used GA and EnergyPlus to optimise thermal, visual comfort and indoor air quality in the design stage. With similar configuration and adding ANN, Yu *et al.* [214] aimed at evaluating energy usage and thermal comfort for the design of the Chinese buildings.

2.6.3 Summary of Retrofit Planning

There is an evident increase in the popularity of optimisation for building retrofit planning, and of MOO in particular. This fact is somewhat because the growing computational power is accessible to address challenges that were previously infeasible. This is likely to continue, with optimisation expanding into areas currently beyond our capabilities. However, the current state of the energy simulation, which is utilised as the calculation tool in energy retrofit optimisation is still such time-consuming that the industrial application seems impracticable. Hence, accelerating the optimisation process will provide sufficient reason to increase interest in optimisation in the industry and to uncover the enormous potential of such methods.

2.7 Chapter Synthesis

In recent years, optimisation of construction and building energy usage have been received great attention as this sector is known as main contributor to air pollution and fossil energy consumption. The regulations and rising fuel prices have forced owners to reduces energy use by means of smart controls, sensors or retrofitting. This concern have become more critical in non-domestic sector as huge amount of energy is wasted due to inefficient management. As a result, various smart technologies has been applied for the purpose of energy saving. Rapid development of the modern technologies including sensors, information, wireless transmission, network communication, cloud computing, and smart devices has been led in a great amount of data accumulation. The traditional modelling of building energy using software and statistical approaches does not satisfy the demand for fast and accurate forecasting, which is essential for DM systems. ML models have shown a great potential as an alternative solution for energy modelling and assessment for different types of buildings.

Figure 2.5 illustrates the summary of this chapter and the research gap motivated this study. Review of seminal literature indicated the necessity of employing ML models in support of deep energy retrofit DM, yet the lack of comprehensive studies to address this gap enabling industry and researchers to deploy potentials of AI-based optimisation methods.

In this chapter, to address objective 1 and partly RQ 1 and RQ3, a broad review of research works in the area of building energy assessment, focusing on the energy retrofit was performed. ML tools applied for the prediction of building energy indicators are discussed, and the input parameters utilised in training the models are identified. It was concluded the selecting suitable features had been limited to the elementary physical characteristics and climate features, as the majority of the seminal works concentrated on the accuracy of developed models. Whilst in the optimisation of building design and energy retrofit, it is of paramount importance that the model should reflect the impact of any alteration or improvement. It was therefore concluded that in order to develop an accurate model to support retrofit DM, it is essential to take many energy-related features into account, rather than the basic parameters identified from the literature review.

By scrutinising several studies, comparing various ML models, it was also concluded that these models would perform quite differently if they are precisely tuned. Moreover, the nature and size of the data utilised for the model development are highly important in the selection of a suitable technique. However, a reasonably large dataset is required to train a generalised and reliable energy model.

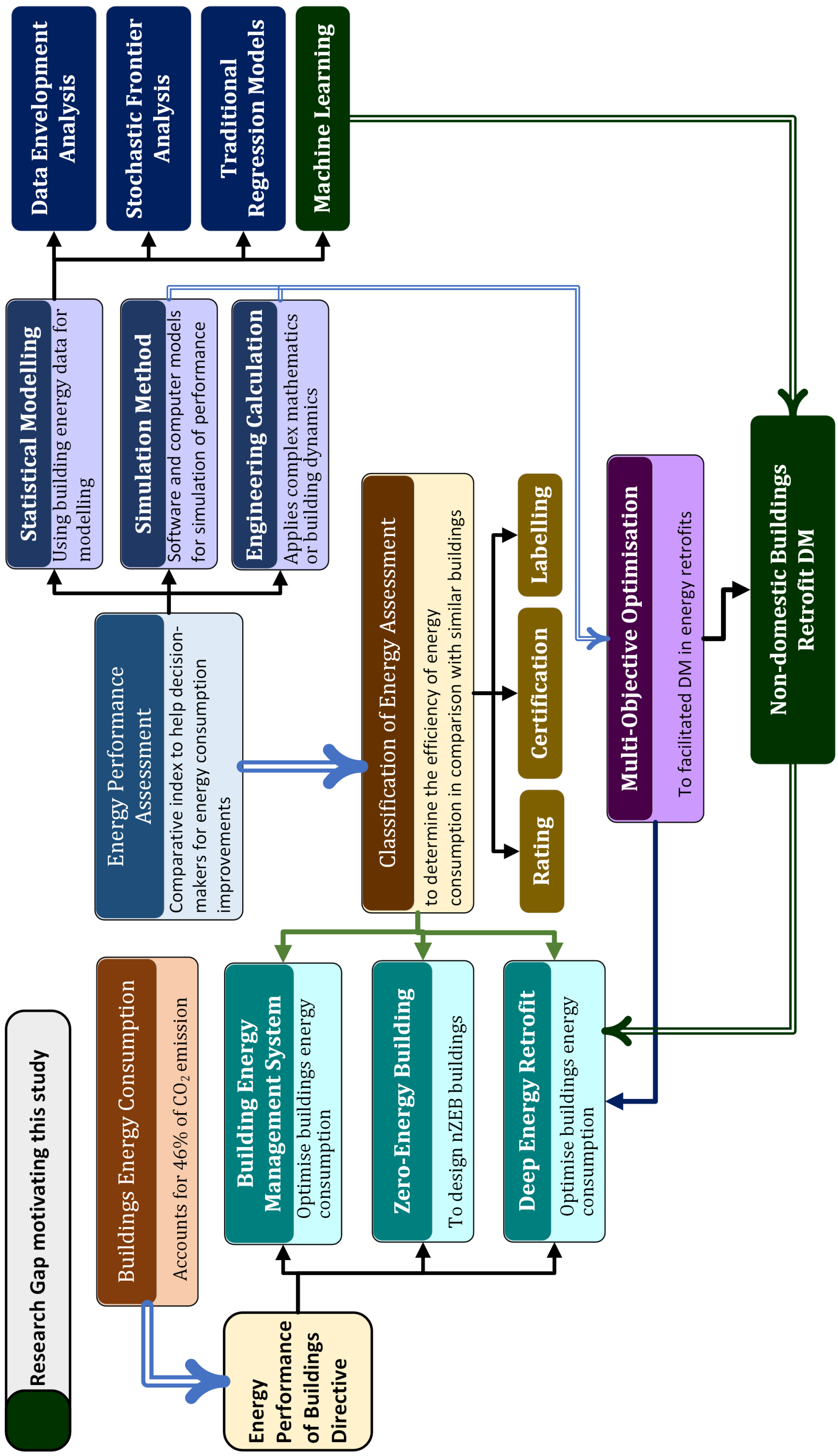


Figure 2.5: Summary of the study framework highlighting the research gap.

To address the mentioned challenges, Chapter 4 lays out a widely-applicable approach to tuning ML models fitted over building energy data. Its investigates the accuracy of most popular ML techniques in the prediction of building energy loads by carrying out specific tuning for each ML model. Then, Chapter 5 outlines a detailed method to train one single model for prediction of both heating and cooling loads of buildings and to maximise the ML model's efficiency. A method for optimising ML models is proposed for forecasting multiple energy loads. Next, Chapter 6 develops an energy performance prediction model for UK non-domestic buildings with the aid of ML techniques. The aim of the ML model is to provide a rapid energy performance calculation engine for assisting multi-objective optimisation of energy retrofit planning. This chapter scrutinises the process of model development, from the investigation of requirements and feature extraction, to the application on a case study. Finally, the model is evaluated through the calculation of energy performance of a case study building variations.

Chapter 3

Research Methodology

3.1 Introduction

This chapter describes the steps adopted to accomplish the objectives of this study and explains the logic behind the selection of each method, tool and approach. Accordingly, the chapter clarifies the implemented research plan given the objectives, as well as describes the nature of the selected methods. The chapter also defines and outlines the links between the objectives and the measures for undertaking the research. In doing so, the chapter prescribes a robust scientific research design that is capable of successfully executing the adopted approach.

Furthermore, This chapter provides an overview and foundation of the research with a focus on its design and structure. The details of data and processes that are particular to each method are elaborated in each chapter to provide continuity.

Firstly, a detailed description of the research design is presented, elaborating the steps and continuity of the research process. Lastly, the main techniques, tools and regulations used thought the study are discussed and explained.

3.2 Research Approach

In general, three types of research design are generally applied to address research problems: qualitative, quantitative and mixed-methods approaches. As suggested by McCusker and Gunaydin [215], each method is suitable for treating different types of investigations.

As defined by the list of objectives (Section 1.5), understanding the most developed trends of energy use in UK's non-domestic buildings and the influences of intrinsic building and operational features on their energy performance are at the heart of this research. As it can be anticipated, the knowledge expected to address the research questions is complicated to obtain without applying empirical data. There are instances of employing theoretical methods similar to simulation models in combination with sensitivity analysis methods to gain understanding of the impacts of different building and operational characteristics. As mentioned in Section 2.3, these methods heavily rely on engineering methods and require substantial processing and time for energy calculations. Consequently, it is believed imperative to employ empirical data throughout the study in order to thoroughly address the proposed questions.

The choice to conduct experiments relying on broad empirical data implies that quantitative methods of analysis would be essential for interpreting the building energy data in the context of statistical modelling (regression). Uses of detailed statistics would allow the latest and historical patterns of energy performance in various non-domestic buildings to be investigated in order to evaluate the factors that determine the robustness of the ML models. Correlation and sensitivity analysis would also provide valuable insights in evaluating and distinguishing the key fundamental characteristics that influence the energy performance of non-domestic buildings, which would be necessary for assessing the probability of adopting more advanced methods. Consequently, a quantitative approach is considered the most appropriate to address the research questions.

3.3 Research Methods

The investigation of potential methodologies has proven that in order to obtain a holistic view of how non-domestic building energy can be modelled to support retrofit decision making, the research should be designed in a way to facilitate both general and specific questions being addressed.

The proposed design incorporates four phases in order to fully exploit the insights that could be acquired from literature, AI techniques and building energy data. The underlying idea is that the analysis of ML models and the employment of AI models utilising established energy data prior to the application on the generated data would yield distinct, yet complementary insights. The flowchart of research activities is shown in Figure 3.1.

The first phase reported in Chapter 2 highlighted the fact that conventional methods of building energy calculations employing software and statistical approaches do not meet the necessities for energy retrofit decision-making with fast and accurate predictions. It has been shown that advanced regression

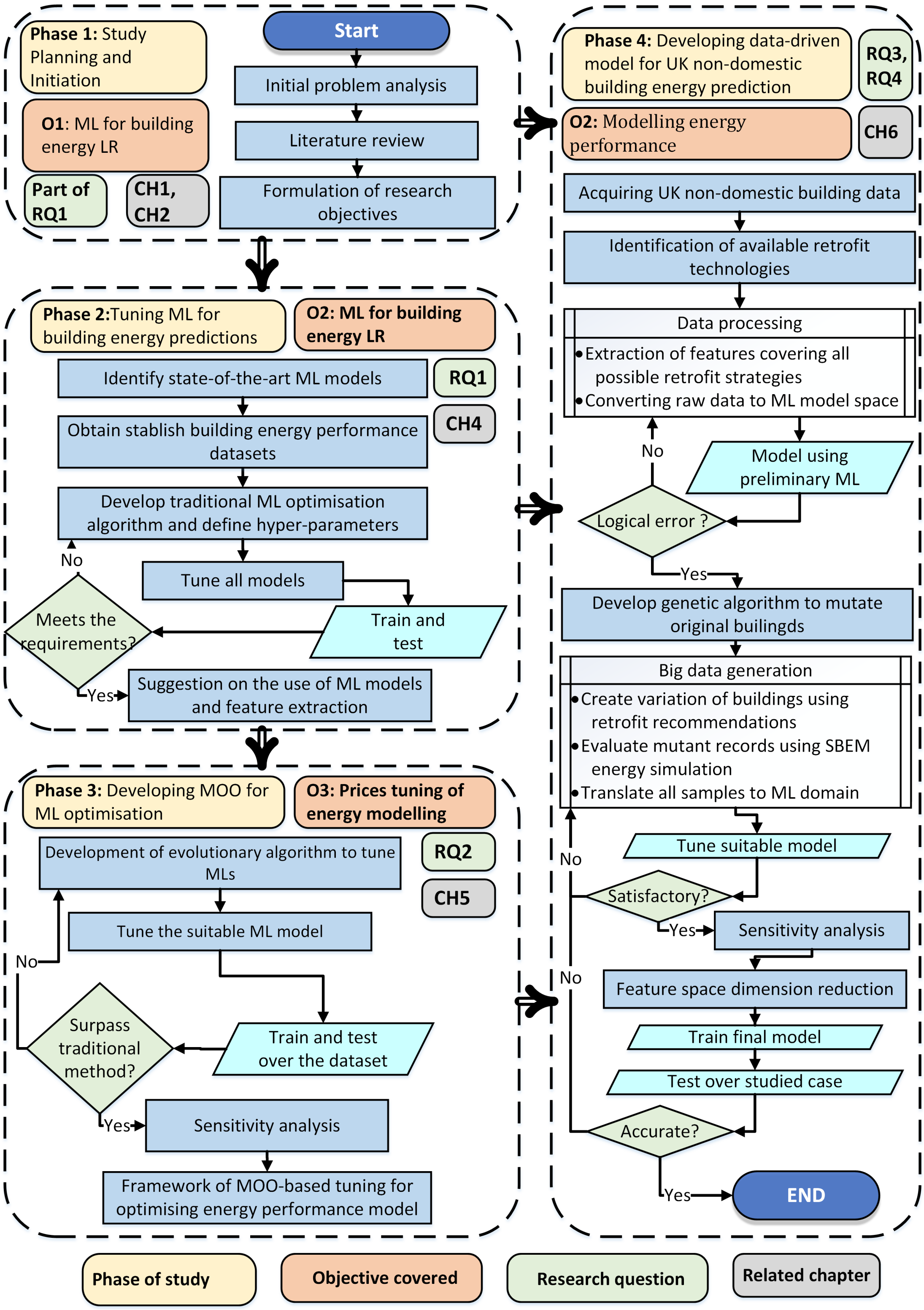


Figure 3.1: Flowchart of research design and methods.

methods, so called ML models, have great potential to substitute engineering methods with high time complexity. However, several challenges have been identified related to data-driven modelling of building energy performance. Firstly, it is essential to choose the most appropriate model for the data and to take full advantage of that. Additionally, one primary process is to select meaningful variables to model building energy efficiency.

In Chapter 2, it was shown that there are a multitude of examples of ML regression models applied to problems related to predicting energy and mass flows in buildings. Each study demonstrates the use of one model type/architecture or the comparison between different model types. However, there is a lack of guidance on how to optimise or 'tune' models to fit the investigated problem for the best predictive accuracy and consistency. In Chapter 2, the feature selection for building energy modelling was also reviewed. Some variables proved to be suitable to be included in modelling for supporting retrofit DM. However, these features are related to climate and buildings' general characteristics. Hence, an in-depth investigation will be carried out to extract a feature space for detail modelling of energy performance.

To answer research question 1 and address objective 2, phase 2 lays out a widely-applicable approach to tuning ML models fitted over building energy data. Before developing an ML model for non-domestic buildings (extracting the features for energy performance and testing the model), it is essential to select the most appropriate ML algorithm. As the feature set is not yet finalised, the use of primitive data using that set would result in poor performance and uncertainty in the selection of the algorithm. Hence, it is ideal to choose the techniques that have had better performance on similar data and application. However, the review of the literature revealed the lack of such guidance. As such, this study utilised previously established datasets that have proven robustness both in terms of generality and accuracy. This phase investigates the accuracy of most popular ML techniques in the prediction of building energy loads by carrying out specific tuning for each ML model and comparing the results of two simulated building energy datasets generated in EnergyPlus and Ecotect. Both datasets are available online for use in research studies. The review of recent literature on the application of MOO showed that many attempts are made to minimise the heating and cooling loads as the metrics for energy efficiency, this being the reason for selecting the datasets, especially EnergyPlus. Hence, the modelling using these data would be not only beneficial for the subsequent phases of this study, but also for other research works considering such optimisations. This research phase uses a grid-search coupled with a cross-validation method to examine the combinations of model parameters. Furthermore, sensitivity analysis techniques are used to evaluate the importance of input variables on the performance of ML models. The accuracy and time complexity of models in predicting heating and cooling loads are demonstrated. Comparing the accuracy of the tuned models with the original research works reveals the significant role of model optimisation. The outcomes of the sensitivity analysis are shown to be of relative importance which results in the identification of unimportant variables and a faster model fitting. This chapter presents the explanation of ML methods, the analysis and the evaluation methods, but the detail of tuning the utilised datasets along with the results are presented in Chapter 4.

The results from phase 2 reveal that simple models with few parameters such as SVM are easy to optimise, however, when the number of hyper-parameters is increased, the search space grows exponentially. For example, to tune an RF with six parameters, a grid search will explore more than four thousand possible configurations. That is why, traditionally, the researchers mostly relied on default values for those hyper-parameters. However, such models provide far more accurate results by precisely tuning in comparison with SVM or Gaussian process regression. Forecasting two or more building energy measures, such as heating and cooling loads or building emission rate and energy usage simultaneously, requires even more expertise and investigation. The use of a complex model and grid search for such applications is not a viable solution due to the complexity in processing time, as well as the selection of the ideal model.

Phase 3 addresses research question 2 and objective 3, and outlines a detailed method to train one single model for prediction of both heating and cooling loads of buildings and to maximise the ML model's efficiency. During this phase, a method for optimising ML models is proposed for forecasting both energy loads. The technique employs MOO with evolutionary algorithms to search the space of possible parameters. The proposed approach not only tunes single models to precisely predict building energy loads but also accelerates the process of model optimisation. The study utilises the same EnergyPlus data in phase 2 to validate the proposed method, and compares the outcomes with the regular ML tuning procedure. The optimised model provides a reliable tool for building designers and engineers to explore a wide variety of available building materials and technologies. The method is detailed in Chapter 5

As indicated in Chapter 2, seminal work in modelling building energy indicators has widely concentrated on the building design and building energy management applications. A few attempts also applied data-driven modelling for retrofit design, but focusing on a building's general physical characteristics while disregarding all possible technologies and the energy policies. Consequently, those models are not suitable for supporting deep energy retrofit planning.

Phase 4 addresses the research question 3 and objective 4 and develops an energy performance prediction model for UK non-domestic buildings with the aid of ML techniques. The aim of the ML model is to provide a rapid energy performance calculation engine for assisting multi-objective optimisation of energy retrofit planning. This phase scrutinises the process of model development, from the investigation of requirements and feature extraction, to the application on a case study. The recommendations from previous steps (Chapters 2, 4 and 5) are considered in generating the features space, the selection of ML methods and maximising the model accuracy. The process takes careful consideration of retrofit technologies and the energy policy in the region (UK). The same approach to identifying important features is adopted from two previous chapters to optimise model time-complexity. Finally, the model is evaluated through the calculation of energy performance for three thousand variations of a case study building and comparison of these with the actual ratings. Modelling non-domestic building energy performance is elaborated in Chapter 6.

Although the dataset utilised in phases 3 and 4 is different from the data collected for modelling non-domestic buildings energy performance in the UK, the nature of both data which are formulated as a set of building characteristics and climate features is similar. However, the aim has been employing widely used building data in selecting the superior ML technique before externally validating the developed model. The comparison of outcomes of phases 3 and 4 with the original studies provide a reliable method to validate the approach in this study.

3.4 Machine Learning for Modelling Energy Performance

ML is generally used to describe computer algorithms that learn from existing data. These algorithms normally use a large amount of data and a relatively small number of input features for learning processes. In recent years, numerous ML techniques have been proposed in the building sector for the estimation of heating and cooling loads, energy consumption and performance in various circumstances.

ML models operate as a black box and need no information on building systems. They discover the relation between various input features and output targets (e.g. energy performance) using given data. When the ML models are trained with enough amount of data, they can be used to predict targets for unseen samples, though the relation of features and the targets is not defined. This procedure is also known as supervised learning in the ML field. In this case, the target energy parameter is calculated using simulation (in general engineering method) and is used for training the model. The general scheme of supervised learning for modelling building energy is illustrated in Figure 3.2.

The second method of ML namely unsupervised learning, has received great attention in building energy analysis. Unsupervised learning also known as unsupervised classification is mainly applied on unlabelled data in order to cluster them based on hidden pattern and similarities underlying in features. This method is very beneficial for the application of energy benchmarking where determination of baseline buildings is crucial for calculating the energy performance of similar cases. Hence, the clustering algorithms provide a more precise tool for grouping various buildings in comparison with the traditional

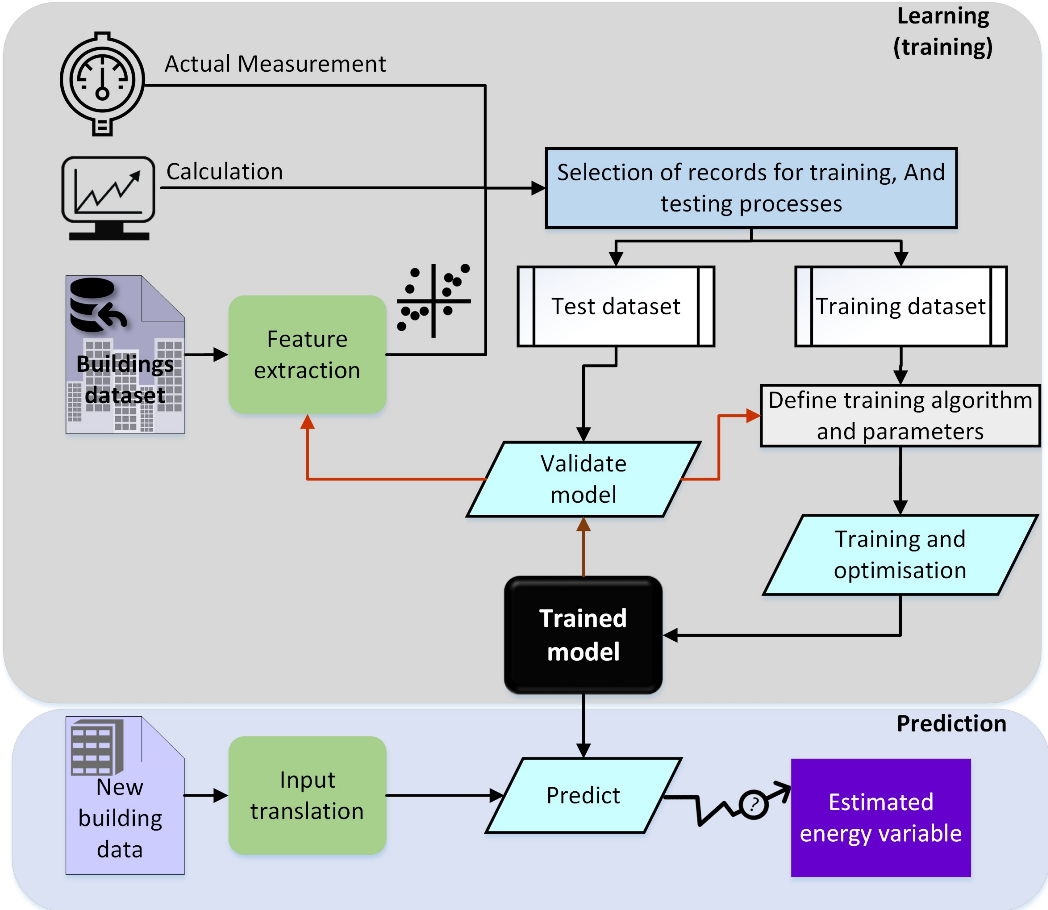


Figure 3.2: General schematic diagram of supervised learning.

method which mainly relies on building usage type. It should be noted that using the clustering algorithm for forming groups, it is not possible to estimate clusters for new buildings. Therefore, in order to determine the reference building for other cases, an extra supervised ML technique should be applied. In this approach, all buildings used for clustering are used as training samples for classification, where the generated labels from clustering are considered to be learning targets. The flowchart of the overall procedure is demonstrated in Figure 3.3.

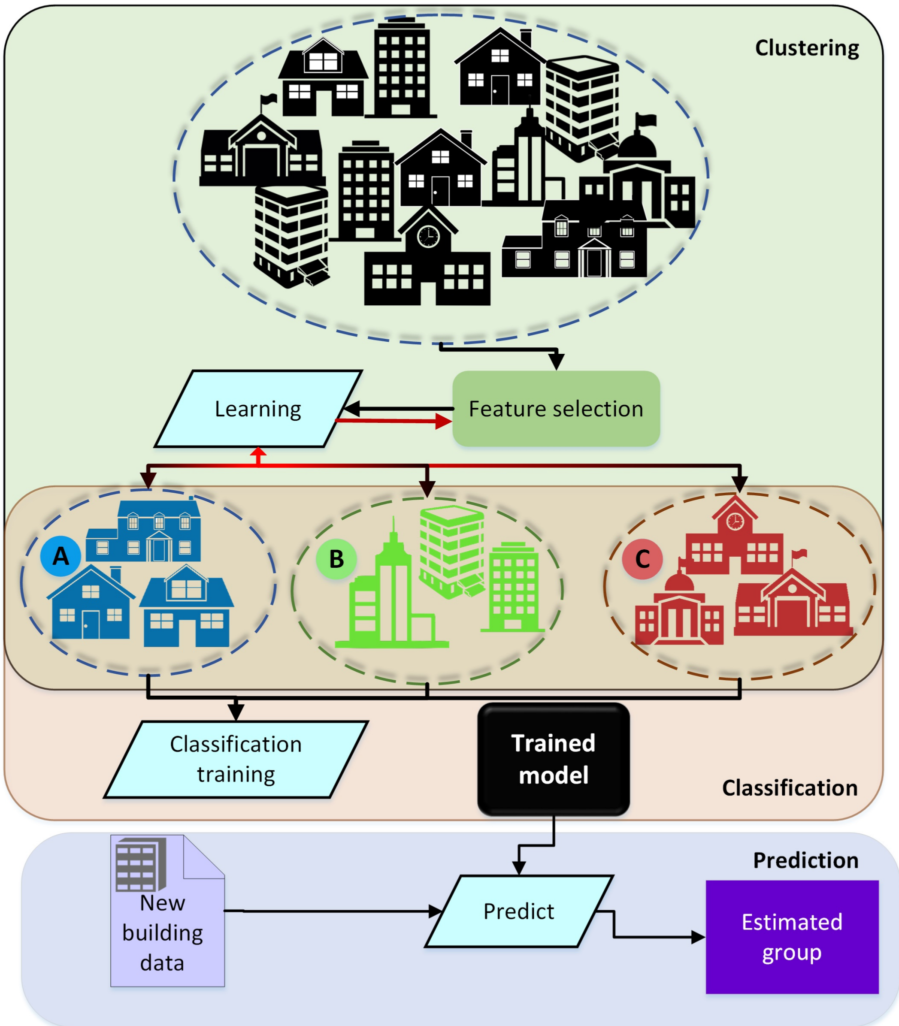


Figure 3.3: General schematic diagram of unsupervised learning for building energy application.

3.5 Description of Machine Learning Models

Five ML algorithms, namely ANN, SVM, GP, RF and GBRT are investigated in this study. As the superiority of these techniques over traditional regression models are abundantly demonstrated in the literature, this research avoid comparison with those basic statistical methods. Basics of each model and the parameters going under optimisation are explained as follows.

3.5.1 Artificial Neural Network

Neural networks have been broadly utilised for building energy estimation and are known as the major ML techniques in this area. They have been successfully used for modelling non-linear problems and complex systems. By applying different techniques, ANNs have the capability to be immune to fault and noise [216] while learning key patterns of building systems.

The main idea of the ANN is obtained from the neurobiological field. Several kinds of ANNs have been proposed for different applications including, Feed Forward Network (FFN), Radial Basis Function Network (RBFN) and recurrent networks (RNN). Each ANN consists of multi-layers (minimum two layers) of neurons and activation functions that form the connections between neurons. Some frequently used functions are linear, sigmoid ad hard limit functions [217]. Based on the application and complexity of the task, a structure is decided, and by feeding the adequate amount of records, the activation function updates the weights and bias.

In the FFN which was the first NN model as well as the simplest one, there are no cycles from input to output neurons and the pieces of information moves in one direction in the network. Figure 3.4 illustrates the general structure of FFN with input, output and one hidden layer.

The RNN uses its internal memory to learn from preceding experiences by allowing loops from output to input nodes. The RNN is proposed in various architectures including fully connected, recursive, long short-term memory, etc. This type of neural network has usually been employed to solve very deep learning tasks such as multivariate time-series prognostication where often more than 1000

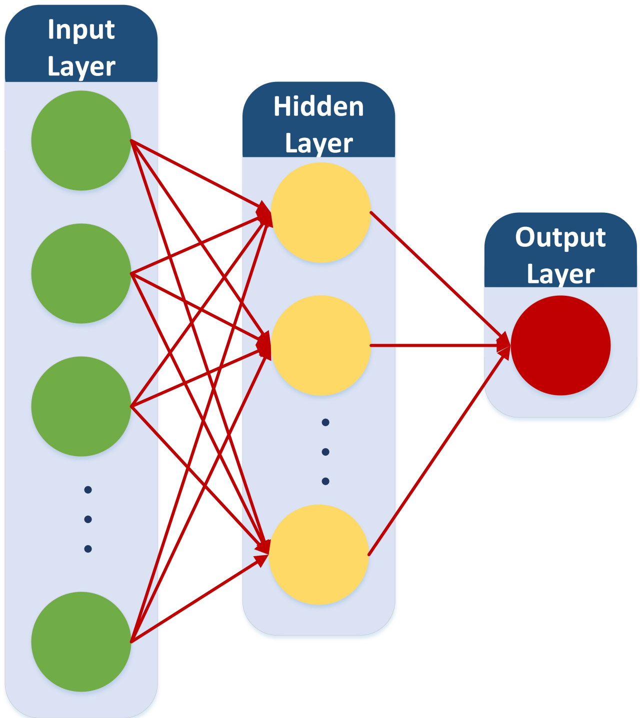


Figure 3.4: Conceptual structure of feed forward neural network with three layers.

layers are needed [218].

In the RBFM, a radial basic function is used as the activation function providing a linear combination of inputs and neuron parameters as output. This type of network is very effective for time series estimation [219–221].

3.5.2 Support Vector Machine

SVMs are highly robust models for solving non-linear problems used in research and industry for regression and classification purposes. As SVMs can be trained with a few numbers of data samples, they could be the right solutions for modelling case studies with no recorded historical data. Furthermore, SVMs are based on the Structural Risk Minimisation (SRM) principle that seeks to minimise an upper bound of the generalisation error consisting of the sum of training error and a confidence level. SVMs with kernel function act as a two-layer ANN, but the number of hyper-parameters is lower than that. Another advantage of SVM over other ML methods is the uniqueness and global optimality of the generated solution, as it does not require non-linear optimisation with the risk of remaining in a local minimum limit. One main drawback of SVMs is the computation time, which has the order almost equal to the cube of problem samples.

Suppose every input parameter comprises a vector X_i (i denotes the ith input component sample), and a corresponding output vector Y_i which can be building heating loads, rating or energy consumption. SVM relates inputs to output parameters using the following equation:

$$Y = W \cdot \phi(X) + b \tag{3.1}$$

where $\phi(X)$ function non-linearly maps X to a higher dimensional feature space. The bias, b, is dependent on the selected kernel function (e.g. b can be equal to zero for Gaussian RBF). W is the weight vector and approximated by empirical risk function as:

$$Minimise: \frac{1}{2}\|W\|^2 + C\frac{1}{1}\sum_{i=1}^{N} L_\varepsilon(Y_i, f(X_i)) \tag{3.2}$$

L_ε is ε-intensity loss function and is defined as:

$$L_\varepsilon(Y_i, f(X_i)) = \begin{cases} |f(x) - Y_i| - \varepsilon, & |f(x) - Y_i| \geq \varepsilon \\ 0, & otherwise \end{cases} \tag{3.3}$$

Here ε denotes the domain of ε-insensitivity and N is the number of training samples. The loss becomes zero when the predicted value drops within the band area and gets the difference value between the predicted and the radius ε of the domain, in case the expected point falls out of that region. The regularised constant C presents the error penalty, which is defined by the user.

SVM rejects the training samples with errors less than the predetermined ε. By acquisition of slack variables ξ and ξ_i^* for calculation of the distance from the band are, equation (3.3) can be expressed as:

$$\underset{\xi,\xi_i^*,W,b}{Minmise}: \frac{1}{2}\|W\|^2 + C\frac{1}{N}\sum_{i=1}^{N}\xi + \xi_i^* \tag{3.4}$$

$$subject\ to \qquad \begin{cases} Y_i - W\cdot\phi(x_i) - b \leq \varepsilon + \xi \\ W\cdot\phi(x_i) + b - Y_i \leq \varepsilon + \xi_i^* \\ \xi \geq 0, \quad \xi_i^* \geq 0 \end{cases}$$

The SVM problem using a kernel function of $K(X_i, X_j)$ (α_i, α_i^* as Lagrange multipliers) can be simplified as:

$$\begin{aligned} \underset{\{\alpha_i\},\{\alpha_i^*\}}{Maximise}: -\varepsilon\sum_{i=1}^{N}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{N}Y_i(\alpha_i^* - \alpha_i) - \\ \frac{1}{2}sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)K(X_i, X_j) \end{aligned} \tag{3.5}$$

$$subject\ to \qquad \sum_{i=1}^{N}(\alpha_i^* - \alpha_i) = 0, \qquad 0 \leq \alpha_i, \alpha_i^* \geq C$$

As mentioned before the number of parameters in SVM with a Gaussian RBF kernel is as few as two, these being C and Gamma.

3.5.3 Gaussian Process

The main drawback of GP modelling is expensive computational cost, especially with the increase of training samples. This is due to the fact that the GP constructs a model by determining the structure of a covariance matrix composed of an $N \times N$ input variable where the matrix inversion required in predictions has a complexity of $O(N^3)$

Given a set of n independent input vectors X_j $(j = 1, \cdots, n)$, the corresponding observations of y_i $(i = 1, \cdots, n)$ are correlated using the covariance function K with normal distribution equal to [183]:

$$P(y; m; k) = \frac{1}{(2\pi)^{n/2}|K(X,X)|^{1/2}} \times \\ exp\left(-\frac{1}{2}(y-m)^T K(X,X)^{-1}(y-m)\right) \tag{3.6}$$

The covariance or kernel function can be derived as:

$$K = \begin{vmatrix} k(x_1,x_1) & k(x_1,x_2) & \cdots & k(x_1,x_n) \\ k(x_2,x_1) & k(x_2,x_2) & \cdots & k(x_2,x_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_n,x_1) & k(x_n,x_2) & \cdots & k(x_n,x_n) \end{vmatrix} \tag{3.7}$$

A white noise, σ, is presumed in order to consider the uncertainty. It is assumed that the samples are corrupted (presumed as new inputs as x^*) by this noise. In this case, the covariance of y is expressed as:

$$cov(y) = K(X,X) + \sigma^2 \tag{3.8}$$

Then y^* can be estimated as below.

$$y^* = \sum_{i=1}^{n} \alpha_i k(x_i, x^*) \tag{3.9}$$

$$\alpha_i = \left(K(X,X) + \sigma^2 I\right)^{-1} y_i \tag{3.10}$$

3.5.4 Random Forest

The RF is an ensemble of randomised Decision Trees (DTs). A DT encompasses the establishment of an ML model in a tree structure form by a non-parametric algorithm. The DT progressively divides the given data into elemental subsets until reaching a single sample residing in each sub-group. The inner and outer sets are called nodes and leaf nodes. The accuracy of the DT is significantly dependent on the samples' distribution in the learning dataset. As such, a DT is always introduced as an unsteady method, where even minor alteration in the input data can change the whole structure. A set of DTs are often employed in conjunction with each other, and calculated an average representative estimated values, in order to address the aforementioned issue. In other words, bagging and optionally bootstrapping are applied in RF with the aim of combining the separate models containing a similar set of information and generating a linear combination from various independent trees. The RF training procedure mechanism is illustrated in Figure 3.5.

3.5.5 Gradient Boosted Regression Trees

Like a RF, a GBRT is an ensemble of other prediction models such as DTs. The principal difference between GBRT and RF is that the latter one is based on fully developed DTs with low bias and high variance, while the former employs

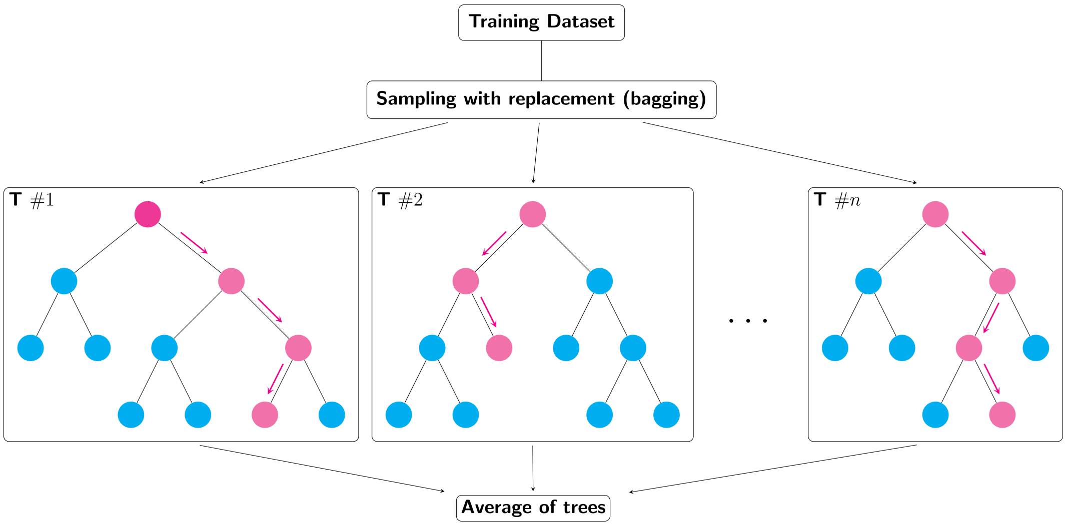


Figure 3.5: Diagram of an RF model with n independent trees.

weak learners (small trees) having high bias and low variance [222]. In the GBRT, trees are not independent of each other; instead, each branch is created based on former simple models through a weighting procedure. This approach is known as boosting algorithm. At each inner node (i.e. the split point) a given dataset is divided into two samples. Let us assume a GBRT with three node trees. There will be one split point in which the best segmentation of the data is decided, and the divergence of the obtained values (from the individual averages) are calculated. By fitting on these residuals, the subsequent DT will seek for another division of data to reduce the error variance.

3.5.6 Model Validation

Validation is the essential method used for the assessment of the ML model stability and the demonstration of model generalisation. It represents how well the model performs on predicting unseen data (the dataset which is not used in training the model). In this study, cross-validation, which is a standard statistical re-sampling method, is used. Figure 3.6 schematically demonstrates the k-fold cross-validation procedure.

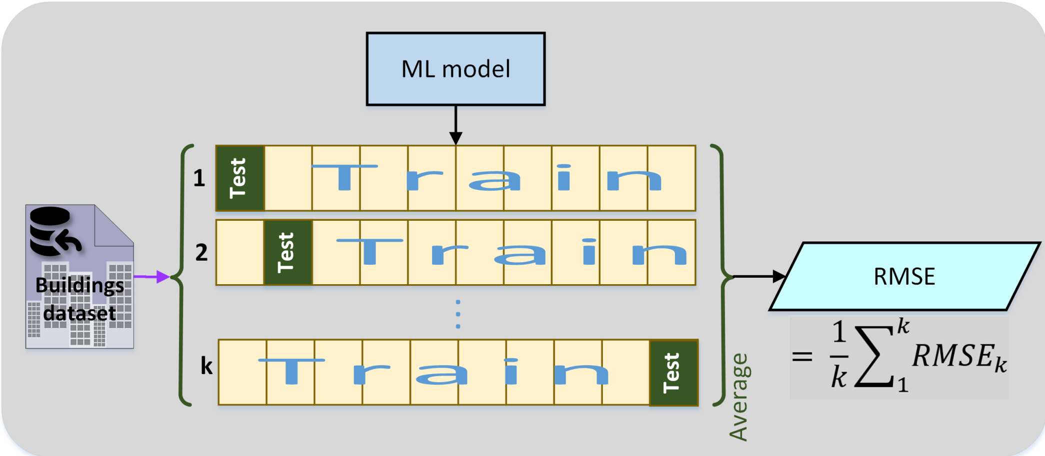


Figure 3.6: Cross-validation technique for evaluating model generalisation.

In this method, each dataset is randomly divided into k folds, including a training subset, which is used for training the ML model, and a testing subset, used to evaluate the model's generalisation efficiency. Then, the average of all k folds accuracies (e.g. RMSE) is calculated and regarded as the final performance. This technique assists the model development procedure in avoiding over-fitting and under-fitting. The former refers to capturing noise and relations which do not generalise accurately to new data. In this case, the trained model runs exceptionally well on the training set, yet poorly at the test set. The latter refers to not capturing relations adequately in the data. The model accuracy would be then poor for both the training and the test sets. In this research, 10-fold cross-validation is employed in different phases except where it is specified.

It is conceivable that using all datasets in the cross-validation procedure would not guarantee the performance of the developed model on a totally new data, as the model would be biased to the utilised data. Therefore, it is essential to test the ML model on a set separate from the main one. In this research, for external validation, the model performance on an educational building used as the case study belongs to the University of Strathclyde and was not logged in the company database. The building detail is processed, and different variations (as it is performed in the process of MOO for retrofit planning) are generated. The trained model accuracy is then evaluated by predicting those samples.

For statistical confidence, in performing sensitivity analysis, all methods are repeated n times (logically) with the dataset randomly permuted in each run.

3.5.7 Feature importance

A potent tool, for identifying the important features is sensitivity analysis. Including Sobol, ML feature importance and permutation importance, its use in this study will be explained in the following section.

Several methods are proposed for the aim of evaluating feature importance [223] including correlation matrices, sensitivity analysis and ML-based methods. The correlation matrix is typically presented as a heat map of Pearson correlation values, and it calculates the linear correlation between features and the target.

The Sobol method aims to decide the dependency of variability in model output upon each of the input features, either considering one variable or the interaction between different elements. It should be noted that the Sobol analysis does not intend to explore the cause of the input variability. It identifies the contribution of any feature and their interactions to the overall model output variance. The idea of this method is that the total unconditional variation of the model output can be expressed as a sum of the variance contribution of first-order effects, V_i, second-order the interaction effects, V_{ij}, third-order effects, etc.

$$V(Y) = \sum_i V_i + \sum_i \sum_{j`1} V_{i,j} + ... \tag{3.11}$$

The total variance is then associated with the singular features and interactions between them. The above phrase can be expressed as:

$$V(Y) = V_{X_i}(E_{X_{\sim i}}(Y|X_i)) + E_{X_i}(V_{X_{\sim i}}(Y|X_i)) \tag{3.12}$$

The first term denotes the model variance conditional on Xi (the first-order effect of Xi) varying between zero and $V(Y)$. $E_{X_{\sim i}}$ represents the mean of Y calculated upon all values of the input matrix X while retaining X_i constant. V_{X_i} is computed over all possible values of X_i. By normalising with the total variance of $V(Y)$, the first-order index for the ith feature can be written as:

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}{V(Y)} \tag{3.13}$$

In decision trees as RF and GBRT, the more a variable is utilised to make critical determinations with the trees, the greater its relative importance. This value is computed for each feature, enabling them to be ranked. The relative importance is determined for a single tree considering the amount by which each split point enhances the accuracy measure of the model. The average value of all importances for an individual feature in all independent trees is calculated.

For a single decision tree, the importance for each variable X_l is calculated as

$$\mathfrak{I}_l^2(T) = \sum_{t=1}^{J-1} \hat{i}_t^2 I(v(t) = l) \tag{3.14}$$

The sum is calculated over $J-1$ internal nodes at each tree, and one of the features $X_{v(t)}$ is utilised to split the region related to that node into two branches. The single variable selected is the one that provides the most significant expected improvement of $\hat{i}_t^2$ in squared error risk over that for a regular fit over the whole branch. The average for all trees is defined as:

$$\mathfrak{I}_l^2 = \frac{1}{M} \sum_{1}^{M} \mathfrak{I}_l^2(T_m) \tag{3.15}$$

To perform the permutation importance, a fully trained model is also required, but a separate test-set is utilised to evaluate the significance of features. In this method, each input variable is iteratively permuted, while keeping others constant. This process is repeated until all features are investigated. The model accuracy alteration due to shuffling of each variable is considered as its importance. Although this technique is computationally expensive, it is a useful complement of the ML importance method, especially in identifying inflated values. Moreover, the sensitivity analysis provides beneficial information on how the model predicts, making it less of a black box. In other words, it reveals which variables play a more significant role in calculating the building energy performance. Hence, this detail can be verified by comparison to the field of knowledge. The influence of the retrofit strategies on the model can also be conceded and substantiated with this method.

3.6 Validity and Reliability

It is essential to perform reliability and validity checks in both qualitative and quantitative research for achieving confidence in the study findings. Validity determines that the results are accurate and it measures the concept or outcome that was expected. Reliability explains if there is consistency in the research approaches [224].

This study used an exhaustive literature review of energy performance assessments and applications of ML techniques on building energy forecasting and identified the enablers of and barriers to modelling non-domestic building energy performance. Based on the findings from the review of seminal works, the research questions and objectives were carefully defined. The research methods and phases were designed in a way to satisfy the goals and answer the questions.

In this study, three different datasets were utilised. Two of them were employed in the investigation of the suitability of ML models and the proposal of the smart ML optimisation method. These data sets were initially generated for research purposes and validated by different studies. The results derived using these sets were evaluated by arbnco specialists and professional reviewers from Q1 journals. The other dataset was obtained from arbnco consultancy platform and used for modelling non-domestic building energy performance. The records were created by licenced energy assessors trained to collect information about existing non-domestic properties for generating EPCs and were assessed to ensure compliance with energy policies. However, thorough data analysis under the supervision of arbnco building physicist and academic experts was conducted in order to reject the records with the probability of errors.

The performance of ML models was assessed using state-of-the-art statistical modelling evaluation methods, including various accuracy measures and k-fold cross-validations. The results from modelling the non-domestic building emission rate (BER) were evaluated and confirmed by arbnco and DataLab

Innovation Centre, who partly funded this study. Furthermore, the performance of the developed model was validated by demonstrating the application on a case study. To that end, an academic building was selected, and three thousand variations were generated using GA to mimic a multi-objective optimisation process. These modified building records were then assessed using the software and the trained model. The energy performance prediction model development aimed at supporting optimisation of building energy retrofit. In this application, the optimisation algorithm generates variation of the intended building to be evaluated for their energy performance. Here, the developed model is validated by estimating retrofit versions of a building that are never seen by the model. Therefore, the gaol of this analysis is to further investigate the stability and generalization of machine learning (i.e. the training and testing the model is not biased by the utilised dataset).

3.7 Ethical Data Collection

The data for UK non-domestic buildings is obtained from arbnco Ltd, and the ethical approval was obtained through the Research and Knowledge Exchange Services department at Strathclyde University, as part of a standard protocol of the University for external collaborations.

3.8 Summary

This chapter provided an account of the main aspects of the research methods utilised in this study, thus establishing the research paradigm of the present thesis. In this chapter, the research methodology was elaborated by explaining various processes and steps that were designed to conduct the study. The procedure for evaluating non-domestic building performance regulated by the government was also demonstrated. Different ML techniques, the methods for assessing them and the datasets adopted/generated were explained. The detail of each phase of the study and the corresponding results are presented in chapters 4 to 6.

Chapter 4

Machine Learning Models for Prediction of Building Energy Performance

4.1 Introduction

The use of ML models requires careful consideration of the accuracy and appropriateness of the data and relationships inferred from the data. In this phase of the study, the research examines a practical aspect of this approach: selecting and tuning regression models for a given dataset. This means selecting the model types, structures, and parameters most appropriate to the problem at hand. As described in the literature review, most previous work in using ML methods in building simulation either compares linear models with nonlinear models or different types of nonlinear models (Chapter 2). In addition, previous works has usually only optimised a limited number of model parameters. The selection of model parameters, however, determines the performance of a model on a given dataset, and this performance varies from one dataset to another. Thus, the previous work does not provide a complete evaluation of different nonlinear models and does not provide sufficient guidance about model selection. Hence, there is a lack of guidance on how to optimise or 'tune' models to fit the problem at hand for the best predictive accuracy and consistency. This chapter demonstrates the optimisation or selection of most proper parameters for training an individual ML and lays out a framework for the selection of the right ML algorithm considering training and prediction time complexities and ease of use. It shows that the process of selecting a model must account not just for predictive accuracy but also model complexity, ease of use, and consistency of predictions.

4.2 Supervised Machine Learning Models

Different ML models were investigated for modelling building energy loads. Established energy datasets were utilised, and the performance of optimised models were compared with the seminal works. Sensitivity analysis was also applied for the identification of important features where the input set was logically large.

The study presented in this chapter used the datasets described by [175] and [179] to demonstrate the performance of different candidate models. This phase, lays out a widely-applicable approach to tuning ML models to building energy data. Though the examples shown here are from simulators, the method is also applicable to measured data.

In this study five ML techniques as described in Section 3.5 including ANN, SVM, GP, RF and GBRT were employed to emulate two BPS tools namely EnergyPlus and Ecotect. A standard method that this part of study used to select optimal hyper-parameters is a grid-search combined with k-fold cross-validation. In this procedure, the data is divided into k exclusive subsets, and each combination of model parameters and architecture is fitted to each distinct group of $k-1$ subsets and tested on the remaining subset. This process provides a distribution of errors for a given model choice on different parts of the dataset, i.e., an estimate of the general applicability of the model to represent the variation in the dataset. Furthermore, different normalisations such as standard, min-max and robust were applied to data before training procedure. Robust scaler eliminates the median and normalises data according to the inter-quartile range.

4.2.1 Models Hyper-parameters

Due to the nature of the datasets, a multilayer perception FFN was utilised in this work. Her Keras package in Python was utilised. The ANN hyper-parameters which go under optimisation are:

- **Optimiser:** the function that updates the weights and bias;
- **Activation:** a non-linear transformation function which is applied over the input, and then the output is fed to the subsequent layer neurons as input. An ANN without activation function will act as a linear regressor and may fail to model complex systems;
- **Initialisation:** the initial values of weights before the optimiser is applied for training;
- **Epoch:** the number of forward and backward passes for all samples of data;
- **Batch size:** specifies the number of samples that are propagated through

the ANN training (i.e. the number of samples in one epoch);

- **Dropout rate:** dropout is a regularisation method for preventing ANN from overfitting and creating more generalised model by randomly rejecting some neurons during training. Droput rate determines the percentage of randomly input exclusion at each layer;
- **Size:** number of neurons in each layer and number of layers.

As mentioned in the previous chapter, the number of parameters in SVM with a Gaussian RBF kernel is few as two which are C and Gamma. Here, support vector regressor from sklearn package was utilised.

For GP model three parameters were tuned: kernel, alpha (α) which is the value added to the diagonal of the kernel matrix (equation 3.9) and the number of restarts of the optimiser for discovering the parameters maximising the log-marginal probability. Two combinations of white noise with RBF and Matern covariance functions were used for GP model kernel. Matern kernel is denied as:

$$K(X, X') = \frac{261 - v}{\Gamma(v)} \left(\frac{\sqrt{2v} \mid x - x' \mid}{I} \right)^{v} K_v \left(\frac{\sqrt{2v} \mid x - x' \mid}{I} \right) \tag{4.1}$$

Here, Γ is the Gamma function and K_v is the modified Bessel function the second-order v [225]. GP implemented using GaussianProcessRegressor from sklearn package.

Determining several hyper-parameters is a prerequisite to adopting RF. The first parameter to determine here is the number of independent trees of the forest. The precision of the model and training is always negatively related to predicting computational complexity; therefore, an optimal model was achieved through balancing these together. There are also other settings to be considered. This includes the number of variables while seeking the best split, whether or not apply bootstrapping while creating independent trees, and a minimum number of a data sample to split on nodes.

Most important parameters for optimising GBRT comprise learning rate (also known as shrinkage) which is a weighting procedure to prevent over-fitting by controlling the contribution of each tree, number of trees, maximum depth of tree and the number of features for searching best division, and the minimum number of data sample to split a node and required in each node. Moreover, the sub-sample parameter defines the fraction of observation to be selected for each tree.

Rather than conventional GBRT model the recently improved version known as eXtreme Gradient Boosting (XGBoost) algorithm [226] was also evaluated with similar parameters, but some differences. The minimum sum of instance weight controls the generalisation similar to minimum sample split in GBRT. The portion of columns when constructing each tree (colsample bytree) similar to maximum features was also considered in the model optimisation. Both RF and GBRT was implemented using ensemble package from sklearn, and XGBoost from xgboost package.

4.3 Evaluation Methods

4.3.1 Performance Evaluation Measurements

Various measurements based on actual and predicted results are calculated in order to evaluate the performance or accuracy of data-driven models. These include Coefficient of Variance (CV), Mean Bias Error (MBE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Squared Percentage error (MSPE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). CV is the variation of the overall prediction error concerning actual mean values. MBE is used to determine the amount over/underestimation of predictions. MSE and MSPE are good inductors of estimation quality. MAE determines the average value of the errors in a set of forecasts and MAPE is the percentage of error per prediction. RMSE has the same unit of actual measurements. In this work, RMSE, MAE and the coefficient of determination (R^2) are used to present the accuracy of ML models. R^2 is the percentage variance in the dependent variable explained by the independent ones. These values are calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum(y_i - \hat{y})^2} \tag{4.2}$$

$$MAE = \frac{1}{N}\sum \mid y_i - \hat{y} \mid \tag{4.3}$$

$$R^2 = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} \tag{4.4}$$

Here, y, $\hat{y}$ and $\bar{y}$ represent the real, estimated and average response values, respectively.

4.4 Selected Datasets for Case Study

Two building datasets simulated using BPS tools were utilised. First data contains 768 variations of a residential building obtained altering eight basic envelope characteristic [179], and the second dataset includes various building type represented by 28 envelope and climate features [227]. Each set and the distribution of variables are presented in this section. The prediction targets for both sets are heating and cooling loads.

4.4.1 Ecotect Dataset

This dataset was developed by Tsanas *et al.* [179] and obtained from UCI (University of California, Irvine) machine learning repository [228]. It includes 12 residential buildings types with the same volume (771.75m^3) and varying envelope features, outlined in Table 4.1. The materials were chosen to achieve the lowest U-values based on availability in the market (walls: 1.78 m^2K/W, floors: 0.86, roofs: 0.50 and windows: 2.26). The window-to-floor ratio is varied from 0% to 40%. The glazing distribution on each façade has 6 variants: (0) uniform, with 25% glazing on each side; (1) 55% glazing on the north façade and 15% on the rest; (2) 55% glazing on the east façade and 15% on the rest; (3) 55% glazing on the south façade and 15% on the rest; (4) 55% glazing on the west façade and 15% on the rest; and, (5) no glazing. All combinations were simulated using Ecotect with weather data from Athens, Greece, and occupancy by seven people conducting mostly sedentary activities. The ventilation was run in a mixed mode with 95% efficiency and thermostat setpoint range of 19-24°C. The operating hours were set to 3 pm - 8 pm (15:00-20:00) for weekdays and 10 am - 3 pm (10:00-15:00) for weekends. The lighting level was set to 300 lx.

Figure 4.1 illustrates the frequency of features as histogram graphs. The correlation between each pair of input and target variables is demonstrated using heatmap matrix in Figure 4.2.

4.4.2 EnergyPlus Dataset

This datasets consists of commercial and residential buildings and was described by [227]. The original commercial building models were downloaded from the US Department of Energy (USDOE) commercial reference building models [229]. The commercial buildings set includes sixteen types of buildings

Table 4.1: List of features that represent the characteristics of residential buildings for prediction of energy loads

Feature	Unit	Range	Variation	Code
		Inputs		
Relative compactness	-	0.62 – 0.98	12	rc
Surface area	m^2	514 – 808	12	sa
Wall area	m^2	245 – 416	7	wa
Roof area	m^2	110 – 220	4	ra
Overall height	m	3.5, 7	2	oh
Orientation	-	2 – 5	4	ori
Glazing area	m^2	0 – 0.4	4	glza
Glazing area distribution		0 – 5	6	glzd
		Targets		
Heating load	KWh/m^2	6 – 43	-	heat
Cooling load	KWh/m^2	10 – 48	-	cool

classified into eight overall groups based on usage. Table 4.2 presents the building types which are considered in the simulations and the frequency of each with unique features. For each subtype, there are three variations for envelope construction: pre-1980, post-1980, and new construction. Each usage type has the same form, area and operation schedules. The residential buildings were described by [230]. Variation in the outputs was also introduced by considering several years of historical weather data from many climates (weather stations) and augmenting this data with synthetic weather generated for some climates [227].

This study used the same regression inputs as originally proposed in [231] as presented in Table 4.3. They describe the feature selection as being based on correlation estimation and Principal Component Analysis (PCA). There are three kinds of input variables: climate, building, or mixed. The climate variables were extracted from one year of weather data only and are independent of the buildings simulated. The building features are related to the physical characteristics of the

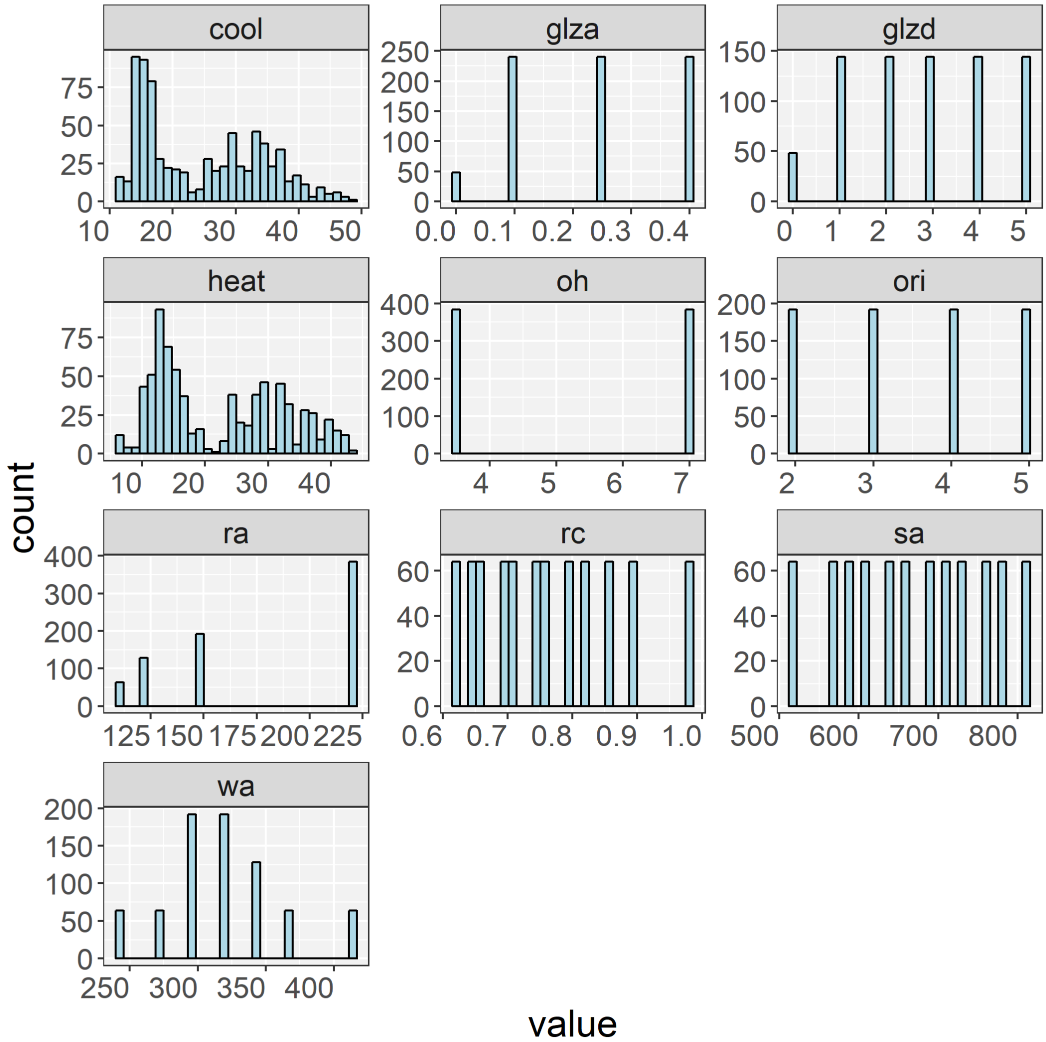


Figure 4.1: Distribution of features for Ecotect data.

building envelope and independent of the climate. These inputs were chosen on the basis of impact on the heating and cooling loads and calculated from geometry, material and structure properties. The mixed parameters represent the interactions between weather and buildings. An input that does not belong to any of these categories, the internal heat gain, was also included to represent the impact of human behaviour.

Table 4.2: Frequency and size of building types in EnergyPlus data

Building Usage	Type	Area (m^2)	Volume (m^3)	No. of E+ zones	No. of samples
Health	Hospital	22,422	88,864	55	3,827
	Outpatient	3,804	11,932	118	5504
Home	Mid-rise Apartment	3,135	9,553	36	37,173
	Single Family				78,532
Hotel	Large	11,345	35,185	43	5,504
	Small	4,014	11,622	67	5,468
Office	Large	46,320	178,146	73	275,345
	Medium	5,503	4,982	18	19,741
	Small	511	1,559	5	5,483
Restaurant	Full Service	5,502	55,035	2	3,824
	Quick Service	232	708	2	5,505
Retail	Stand Alone	2,294	13,993	5	5,503
	Strip_Mall	2,090	10,831	10	5,498
	Supermarket	45,002	900,272	6	5,554
School	Primary	6,871	27,484	25	5,505
	Secondary	19,592	95,216	46	5,507
Warehouse	–	4,835	39,241	3	5,492

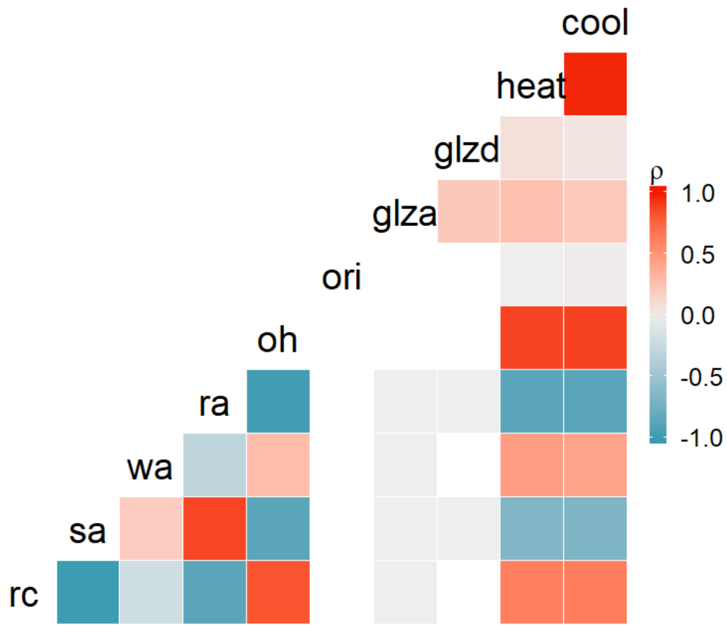


Figure 4.2: Ecotect data features correlation map.

Figure 4.3 illustrates the frequency of features as histogram graphs for EnergyPlus dataset. It can be seen that the each variable is relatively distributed over the possible predefined values. The correlation heat-map matrix presented in Figure 4.4 shows the independency of different features especially building physics related ones from each other.

4.5 Comparison of Models Accuracy

All models were implemented using Python programming language and tests were carried out on a PC with Intel Core i7-6700 3.4GHz CPU, 32GB RAM.

Table 4.3: List of EnrgyPlus features extracted for model training

Group	QTY	Stats	Description	Range	Code	Unit
Building	U-value	Average	Average U-value of envelope	0.14–6.06	*uval*	W/m^2K
	Thermal Mass	Sum	Sum of thermal storage capacity	1e-4–7.61	*tmass*	MWh/K
	Envelope Ratios	Ratio	Ratio of window area to wall area	0.58–85.00	*wwr*	-
			Ratio of window area to floor area	0.01–0.42	*wfr*	-
	Massing	Ratio	Form Factor (Volume / Wall Area)	2.47–17.14	*ff*	-
			Roof Ratio (Roof / Wall Area)	0.31–2.73	*rr*	-
Mixed	Shading	Average	Average sunlit percentage of envelope	0.35–100	*avgsunperc*	%
	Infiltration	Sum	Annual sum of energy gained due to infiltration	0–0.74	*suminfgain*	GWh
			Annual sum of energy lost due to infiltration	-2.7– -1e-4	*suminfloss*	
Other		Sum	Annual sum of Internal Heat Gain	0.03–5.24	*sumIHG*	GWh

The stated goal of this phase was to highlight the importance of tuning nonlinear regression models (ML models) to achieve the best predictive performance for a given use case. To put this work in context, it is worth noting the results from the original studies that introduced the datasets used here [175, 179]. Tsansa *et al.* [179] reported RMSEs of 1.014 and 2.567 for

Table 4.3 (cont.): List of EnrgyPlus features extracted for model training.

Grp	QTY	Stats	Name	Range	Code	Unit
Climate	Degree Days	Sum	Annual sum of cooling degree days	(9.6–160)e4	*cdd*	*C-day*
			Annual sum of heating degree days	424–64878	*hdd*	
	Dry Bulb Temp (Hourly)	Avg.	Annual average of dry bulb temperature	-3.11–28.39	*avgtdb*	*C*
		Median	Median dry bulb temperature	-7.20–30	*medtdb*	
		IQR	Inter-quartile range of dry bulb Temp	3.6–34	*iqrtdb*	
	Dry Point Temp (Hourly)	Avg.	Annual average of dry point temperature	-7.41–21.43	*avgtdp*	*C*
		Median	Median dew point temperature	-6.4–24.2	*medtdp*	
		IQR	Inter-quartile range of dew point temperature	0–26.8	*iqrtdp*	
	Global Horizontal Irradiation (Hourly)	Avg.	Annual average of global horizontal irradiation	190–509	*avghi*	*MWh/m2*
		Sum	Annual sum of global horizontal irradiation	0.40–2.23	*sumghi*	
		IQR	Inter-quartile range of global horizontal irradiation	(0.84–5.2)e-3	*iqrghi*	
	Direct Normal Irradiation (Hourly)	Avg.	Annual average of direct normal irradiation	57–676	*avgdni*	*MWh/m2*
		Sum	Annual sum of direct normal irradiation	-10.34–3.15	*sumdni*	
		IQR	Inter-quartile range of direct normal irradiation	(0.38–26.3)e-4	*iqrdni*	
	Humidity (Hourly)	Avg.	Annual average of relative humidity	22–98	*avrh*	%
		Median	Median relative humidity	18–99.6	*medrh*	

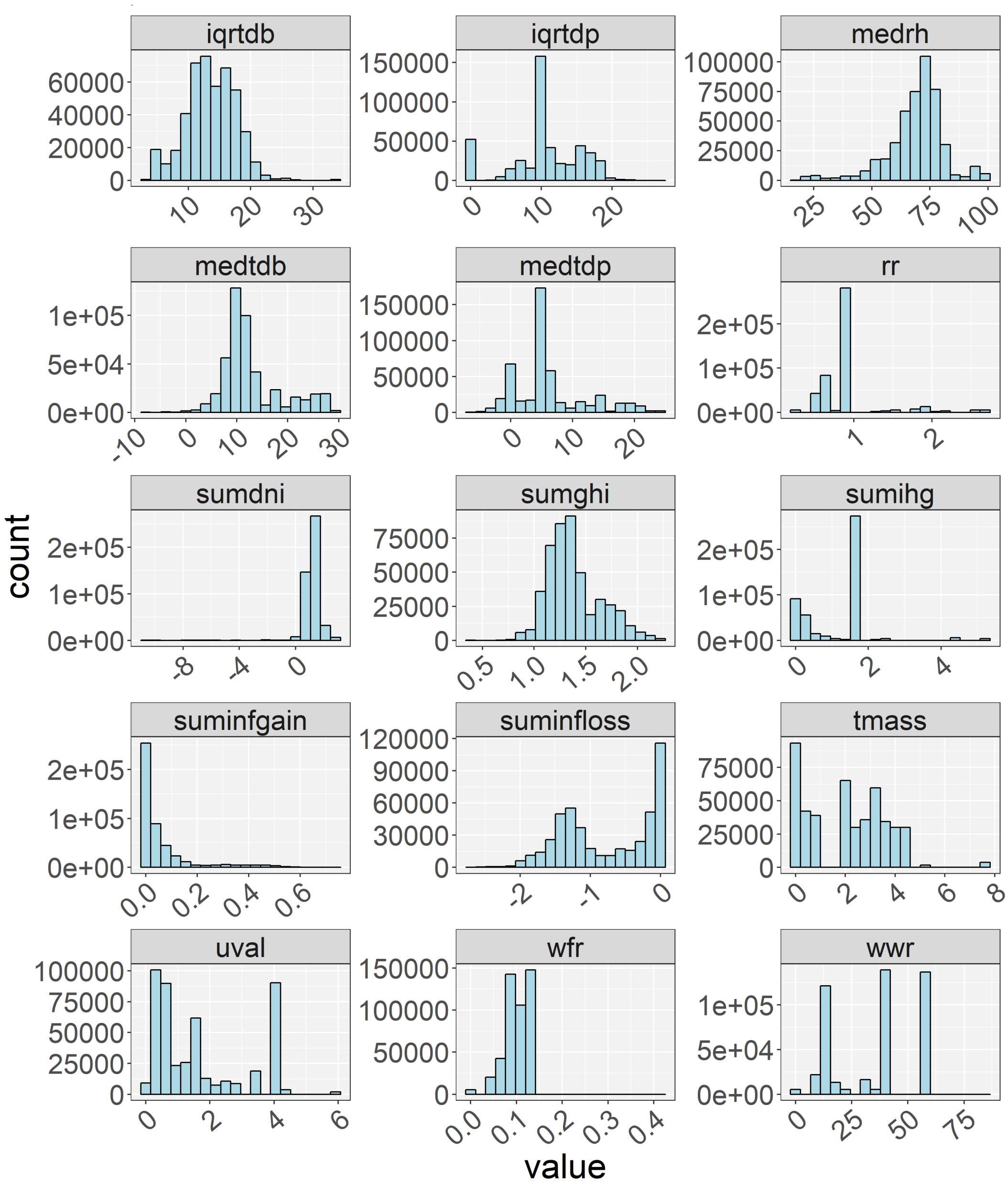


Figure 4.3: Distribution of features for EnergyPlus data.

heating and cooling loads, respectively. The best RF model in this work achieved 0.476 and 1.585 for the same variants, a roughly 40% improvement in accuracy in term of RMSE (kWh/m^2). Rastogi *et al.* [175] reported an error of 10-15 kWh/m^2 on the EnergyPlus dataset while this research achieved 6-10

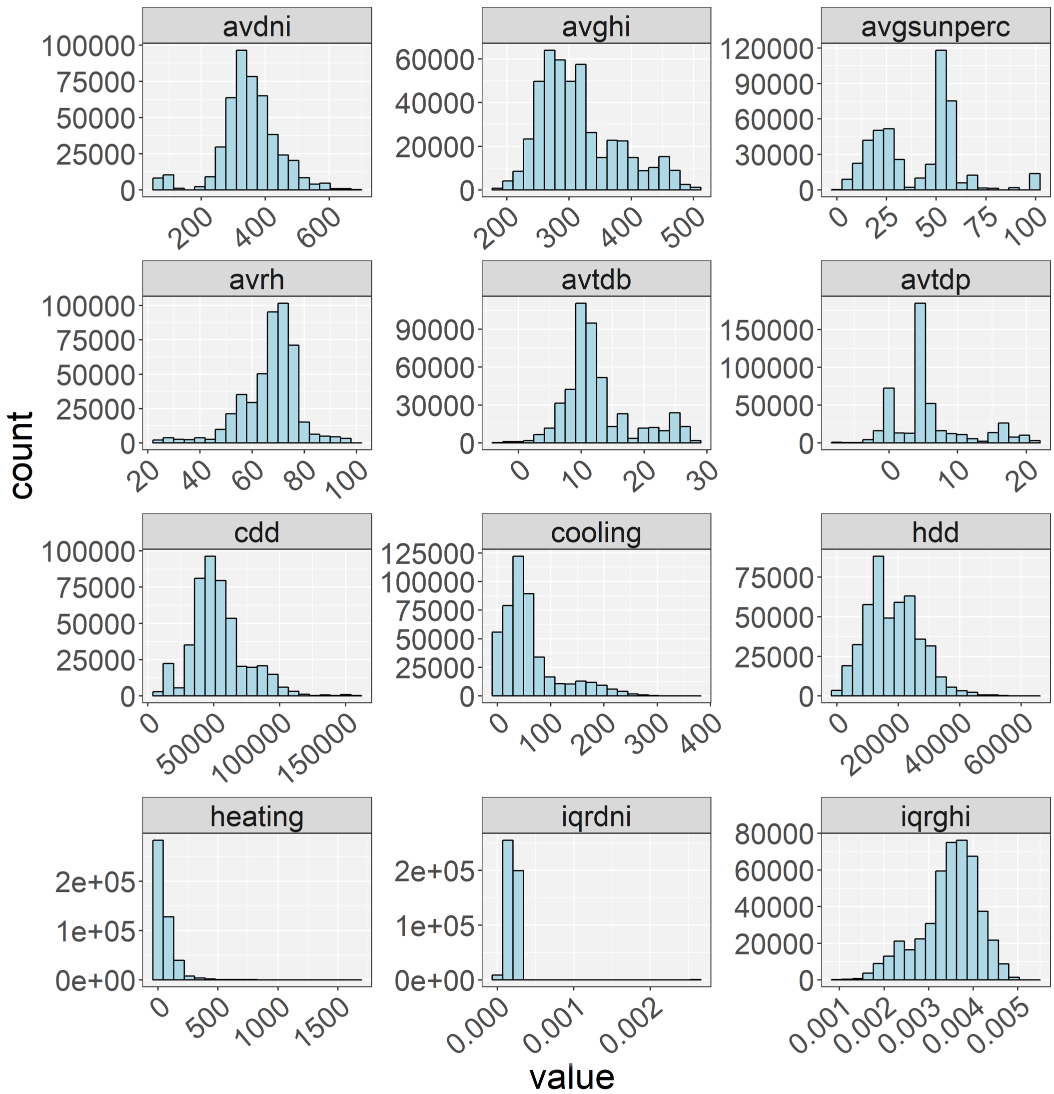


Figure 4.3 (cont.): Distribution of features for EnergyPlus data.

kWh/m^2. Tables 4.4 and 4.5 give an overview of results for the Ecotect and EnergyPlus datasets, respectively. The detail result of tuning models is presented in Appendix B.

The tables contain Coefficients of Determination (R^2), RMSE, MAE, fit time, test time, and number of parameters for the best combination of hyper-parameters; the average fitting time of all tested models; and the total

Table 4.4: Result of tuning ML model for Ecotect simulated dataset.

	SVM		RF		NN		GP		GBRT		XGBoost	
	Heat	Cool	Heat	Cool	Heat	Cool	Heat	Cool	Heat	Cool	Heat	Cool
R^2	0.996	0.972	0.998	0.973	0.997	0968	0.981	0.944	0.999	0.995	0.999	0.998
RMSE	0.475	1.622	0.476	1.585	0.491	1.711	1.381	2.279	0.366	0.677	0.300	0.401
MAE	0.654	1.082	0.332	0.98	0.369	1.120	0.852	1.579	0.254	0.486	0.189	0.294
Fit time (s)	2.19	21.09	0.75	0.73	0.106	0.131	18.86	24.63	0.499	0.655	0.326	0.585
Mean fit time (s)	323.77	177.28	0.72	0.75	1.23	0.99	17.00	18.65	0.20	0.19	0.28	0.28
Test time	0.005	0.005	0.090	0.104	0.001	0.001	0.019	0.018	0.021	0.031	0.045	0.107
Number of parameters	2		3		7		3		7		6	
Total iteration	21		36		3240		30		3456		2160	

Table 4.5: Result of tuning ML model for 5000 records of EnergyPlus dataset.

	SVM		RF		NN		GBRT		XGBoost	
	Heat	Cool	Heat	Cool	Heat	Cool	Heat	Cool	Heat	Cool
R^2	0.965	0.973	0.973	0.968	0.966	0969	0.980	0.986	0.982	0.986
RMSE	14.318	8.763	12.720	9.400	14.068	9.376	10.721	6.296	10.386	6.270
MAE	5.622	3.465	5.057	4.841	7.472	4.932	4.400	3.365	4.130	3.143
Fit time (s)	177.66	406.31	6.35	34.873	126.29	10.88	6.363	1.789	4.897	4.871
Mean fit time (s)	1641.91	1197.16	17.6	19.54	21.32	17.19	4.85	4.92	4.61	4.55
Test time	0.483	0.507	0.333	0.595	0.008	0.010	0.244	0.078	0.228	0.219
Number of parameters	2		3		7		3		7	
Total iteration	21		36		3240		3456		2160	

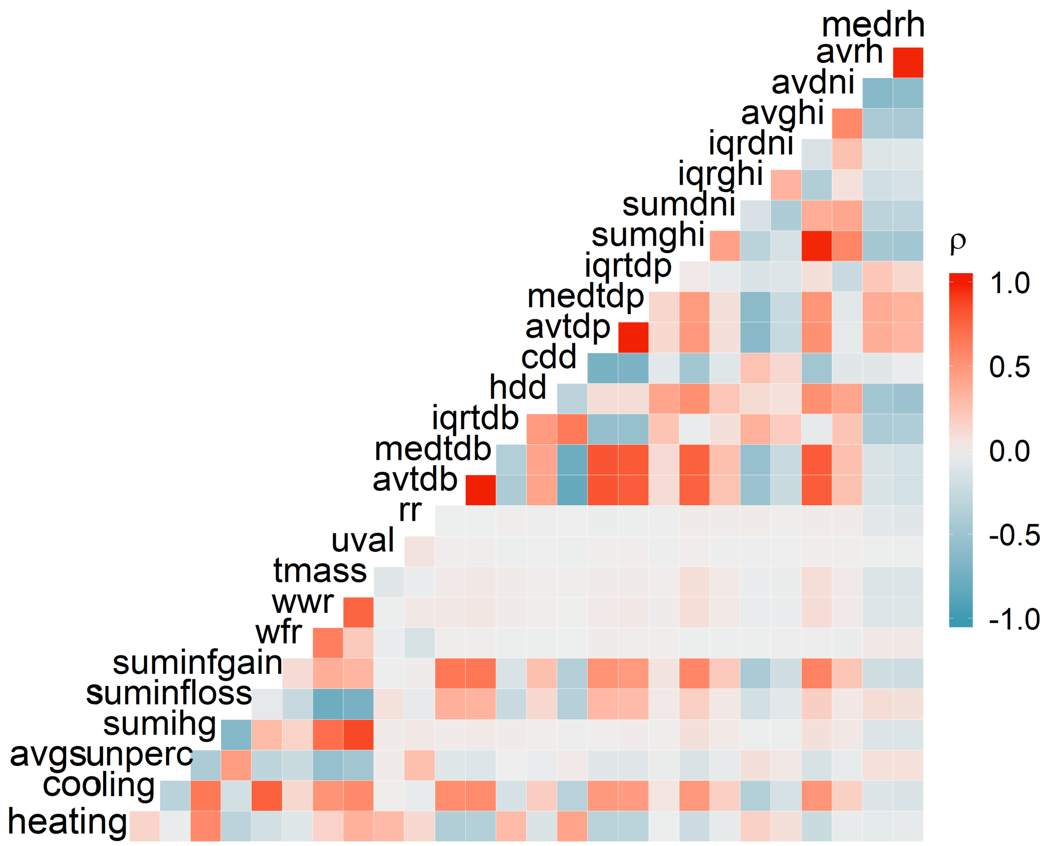


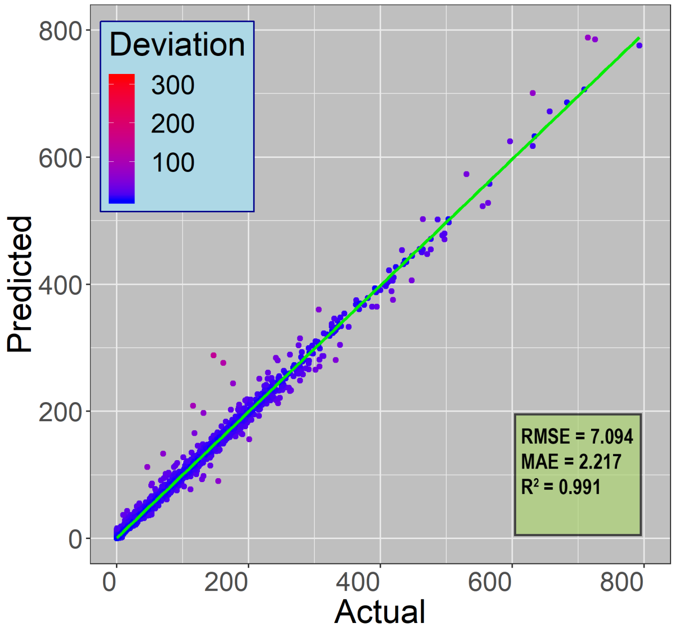
Figure 4.4: EnergyPlus data features correlation map.

number of iterations for comparison of time complexity. Here, the test time is the average of predictions of all folds (192 data points per fold for Ecotect and 1,000 for Energy Plus). For EnergyPlus data, GP was excluded from the comparison because the training time was extremely high for large datasets. This study at this step tuned all models separately for heating and cooling loads. It was ascertained that none of the techniques obtained the best accuracies for both target values using the same combination of hyper-parameters. This inconsistency indicates that the importance of input variables as well as the corresponding weights are different.

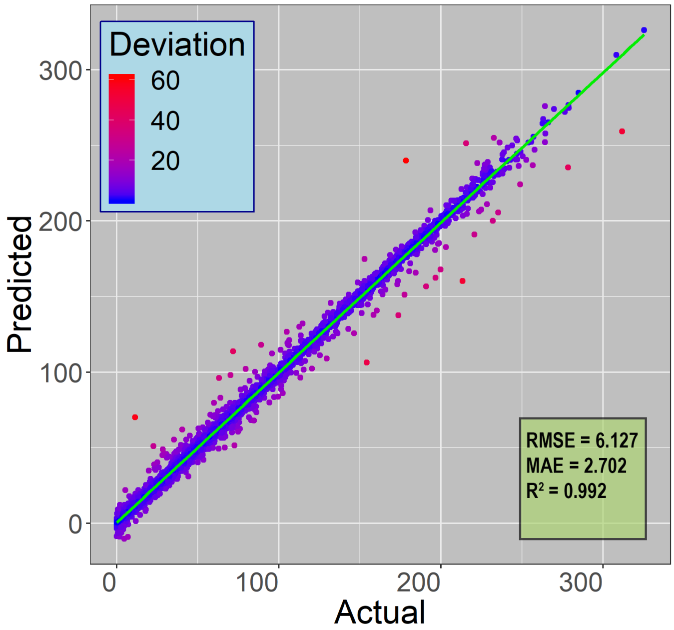
Though the datasets were drawn from different simulators, similarities in the performance of the models did emerge. The lowest RMSE for both heating and cooling loads was achieved by XGBoost, followed by GBRT and RF. These models are all based on decision trees, but unlike RF the other two do not build independent trees. Hence, they train models slightly faster than RF. Considering prediction time in addition to accuracy, however, GBRT is slightly faster than XGBoost but has comparable accuracy. The NN models tend to have the fastest prediction times, which might make them more appropriate for applications requiring very large numbers of simulation estimates. For example, optimising many building parameters, each with several possible choices, under a sample of uncertain operating conditions, such as the problem described in [175]. This work found that GP is the slowest and least accurate model. This is partially due to the challenge of using large datasets with GP regression; since the time complexity of GP is $O(N^3)$ (where N is the number of data points used for training/fitting), the training speed is not comparable with other ML models and inversion of matrices of size $\{N, N\}$ is unfeasible for large N. Thus, studies using GP have used small datasets, usually less than a few thousand [103, 170, 172, 173, 175, 176]. However, since GP regression allows for the automatic estimation of prediction uncertainty, it is useful in some cases. An example is the estimation of summary statistics, where it is more informative to know the uncertainty of, e.g., annual heating and cooling loads, rather than just a point estimate. Although all models predict the energy loads with high accuracy, the use case should determine the most appropriate model. For example, increasing the number of records (size of training data), the fitting and forecasting time of SVM rises significantly. The training size of NN is slightly increased as well, but it is still the fastest predictor by a considerable margin (10-20 times faster). GBRT and its variant XGBoost achieved the best RMSE. However, the increased accuracy and sophistication of models like NN and XGBoost comes with the penalty of requiring very large training datasets (e.g., the 25,000 simulations used here). This could be an issue where a model has to be trained on the fly, i.e., where simulating 25,000 distinct cases to train an accurate model is prohibitively expensive. As expected, using more data to fit a model increases the predictive accuracy of all models, such that complex models with more parameters lose out to simpler models that have seen more data, provided the simpler models can use the additional data available. In summary, where sufficient training data is available and the testing or use cases are not too dissimilar from the training data, the use of models such as GBRT and NN improves accuracy. Where training data is harder to generate, or a model must be trained on the fly with a small dataset, techniques such as GP provide adequate predictions.

4.6 Performance of the Best Model

The performance characteristics of the best models for each dataset is now discussed. The results are illustrated using two kinds of plots: predicted (estimated) loads ($\hat{y}$) against loads from the simulator (y), and the distribution of errors between simulated-predicted pairs ($\hat{y} - y$). Figures 4.5 and 4.6 show the values predicted by tuned GBRT models against their corresponding simulated heating and cooling loads for the Ecotect and EnergyPlus datasets, respectively. The error distributions of these estimations are given in Figure 4.7 and 4.8 with a red dashed line representing a theoretical normal PDF with the same parameters.

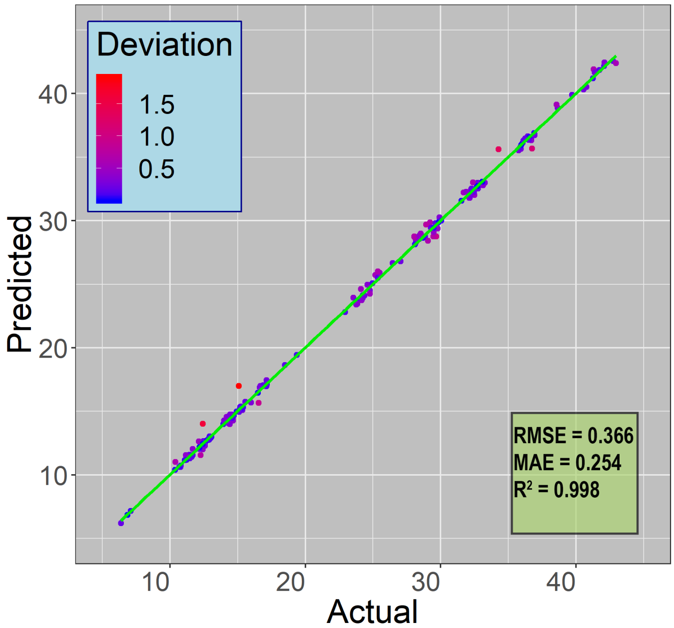


(a)

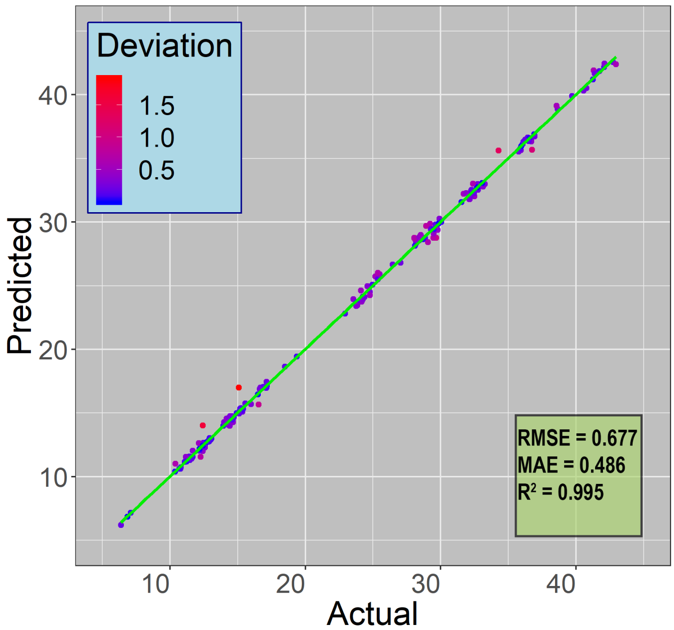


(b)

Figure 4.5: Actual and predicted (a) heating and (b) cooling loads of EnergyPlus dataset.

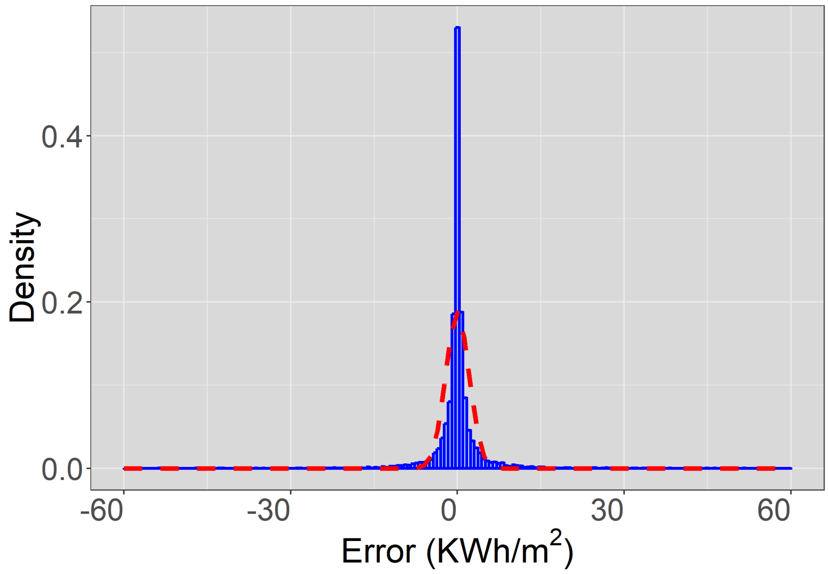


(a)

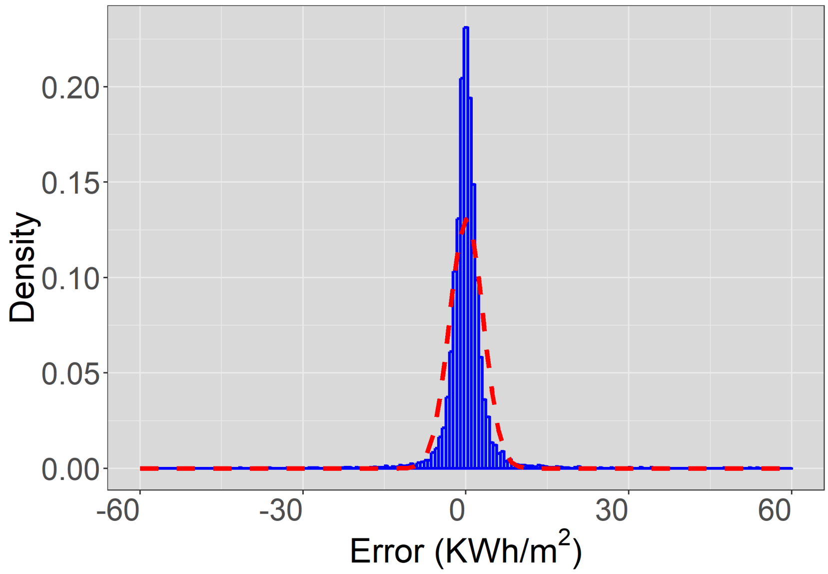


(b)

Figure 4.6: Actual and predicted (a) heating and (b) cooling loads of Ecotect dataset using GBRT model.

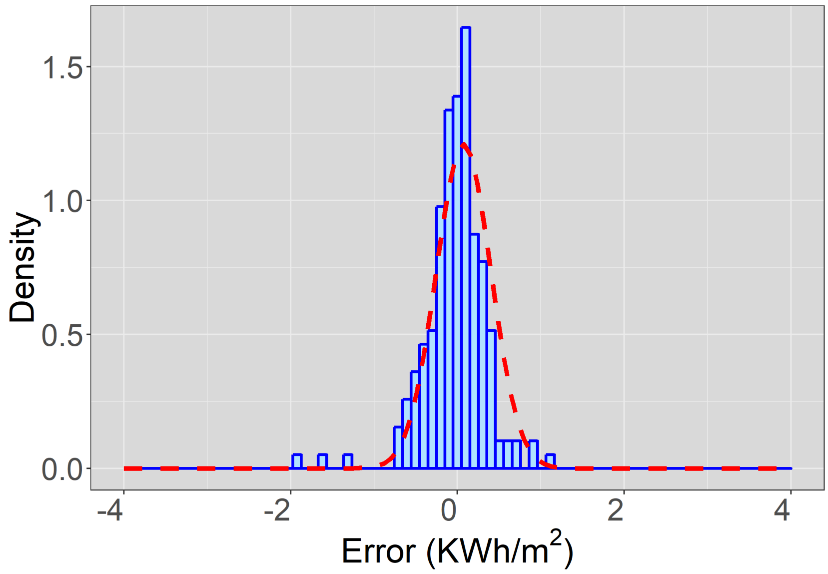


(a)

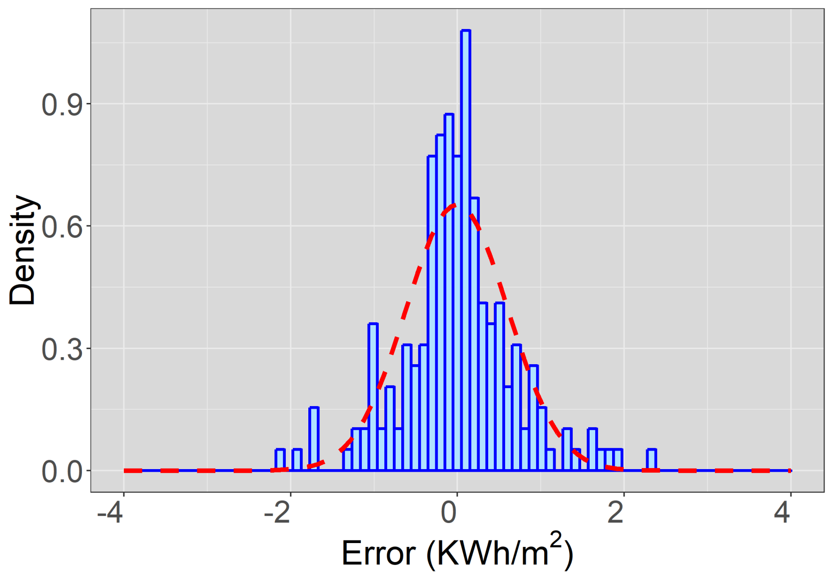


(b)

Figure 4.7: Error distribution of (a) heating and (b) cooling loads prediction for EnergyPlus dataset.



(a)



(b)

Figure 4.8: Error distribution of (a) heating and (b) cooling loads prediction for Ecotect dataset.

4.6.1 Effect of Increasing Size of Training Data

Given that using large datasets for training seems to improve the predictive accuracy of all models, the research investigated the effect of increasing the size of the training dataset on accuracy. Figure 4.9 shows RMSE versus size of training dataset for the GBRT model. A 10 fold cross-validation was used to obtain the worst, best and mean RMSE over all folds. Mean training time is also displayed as the top axis to show computational cost. Although the best result was obtained by the highest number of samples tested, 25,000 is enough to build a reliable model considering the fitting time and error gap. At this point, the mean RMSE is equal to 7.770 kWh/m^2 and time required to fit the model is 66.02 seconds. On the other hand, using 400,000 samples and fitting over 2600 seconds, mean RMSE only goes down to 2.338 kWh/m^2 (4% of average heating loads).

4.7 Feature Selection and Importance

To emphasise the importance of features in predicting different loads, this section presents a sensitivity analysis using two approaches. First, it presents the feature importance calculated by the RF models. RF creates many decision trees and the amount of weighted variance explained by each feature can be calculated for each tree. For a forest, the variance explained by each feature can be averaged and the features ranked according to this measure. Here, the research trained 30 RF models using 100,000 randomly selected samples to obtain an empirical distribution of feature importance, shown in Figure 4.10.

The study used a global variance-based method called the Sobol method [232, 233]. Unlike RF, GBRT does not generate unique trees. Rather, each trees is correlated to the last. To facilitate a comparison, this work fitted

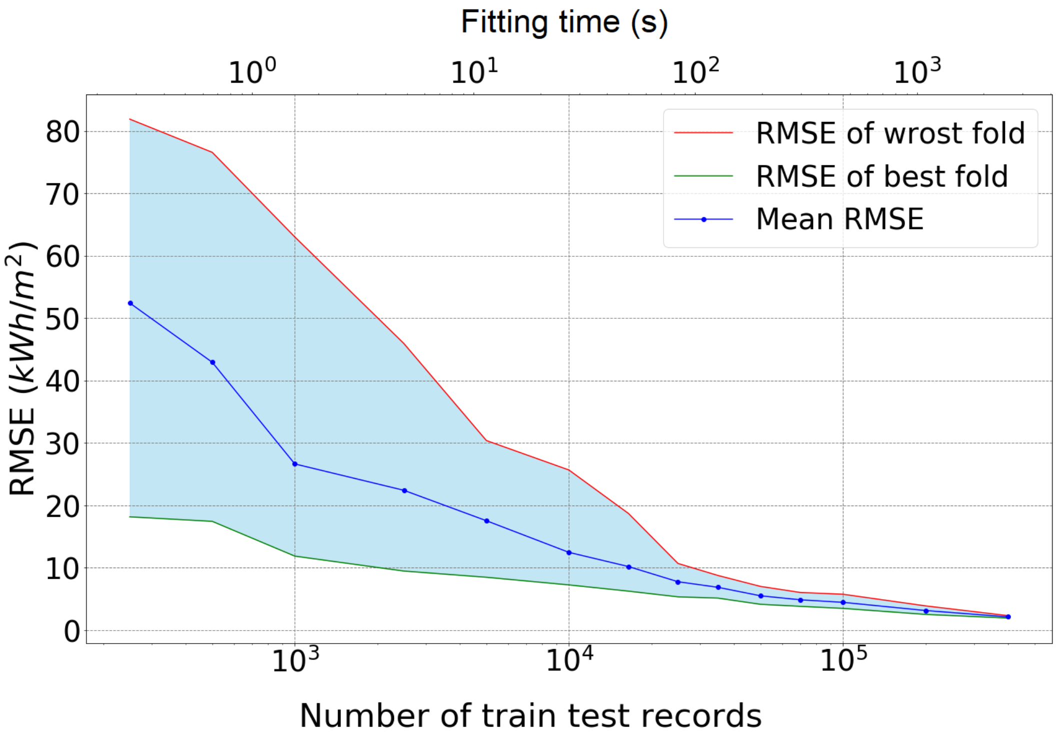
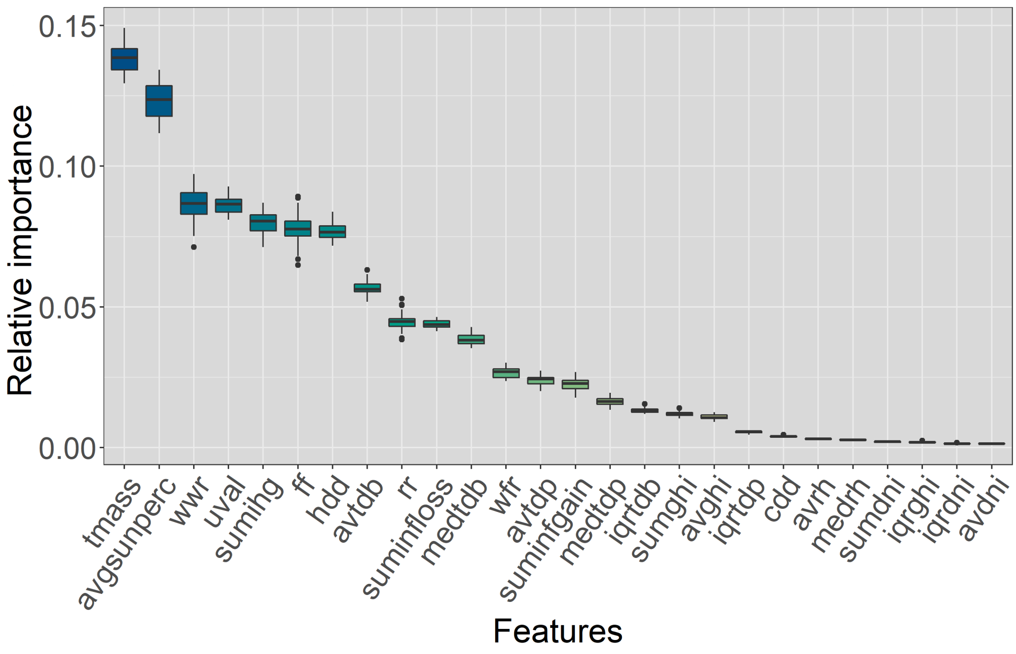


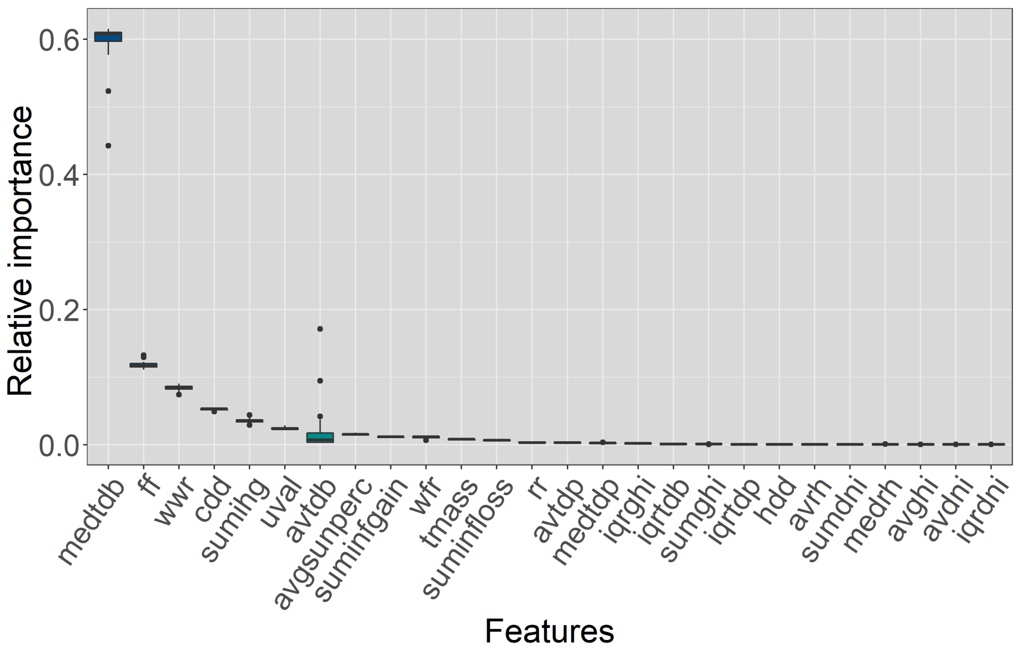
Figure 4.9: RMSE for heating load against number of total number of samples used for training.

30 different models and used them to evaluate the 150,000 samples generated by the algorithm. The Sobol first-order indices of features is illustrated in Figure 4.11. It can be seen that the importance of features to this method is less stable in Sobol than RF. However, since it is calculated directly from the original data, it is more representative of the features of the dataset itself.

For a final test, the effect of dropping variable that the model does not deem to be important was examined. Based on the results of the Sobol comparison, the following features are identified to drop: 'avrh', 'avdni', 'iqrdni', 'iqrghi', 'medrh', 'sumdni' for both loads, and 'avghi', 'sumghi' for cooling only. All of the dropped variables are climate-related, which implies that there may be too many variables

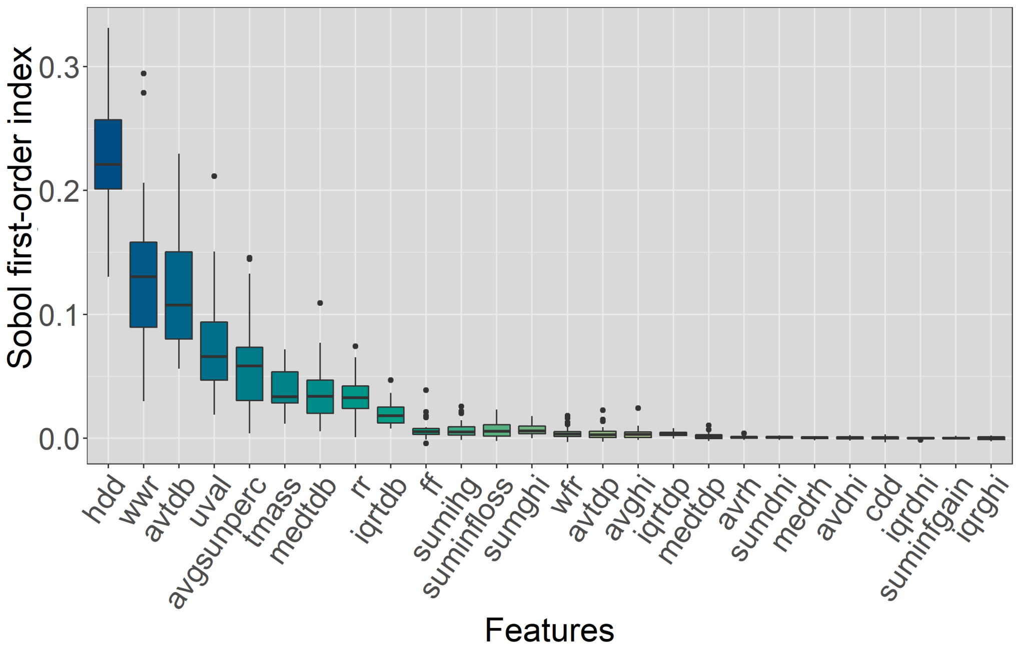


(a)

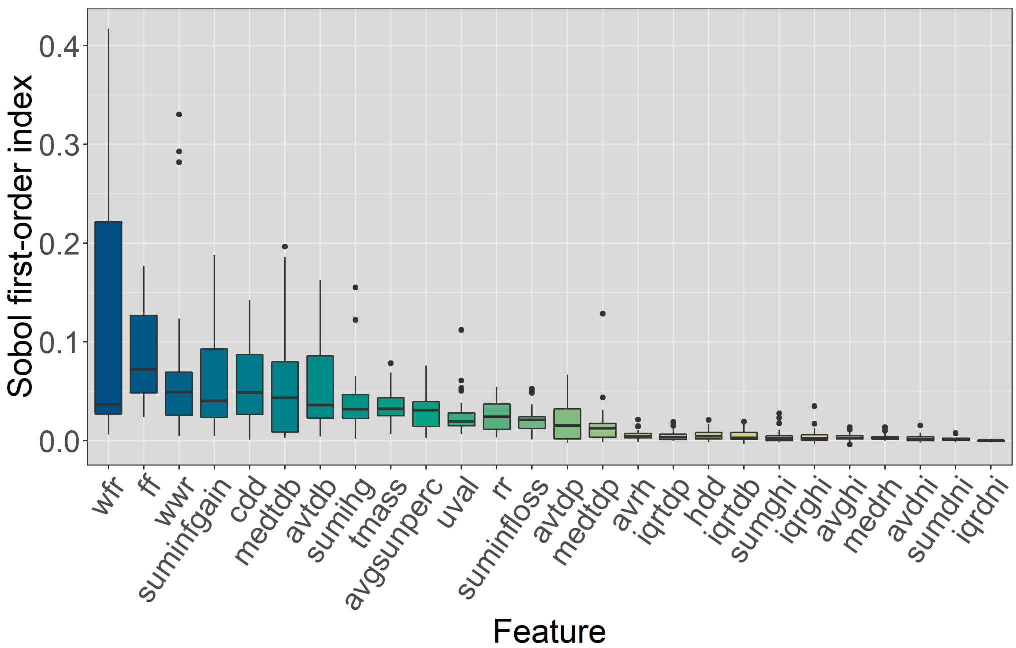


(b)

Figure 4.10: Importance of features for (a) heating and (b) cooling loads prediction using RF model.



(a)



(b)

Figure 4.11: Sobol first-order indices of features in predicting (a) heating and (b) cooling loads using best ML model.

used to explain variance due to climate.

The GBRT with fewer features was also trained and tested over 10 folds with 25,000 random samples. The results of training a model with a reduced feature set is compared with using the full set of features in Table 4.6. It can be seen that removing features to which the model is apparently insensitive does not negatively affect the model performance. However, the time complexity of training model is reduced due to a reduction in the size of the dataset. Given that this result applies only to this dataset and cannot be generalised to all buildings or EnergyPlus simulations, this is not a repeatable result unless there is a confidence that the dataset used for training represents the use case or problem completely.

Table 4.6: Performance comparison of ML models with full and reduced feature sets determined by sensitivity analysis.

	Heating Load		Cooling Load	
	All inputs	Selected inputs	All inputs	Selected inputs
RMSE	7.871	7.648	4.455	4.384
MAE	2.127	2.085	2.314	2.310
R^2	0.991	0.991	0.993	9.993
Fit time (s)	61.621	48.420	9.387	7.700
Test time (s)	0.642	0.622	0.151	0.145

4.8 Summary

This chapter elaborated Phase 2 of the study which addressed the gap in using ML methods (part of RQ1) for estimating building energy loads through a comprehensive study of common ML methods fitting over energy simulation data. As became evident in Chapter 2, despite the wide usage of MLs in this field, a conclusion on selecting the right model for the energy prediction was not possible. The main reason is that most of the research works have focused on the first eminent part of statistical modelling which is features selection. The chapter covered Objective 2 of the study by investigating ML techniques to facilitate the model selection procedure.

This chapter discussed the importance of ML model optimisation in providing a fair comparison of different methods in term of accuracy, the simplicity of tuning and training and response times of model. This research optimised the hyper-parameters of each model for both heating and cooling loads to obtain the best precision. It was also indicated that when there are two energy indices as cooling and heating loads to be estimated by model, it is desired to optimise and train separate machines. To that end, the role of ML model in recognising most impacting factor in prediction of building loads was also investigated. The other key outcome of the stage presented in this chapter was a set of recommendations for the quick selection of ML model based on the data and usage.

It was ascertained that the standard and advanced GBRTs provide the most accurate predictions, considering the RMSE value. However, when the data was simple (in term of input variables and size), SVM was proven to be the best choice because of simplicity and the speed of calculations. The results also ascertained that for complex data sets, multi-layer NNs are more appropriate when there is a massive demand for ever-more energy simulations. In this case, NN was proven to be capable of estimating incredibly faster than other MLs methods. It should be noted that NN is complicated, and requires an expert to particularly tune it for each studied case; otherwise, NNs could fail quickly.

Comparison of tuned models with previous studies highlighted the importance of determining the hyper-parameters for each data set, and the fact that this can become more crucial by increasing the size and intricacy of the examinations set. By fitting individual models for heating and cooling loads, it was shown that one assorted set of model parameters could not accurately estimate both values. Therefore, unlike previous studies, it is recommended by this work to train models for each energy load independently, unless a method for optimising a model with two targets are utilised. The other approach would be the implementation of a specific sorting algorithm to find balanced values. As results signified, it is suggested to attain a higher accuracy feeding the machines with more number of instances is essential. It might not be a solution for measured historical data; however further simulation using various values of inputs could be aggregated during the design stage prior to optimising the building. Another identified critical factor was that the features must be thoroughly selected/created for representing building characteristics and needs should be appropriately investigated before developing models.

The findings of this study in the second stage concurred with the seminal literature by demonstrating the fact that MLs techniques are overtly superior over the conventional statistical and engineering methods in building energy calculation. This study also revealed the further power of those ML methods and newly developed ones when they thoroughly optimised. There are several ready to use software packages (e.g. Matlab) providing various ML methods with few parameters to modify. Nevertheless, it is advisable to use simpler models like SVM or RF with an advanced programming language, such as Python and R.

Finally, the most important features was recognised using sensitivity analysis methods, and the investigation of the model with reduced dimension revealed that even though the computational cost of building model is reduced, the performance didn't alter. This analysis demonstrated the capability of MLs in eliminating inessential input parameters, while most statistical methods are susceptible to these type of features.

The methods discussed in this phase proved the efficiency of ML models in predicting building energy loads as well as performance. The fast and accurate calculation of those values paves pathways for more informed and productive design decisions for built environments. Furthermore, along with the optimisation algorithms, ML seems as a promising solution for efficacious retrofit planning of complex buildings, where engineers are not capable of massive calculations.

Chapter 5

Multi-Objective Optimisation for Accelerating Machine Learning Modelling for Predicting Building Energy Performance

5.1 Introduction

As indicated in Chapter 2, ML techniques have been widely used for modelling building energy loads and performance, however, the default values for hyper-parameters have been used in this field. In Chapter 4, it was demonstrated that tuning ML models can significantly increase their accuracy.

Simple models with few parameters like SVM are easy to optimise, but when the number of hyper-parameters is increased the search space grows exponentially. For example, to tune an RF with six parameters, a grid-search will explore more than four thousands possible configurations. That is why traditionally, the researchers mostly relied on default values for those hyper-parameters. However, such models provide far more accurate results by precisely tuning in comparison with SVM or Gaussian process regression.

Forecasting two or more building energy measures such as heating and cooling loads simultaneously requires even more expertise and investigation. The use of complex model and grid-search for such applications is not a viable solution, due to the complexity in processing time as well as the selection of the ideal model. This chapter elaborates Phase 3 of this study which outlines a detailed method to train one single model for prediction of both heating and cooling loads of buildings and maximise the ML model's efficiency. The method not only accelerates the ML optimisation process, but also provide fine-tuning of the model as the hyper-parameters aren't selected from predefined discrete values, but smartly from a given continues space. Though the demonstration presented here are from simulated data, the approach is also applicable to measured energy data.

In the proposed method in this stage, evolutionary-based multi-objective optimisation (MOO) algorithm was employed to smartly explore the ML model's configuration parameters space and suggest a set of packages for maximising ML accuracy for both heating and cooling load predictions. Here, despite the recommendations from Chapter 4 an RF model is employed because a Python implementation is capable of providing the multivariate forecasting. The study utilises simulated building energy data generated in EnergyPlus (th same dataset introduced in Section 4.4.2 is utilised.) to validate the proposed method, and compares the outcomes with the regular ML tuning procedure (presented in Chapter 4).

5.2 Optimisation Based on Evolutionary Algorithms

In traditional grid-search method, a specified set of possible values for each parameter is required. However, evolutionary algorithms are able to select the values from a determined continuous space or a discrete set.

In the proposed method, a MOO technique is utilised to exploit genetic algorithm in the optimisation of ML models for prediction of heating and cooling loads of buildings. Figure 5.1 demonstrates the proposed optimisation procedure for selecting the best hyper-parameters. Here, the ML parameters are defined as the MOO variables to generate several sets with which ML model accuracy is maximised for forecasting both energy loads. Most implementations of the established ML models such as NN and RF support the concurrent prediction of multiple targets. However, choosing a set of hyper-parameters might improve the prediction accuracy of one target but less the accuracy of the other objective function.

In the proposed approach, the ML algorithm parameters are given to the evolutionary algorithm as continuous spaces based on knowledge on the algorithm functioning. First, MOO is initiated with pre-set values (in this study, default values suggested by the Python library were used) to create a model. This is evaluated using a 10-fold cross validation method. In this approach, the dataset is divided into 10 equal segments. Then a model is trained using 9 parts and tested on the remaining one, and this procedure is repeated until the accuracy of the model is assessed covering all parts. Finally, the average values of the model performance (e.g. mean absolute error) of all 10 folds is sent to the MOO. It continues generating new samples and evaluating models until it reaches 500 iterations.

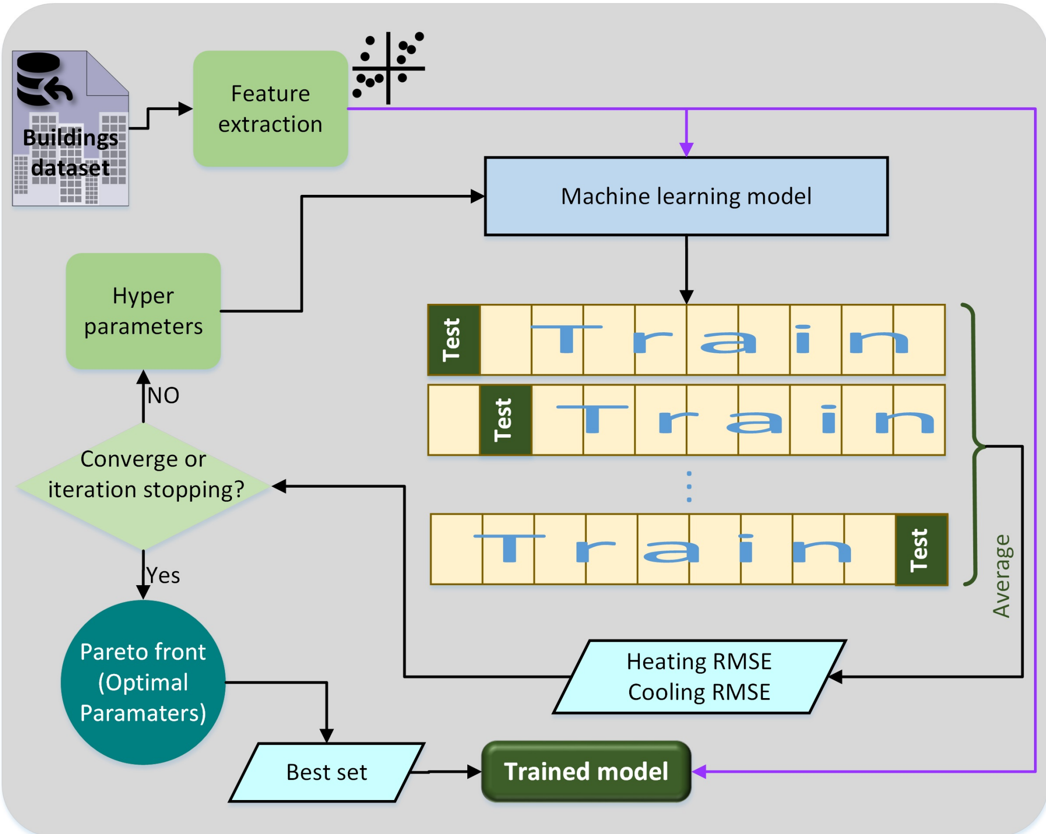


Figure 5.1: Schematic diagram of the proposed ML optimisation method.

5.2.1 Multi-Objective Optimisation

There are several tuning methods for optimising the MLs for accurate predictions. These approaches include grid and random search techniques, evolutionary algorithms or Bayesian optimisation. Generally, these methods are applied to optimise a single objective criterion. However, in applications where two or more objective functions (i.e. heating and cooling loads) are optimised, those approaches are not adequate to designate the behaviour of the ML, and the Pareto front of multiple criteria has to be considered. Usually, for each objective, an ML is independently tuned to get the best hyper-parameters, and the most accurate model and its configuration are selected eventually. The main disadvantage of this strategy is the high time-complexity of tuning the separate models. This research at this stage proposes a MOO method for automated hyper-parameter selection in modelling the heating and cooling loads of a building. The proposed method reduces the time required for tuning, speeds up the model predictions and decreases human effort for implementing ML.

The general MOO problem is presented mathematically as: *Minimise*:

$$F(\hat{x}) = [f_1(\hat{x}), f_2(\hat{x}), \cdots, f_m(\hat{x})]^T \tag{5.1}$$

Subject to:

$$g(\hat{x}) \leq 0$$

$$h(\hat{x}) = 0$$

where

$$x_i^{min} \leq x_i \leq x_i^{max} (i = 1, 2, \cdots, n)$$

$$x = [x_1, x_2, \cdots, x_n]^T \in \mathit{\Theta}$$

$$y = [y_1, y_2, \cdots, y_n]^T \in \mathit{\Psi}$$

Here m is the number of objective functions which is three in this case. $\mathit{\Theta}$ is the search space with n dimensions and identified by upper and lower bounds of decision variables $x_i (i = 1, 2, \cdots, n)$.

$$x^{max} = [x_1^{max}, x_2^{max}, \cdots, x_n^{max}]^T \tag{5.2}$$

$$x^{min} = [x_1^{min}, x_2^{min}, \cdots, x_n^{min}]^T \tag{5.3}$$

Ψ is an m-dimensional vector space of objective functions and defined by Θ and the objective function $f(x) \cdot g_j(\vec{x}) \leq 0 (j = 1, 2, \cdots, p)$ and $h(\vec{x}) = 0 (j = 1, 2, \cdots, q)$ denotes p and q which are respectively the number of inequality and equality constraints. If both p and q are equal to zero, then the problem is simplified as an unconstrained optimisation problem.

Figure 5.2 shows a hypothetical Pareto frontier for the optimisation of two objective functions which are energy loads estimation errors. These solutions (set of ML hyper-parameters) have been enclosed by a vector of an ideal solution and a vector of dominated results, delimiting the upper and the lower borders of optimal packages. An ideal or utopia point is a theoretical notion relative to an ideal target in which each objective is optimised without paying attention to the satisfaction of the others. MOO tries to produce solutions as close to the Pareto optimal front with a possible uniform distribution. When the non-dominated solutions are recognised, decision-makers choose one as a final answer in accordance with the problem and individual preferences.

The tuning method used in this study involves an improved multi-objective genetic algorithm (NSGA-II) [234]. Genetic algorithm is initiated by randomly generated solutions as a population and sorts them into fronts based on non-domination criteria. These solutions are evolved from one generation to another based on the objective evaluation, selection, crossover and mutation operators.

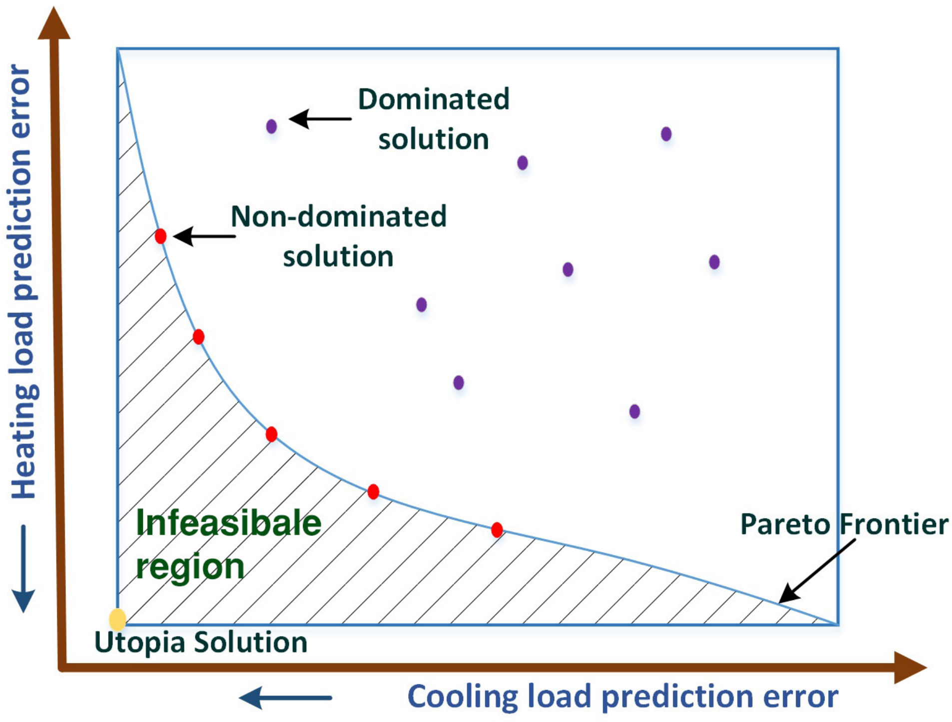


Figure 5.2: An example Pareto frontier of minimising errors in heating and cooling loads predictions.

5.2.2 Evaluation Criteria and Optimisation Variables

The objective functions for the optimisation problem in this study are accuracy of the model (i.e. RMSE) for prediction of both heating and cooling loads. To this end, model accuracy for both loads is calculated by comparison of predicted and actual values. Each model was evaluated using k-fold cross-validation in which the accuracy of each fold was calculated as RMSE of the prediction test set. The average RMSE value of heating and cooling loads in all folds was computed and regarded as the final value for the objective functions.

When the MOO algorithm generates a population, each solution contains a set of RF parameters. Table 5.1 summarises these variables and presents the range of values defined to the optimisation algorithm.

Table 5.1: List of RF parameters which are considered as MOO variables

Parameter	Description	Type	Values
$n\_estimator$	Count of independent trees in the formation of the forest	Integer	200 – 1200
$max\_features$	Count of input variables in creating each independent tree	Category	26, 5
max_depth	The maximum depth of the tree	Integer	10 – 100
$min\_samples\_split$	The minimum samples in splitting an internal node	Integer	2 – 10
$min\_samples\_leaf$	The minimum number of samples required to be at a leaf node	Integer	1 – 10
bootstrap	Whether or not to apply bootstrapping samples while generating the trees	Boolean	True, False

5.3 Performance of Intelligent Tuning Method

This study used Python programming language and packages for implementing the proposed algorithms. The study used a PC with Intel Core i7-6700 3.4GHz CPU, 32GB RAM (with no utilisation of GPU processing) for running the experiments.

Using conventional grid-search method requires further investigation to decide the topmost hyper-parameters for the ML model. Besides, the existing solutions are not developed to calculate the accuracy of predicting multiple targets. Hence, a custom function is needed to perform the task. The proposed method generated non-dominating solutions in which models accuracy in estimating heating and cooling loads were the highest. Furthermore, in a grid-search, it is not possible to search every potential value for the parameters in the grid due to the size of the vast search space. Therefore, as the hyper-parameters are discretely introduced to the grid, the chance of success of the optimisation algorithm, which smartly selects the values from predefined intervals is higher to build a model with more reliable accuracy.

Figure 5.3 demonstrates the top 5 solutions, the ML parameters and models accuracies for heating and cooling loads in terms of RMSE. These are the non-domination packages as outcomes of applying MOO on tuning the RF model. Among those, the two closest solutions to the utopian point are $S4$ and $S5$. The number of trees in $S4$ is lower than $S5$ resulting in faster training and predictions. As such, $S4$ was suggested as the final set of parameters for modelling energy loads of the selected building dataset.

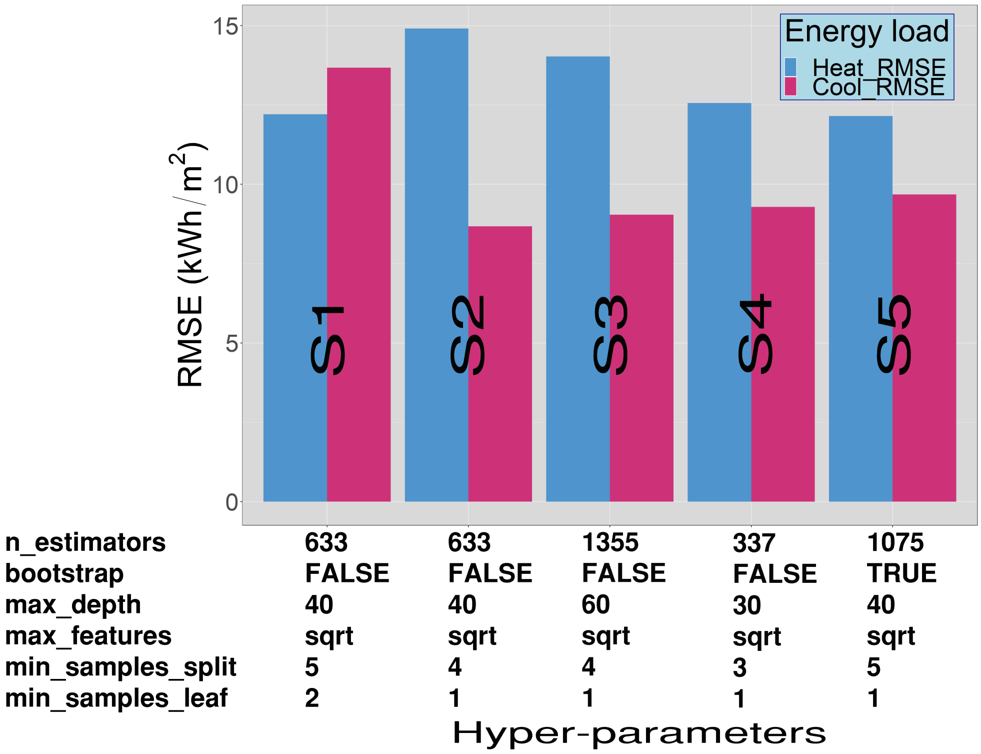


Figure 5.3: Top solutions provided by MOO for predicting heating and cooling loads of buildings.

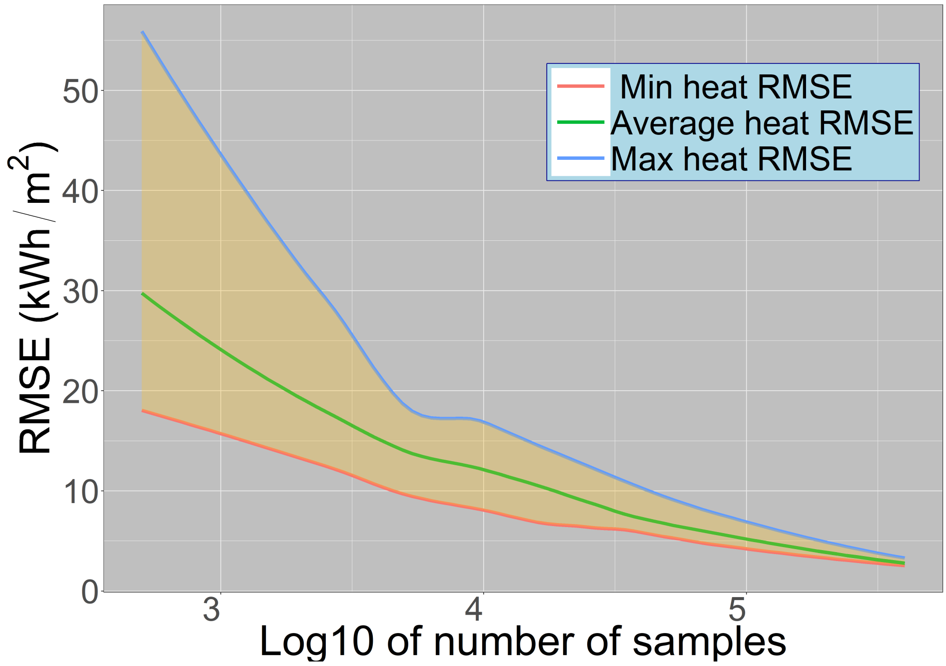
Performance of the selected model was tested using a 10-fold cross-validation over 5,000 randomly selected samples. The results, along with the results from Grid search, and the original study are summarised in Table 5.2. It can be seen that the selection of the right ML model and optimising the parameters using a Grid search method, the accuracy of predicting energy loads is considerably increased. The proposed MOO approach not only reduces the tuning time but also improves the performance of the models by precise tuning. The selection of 1,500 as the number of evolutionary algorithm iterations was based on a rule of thumb while the best model was identified at the 879th iteration.

Table 5.2: Results comparison of the proposed method, grid-search and the original study

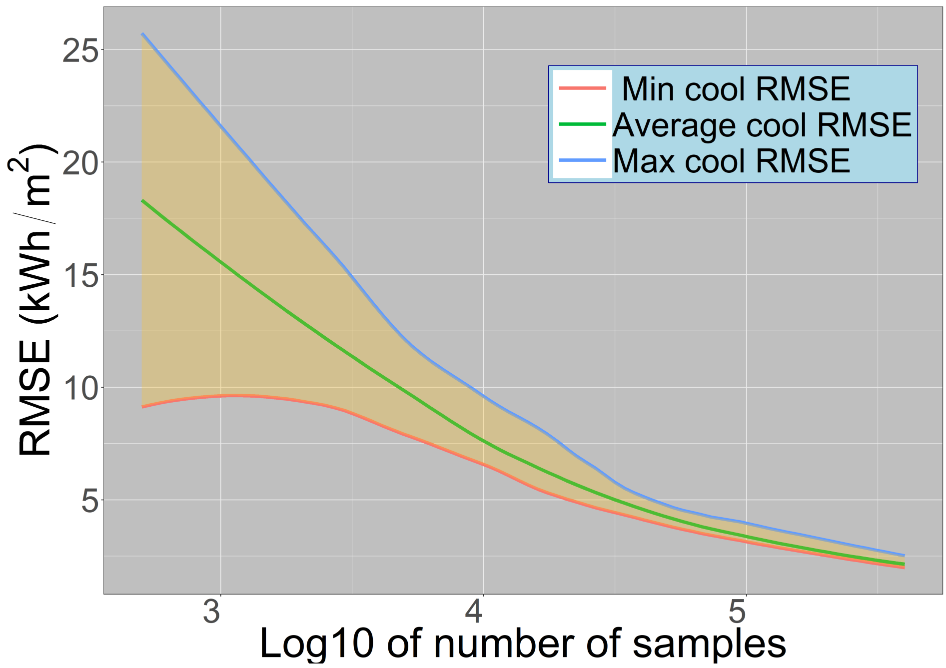
	Best RMSE		Complexity	
Method	Heating	Cooling	No. of Iterations	Tuning time (h)
Moo	12.56	9.28	1,500	79
Grid-search	12.72	9.4	7,000	349
Original Study [175]	25.05	12.84	Using 4,000 random samples and Gaussian Process Regression	

5.4 Evaluation of the Trained Model

To illustrate the effect of data size on the accuracy of supervised models, RMSE was plotted versus the number of training and test records forecasting heating and cooling loads of EnergyPlus data which is depicted in Figure 5.4. To evaluate the accuracy and generalisation of RF model in predicting energy loads, the 10-fold cross-validation method was also utilised. The prediction confidence intervals, which are maximum and minimum values of all folds along with the mean value, are illustrated in Figure 5.4. Figure 5.5 shows the average training and testing times versus the number of records.



(a)



(b)

Figure 5.4: RMSE of predicting (a) heating and (b) cooling loads by varying the number of total number of samples used for training

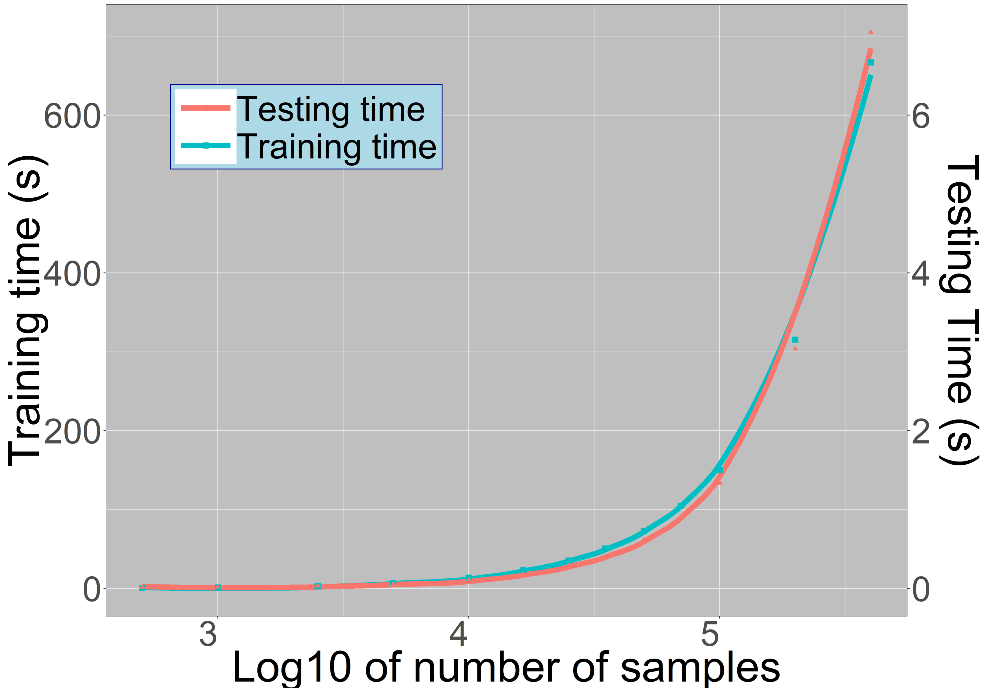


Figure 5.5: Average training and testing time of energy loads models the versus number of records.

From two figures, it can be seen that there is a trade-off between accuracy and time complexity of the model. However, the results indicate that the sample size of 45,000 is sufficient for training a dependable model. With that record size, the model which was trained and tested at an average of 64.14 and 0.51 seconds achieved the RMSE of 6.97 and 4.61 kWh/m^2 for heating and cooling loads, respectively. It should be noted that this testing time was spent for the forecasting of 4,500 samples. This figure denotes that the model has the capability of processing 8,8000 building records in one second.

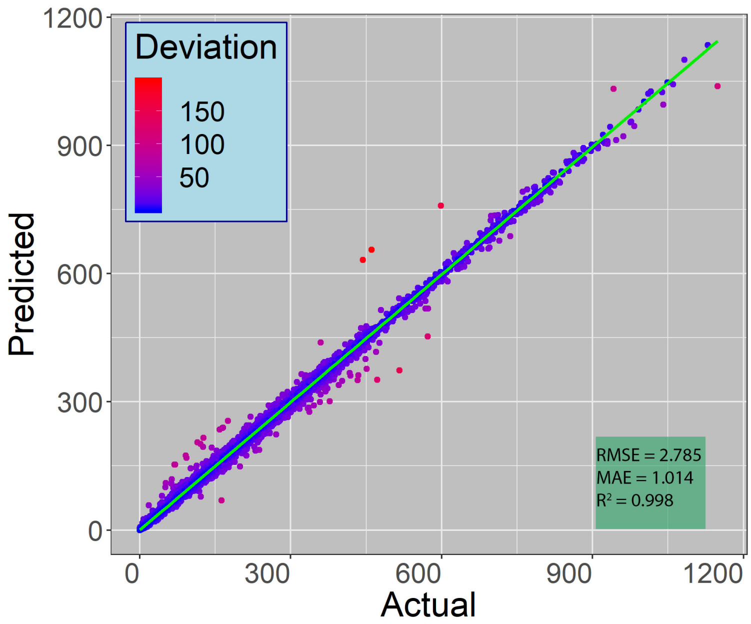
The calculated confidence intervals at that point, assure building a reliable model not only because of the narrow band but also due to the fact that the data covers the space of possible values of the selected features for the building design. Moreover, the use of 10-fold cross-validation and a random selection of records grantee a fair test procedure. Therefore, the upper bound of the RMSE in the presented graph could be considered as models' worst performance.

To show the model performance using the full capacity of generated data, 400,000 records were fitted into a model in 6672 seconds achieving the accuracy of 2.78 and 2.12 kWh/m^2 for heating and cooling loads (4% of mean energy load values). Figure 5.6 shows the predicted (model estimation) vs actual (simulated) values of energy loads testing over 30,000 buildings. The error distributions are illustrated in Figure 5.7.

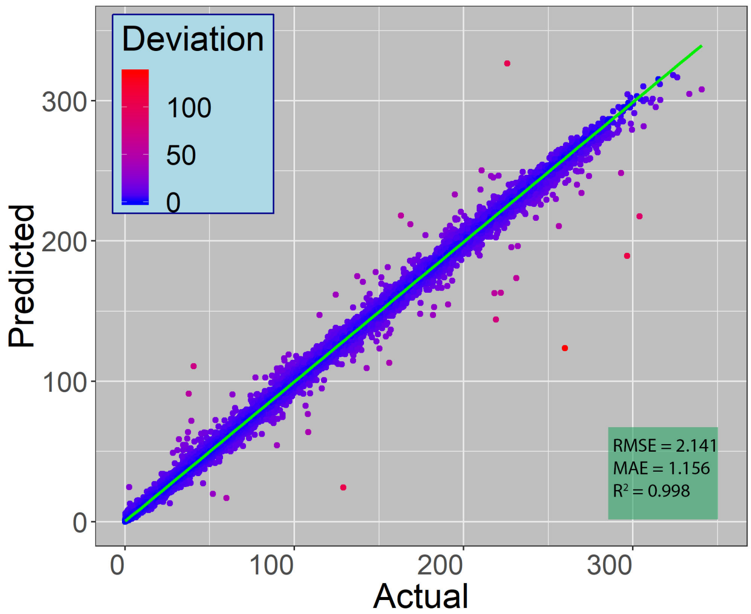
5.5 Feature Space Reduction

Due to the nature of RF models in training independent trees in which different feature set is selected, they are able to determine input variables importance in target estimation. This competency provides useful information in the analysis of the studied system. In this study, 30 RF models were fitted over 100,000 random building samples to generate a better empirical distribution of feature importance. Figure 5.8 illustrates the results of the sensitivity analysis of these RF models, which were configured based on the MOO algorithm outputs (best hyper-parameters set).

In comparison with the results from training two different models for each of heating and cooling loads (Chapter 4), it can be seen the important features in the model is a combination of those in two separate models (refer to Section 4.7). Moreover, the results indicated that prediction of heating loads mostly rely on building characteristics while cooling load forecasting depends on weather features. Here, the unimportant variables are 'avrh', 'avdni', 'iqrdni', 'iqrghi', 'medrh', 'sumdni', however, 'avghi' and 'sumghi', which had an insignificant

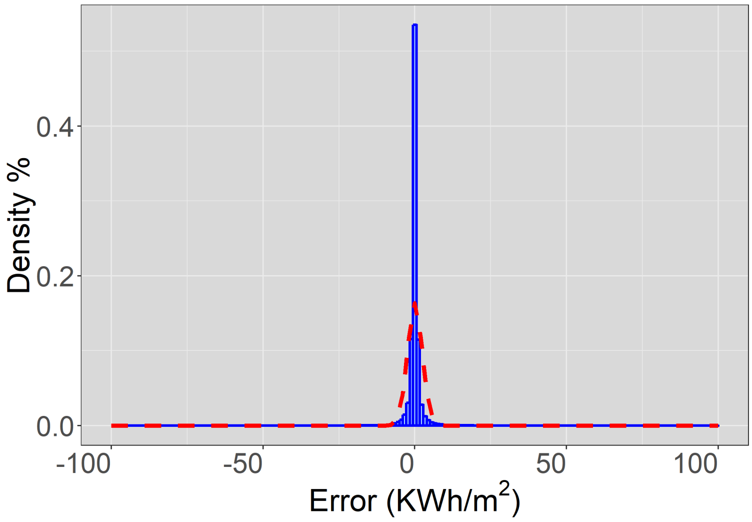


(a)

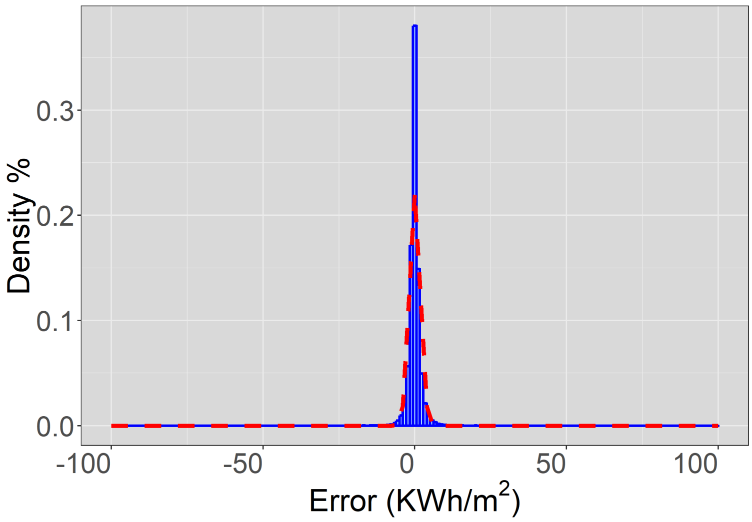


(b)

Figure 5.6: Actual and predicted (a) heating and (b) cooling using single optimised model.



(a)



(b)

Figure 5.7: Error distribution of (a) heating and (b) cooling loads prediction.

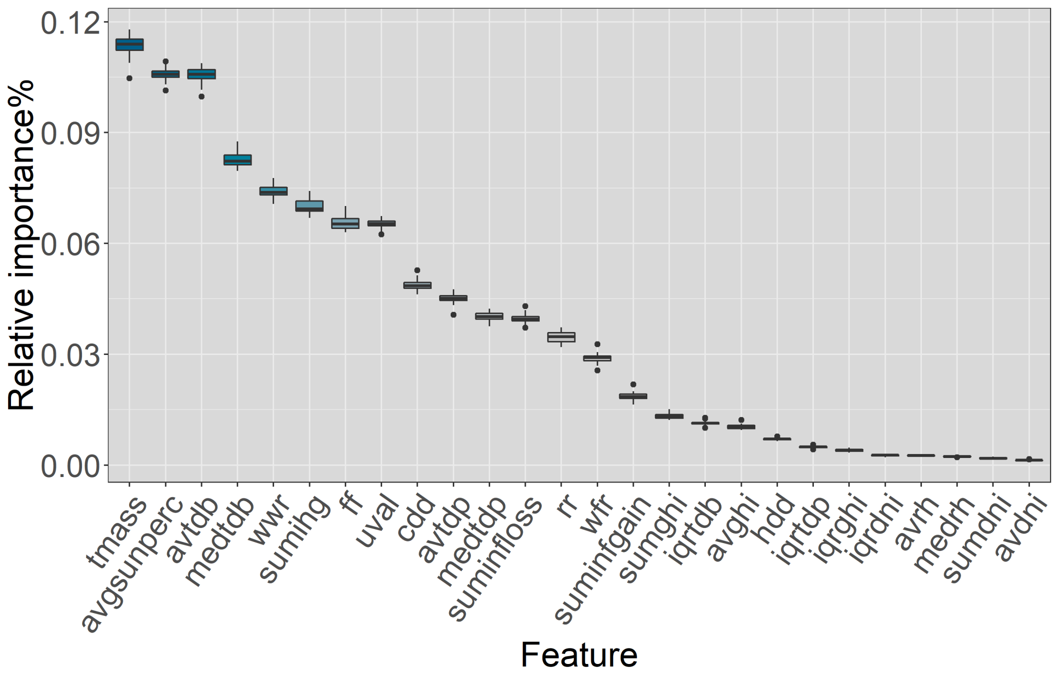


Figure 5.8: Importance of features for energy loads prediction using RF model.

impact on modelling cooling loads still play a considerable role in this model. Although the advanced machine learning can ignore unimportant features despite the traditional statistical modelling, removing those from the data can reduce the model time complexity and slightly increase the accuracy. Table 5.3 presents the results of testing the model by removing the identified features. It can be seen that the RMSE fluctuations of the folds are also reduced compared to the original model.

5.6 Summary

This chapter detailed Phase 3 of the study which addressed the issues regarding inaccurate modelling of building energy loads using ML techniques (RQ2). The latest attempt to enhance the performance of those ML models as shown in Chapter 4, included exhaustive exploration of variable parameters to

Table 5.3: Performance comparison of ML models including all features and removing unimportant ones.

Parameters	All inputs		Selected inputs	
	Heating	Cooling	Heating	Cooling
RMSE (kWh/m^2)	6.97±3.29	4.61±2.02	6.19±1.55	4.48±1.64
MAE (kWh/m^2)	2.54	2.36	2.44	2.22
R^2	0.992	0.993	0.993	9.993
Fit time (s)	64.16		57.12	
Test time (s)	0.51		0.49	

choose the best performing model. To achieve Objective 4, this phase has proposed a method based on MOO to expedite the process of selecting hyper-parameters, and simultaneously to optimise one single model for forecasting both heating and cooling loads. The main advantages of this method over traditional approaches include a reduction in the time complexity of creating reliable models and improvements in the accuracy of predictions by fine-tuning of the ML models. The method at each step of Genetic evolution, precisely selects/mutates model parameters, in contrast with the traditional approach where the parameters are defined based on the experience. The proposed approach was evaluated by implementing the random forest decision tree algorithm and testing the accuracy over a building data which was simulated using EnergyPlus. The effectiveness of the proposed approach was demonstrated through comparisons with conventional grid-search methods and traditional statistical modelling.

The finding of the study at this step revealed the potential of combining ML and AI optimisation (i.e. evolutionary MOO algorithm) for developing building energy models. By the increase in the amount of data, it is possible to generate more accurate models, however, handling big data and iterative training such massive data becomes cumbersome. Hence, the application of smart evolutionary algorithms becomes essential in dealing with complex data such as non-domestic buildings.

The next chapter is dedicated to describing the final phase of this study which is modelling non-domestic building energy performance, considering the recommendations from this chapter as well as Chapters 2 and 4 . After extracting the desired set of features, a GBRT model will be trained and optimised using state-of-the-art evolutionary algorithms to support decision-making in retrofit planning.

Chapter 6

Modelling Energy Performance of Non-Domestic Buildings

6.1 Introduction

Chapter 6 elaborates the last phase of the study, which develops an energy performance prediction model for the UK non-domestic buildings with the aid of ML techniques. The aim of the ML model is to provide a rapid energy performance calculation engine for assisting multi-objective optimisation of energy retrofit planning. The study in this phase lays out the process of model development from the investigation of requirements and feature extraction to the application on a case study. It also employs sensitivity analysis methods to evaluate the effectiveness of the feature set in covering retrofit technologies. The ML model is tuned using advanced evolutionary algorithms to reach its highest potential. The optimised model provides a robust and reliable tool for building engineers enabling them to enlarge the space of the possible technologies.

6.2 Building Energy Performance Modelling

Phases 2 and 3 of this study, which were elaborated in Chapters 4 and 5 proposed an appropriate ML model for building energy modelling and an intelligent approach to optimise the developed model. They also outlined recommendations on developing a feature set and analysis of their impact on the model. Based on the findings from previous phases, Figure 6.1 illustrates the procedure of research in the final stage.

Modelling whole building energy consumption or performance is more complicated than forecasting the loads for a single building, as it requires details of building characteristics rather than weather or occupancy information (refer to Chapter 2, Section 2.4).

Before applying an ML, it is required to transform the building raw data to a form to be amenable to learning. This procedure includes extracting meaningful input variables (features) from the available data. Each application requires specific considerations when applying this transformation. As the aim of this study was to provide a fast energy efficiency estimation tool for retrofit planning applications, it was essential to take all the available retrofit technologies into account. Hence, not only the model should produce accurate energy performance predictions, but also the effect of an alteration due to a single building upgrade should be considered. The features could be numeric or categorical, however, categorical variables are not preferable as they have to be converted to several binary variables which increases the feature space and consequently the time complexity.

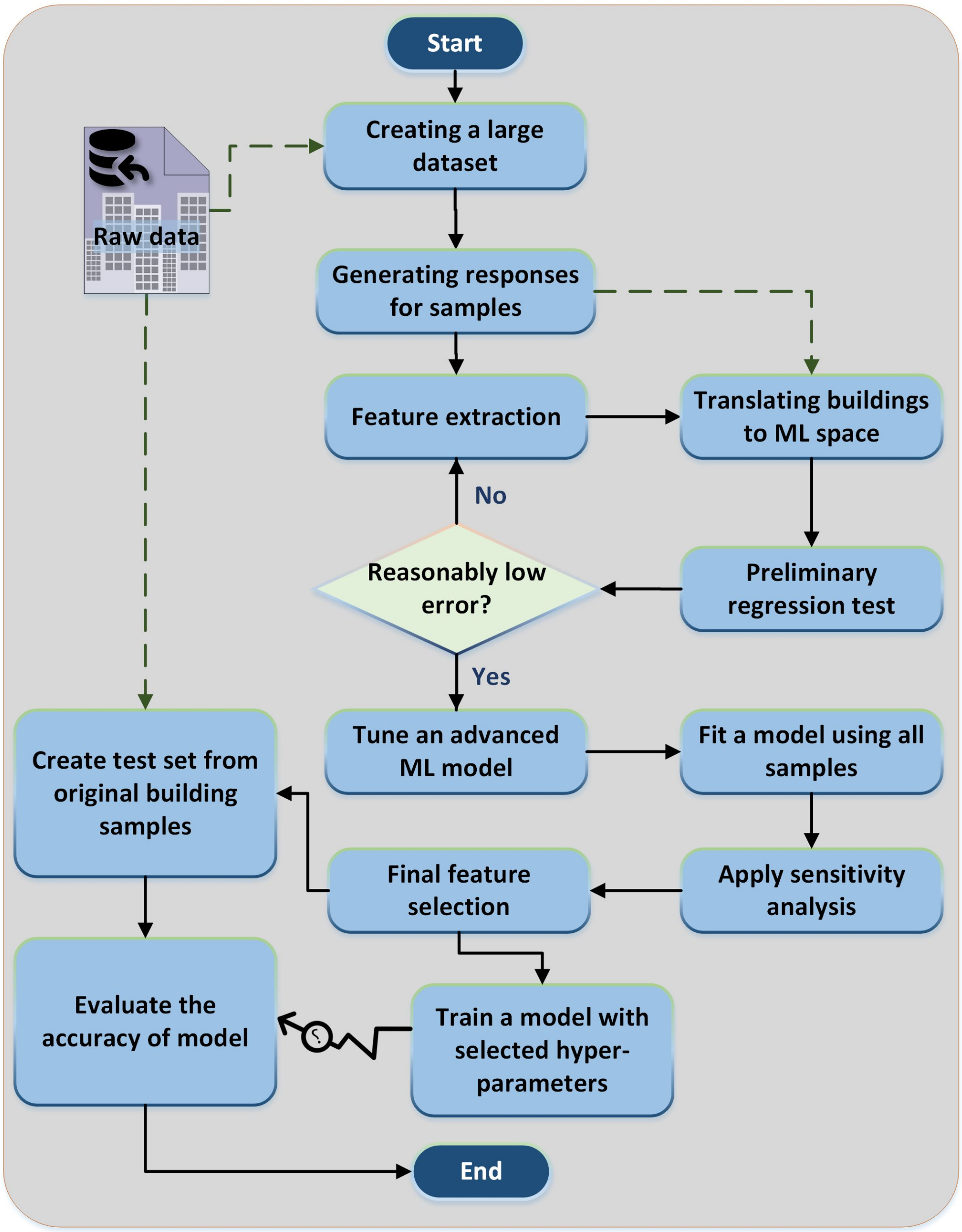


Figure 6.1: Specific setting and environment of the conducted usability tests.

When the features are selected, all data is transferred to the ML space. At this step training ML models is essential to evaluate the accuracy of predictions using the selected set of variables. Machine learning requires a reasonable amount of data, the more precise data, the more accurate the model. .

Based on the finding from phase 2, GBRT was selected as the main ML algorithm to train the model, however, in the preliminary steps of extracting features SVM was utilised. This research used Sequential Model-based Algorithm Configuration (SMAC) [235] for smart optimisation of the GBRT models.

6.3 Energy Performance Calculation

Building energy performance benchmarking has existed since the 1980s. Traditionally, these standards have provided the quality of the buildings in consuming energy against their similar peers. Therefore, the aim has been to inspire the owners to consume in a more efficient manner [71]. However, these schemes have been utilised voluntarily. Hence, there has been a necessity for a legal framework to exert the potential of the benchmarking in reducing energy consumption and consequently, carbon emissions.

The EPC and DEC programs were adopted in the UK to satisfy EPBD requirements. Even though both programs geared towards increasing the energy performance of non-domestic buildings, they are different from in what concerns the developed methods.

The EPC scheme is developed to express the energy-efficiency of buildings regarding their asset ratings which are calculated using simulations. These ratings indicate the carbon emissions of a building which is used under standard conditions. Therefore, EPCs aim at the performance assessment of buildings concerning their fabric and services [236]. DECs, on the contrary, are certificates which denote the efficiency of the energy usage of a building when it is occupied. The principal distinction from the EPC is that operational ratings in this scheme are calculated based on the actual energy consumption, meaning that DECs display how, in reality, energy is consumed by occupants. The certificate also includes the inefficient uses of the energy [236]. Hence DECs encourage the occupants to behave in a more energy-efficient manner.

The operational ratings are calculated by comparing the carbon emissions of the building with the benchmark building. The benchmark indicates the typical performance of similar buildings and can be notional or actual [237].

$$\begin{aligned} &Operational\ Rating = \\ &\qquad \frac{Acual\ building\ emissin\ rate\ (kgCO_2/m^2/)}{Adapted\ energy\ benchmark\ (kg/m^2/year)} \times 100 \end{aligned} \tag{6.1}$$

Asset ratings for EPCs are produced based on the government's Standard Assessment Procedure (SAP) for new buildings. In the case of existing buildings, both the operational rating reflecting the actual energy usage and the asset rating, based on the reduced-data SAP, are applied. Asset rating is calculated as:

$$EPC\ Rating = \frac{Acual\ building\ emissin\ rate\ (kgCO_2/m^2/)}{Standard\ emissin\ rate\ (kgCO_2/m^2/year)} \times 50 \tag{6.2}$$

The Standard Emission Rate (SER) is determined by applying a fixed improvement factor to the emissions from a reference building. EPCs are intended to send market signals about the relative performance of comparable buildings, and so it is necessary that the notional reference building should be the same for all buildings of a given type. The reference building specifications introduced in 2015 are assigned based upon the servicing strategy identified for each zone within the proposed building. There are therefore two reference building specifications for: a) Heated and naturally ventilated zones, and b) Heated and mechanically ventilated or heated and cooled zones [238].

The 'reference building', is a version of the actual building modified in accordance with rules relating to glazing area, insulation and system efficiency. Each space must contain the same activity as proposed for the equivalent space in the actual building. The reference building is also subject to the standard operating conditions, and it is created within the Building Research Establishment (BRE) Simple Building Energy Model (SBEM) tool. Both actual and reference buildings have monthly heat balances performed for standard weather data appropriate to the building location. Results are automatically fed into the BRUKL compliance calculator provided by BRE.

The energy performance standards of the reference building are based on a concurrent specification that delivers a 43% reduction in CO2 emissions relative to the 2010 energy performance standards based on an assumed build mix. This means that the emissions target for some buildings will improve by more than this percentage, others by less [238].

The operational energy performance and asset ratings are displayed in terms of seven-letter ranks, from A (the lowest number, the best) to G (the worst). It can be seen in equation (6.2) that a building with an energy consumption similar to the typical performance of buildings in that class will get an operational rating of 50, i.e. between the grades D and E (refer to Figure 6.2).

The DEC program initially required non-domestic public buildings with a floor area larger than $1000m^2$ to produce and display the rating in a noticeable location in the building. The floor area threshold was reduced to 500 m^2 in 2013 and then to $250m^2$ in 2015 [239].

In order to satisfy the requirements set out by EPBD, targeting both new and

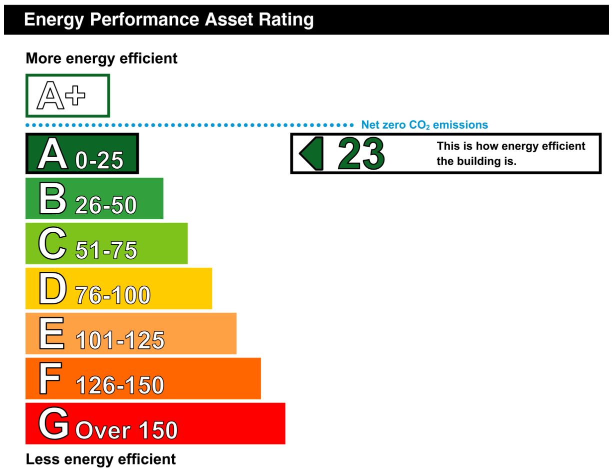


Figure 6.2: The UK energy performance certificate for non-domestic buildings.

existing buildings in the UK, the Royal Assent granted the Energy Act 2011. The act presents the provision for energy efficiency rules, especially focusing on leased properties, as two-thirds of non-domestic buildings are rented. The act makes it illegal to lease out the building if it does not meet the Minimum Energy Efficiency Standards (MEES). The minimum EPC rating is ‘E’ which came in to force in April 2018 for new leases and in April 2020 for existing leases [6]. The owners of buildings with EPC of ‘F’ or ‘G’ would not be able to lease their properties unless amendments are done, or an exemption applies. The main exception is related to the economic efficiency of the improvements, which is assessed using the viability test. This test for non-domestic buildings implies that the selected retrofit works should not be higher than the energy bill savings for seven years. However, selecting a cost-effective retrofit plan is challenging and demands for computer optimisation algorithms to search for the possible combinations of technologies. This issue becomes more dominant for complex and large scale non-domestic buildings.

Leases for less than six months or over ninety-nine years are also exempted from the rule. Another exemption is when the necessary improvement works reduce the value of the property by five per cent. Specific buildings with characteristics that could be altered in the process (e.g. historical buildings) are also expected to be excluded from the regulations.

As mentioned earlier, over 15% of UK's non-domestic stock possesses EPC ratings of 'F' or 'G', while 20% are rated 'E'. Nevertheless, further research suggests that the number of non-compliant properties might increase if the calculation method for EPCs is updated with the recently proposed modifications [42, 240]. Accordingly, sustainability must not be neglected by commercial property landlords and investors.

In 2018, most investors in building sector became concerned about the EPC ratings, as poor rating influences the investment value of their property asset. As a result, commercial landlords are facing billions of pounds costs to bring their properties up to legal energy performance standards.

The EPC calculation tool for non-domestic buildings in the UK is SBEM which is a quasi-steady state based developed by the BRE for implementing national calculation methods. SBEM employs a non-graphical MS Access based interface (iSBEM) for creating data input. Apart from the highly time-consuming input method, it is mainly restricted by the incompetence of the calculation method to model complicated HVAC systems [236].

The challenges mentioned above have led to the authorisation of the approved third-party software tools possessing the capacities to fulfil the modelling needs with functional complexities of non-domestic buildings [241]. SBEM front end interfaces (FI-SBEM) and Dynamic Simulation Modelling

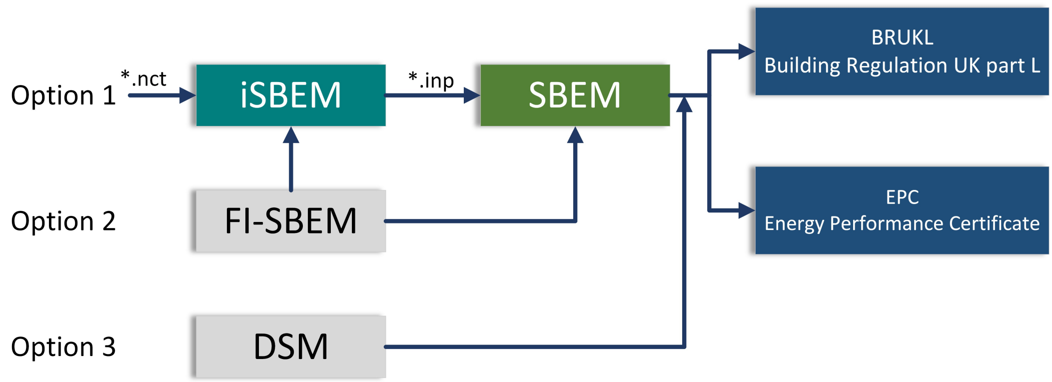


Figure 6.3: The UK building energy assessment tools options.

(DSM) tools are the two permitted primary classes [236]. FI-SBEM includes DesignBuilder, Design Database, G-iSBEM, LifespanSBEM and Virtual Environment with the capability to produce EPCs. DSM approved software are TAS, Virtual Environment and DesignBuilder [68]. These options are depicted in Figure 6.3.

6.4 Model Parameter Fine-tuning

The importance of ML hyper-parameter optimisation forecasting building energy has been highlighted in the Phases 2 and 3 per presented in Chapters 4 and 5. The traditional method for tuning ML models has been the exploration of all possible configurations of model parameters using grid search (Section 4.2). However, this method can be extremely laborious for complex models as ANN and GBRT for they have many parameters to be tuned. Phase 3 used a multi-objective optimisation based on genetic algorithm (GA) to tune model for accurate estimation of cooling and heating loads at the same time (Section 5.2.1). In this phase, as the aim is to model only energy performance of buildings (building emission rate), a simpler evolutionary algorithm namely sequential model-based algorithm configuration (SMAC) [235] was employed for

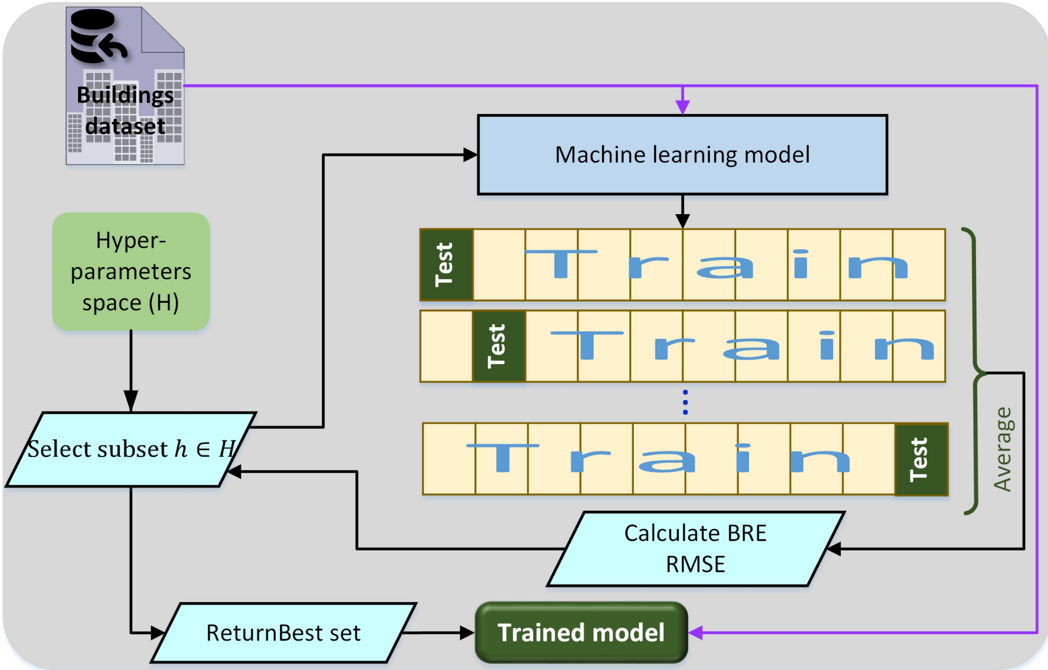


Figure 6.4: Diagram of hyper-parameter optimisation method for modelling buildings BER.

smart optimisation of the ML models.

Figure 6.4 illustrates the mechanism of tuning algorithm coupled with cross-validation testing. First, the possible space for all hyper-parameter going under optimisation is defined. Next, the algorithm starts with the specified default values and sends it to the evaluation function to build a model for BER prediction. It then continues based on the evaluated RMSE and smartly creates new configurations. Finally, it stops when the number of iterations reaches the maximum value, which i.e. 800 in this case. Whereas, using the grid search method, the number of repetition would be around 3,500. As mentioned in the previous chapter, smart ML optimisation not only reduces the time complexity but also allows for the selection of precise tuning.

6.5 Feature Engineering

Ng [242] defines feature engineering as follows:
"*Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work. Feature engineering is fundamental to the application of machine learning and is both difficult and expensive. The need for manual feature engineering can be obviated by automated feature learning.*"

For an ML algorithm to predict with high performance, the most explicit and deepest relationship of data details should be exposed to it in the form of features. For the building energy performance modelling, it requires strong expertise in building physics and retrofit technologies on one side, and creative feature extraction methods on the other side to interpret this knowledge into useful features.

Feature engineering is not a one-step procedure, but several processes are iterated until the satisfactory result is achieved. Figure 6.6 demonstrates the life cycle of feature engineering which is adopted in this study.

Firstly, the raw data, including several thousands of non-domestic records, are collected. Then, potential features related to building characteristics are selected. This also includes combining datasets from different building energy data to generate unique and independent features. Next, statistical analysis is performed to evaluate the impact of derived features. This step consists of an investigation of data to identify potential outliers and correlation analysis. The subsequent stage, which is very important to achieve the main objective of this study, is engineering new features. In this step, it is essential to consider retrofit

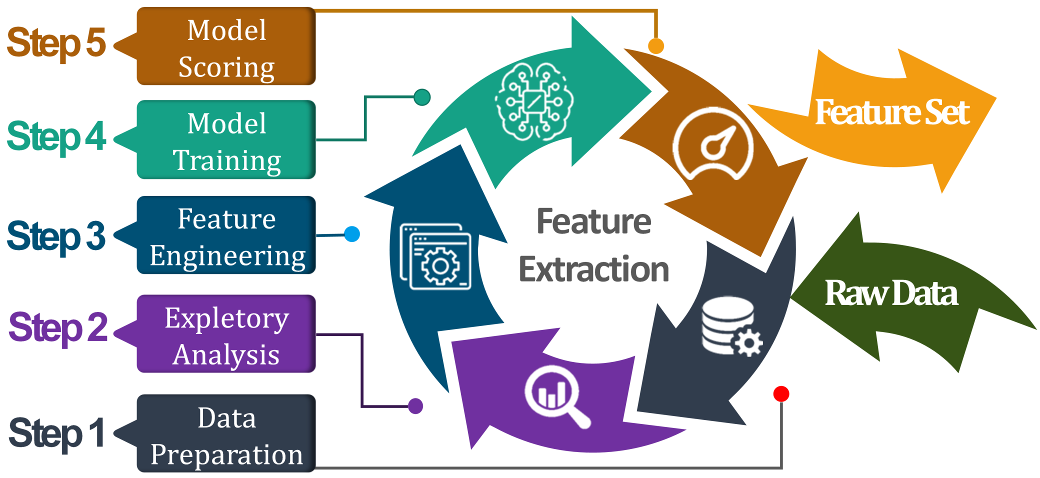


Figure 6.5: Feature extraction circular procedure.

technologies to be covered by the variables, as the aim of this study is not only to accurately predict energy performance but also to effectively support retrofit DM. This process is, therefore, for creating new features from existing variables based on knowledge on retrofit planning and energy performance calculations. It also includes translating categorical variables to the ML model usable form. When the final feature set is decided, a model is trained over it and then scored using the evaluation method, which was described earlier in this chapter. All these steps are repeated until the model performance is satisfactory.

6.5.1 Data Engineering

The studied data was collected from arbnco company's arbn consult platform [243] which consists of 4,900 records related to non-domestic buildings distributed all over the UK. All of these records were assessed and labelled using the latest version of SBEM software considering the most up-to-date regulations (as discussed in Section 6.3). The buildings detail are submitted as ".inp" files by assessors, engineers or owners. These files includes the detail of building type, building geometry, construction, use, HVAC and lighting equipment. Despite EnergyPlus input files that are nested based on geometric zones, SBEM files are assorted by HVAC zones. These zones are categorised into unconditioned and conditioned. The latter can be heated, cooled, ventilated or mix of them. unconditioned or conditioned The files then went through a whole building energy simulation, and the BER was calculated. The Standard Emission Eate (SER) was also derived for a notional building. The EPC is calculated based on these rates using Eq. 6.2. This study aimed at developing an accurate and fast prediction model for building BER.

It should be noted that in the UK the SBEM versions for buildings located in Scotland and England. The differences are related to consideration of the reference building and derivation of EPC from the calculated BER values. A building in England may appear to be more energy-efficient than that same building in Scotland due to the comparison to different reference buildings. However, this study targeted prediction of the BER to be able to take advantage of the vast dataset all around the UK. When the BER is estimated with a simple formula EPC can be derived for England and Wales or Scotland.

From these records, around 80,000 samples were mutated using possible alterations to create a large dataset to train a robust and general model. Most of these mutated buildings have better energy performance than their original versions. The method is advantageous for this study, as it aims at creating a model most suitable for predicting energy efficiency of potential retrofitted versions of a building to be used in an optimisation process. All mutated buildings were then evaluated using the software and recorded with their assessed BER values.

Details of the distribution of buildings categorised in different usage type and weather locations are presented in Appendix B.

6.6 Feature Engineering

Ng [242] defines feature engineering as follows:
"*Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work. Feature engineering is fundamental to the application of machine learning and is both difficult and expensive. The need for manual feature engineering can be obviated by automated feature learning.*"

For an ML algorithm to predict with high performance, the most explicit and deepest relationship of data details should be exposed to it in the form of features. For the building energy performance modelling, it requires strong expertise in building physics and retrofit technologies on one side, and creative feature extraction methods on the other side to interpret this knowledge into useful features.

Feature engineering is not a one-step procedure, but several processes are iterated until the satisfactory result is achieved. Figure 6.6 demonstrates the life cycle of feature engineering which is adopted in this study.

Firstly, the raw data, including several thousands of non-domestic records, are collected. Then, potential features related to building characteristics are selected. This also includes combining datasets from different building energy data to generate unique and independent features. Next, statistical analysis is performed to evaluate the impact of derived features. This step consists of an

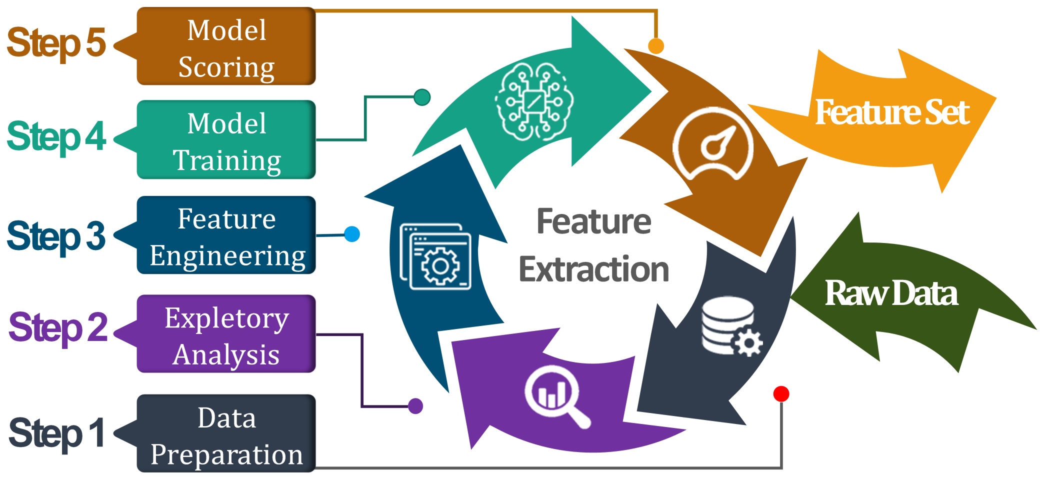


Figure 6.6: Feature extraction circular procedure.

investigation of data to identify potential outliers and correlation analysis. The subsequent stage, which is very important to achieve the main objective of this study, is engineering new features. In this step, it is essential to consider retrofit technologies to be covered by the variables, as the aim of this study is not only to accurately predict energy performance but also to effectively support retrofit DM. This process is, therefore, for creating new features from existing variables based on knowledge on retrofit planning and energy performance calculations. It also includes translating categorical variables to the ML model usable form. When the final feature set is decided, a model is trained over it and then scored using the evaluation method, which was described earlier in this chapter. All these steps are repeated until the model performance is satisfactory.

6.6.1 Feature Extraction

Extracting features for modelling building energy indices is dependant on the several parameters including prediction period (hourly, monthly, annually, etc.), target (electricity, cooling, heating or whole building demand) and the studied case (i.e. investigating one case or a group of records). Short-term predictions normally aim at modelling single cases and involve few features mostly weather related and in some instances the calendar nominal attributes (refer to Section 2.4). However, when dealing with the whole building energy performance simulations, a high number of variables should be taken into account. In this research stage, as the focus has been to aid retrofit optimisation, it was essential to ensure that every possible alteration would be reflected by one or multiple variables in the model. Hence, before defining the ML input space, the potential retrofit technologies were identified.

Table 6.1 presents the available retrofit recommendations to improve energy performance of non-domestic stock in the UK.

6.6.2 Input Feature Selection

In this phase, to check the significance of the selected variables in the regression model, the trained GBRT model itself was used to determine what features are more important.

The permutation importance was also employed, in which the number of random shuffles for each feature was set to 50, which made the total number of model evaluations to 2,200. Although this technique is computationally expensive, it is a useful complement of GBRT importance method, especially in identifying inflated values (for the detail of these methods, please refer to Section 3.5.7).

Table 6.1: Available retrofit recommendations for EPC rating improvement

Code	Description
C2	Modify the seasonal and nominal efficiency properties of comfort cooling plant to mimic the replacement of existing chiller with a system compliant with the building regulations as defined in non-domestic building services compliance, guide 2013 (NDBSC-2013), Section 9.
E2	Modify the roof thermal properties to mimic the effect of insulating the roof in accordance with Approved Document L2B: Conservation of fuel and power in existing buildings other than dwellings. Section 5, Retaining thermal elements
E4	Modify envelope thermal properties of cavity walls to mimic the effect of insulating the cavity in accordance with Approved Document L2B: Conservation of fuel and power in existing buildings other than dwellings. Section 5, Retaining thermal elements
E8	Modify the glazing thermal properties to mimic the effect of replacing existing glazing in accordance with Approved Document L2B: Conservation of fuel and power in existing buildings other than dwellings. Section 4, Work on controlled fittings and services
H1	Modify low-temperature hot water boilers' system seasonal energy efficiency to replicate the replacement of inefficient buildings as per NDBSC-2013 Section 2 Gas, oil and biomass-fired boilers
H7	Modify the heating system to mimic the installation of an optimum start/stop controller to the heating system as per the heating efficiency credits system outlined in NDBSC-2013, Section 3: Gas, oil and biomass-fired boilers
H8	Modify the heating system to mimic the installation of weather compensation systems to the heating system as per the heating efficiency credits system outlined in NDBSC-2013, Section 3: Gas, oil and biomass-fired boilers
L2	Modify zonal lighting system properties for zones with Tungsten or Halogen filament lamps to mimic a like-for-like replacement with high-efficiency lamps in accordance with NDBSC-2013, Section 12: Lighting

Table 6.1 (cont.) Available retrofit recommendations for EPC rating improvement.

Code	Description
L5	Modify zonal lighting system properties for zones with T8 fluorescent tube light to mimic a like-for-like replacement with high-efficiency T5 fluorescent tubes in accordance with NDBSC-2013, Section 12: Lighting
L8	Modify zonal lighting system properties for zones with T12 fluorescent tube light to mimic a like-for-like replacement with high-efficiency T5 fluorescent tubes in accordance with NDBSC-2013, Section 12: Lighting
R5	Modify or create a HVAC whose heating and comfort cooling demand are served by an air source heat pump in accordance with NDBSC-2013, Heat pumps
V1	Modify the g-value of glazing systems to mimic the application of solar control film to all transparent surfaces
W1	Modify the existing domestic hot water system to mimic the installation of a high-efficiency version in accordance with NDBSC-2013, Section 8: Domestic hot water
W2	Modify the centralised domestic hot water systems to mimic replacing the systems with instantaneous point of use systems.
W3	Replace or install domestic hot water cylinder jacket in accordance with NDBSC-2013, Section 8: Domestic hot water
MTR	Improve the building metadata to reflect the nominal energy consumption benefits of installing sub-metering
AFM	Modify existing air handling unit efficiencies to mimic the installation of a high-efficiency system in accordance with NDBSC-2013, Section 10: Air distribution
AHR	Modify the existing mechanical ventilation system to mimic the installation of a high-efficiency rotary heat exchanger in accordance with NDBSC-2013, Section 10: Air distribution
DSF	Modify the properties of zones with high ceilings to mimic the installation of destratification fans.
FC	Modify the energy efficiency properties of existing fan-coil units to mimic the installation of high-efficiency units in accordance with NDBSC-2013, Section 1.7: Summary of recommendation minimum energy efficiency standards

Table 6.1 (cont.) Available retrofit recommendations for EPC rating improvement.

Code	Description
RAD	Modify existing convection heating systems in industrial and warehouse areas with a ceiling-mount radiant heating system in accordance with NDBSC-2013 Section 5: Gas and oil-fired radiant heaters.
VSD	Modify existing low-temperature hot water boilers to mimic the installation of variable speed pumps.
WET	Modify existing direct electric heating systems with a high-efficiency wet radiator system served by a low-temperature hot water boiler in accordance with NDBSC-2013, Section 2: Gas, oil and biomass-fired boilers
8LO	Modify zonal lighting system properties for zones with T8 fluorescent tube light to mimic a lamp-luminaire replacement with high-efficiency T5 fluorescent tube systems in accordance with NDBSC-2013, Section 12: Lighting
DLD	Mimic the installation of photoelectric daylight dimming controls
HLU	Modify zonal lighting system properties for zones with Tungsten or Halogen filament lamps to mimic a lamp-luminaire replacement with high-efficiency systems in accordance with NDBSC-2013, Section 12: Lighting
HPL	Modify zonal lighting system properties for zones with High Pressure Sodium or High-Pressure Mercury to mimic a lamp-luminaire replacement with high-efficiency systems in accordance with NDBSC-2013, Section 12: Lighting
HPT	Modify zonal lighting system properties for zones with T5 fluorescent tubes to mimic a lamp-luminaire replacement with high-efficiency systems in accordance with NDBSC-2013, Section 12: Lighting
PIR	Modify zonal lighting system properties to mimic the installation of passive infrared occupancy sensors.
T8L	Modify zonal lighting system properties for zones with T8 fluorescent tubes to mimic a lamp-luminaire replacement with high-efficiency systems in accordance with NDBSC-2013, Section 12: Lighting

6.7 Evaluation of Energy Performance Model

6.7.1 Extracted Features

The procedure of selecting the features for modelling energy performance was conducted by iterative processes, as explained earlier in 6.6. Based on recommendations from findings of Phase 2 presented at Section 4.5, the primitive models for evaluation of generated input set were trained and tested using SVM. At each iteration, new features were defined and the function for extracting them from building ".inp" files were formulated, some uninfluential variables were removed, or some with certain effects (based on the building physics knowledge) were recalculated/modified.

Table 6.2 shows the final extracted features from buildings characteristics available in logged assessment files and their description. Most of these variables are calculated, and some are directly taken from the input models. Column "Calculation" in Table 6.2 explains the formulation of those derived features. "Mutable" column determines if a feature is changeable, and if so the recommendations that affects the variable is shown in the last column, "Covered solutions". The complex features and their calculation methods are elaborated in Appendix C.

Figure 6.7 illustrates the frequency of features as histogram graphs. The correlation between each pair of input and target variables is demonstrated using heatmap matrix in Figure 6.8.

Table 6.2: Features extracted for training BER prediction model

Feature	Description	Calculation	Mutable	Covered solutions
SER	Standard emission rate	Calculated from initial SBEM run for a notional building	No	-
DHW_Dem	Domestic hot water demand	DHW system demand normalised by area	Yes	W1, W2, W3, VSD
U_Trans	Equivalent U-value of the transparent part of the external surface (windows)	(window) area-weighted average of the U-values of individual external windows	Yes	E8
ST_ExW	Equivalent solar transmittivity of the external windows	(window) area-weighted average of the solar transmittivity of individual external walls	Yes	E8, V1
U_Opaq	Equivalent U-value of the opaque part of the external surfaces (walls)	(wall) area-weighted average of the U-values of individual external walls	Yes	E4
WWR	Window to wall ratio	Ratio of total window area to total wall area	No	-
SFP_Vent	Specific fan power, ventilation, terminal units and exhaust (terminal unit energy demand)	One value per HVAC system	Yes	FC, AFM, AHR
PL_H	Peak load of heating demand	Heating system design peak load (kW)	Yes	V1, E4

Table 6.2 (cont.) Features extracted for training BER prediction model

Feature	Description	Calculation	Mutable	Covered solutions
AIR	Air Infiltration Rate	Annual sum of energy gained due to infiltration normalised by area	Yes	H1, H7, H8, R5, MTR, RAD, WET, DSF
IGC	Internal gain from equipment for cooling spaces		No	-
LPD	Lighting power density		Yes	8LO, DLD, HLU, HPL, HPT, PIR, T8L, L2, L5, L8
SR_H	Heated space ratio	Ratio of total heated space to total space	No	-
SR_C	Cooled space ratio	Ratio of total cooled space to total space	No	-
SR_Vent	Ventilated space ratio	Ratio of total ventilated space to total space	No	-
SR_UC	Unconditioned space ratio	Ratio of total unconditioned space to total space	No	-
VSR_diab	Internal diabatic vertical surfaces ratio	Ratio of total internal diabatic vertical surface area to total area of all vertical surfaces	No	-

Table 6.2 (cont.) Features extracted for training BER prediction model

Feature	Description	Calculation	Mutable	Covered solutions
VSR_adia	Internal adiabatic vertical surfaces ratio	Ratio of total internal adiabatic vertical surface area to total area of all vertical surfaces	No	-
VSR_ext	External vertical surfaces ratio	Ratio of total external vertical surface area to total area of all vertical surfaces	No	-
IHG	Internal heat gain	Annual sum of Internal gain from equipment for heated spaces normalized by area	Yes	8LO, DLD, HLU, HPL, HPT, PIR, T8L, L2, L5, L8, E2, E4, E8, H1, H7, H8, R5, MTR, RAD, WET
WFR	Wall to floor ratio	Ratio of total walls area to total floor area	No	-
RWR	Roof to wall ratio	Ratio of total roof area to total wall area	No	-
ICO	Heat transfer from conditioned to unconditioned spaces		No	-
ECS	Efficiency of cooling system		Yes	C2
EHS	Efficiency of heating system	Weighted heating area adjusted by fuel emissions factor	Yes	VSD, R5, WET, RAD

Table 6.2 (cont.) Features extracted for training BER prediction model

Feature	Description	Calculation	Mutable	Covered solutions
I_N	Solar radiation on the cumulative North-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_S	Solar radiation on the cumulative South-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_W	Solar radiation on the cumulative West-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_E	Solar radiation on the cumulative East-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_SE	Solar radiation on the cumulative SE-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_NE	Solar radiation on the cumulative NE-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_SW	Solar radiation on the cumulative SW-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_NW	Solar radiation on the cumulative NW-facing external surface in zones with heating (unit insolation multiplied by area)		No	-
I_H	Solar radiation on the roof (unit insolation multiplied by area)		No	-
I_VC	Solar irradiance, vertical surfaces in cooled spaces (direct +diffuse solar gains peak July)		Yes	E2
I_VH	Solar irradiance, horizontal surfaces in heated spaces (Direct +diffuse solar)		Yes	E2

Table 6.2 (cont.) Features extracted for training BER prediction model

Feature	Description	Calculation	Mutable	Covered solutions
CI_N	Average irradiance on North facing surface for cool zones		No	-
CI_S	Average irradiance on South facing surface for cool zones		No	-
CI_W	Average irradiance on West facing surface for cool zones		No	-
CI_E	Average irradiance on East facing surface for cool zones		No	-
CI_SE	Average irradiance on SE facing surface for cool zones		No	-
CI_NE	Average irradiance on NE facing surface for cool zones		No	-
CI_SW	Average irradiance on SW facing surface for cool zones		No	-
CI_NW	Average irradiance on NW facing surface for cool zones		No	-

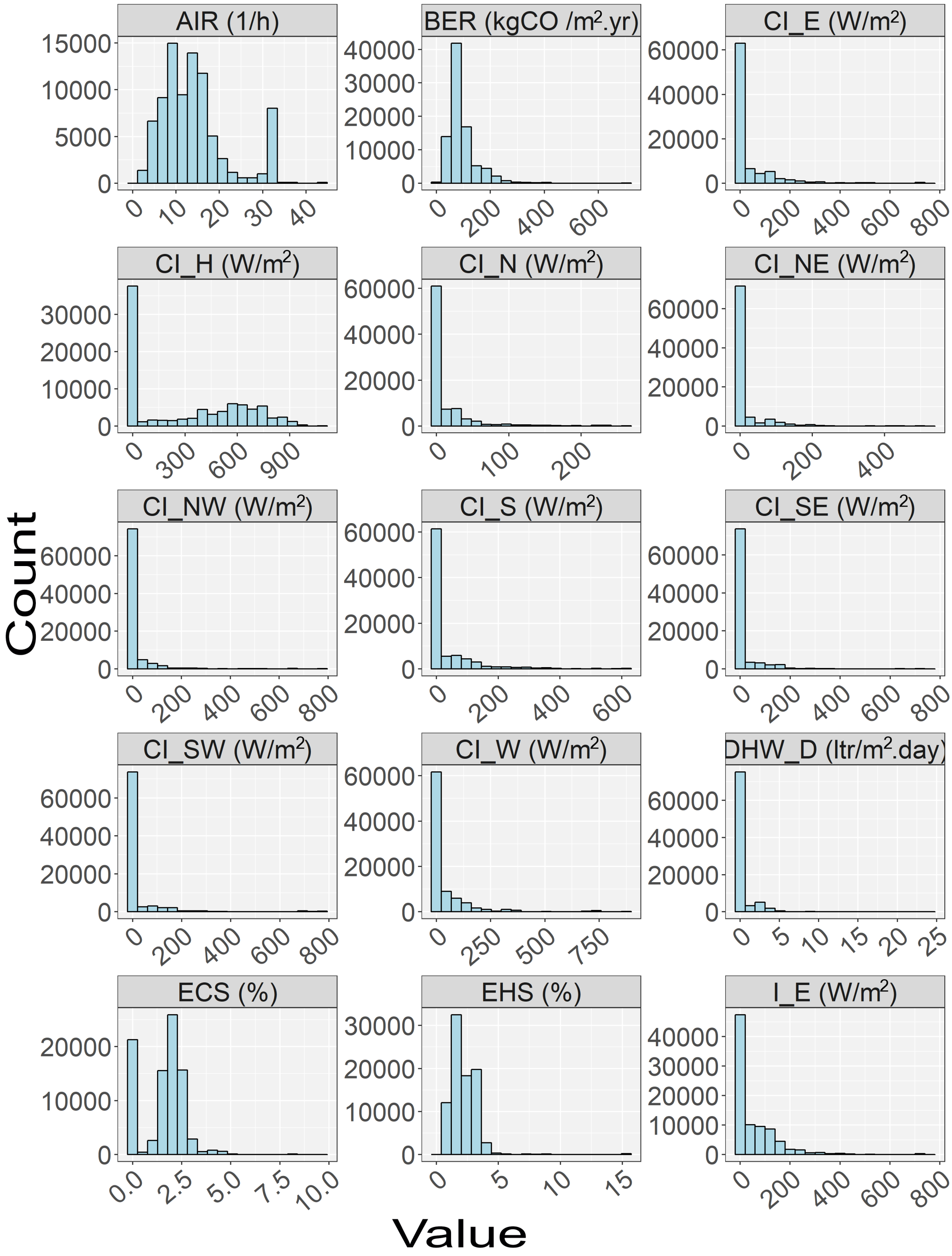


Figure 6.7: Distribution of the selected features for building energy data.

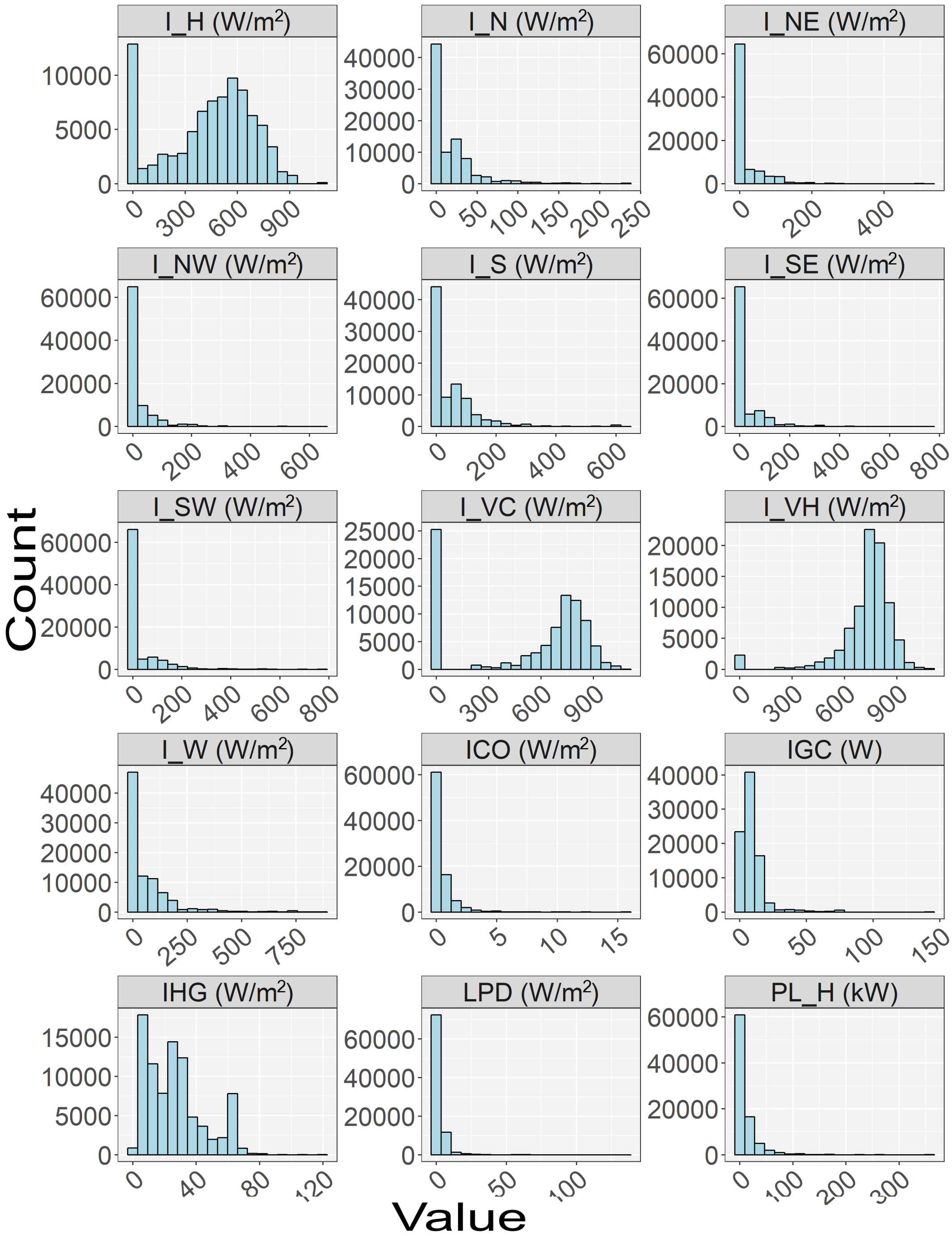


Figure 6.7 (cont.) Distribution of the selected features for building energy data.

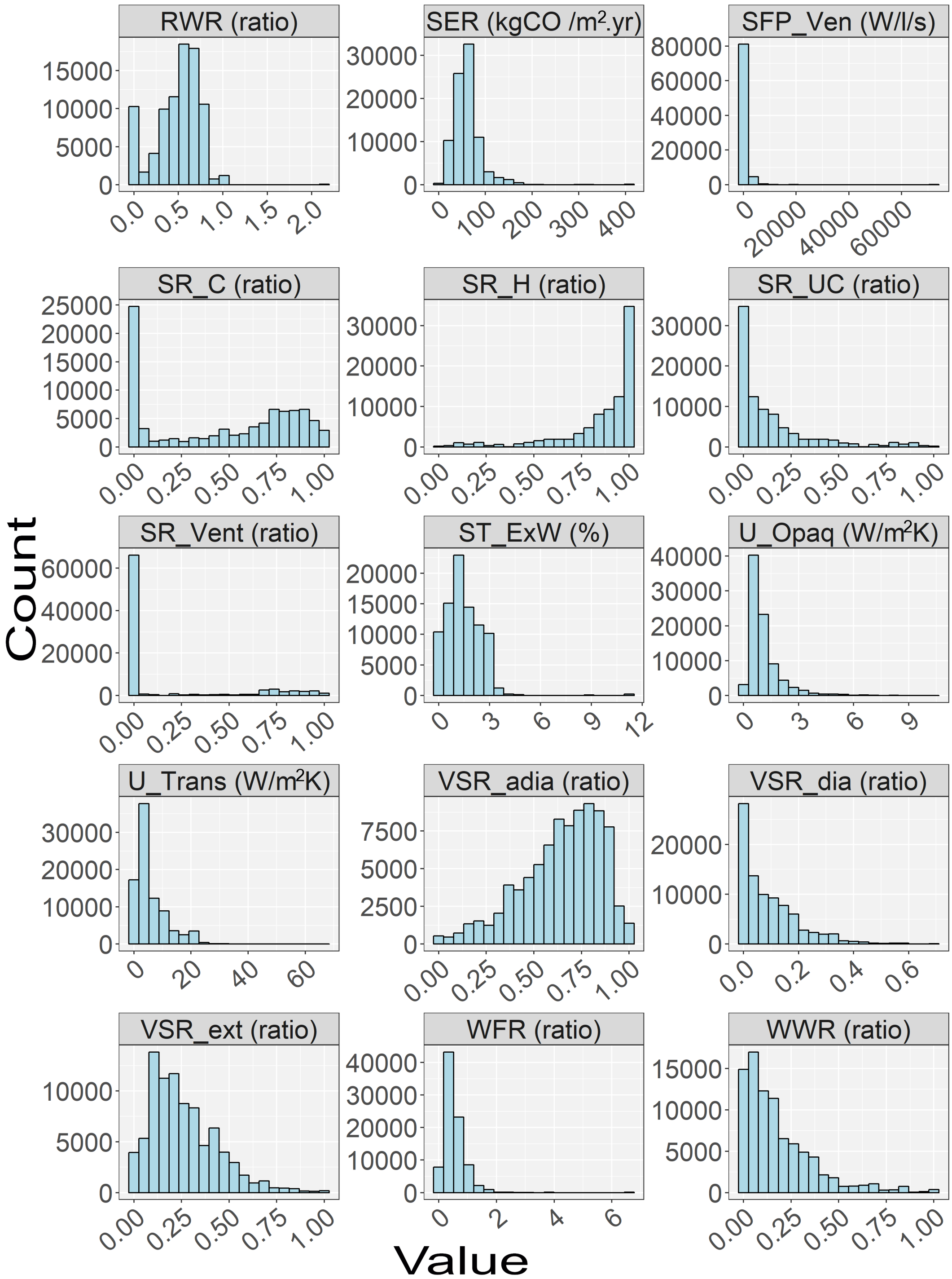


Figure 6.7 (cont.) **Distribution of the selected features for building energy data.**

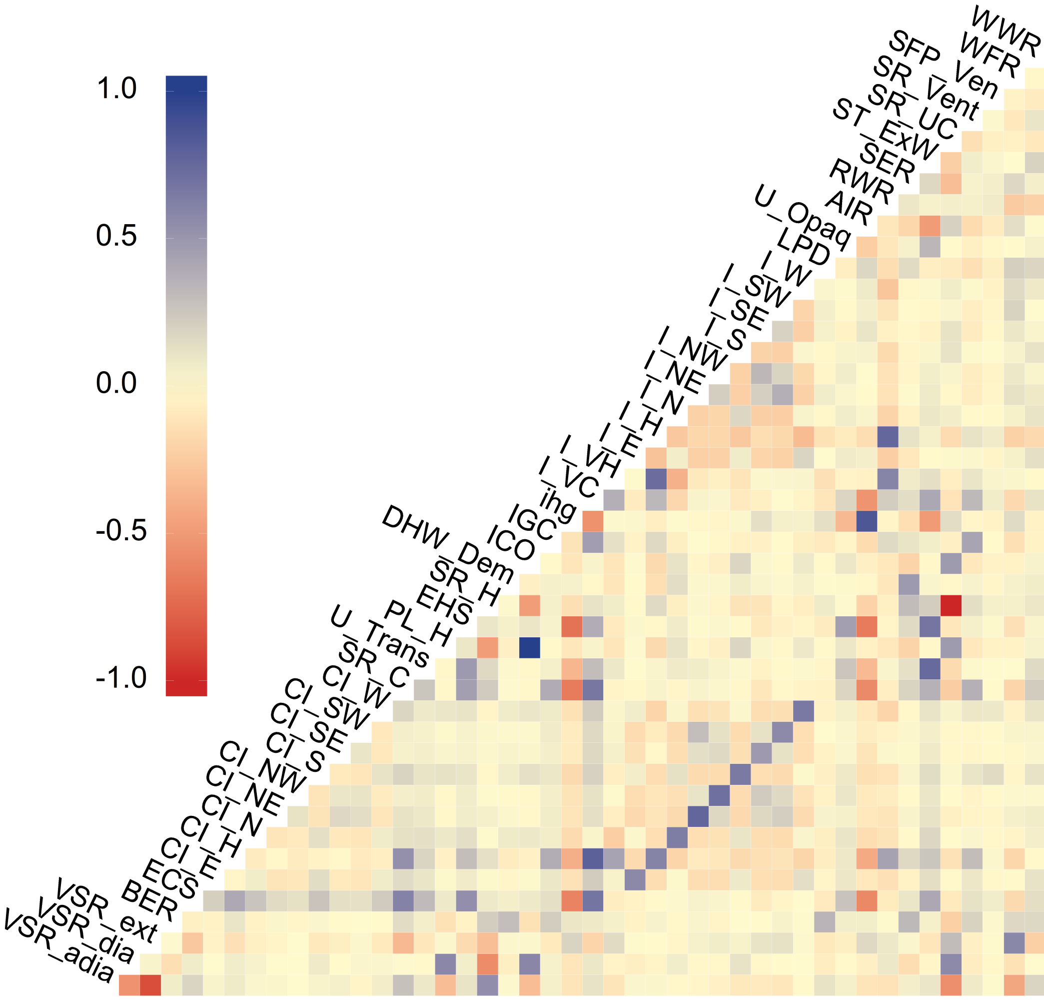


Figure 6.8: Non-domestic building data features values represented as a heat correlation map.

As depicted in Figure 6.8, there are no direct correlations between the selected variables and BER. It is not also possible to evidently identify which variable can be removed without affecting the model precision.

6.7.2 Model Optimisation

As mentioned before, an ML model was optimised using the generated as well as actual data. To this end, 5,000 records were randomly selected, and the

GBRT model was tuned using SMAC algorithm over that set. Here, this research phase used a five fold-cross validation for evaluating the performance of each model configuration. The tuning algorithm output after 1,000 iterations was the hyper-parameter set with which the model reached the RMSE accuracy of 7.01 CO_2Kg/m^2 (mean RMSE of all folds). Next, the same configuration was used for modelling variant number of records up to 80,000. Each model was tested using 10-fold cross-validation , and the results were recorded as the worst, average and best RMSE of all folds, as demonstrated in Figure 6.9.

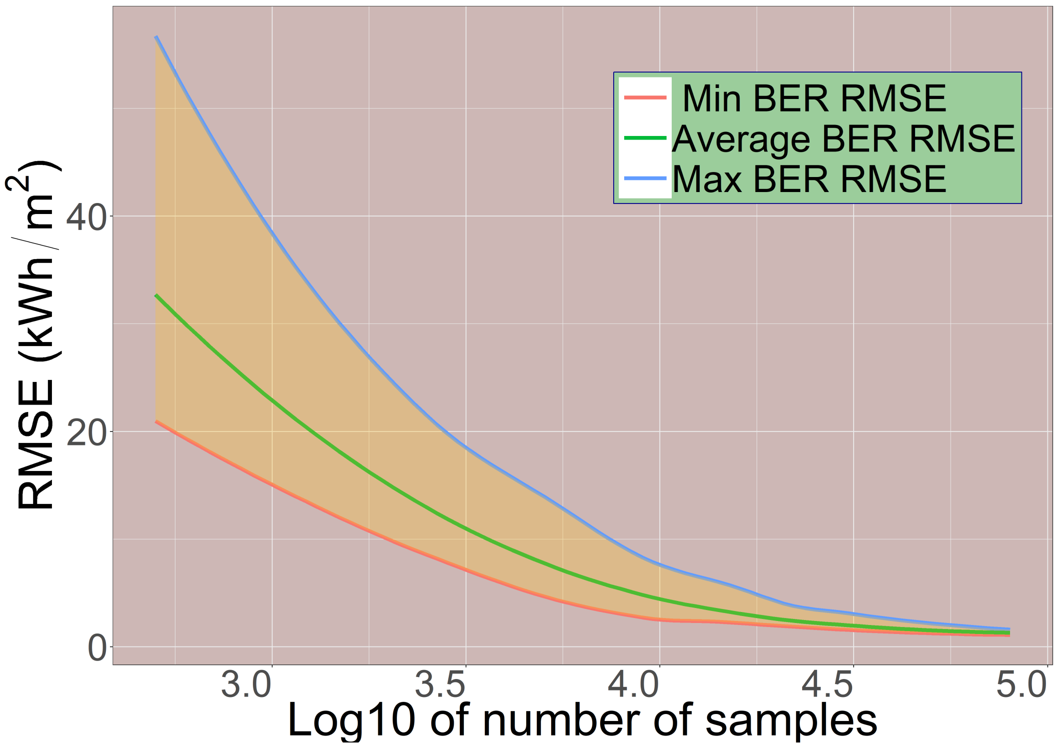


Figure 6.9: Average, min and max RMSE of all folds in BER prediction against total number of train-test records

As it is seen in Figure 6.9, 30,000 samples of building assessment records are adequate to build a reliable model, as at this point, the prediction interval of $[2.5546231, 1.572446264]$ with an average RMSE of 1.92 CO_2Kg/m^2 is achieved. Considering the average actual BER of 94.04 CO_2Kg/m^2 for all building records, the attained error, which is only 2% of the target mean value has been a promising achievement. Using the full dataset, the average RMSE of 1.25 CO_2Kg/m^2 equal to 1.3% of the target mean value could be achieved with the acceptable cost of sacrificing time. The average spent time for fitting models with 30,000 and 80,000 samples was recorded as 7.12 and 31.22 seconds.

6.8 Sensitivity Analysis

The modelling non-domestic building in this study has concentrated on the retrofit planning, therefore the feature engineering targeted not only at accurately predicting building energy performance but also the ability of the model in calculating the alteration. As such, it is beneficial to investigate the impact of each selected variable on estimating buildings energy performance. To this end, the GBRT model was trained 30 times each using randomly selected records (30,000) and different random states (please refer to Section 3.5.7 and 6.6.2 for detail of sensitivity analysis). The results are illustrated in Figure 6.10 plotting the relative importance of features as a box and whiskers plot.

The result of permutation importance analysis considering a model trained over 80% of full data and the rest for testing is presented in Figure 6.11. It can be seen that very similar results presented in Figure 6.10 was achieved. This shows that the GBRT model hasn't been biased in the training procedure and inflating the feature importances.

Consequently, the most significant features are related to domestic hot water, internal heat gain and lighting. These parameters cover the improvement of the hot water system, replacing the lamps and heating systems. SER which is indirectly calculated from the building energy assessment procedure, along with

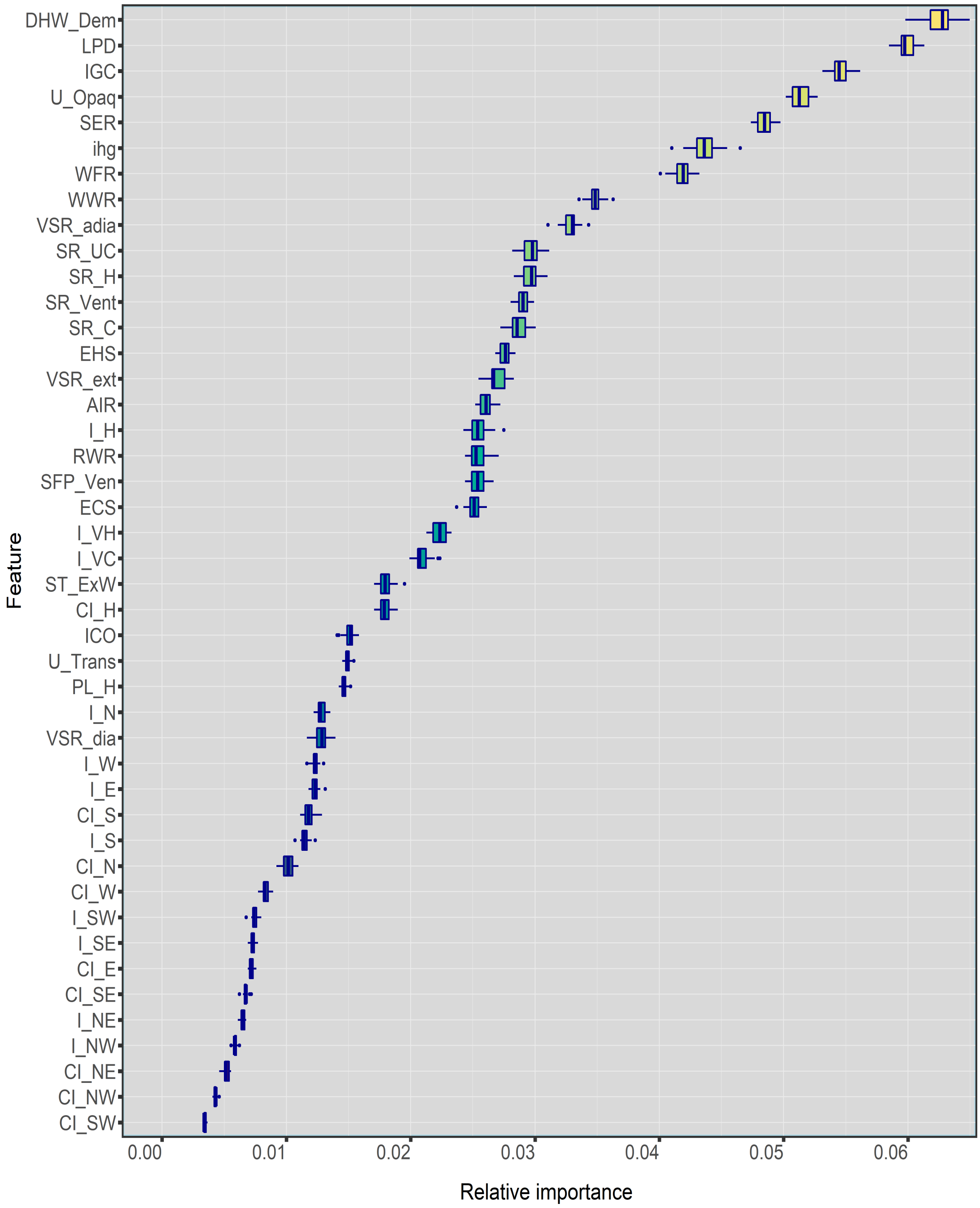


Figure 6.10: Relative importance of the selected features for modelling non-domestic buildings in the UK

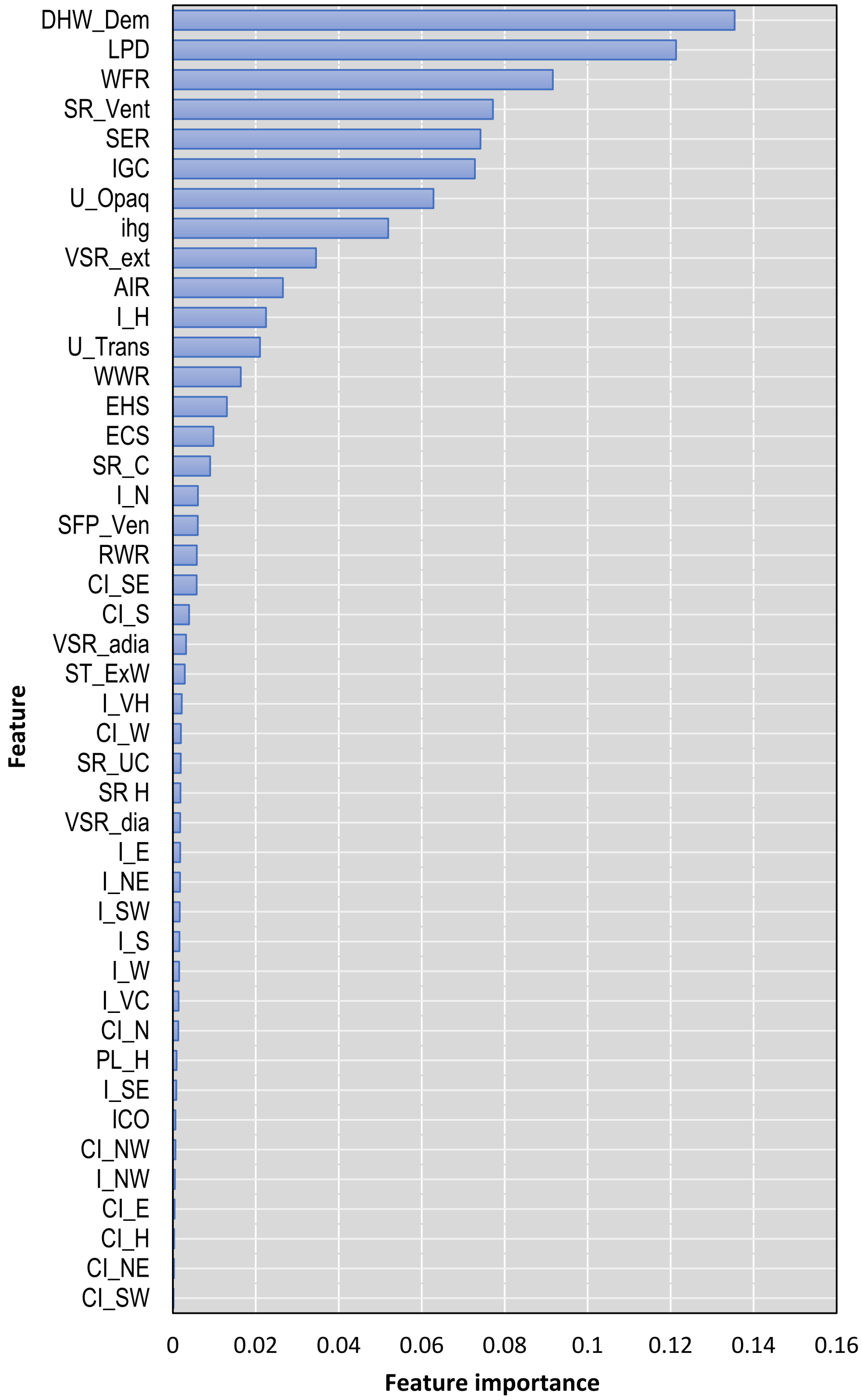
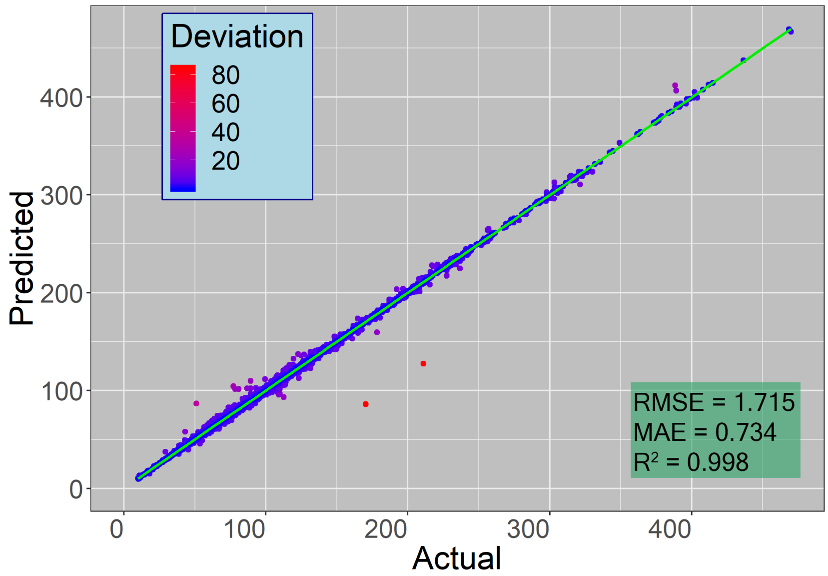


Figure 6.11: Importance of the selected features evaluated by permutation importance method

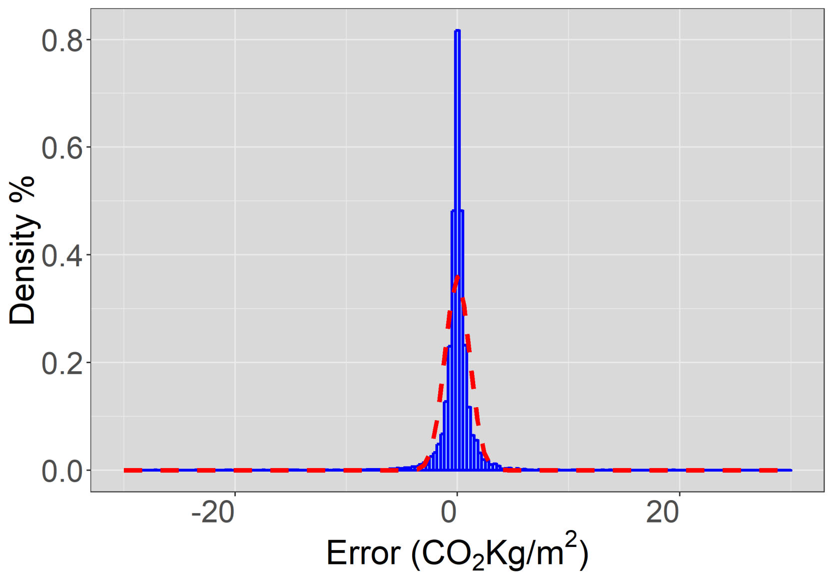
the wall to floor and window to wall ratios are not mutable, that is to say in energy retrofitting the structure of the building is not altered. However, they play an influential role in predicting energy performance. Other immutable features with high impact having almost the same relative importance values, are space ratios, followed by air infiltration rate, terminal unit energy demand and cooling system efficiency. As it can be anticipated, roof to wall ratio, solar radiation on the roof and generally solar radiation have medium to low impact, due to the UK climate.

It should be noted that the importance of the features in the prediction of building energy performance is dependant on the data utilised for developing the model. As such, this conclusion is not generalised for countries with different climates and policies (software to check the energy performance), though the features extraction proposed in the study lays the base for the development of robust models to support building energy retrofit decision making and policies. Furthermore, the data and results can be transferred to the new domain for expedite model development.

To demonstrate the performance of model with dropping less important features (CI_SW, CI_NW, CI_NE, I_NW, I_NE, CI_SE, CI_E, I_SE, I_SW, CI_W), a model was trained using 30,000 records and tested over 8,000 samples. Both train and test sets were randomly selected among available 80,000 building records. The results are demonstrated as plot of predicted energy performances versus real simulation values and distribution of error between simulated-predicted pairs in Figure 6.12.



(a)



(b)

Figure 6.12: (a) Actual and predicted building emission rates and (b) error histogram of testing over 8,000 samples.

6.9 A Case Study

The energy performance prediction model development aimed at supporting the optimisation of building energy retrofits. In this application, the optimisation algorithm generates variations of the target building to be evaluated for their energy performance. Here, the developed model is validated by estimating retrofit versions of a building that are never seen by the model. Therefore, the goal of this analysis is to further investigate the stability and generalization of machine learning (i.e. the training and testing the model is not biased by the utilised dataset).

To evaluate the efficiency of the developed model on prediction of a building variations, one floor from a non-domestic building located in Glasgow City was selected. To that end, the detail and data for the eighth floor of Graham Hills building were obtained from estates department of the University of Strathclyde. The obtained building surveyed floor plan was overlaid with the model in DesignBuilder to create the case study zoning, as shown in Figure 6.13.

All zones have natural ventilation except for toilets which have local extract fans. Although the eighth floor exclusively uses low-temperature hot water boilers with wet radiators, other levels share several different systems, some of which including cooling and mechanical ventilation. The DHW system does not share heat generation with the wet radiator systems. Details of the case study building envelope is provided in Appendix D.

Considering the recommendations introduced in Table 6.1 and by the means of the GA, the studied building was mutated into 3,000 distinct retrofitted versions. All generated building models were assessed by the software and received the emission ratings, which vary from 51 to 80 CO_2Kg/m^2. The process of evaluating all generated data using the SBEM tool took almost three days.

The evaluation procedure followed six steps which are presented as follow:

Step1: GBRT model was trained using the prepared dataset from the collected records

Step2: Retrofit variations of the case study building was generated to emulated multi-objective optimisation of retrofit planning

Step3: Retrofit versions was simulated and received their associated BERs

Step4: Data was translated from raw form (building energy model readable for SBME) to ML space (defined as set of features)

Step5: GBRT model predicted the BER values

Step6: The model accuracy was calculated by comparison of predicted (from Step 5) and actual (from Step 3) values

In order to take full advantage of the ML model for this case study, the model was fitted using the whole training set. Then the trained model was used to predict the energy performance of the mutated records. Testing all samples took only 0.22 seconds while having RSME, MAE and R^2 of 1.02, 0.47 and 0.98, respectively.

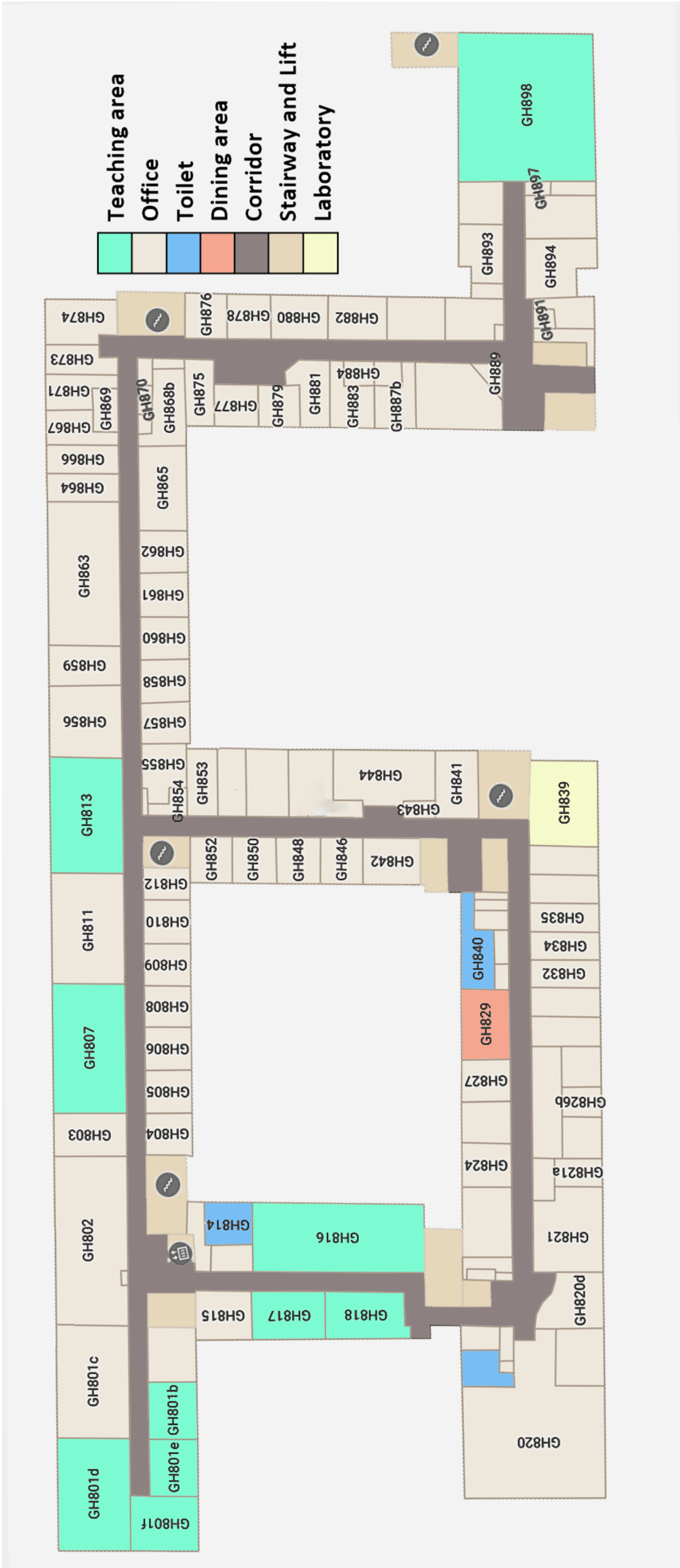


Figure 6.13: Case study floor plan showing the zones with activities

Figure 6.14 demonstrates the performance of the predictions as the error histogram.

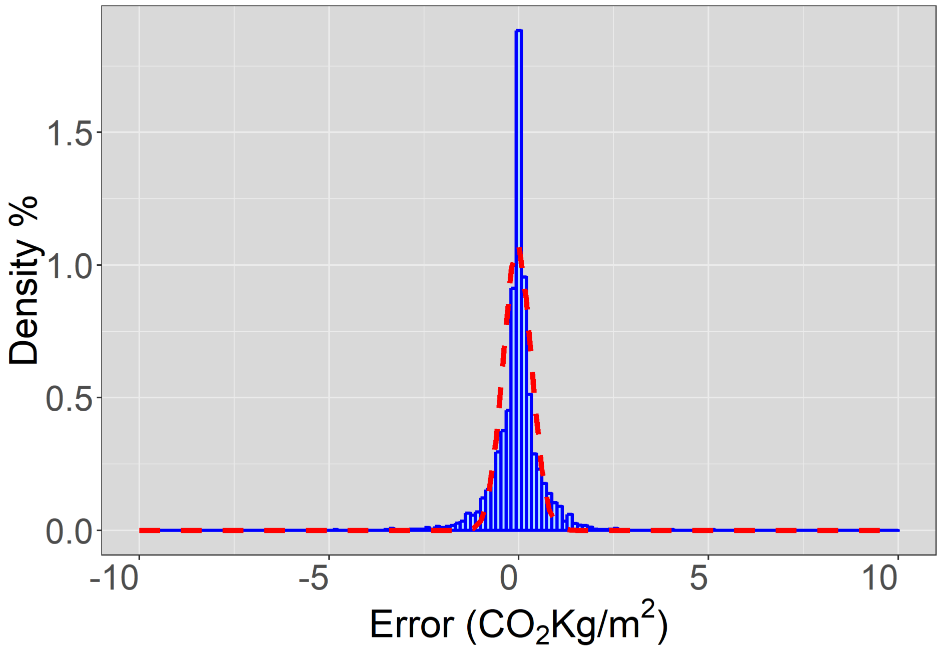


Figure 6.14: Error histogram of predicting 3,000 variations of the Graham Hill building

The obtained RMSE is equal to 1.7% of the average BER value, which is 58.3 CO_2Kg/m^2. It can also be seen in Figure 6.14 that majority of the residuals are cumulated around zero, proving the success of training a model with high accuracy and generality.

6.10 Summary

The final phase of the study presented in this chapter addressed the issues regarding lack of modelling of building energy performance considering related policies. As mentioned in the reviewed literature, most research studies concentrated on the fast prediction of building energy demand to support design stage or considered single building optimisation. The latest attempt to enhance the existing building energy efficiency included MOO method to find the best performing retrofit plan. This phase has developed a statistical model of energy performance for UK non-domestic buildings to support retrofit optimisation. The main advantages of this method over utilisation of a simulation software include a significant reduction in the time complexity of energy performance calculation, the potential to investigate a more comprehensive range of retrofit technologies, and consequently the ability to perform a proper inspection of retrofit exemptions denoted by the policies.

In the proposed method, the essential characteristics of the non-domestic building affecting the energy performance were identified and formulated as a set of numerical features. The feature extraction considered available retrofit technologies in the market to cover the potential improvements. Next, real-world data was processed and translated into the defined feature set for performing statistical modelling. The data was also extended by mutating the records and evaluating them using energy simulation software. GBRT model was then trained and tuned over the records and tested using cross-validation method. The effectiveness of feature extraction and engineering was also evaluated by employing sensitivity analysis.

The proposed approach was evaluated using a real non-domestic building as a case study and testing the accuracy of the ML model over the retrofit (mutated) versions which was simulated to get the emission rates. The precision of the developed model was validated through comparisons with the simulations. Development of an accurate model for estimation of the energy performance with speedy and robust process lays the groundwork for more informed and prolific decisions for energy retrofit planning.

The proposed model solves two significant problems with the existing tools which leverage SBEM, static retrofit package definitions and blindness to indirect service dependence. The former is a limitation on the size of the solution space that can be exhaustively explored. The latter are scenarios where retrofitting one building service increases demand on another to the extent that the energy savings for the isolated service demand are negated by the increased demand on the dependent service. The typical example of SBEM is the relationship between Tungsten or Halogen lighting and direct or storage electric heating where heating is the dependent service. As far as SBEM is concerned, lighting fixtures both contribute significantly to space heating and their contributions when considered with also meeting the lighting demand, are more efficient than the electric heating system in tempering the space. The existing model, which works based on an exhaustive search of the solution space using linear estimation, treats the retrofit an antagonistic matter. As such, it will not serve as a component of a candidate retrofit strategy. The proposed model solves and can leverage the underpinning diminishment of energy savings. It solves the problem by producing an estimate that is sufficiently accurate to be considered as a proxy for a nonlinear estimation of each retrofit scenario meaning a retrofit which might be antagonistic in isolation is considered in compound scenarios. The model, being many orders of magnitude faster than existing models, enables variable calibration of individual and grouped retrofit technologies. This can be leveraged during MOO with the nonlinear relationship between multiple objectives to find the Pareto fronts that approach losses to meet another objective.

It was discussed how the proposed model expands the solution space of the existing model. The solution space inherently changes every time what is known about the building or retrofits change. Therefore, it is desirable to calibrate the input parameters when a significant input is modified. For example, the model may suggest technology at an estimated price. The proposed model enables the introduction of tender specifications to MOO, offer a means of optimising the bid for the tendering party or enable the owner to hold tender-vs-tender MOO. Generally, the performance of the proposed model should facilitate consideration for occupant wellbeing benefits or other less conventional objectives.

This chapter highlights the significance of feature extraction and engineering in the estimation of energy indices applying the built-in mechanisms of GBRT. There have been several assumptions and limitations in creating building models and simulations that affect energy predictions. Accordingly, as indicated in the literature and emphasised in this study, the feature extraction and optimisation of machine learning should be based on the application. The presented results also revealed the practically of ML-based modelling in neglecting irrelevant variables without influencing the accuracy.

The chapter emphasises the capacity of ML methods in the built environment where calculation and simulation for energy indicators applying engineering methods sometimes become cumbersome. So far, it has been estimated that solely 4% of data captured in the industrial environments are being employed with a meaningful and significant contribution. That is why Industry 4.0 has put more emphasis on the utilisation of technologies that could take advantage of the ever-growing data [244].

A technological innovation's short-term value can be measured by its ability to improve human capacity for an action in one or more metrics higher than its negation on the other parameters. This chapter presented an approach on several metrics which significantly improved developers' capacity to exploit AI optimisation effectively. It will facilitate significant improvements model design and implementation. Reducing the duration of the process, it essentially increases the frequency of model calibrations , hence leading to opportunity to reduce the cost per calibration. It also increases capacity to refine model creation by processing for progressive interactive training models to reduce reliance hierarchical reinforcement learning.

As policy contracts on ineffective energy usage and due to the shortcomings of building energy management systems, the obligation for more efficient designs and retrofits increases. Recently, research work emphasised on designing buildings considering medium-term climate change, yet neglecting the occupant size and behavioural uncertainties. Reflecting such variables drastically expands the problem space whilst likely decreasing the traditional alternatives of the solution space.

There are significant implications of this study not only on the industry in terms of informing the retrofit planning process and making it more efficient but also for the energy policy-making in terms of utilising the approaches demonstrated in this work to evaluate the effectiveness and issues of the methods in use.

Chapter 7

Conclusion: Contributions, Impacts and Recommendations for Future Studies

7.1 Introduction

This chapter summarises the study findings for each objective. The chapter includes four main sections, justification of how the research objective are achieved, contributions to knowledge, implications on the practice, and recommendations for the future work.

7.2 Achievement of Research Objectives

7.2.1 Objective 1

To investigate advances in building energy numerical modelling focusing on the use of ML methods A broad review of research works in the area of building energy assessment, focusing on the energy retrofit was performed. ML tools applied for the prediction of building energy indicators are discussed, and the input parameters utilised in training the models are identified. It was concluded the selecting suitable features had been limited to the elementary physical characteristics and climate features, as the majority of the seminal works concentrated on the accuracy of developed models. Whilst in the optimisation of building design and energy retrofit, it is of paramount importance that the model should reflect the impact of any alteration or improvement. It was therefore concluded that in order to develop an accurate model to support retrofit DM, it is essential to take many energy-related features into account, rather than the basic parameters identified from the literature review.

By scrutinising several studies, comparing various ML models, it was also concluded that these models would perform quite differently if they are precisely tuned. Moreover, the nature and size of the data utilised for the model development are highly important in the selection of a suitable technique. However, a reasonably large dataset is required to train a generalised and reliable energy model.

7.2.2 Objective 2

To scrutinise ML techniques in building energy application and propose the ML selection framework

The study, in addressing the second objective, investigated the most established ML techniques, which are widely available as programming libraries or packages. The accuracy of these models fitted by using datasets of building energy loads was analysed. To address the issue identified in the literature review (unfair comparison of models), the research carried out specific tuning for each model using a grid-search approach, in which models are evaluated by employing cross-validation methods. The study set recommendations for the quick selection of an ML model based on the data and application (e.g. short-time predictions for BEM or long-term energy estimation for building design).

The research showed that even though an exhaustive search method is a solid choice for comparison of ML models, the time complexity of the process is still expensive. Therefore, in practice, where energy models are trained and optimised repeatedly to be aligned with energy policy updates, a more expedite and precise method is required.

7.2.3 Objective 3

To propose an intelligent method for the development of accurate energy forecasting ML models

To address Objective 3, this study laid out a precise approach to tune an ML model for prediction of one or more energy indicators. The technique applied MOO based on evolutionary algorithms to explore the ML hyper-parameters space. The proposed method not only increased the time complexity of ML optimisation, but also improved the overall model accuracy.

The proposed method was evaluated by implementing an ML model capable of predicting multiple targets concurrently. The performance of the proposed approach was confirmed by comparisons with traditional search and statistical modelling methods. The study proved the efficient application of smart evolutionary algorithms in dealing with complex non-domestic buildings energy data. The role of sensitivity analysis in developing more accurate and expedited models was also studied.

7.2.4 Objective 4

To develop a energy performance modelling for accelerated energy assessment of non-domestic buildings

This objective was addressed by the development of an ML model for calculation of non-domestic buildings energy performance. The model provided rapid energy performance predictions for supporting MOO-based DM for energy retrofit planning of complex non-domestic buildings. The goal was achieved by succeeding the process as follow:

- Thoughtful consideration of retrofit technologies and the energy policy in the market was identified;
- A dataset of energy performance certificates for non-domestic buildings in the UK was obtained, analysed, and processed;
- An iterative procedure was adopted to extract and define a set of features, which are understandable to the ML model, and reasonable accuracy could be achieved. To this end, basic parameters related to building characteristics were selected, then sophisticated features were defined, and calculation algorithms were prepared. Subsequently, data from the form of raw assessment files were translated into the defined feature space. The

process was followed by training a model to evaluate the extracted features;

- Dataset was expanded by employing GA and applying retrofit recommendations on the available non-domestic records. A large amount of data was generated and assessed to receive the corresponding energy ratings;
- An advanced ML model was tuned over the final input set and using evolutionary algorithms, trained, and tested by means of cross-validation method. The research also identified a sufficient number of samples for creating an accurate model.

The model was evaluated using 10-fold cross-validation, for which the average RMSE of all folds was achieved as low as 1.25 CO_2Kg/m^2 (1.13% of the calculated emission rate). This evaluation approach and delivered error proved the generality and accuracy of the developed model.

7.2.5 Objective 5

To evaluate the energy performance ML model by use of genetic algorithm and application on a case study

To address Objective 5 and the question on how well the accuracy of the developed model would be on prediction of a new building records, this study utilised a case study property, which was neither extracted from the original dataset nor used in the model training and generalisation tests. This non-domestic academic building record was processed and used for generating three thousand variations. This procedure employed GA and applied the retrofit recommendation to mimic an AI optimisation approach. Predicting the energy performance for the studied building records took less than one second while achieving RMSE of 1.7 CO_2Kg/m^2. The performance of the developed model is perceivable by comparing these values to the average calculated BER value of 58.3 CO_2Kg/m^2 and three days of simulation time to obtain BER values.

7.3 Implication for Practice

Studies within the context of doctoral education are expected to provide implications of significant value to the field of study [33]. Having an industry impact has always been central to the evaluation of the level of contribution of construction management research [30]. In other words, AEC research should examine real-world realities to enhance the efficiency of the building industry [245]. In fact, "academic research in applied disciplines such as building engineering has the dual mission of simultaneously contributing to the solution of practical problems and creating theoretical and conceptual knowledge" [246]. As discussed in detail in Chapter 1, this intention was included among the drivers directing the present study.

With the utilisation of AI technologies within the construction context growing exponentially and modelling the energy performance as the core component of energy retrofit DM, this study's outcomes could be beneficial for building designers, construction engineers and consultancy companies and energy policymakers. Building designers could benefit from the findings, particularly those findings that relate to the selection of ML techniques and tuning energy models. This benefit could be achieved by treating the pertinent findings as instructions for adapting their traditional ML modelling and optimisation procedures. In relation to generic practitioners, a salient example of potential benefit is derived from the findings related to knowledge, skills and abilities of ML models in the identification of important features in energy modelling. Specifically, the findings provide guidelines to precisely consider the impact of building alterations in the developed models. The construction industry could directly benefit from the outcome of the study related to developing a retrofit-specific energy modelling for assessing their recommendation packages. Feature analysis methods would also be used for evaluation of the building input parameters to inform clients in the case. The alternative method for retrofit DM is demonstrated in Figure 7.1.

As it was stated in Sections 1.3 and 6.6.2, the ML model and its integration with MOO would also be beneficial for evaluation of policy compliance assessment and developing evaluation tools.

It should be noted again that the ML model is not proposed to ultimately replace the engineering methods, but to promote the DM process where massive calculations are required. In practice, when a retrofit configuration or building design is selected with the support of a data-driven model, it should be evaluated by the base engineering method for the detail energy simulation (e.g. EnergyPlus and SBEM simulations in Phases 2 and 4 of this study).

There are significant implications of this work not only on the industry, in terms of informing the design process and making it more efficient but also for the energy modelling software industry, in terms of utilising the approaches demonstrated in this research in the development of their software solutions.

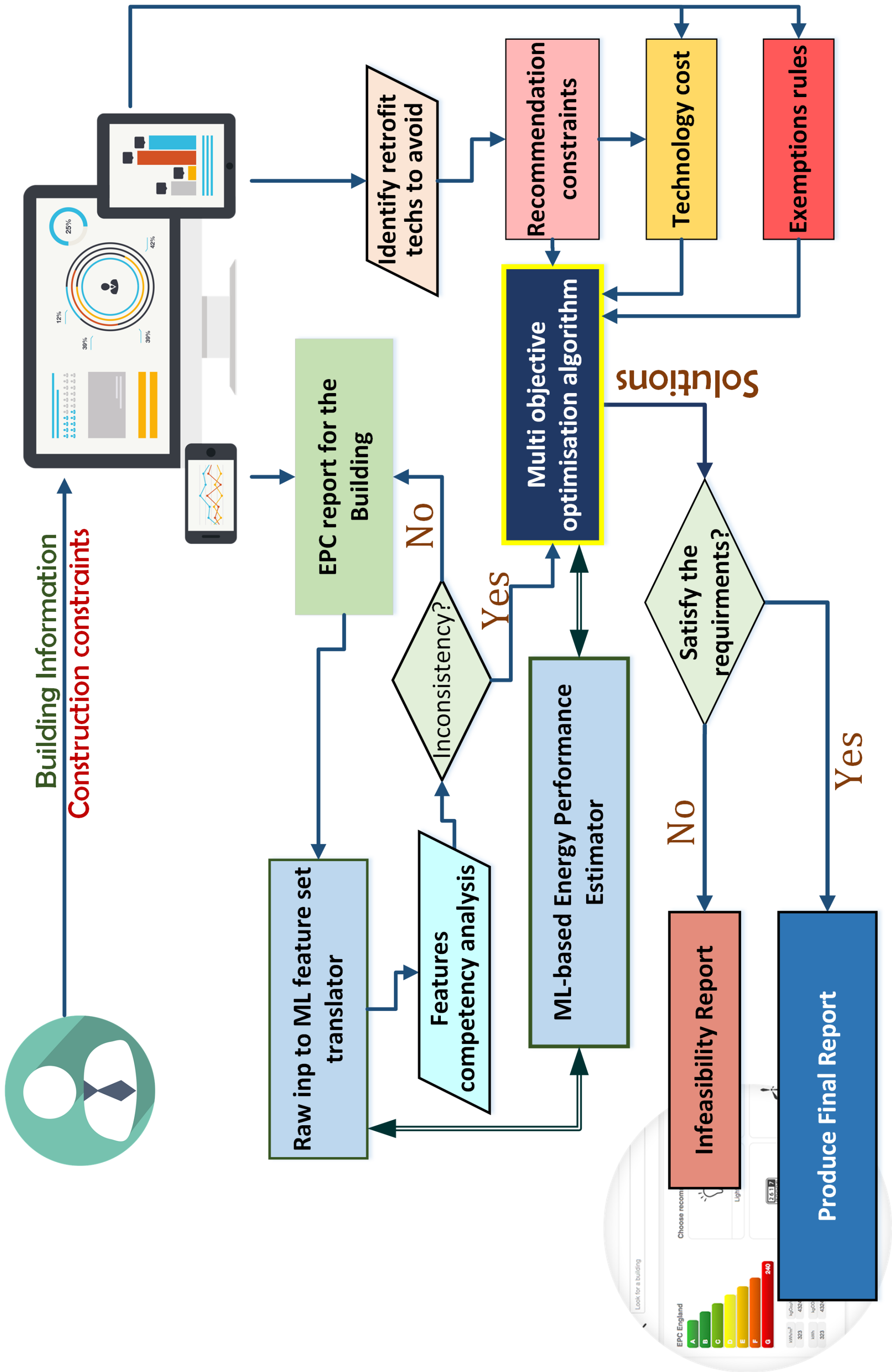


Figure 7.1: Application of ML coupled with MOO for retrofit DM.

7.4 Research Limitations

For modelling energy performance, available retrofitting technologies for glazing, wall and roof insulation, lighting, heating, ventilation, and air conditioning (HVAC) systems and integration of solar energy systems for improving the energy performance of buildings were considered for feature extraction and for generating variations of the case studies. However, new/outdated technologies can be added/removed for other regions by updating/adding features. The effect of occupancy on the energy consumption of buildings was out of the scope of this work as it requires extensive and comprehensive research to be undertaken. This thesis only focused on modelling the energy performance to support deep energy retrofitting of non-domestic buildings. Furthermore, as the data collected from the UK building stock and the regulations in this region were considered in energy modelling, the feature generation is limited to the specific area. This limitation mostly affects the analysis of the effects of climate variables on buildings deep energy retrofit.

7.5 Further Works

Blaster *et al.* [247] described research a cyclical process which "can be entered at any point, in a never ending process; will cause you to reconsider your practice; and will return you to a different starting place". Taking into consideration the limitations described in the Section 1.8 alongside the present study's findings, several opportunities for future research came to light. These opportunities are summarised as follows:

- The data utilised for modelling building energy performance was related to properties located throughout the UK. To consider the climate impact on the energy performance of buildings, several features were identified.

However, as it was expected, the sensitivity analysis revealed that those variables have very low importance. In order to investigate how well climate effect is considered with the standard calculation method, a more extensive data of buildings distributed in diverse climates is essential. This requires multidisciplinary research to process and prepare a cloud-based database.

- Chapter 2 indicated that several countries which reacted to global warming and set energy regulations for the building sector have adopted different approaches to assess and rate the energy performance of their buildings. A new study would evaluate different standard methods adopted by these countries and conclude the weakness and advantages of each approach. This research would result in the development of a global benchmarking system to be enforced.
- The energy regulations targeted non-domestic properties have only focused on the physical building characteristics and the energy-related equipment. As such, in the development of the energy performance prediction model, different types of non-domestic buildings were considered. However, in reality, these properties have one distinct difference, and that is the behaviour of their occupant or users. Analysis of occupant role in energy consumption pattern is not a new area, yet answering the question on how this behaviour could be considered in the benchmarking methods and how measured data could facilitate this procedure requires extensive research works.
- In Chapters 1 and 2, it was stated that potential of AI has not been fully exploited in building energy optimisation and standards due to the lack of in interdisciplinary research works. One very potential ML tool is clustering that classifies buildings using various features and characteristics instead of considering only type or topology. A multidisciplinary research on the application of unsupervised learning and building energy coupled with a

comprehensive energy data would result in more effective benchmarking methods. Smartly determination of reference buildings leads in more precise energy labelling, comparing to traditional definition of notional buildings. Moreover, combination of clustering with classification allows to estimate the reference building for future cases. This area has not been studied thoroughly and seems to be a trending topic in near future as the global concern about energy is increases and many countries put efforts to regulate the energy consumer industries especially buildings and construction.

Bibliography

[1] S. Kelly, D. Crawford-Brown, and M. G. Pollitt, "Building performance evaluation and certification in the UK: Is SAP fit for purpose?" *Renewable and Sustainable Energy Reviews*, vol. 16, no. 9, pp. 6861–6878, 2012.

[2] C. Filippin, "Benchmarking the energy efficiency and greenhouse gases emissions of school buildings in central Argentina," *Building and Environment*, vol. 35, no. 5, pp. 407–414, 2000.

[3] X. Li, C. P. Bowers, and T. Schnier, "Classification of energy consumption in buildings with outlier detection," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 11, pp. 3639–3644, 2010.

[4] M. Bell, "Energy Efficiency in Existing Buildings: the Role of Building Regulations," in *Proceedings of Construction and Building Research (COBRA) Conference*, no. September, 2004, pp. 7–8.

[5] T. Ibn-Mohammed, R. Greenough, S. Taylor, L. Ozawa-Meida, and A. Acquaye, "Integrating economic considerations with operational and embodied emissions into a decision support system for the optimal ranking of building retrofit options," *Building and Environment*, vol. 72, pp. 82–101, 2014.

[6] T. Delay, S. Farmer, and T. Jennings, "Building the future, today: transforming the economic and carbon performance of the buildings we work in," Carbon Trust, Tech. Rep., 2009. [Online]. Available: http://www.carbontrust.com/media/77252/ctc765_building_the_future__today.pdf

[7] Committee on Climate Change, "Meeting Carbon Budgets: Progress Report on Climate Change, Chapter 3: Progress reducing emissions from buildings," Committee on Climate Change, Tech. Rep., 2013. [Online]. Available: https://www.theccc.org.uk/wp-content/uploads/2013/06/CCC-Prog-Rep_Chap3_singles_web_1.pdf

[8] O. M. Jensen, A. R. Hansen, and J. Kragh, "Market response to the public display of energy performance rating at property sales," *Energy Policy*, vol. 93, pp. 229–235, 2016.

[9] C. . L. G. Ministry of Housing, "Live tables on Energy Performance of Buildings Certificates," Tech. Rep., 2020. [Online]. Available: http://bit.ly/3bP98lb

[10] UK Department of Energy & Climate, "Private Rented Sector Minimum Energy Efficiency Standard Regulations (Non- Domestic, England and Wales)," Department of Energy and Climate Change (DECC)., London, Tech. Rep. July, 2014. [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/401378/Non_Dom_PRS_Energy_Efficiency_Regulations_-_Gov_Response__FINAL_1_1__04_02_15_.pdf

[11] D. B. Crawley, L. K. Lawrie, F. C. Winkelmann, W. F. Buhl, Y. J. Huang, C. O. Pedersen, R. K. Strand, R. J. Liesen, D. E. Fisher, M. J. Witte, and J. Glazer, "EnergyPlus: Creating a new-generation building energy

simulation program," *Energy and Buildings*, vol. 33, no. 4, pp. 319–331, apr 2001.

[12] TRNSYS17, "A Transient Systems Simulation Program," pp. 1–5, 2015. [Online]. Available: http://sel.me.wisc.edu/trnsys/

[13] The Energy Systems Research Unit (ESRU), "ESP-r," 2011. [Online]. Available: http://www.esru.strath.ac.uk/Programs/ESP-r.htm

[14] C. Pountney, "Better carbon saving: using a genetic algorithm to optimise building carbon reductions," in *Proceedings of the 2012 Building Simulation and Optimization Conference*, no. September, 2012, pp. 165–172. [Online]. Available: http://www.ibpsa.org/proceedings/BSO2012/3A1.pdf

[15] I. García Kerdan, R. Raslan, and P. Ruyssevelt, "An exergy-based multi-objective optimisation model for energy retrofit strategies in non-domestic buildings," *Energy*, vol. 117, pp. 506–522, 2016.

[16] E. Asadi, M. G. da Silva, C. H. Antunes, and L. Dias, "State of the Art on Retrofit Strategies Selection Using Multi-objective Optimization and Genetic Algorithms," in *Nearly Zero Energy Building Refurbishment*. Springer, 2013, pp. 279–297.

[17] M. Ferrara, A. Rolfo, F. Prunotto, and E. Fabrizio, "EDeSSOpt – Energy Demand and Supply Simultaneous Optimization for cost-optimized design: Application to a multi-family building," *Applied Energy*, vol. 236, pp. 1231–1248, 2019.

[18] N. Delgarm, B. Sajadi, S. Delgarm, and F. Kowsary, "A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: Case study in Iran," *Energy and Buildings*, vol. 127, pp. 552–560, 2016.

[19] F. Ascione, N. Bianco, G. M. Mauro, and G. P. Vanoli, "A new comprehensive framework for the multi-objective optimization of building energy design: Harlequin," *Applied Energy*, vol. 241, pp. 331–361, 2019.

[20] F. Bre and V. D. Fachinotti, "A computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings," *Energy and Buildings*, vol. 154, pp. 283–294, 2017.

[21] F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "Multi-stage and multi-objective optimization for energy retrofitting a developed hospital reference building: A new approach to assess cost-optimality," *Applied Energy*, vol. 174, pp. 37–68, 2016.

[22] C. Diakaki, E. Grigoroudis, N. Kabelis, D. Kolokotsa, K. Kalaitzakis, and G. Stavrakakis, "A multi-objective decision model for the improvement of energy efficiency in buildings," *Energy*, vol. 35, no. 12, pp. 5483–5496, 2010.

[23] E. Asadi, M. G. D. Silva, C. H. Antunes, L. Dias, and L. Glicksman, "Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application," *Energy and Buildings*, vol. 81, pp. 444–456, oct 2014.

[24] E. Asadi, M. G. da Silva, C. H. Antunes, and L. Dias, "A multi-objective optimization model for building retrofit strategies using TRNSYS simulations, GenOpt and MATLAB," *Building and Environment*, vol. 56, pp. 370–378, 2012.

[25] F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort," *Energy and Buildings*, vol. 111, pp. 131–144, 2016.

[26] A. Jafari and V. Valentin, "An optimization framework for building energy retrofits decision-making," *Building and Environment*, vol. 115, pp. 118–129, 2017.

[27] E. M. Malatji, J. Zhang, and X. Xia, "A multiple objective optimisation model for building energy efficiency investment decision," *Energy and Buildings*, vol. 61, pp. 81–87, 2013.

[28] J. Si, "Green retrofit of existing non-domestic buildings as a multi criteria decision making process," Ph.D. dissertation, 2017.

[29] P. Glasziou, J. Vandenbroucke, and I. Chalmers, "Assessing the quality of research," *British Medical Journal*, vol. 328, no. 7430, pp. 39–41, 2004.

[30] D. Gann, "Putting academic ideas into practice: technological progress and the absorptive capacity of construction organizations," *Construction Management and Economics*, vol. 19, no. 3, pp. 321–330, 2001.

[31] J. P. Wilson and C. Beard, "Constructing a sustainable learning organization: Marks and Spencer's first Plan A learning store," *Learning Organization*, vol. 21, no. 2, pp. 98–112, 2014.

[32] S. S. Hosseini, K. Agbossou, S. Kelouwani, and A. Cardenas, "Non-intrusive load monitoring through home energy management systems: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 79, pp. 1266–1274, 2017.

[33] P. Tinkler and C. Jackson, *The doctoral examination process a handbook for students, examiners and supervisors.* McGraw-Hill Education (UK), 2006, vol. 31, no. 1.

[34] A. Panas and J. Pantouvakis, "Evaluating Research Methodology in Construction Productivity Studies," *The Built & Human Environment Review*, vol. 3, no. 1, pp. 63–85, 2010.

[35] R. B. Handfield and S. A. Melnyk, "The scientific theory-building process: A primer using the case of TQM," *Journal of Operations Management*, vol. 16, no. 4, pp. 321–339, 1998.

[36] G. Clarke and I. Lunt, "The concept of 'originality' in the Ph.D.: How is it interpreted by examiners?" *Assessment and Evaluation in Higher Education*, vol. 39, no. 7, pp. 803–820, 2014.

[37] Intergovernmental Panel on Climate Change, "Climate Change 2014 Mitigation of Climate Change," IPCC, Cambridge, Tech. Rep., 2014.

[38] C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White, *Climate change 2014 impacts, adaptation and vulnerability: Part A: Global and sectoral aspects: Working group II contribution to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge: Cambridge University Press, 2014.

[39] J. van der Heijden, *Governance for Urban Sustainability and Resilience*. Edward Elgar Publishing, 2014.

[40] W. Abrahamse, L. Steg, C. Vlek, and T. Rothengatter, "The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents," *Journal of Environmental Psychology*, vol. 27, no. 4, pp. 265–276, dec 2007.

[41] J. Laustsen, "Energy Efficiency Requirements in Building Codes , Energy Efficiency Policies for New Buildings," *Buildings*, no. March, pp. 1–85, 2008.

[42] E. Mulliner and L. Kirsten, "Preparation for the Energy Act 2011 and minimum energy efficiency standards in UK commercial property," *International Journal of Strategic Property Management*, vol. 21, no. 2, 2017.

[43] A. Stafford, C. Gorse, and L. Shao, "The Retrofit Challenge: Delivering Low Carbon Buildings," *Research Insights into Building Retrofit for the UK*, pp. 1–32, 2011. [Online]. Available: http://www.superhomes.org.uk/wp-content/uploads/2012/01/Retrofit_Challenge_2011.pdf

[44] G. Pivo, "Responsible property investment criteria developed using the Delphi Method," *Building Research and Information*, vol. 36, no. 1, pp. 20–36, 2008.

[45] A. Chegut, P. Eichholtz, and N. Kok, "Supply, Demand and the Value of Green Buildings," *Urban Studies*, vol. 51, no. 1, pp. 22–43, jan 2014.

[46] F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "A new methodology for cost-optimal analysis by means of the multi-objective optimization of building energy performance," *Energy and Buildings*, vol. 88, pp. 78–90, 2015.

[47] S. Wang, C. Yan, and F. Xiao, "Quantitative energy performance assessment methods for existing buildings," *Energy and Buildings*, vol. 55, pp. 873–888, 2012.

[48] T. Hong, C. Koo, J. Kim, M. Lee, and K. Jeong, "A review on sustainable construction management strategies for monitoring, diagnosing and retrofitting the building's dynamic energy performance: Focused on the

operation and maintenance phase," *Applied Energy*, vol. 155, pp. 671–707, 2015.

[49] T. Nikolaou, D. Kolokotsa, G. Stavrakakis, A. Apostolou, and C. Munteanu, "Managing Indoor Environments and Energy in Buildings with Integrated Intelligent Systems," in *Managing Indoor Environments and Energy in Buildings with Integrated Intelligent Systems.* Springer International Publishing, 2015, ch. 2, p. 261.

[50] T. Nikolaou, D. Kolokotsa, and G. Stavrakakis, "Review on methodologies for energy benchmarking, rating and classification of buildings," *Advances in Building Energy Research*, vol. 5, no. 1, pp. 53–70, 2011.

[51] W. L. Lee, F. W. Yik, and J. Burnett, "A method to assess the energy performance of existing commercial complexes," *Indoor and Built Environment*, vol. 12, no. 5, pp. 311–327, 2003.

[52] W. Chung, Y. Hui, and Y. Lam, "Benchmarking the energy efficiency of commercial buildings," *Applied Energy*, vol. 83, no. 1, pp. 1–14, 2006.

[53] R. Cole, "Building environmental performance assessment criteria, BEPAC," National Institute of Standards and Technology, Gaithersburg, MD (United States), Tech. Rep., 1994. [Online]. Available: http://cat.inist.fr/?aModele=afficheN&cpsidt=3439278

[54] C. B. Meeks and V. Brannigan, "Performance based codes: Economic efficiency and distribution equity," in *Interflam*, vol. 96, 1996, p. 7th.

[55] R. K. Strand, "Energy Estimating and Modeling Methods," *ASHREA Handbook. Fundamentals*, no. 1, pp. 19.1–38, 2009.

[56] Coakley, P. Raftery, and M. Keane, "A review of methods to match building energy simulation models to measured data," *Renewable & Sustainable Energy Reviews*, vol. 37, pp. 123–141, 2014.

[57] S. M. Hong, G. Paterson, E. Burman, P. Steadman, and D. Mumovic, "A comparative study of benchmarking approaches for non-domestic buildings: Part 1 – Top-down approach," *International Journal of Sustainable Built Environment*, vol. 2, no. 2, pp. 119–130, 2013.

[58] E. Burman, S. M. Hong, G. Paterson, J. Kimpian, and D. Mumovic, "A comparative study of benchmarking approaches for non-domestic buildings: Part 2 – Bottom-up approach," *International Journal of Sustainable Built Environment*, vol. 3, no. 2, pp. 247–261, 2014.

[59] M. Ouf and M. H. Issa, "Energy consumption analysis of school buildings in Manitoba, Canada," *International Journal of Sustainable Built Environment*, vol. 6, no. 2, pp. 359–371, 2017.

[60] E. H. Borgstein, R. Lamberts, and J. L. Hensen, "Evaluating energy performance in non-domestic buildings: A review," *Energy and Buildings*, vol. 128, pp. 734–755, 2016.

[61] S.-b. Leigh, J.-s. Won, and J.-i. Bae, "An Energy Management Process and Prediction of Energy Use in an Of fi ce Building," *Journal of Asian Architecture and Building Engineering*, vol. 4, no. November, pp. 501–508, 2005.

[62] E. Mathews, P. Richards, and C. Lombard, "A first-order thermal model for building design," *Energy and Buildings*, vol. 21, no. 2, pp. 133–145, 1994.

[63] S. Wang and Y. Chen, "A novel and simple building load calculation model for building and system dynamic simulation," *Applied Thermal Engineering*, vol. 21, no. 6, pp. 683–702, 2001.

[64] V. Corrado, H. E. Mechri, and E. Fabrizio, "Building energy performance assessment through simplified models: Application of the iso 13790 quasi-steady state method," in *International Building Performance Simulation Association 2007*, no. September 2015, 2007, pp. 79–86. [Online]. Available: www.ibpsa.org/proceedings/bs2007/p640_final.pdf

[65] R. Kramer, J. V. Schijndel, and H. Schellen, "Inverse modeling of simplified hygrothermal building models to predict and characterize indoor climates," *Building and Environment*, vol. 68, pp. 87–99, 2013.

[66] R. Kramer, J. van Schijndel, and H. Schellen, "Simplified thermal and hygric building models: A literature review," *Frontiers of Architectural Research*, vol. 1, no. 4, pp. 318–325, 2012.

[67] H. van Dijk, M. Spiekman, and P. de Wilde, "A monthly method for calculating energy performance in the context of european building regulations," in *International Building Performance Simulation Association 2005*, 2005, pp. 255–262. [Online]. Available: www.ibpsa.org/proceedings/BS2005/BS05_0255_262.pdf

[68] R. Raslan and M. Davies, "Results variability in accredited building energy performance compliance demonstration software in the UK: an inter-model comparative study," *Journal of Building Performance Simulation*, vol. 3, no. 1, pp. 63–85, 2010.

[69] E. Verhalten, "Energy performance of buildings — Calculation of energy use for space heating and cooling Contents," International Organization for Standardization, Tech. Rep., 2004. [Online].

Available: http://www.cres.gr/greenbuilding/PDF/prend/set3/WI_14_TC-draft-ISO13790_2006-07-10.pdf

[70] ISO 16346, "Energy performance of buildings-Assessment of overall energy performance," International Organization for Standardization, Tech. Rep., 2013. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso:16346:ed-1:v1:en

[71] J. Field, J. Soper, P. Jones, W. Bordass, and P. Grigg, "Energy performance of occupied non-domestic buildings: Assessment by analysing end-use energy consumptions," *Building Services Engineering Research and Technology*, vol. 18, no. 1, pp. 39–46, feb 1997.

[72] Carbon Trust, "Best Practice Programme Energy Consumption Guide 19: Energy use in offices," Carbon Trust, Tech. Rep., 2000.

[73] The Chartered Institution of Building Services Engineers (CIBSE), "CIBSE: Energy Benchmarks," CIBSE, London, UK, Tech. Rep. 2, 2008. [Online]. Available: http://www.cibse.org/getmedia/24a8eb88-875e-4f21-9629-008d7af7bdc7/Technical-Report_CIBSE-Report-on-45000-DECs.pdf.aspx

[74] N. Delgarm, B. Sajadi, F. Kowsary, and S. Delgarm, "Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)," *Applied Energy*, vol. 170, pp. 293–303, 2016.

[75] A. T. Nguyen, S. Reiter, and P. Rigo, "A review on simulation-based optimization methods applied to building performance analysis," *Applied Energy*, vol. 113, pp. 1043–1058, 2014.

[76] J. Hensen and R. Lamberts, *Building performance simulation for design and operation.* Routledge, 2011.

[77] F. C. Winkelmann, B. E. Birdsall, W. F. Buhl, K. L. Ellington, A. E. Erdem, J. J. Hirsch, and S. Gates, "DOE-2 supplement: version 2.1 E," Tech. Rep., 1993. [Online]. Available: doe2.com/download/doe-21e/DOE-2SupplementVersion21E.pdf

[78] K. Wittchen, K. Johnson, and K. Grau, "BSim user's guide," Danish Building Research Institute, Tech. Rep., 2013.

[79] D. Yan and Y. Jiang, "An overview of an integrated building simulation tool - Designer's simulation toolkit (dest)," in *International Building Performance Simulation Association 2005*, 2005, pp. 1393–1400. [Online]. Available: www.ibpsa.org/proceedings/bs2005/bs05_1393_1400.pdf

[80] D. B. Crawley, J. W. Hand, M. Kummert, and B. T. Griffith, "Contrasting the capabilities of building energy performance simulation programs," *Building Energy Tools Directory*, vol. 43, no. 4, pp. 661–673, 2006.

[81] J. D. Balcomb, "Energy-10: a Design-Tool Computer Program," in *5th International IBPSA Conference*, vol. 2, 1997, pp. 49–56.

[82] J. J. Hirsch, "eQuest Quick energy simulation tool," 2014. [Online]. Available: http://www.doe2.com/equest/

[83] S.-S. Lee and G. M. Maxwell, "Empirical validation of building energy simulation software; DOE2.E, HAP and TRACE," Ph.D. dissertation, IOWA STATE UNIVERSITY, 1999.

[84] NREL, "SUNREL Energy Simulation Software," pp. 1–2, 2005. [Online]. Available: https://www.nrel.gov/buildings/sunrel.html

[85] J. S. Hygh, J. F. DeCarolis, D. B. Hill, and S. R. Ranjithan, "Multivariate regression as an energy assessment tool in early building design," *Building and Environment*, vol. 57, pp. 165–175, 2012.

[86] D. Ruch, L. Chen, J. S. Haberl, and D. E. Claridge, "A Change-Point Principal Component Analysis (CP/PCA) Method for Predicting Energy Usage in Commercial Buildings: The PCA Model," *Journal of Solar Energy Engineering*, vol. 115, no. 2, p. 77, 1993.

[87] W. Chung, "Review of building energy-use performance benchmarking methodologies," *Applied Energy*, vol. 88, no. 5, pp. 1470–1479, 2011.

[88] W. Meeusen and J. van Den Broeck, "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," *International Economic Review*, vol. 18, no. 2, p. 435, 1977.

[89] K. Cullinane, T. F. Wang, D. W. Song, and P. Ji, "The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis," *Transportation Research Part A: Policy and Practice*, vol. 40, no. 4, pp. 354–374, 2006.

[90] J. Buck and D. Young, "The potential for energy efficiency gains in the Canadian commercial building sector: A stochastic frontier study," *Elsevier*, vol. 32, no. 9, pp. 1769–1780, 2007.

[91] W.-S. Lee and K.-P. Lee, "Benchmarking the performance of building energy management using data envelopment analysis," *Applied Thermal Engineering*, vol. 29, no. 16, pp. 3269–3273, 2009.

[92] S. H. Mousavi-Avval, S. Rafiee, A. Jafari, and A. Mohammadi, "Optimization of energy consumption for soybean production using Data

Envelopment Analysis (DEA) approach," *Applied Energy*, vol. 88, no. 11, pp. 3765–3772, 2011.

[93] L. Pérez-Lombard, J. Ortiz, R. González, and I. R. Maestre, "A review of benchmarking, rating and labelling concepts within the framework of building energy certification schemes," *Energy and Buildings*, vol. 41, no. 3, pp. 272–278, 2009.

[94] J. Stein and A. Meier, "Accuracy of home energy rating systems," *Energy*, vol. 25, no. 4, pp. 339–354, 2000.

[95] R. Cohen and B. Bordass, "Mandating transparency about building energy performance in use," *Building Research and Information*, vol. 43, no. 4, pp. 534–552, 2015.

[96] M. Aydinalp, V. I. Ugursal, and A. S. Fung, "Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks," *Applied Energy*, vol. 79, no. 2, pp. 159–178, 2004.

[97] Q. Li, Q. Meng, J. Cai, H. Yoshino, and A. Mochida, "Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks," *Energy Conversion and Management*, vol. 50, no. 1, pp. 90–96, 2009.

[98] Sholahudin, A. G. Alam, C. I. Baek, and H. Han, "Prediction and Analysis of Building Energy Efficiency Using Artificial Neural Network and Design of Experiments," *Applied Mechanics and Materials*, vol. 819, pp. 541–545, 2016.

[99] S. Karatasou, M. Santamouris, and V. Geros, "Modeling and predicting building's energy use with artificial neural networks: Methods and results," *Energy and Buildings*, vol. 38, no. 8, pp. 949–958, 2006.

[100] S.-M. M. Hong, G. Paterson, D. Mumovic, and P. Steadman, "Improved benchmarking comparability for energy consumption in schools," *Building Research & Information*, vol. 42, no. 1, pp. 47–61, 2014.

[101] S. Ferlito, M. Atrigna, G. Graditi, S. De Vito, M. Salvato, A. Buonanno, and G. Di Francia, "Predictive models for building's energy consumption: An Artificial Neural Network (ANN) approach," in *Proceedings of the 2015 18th AISEM Annual Conference, AISEM 2015*, 2015, pp. 1–4.

[102] M.-Y. Cheng and M.-T. Cao, "Accurately predicting building energy performance using evolutionary multivariate adaptive regression splines," *Applied Soft Computing*, vol. 22, pp. 178–188, 2014.

[103] Y. Zhang, Z. O'Neill, B. Dong, and G. Augenbroe, "Comparisons of inverse modeling approaches for predicting building energy performance," *Building and Environment*, vol. 86, pp. 177–190, 2015.

[104] F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach," *Energy*, vol. 118, pp. 999–1017, 2017.

[105] G. Mihalakakou, M. Santamouris, and A. Tsangrassoulis, "On the energy consumption in residential buildings," *Energy and Buildings*, vol. 34, no. 7, pp. 727–736, 2002.

[106] F. Magoulès, H. X. Zhao, and D. Elizondo, "Development of an RDP neural network for building energy consumption fault detection and diagnosis," *Energy and Buildings*, vol. 62, pp. 133–138, 2013.

[107] S. Kalogirou, S. Lalot, G. Florides, and B. Desmet, "Development of a neural network-based fault diagnostic system for solar thermal applications," *Solar Energy*, vol. 82, no. 2, pp. 164–172, 2008.

[108] H. He, D. Menicucci, T. Caudell, and A. Mammoli, "Real-time fault detection for solar hot water systems using adaptive resonance theory neural networks," in *ASME 2011 5th International Conference on Energy Sustainability, ES 2011*, no. PARTS A, B, AND C, 2011, pp. 1059–1065.

[109] Z. Du, B. Fan, X. Jin, and J. Chi, "Fault detection and diagnosis for buildings and HVAC systems using combined neural networks and subtractive clustering analysis," *Building and Environment*, vol. 73, pp. 1–11, 2013.

[110] S. A. Kalogirou, "Applications of artificial neural-networks for energy systems," *Applied Energy*, vol. 67, no. 1-2, pp. 17–35, 2000.

[111] M. Benedetti, V. Cesarotti, V. Introna, and J. Serranti, "Energy consumption control automation using Artificial Neural Networks and adaptive algorithms: Proposal of a new methodology and case study," *Applied Energy*, vol. 165, pp. 60–71, 2016.

[112] I.-H. Yang, M.-S. Yeo, and K.-W. Kim, "Application of artificial neural network to predict the optimal start time for heating system in building," *Energy Conversion and Management*, vol. 44, no. 17, pp. 2791–2809, 2003.

[113] J. Ahn, S. Cho, and D. H. Chung, "Analysis of energy and control efficiencies of fuzzy logic and artificial neural network technologies in the heating energy supply system responding to the changes of user demands," *Applied Energy*, vol. 190, pp. 222–231, 2017.

[114] R. Yang and L. Wang, "Development of multi-agent system for building energy and comfort management based on occupant behaviors," *Energy and Buildings*, vol. 56, pp. 1–7, 2013.

[115] H. Huang, L. Chen, and E. Hu, "A neural network-based multi-zone modelling approach for predictive control system design in commercial buildings," *Energy and Buildings*, vol. 97, pp. 86–97, 2015.

[116] R. Mena, F. Rodríguez, M. Castilla, and M. R. Arahal, "A prediction model based on neural networks for the energy consumption of a bioclimatic building," *Energy and Buildings*, vol. 82, pp. 142–155, 2014.

[117] P. A. González and J. M. Zamarreño, "Prediction of hourly energy consumption in buildings based on a feedback artificial neural network," *Energy and Buildings*, vol. 37, no. 6, pp. 595–601, 2005.

[118] K. Li, C. Hu, G. Liu, and W. Xue, "Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis," *Energy and Buildings*, vol. 108, pp. 106–113, 2015.

[119] R. Platon, V. R. Dehkordi, and J. Martel, "Hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis," *Energy & Buildings*, vol. 92, pp. 10–18, 2015.

[120] M. Yalcintas and U. A. Ozturk, "An energy benchmarking model based on artificial neural network method utilizing US Commercial Buildings Energy Consumption Survey (CBECS) database," *International Journal of Energy Research*, vol. 31, no. 4, pp. 412–421, 2007.

[121] M. Yalcintas, “An energy benchmarking model based on artificial neural network method with a case example for tropical climates,” *International Journal of Energy Research*, vol. 30, no. 14, pp. 1158–1174, 2006.

[122] S. L. Wong, K. K. W. Wan, and T. N. T. Lam, “Artificial neural networks for energy analysis of office buildings with daylighting,” *Applied Energy*, vol. 87, no. 2, pp. 551–557, 2010.

[123] M. Lundin, S. Andersson, and R. Ã–stin, “Development and validation of a method aimed at estimating building performance parameters,” *Energy and Buildings*, vol. 36, no. 9, pp. 905–914, 2004.

[124] C. Buratti, M. Barbanera, and D. Palladino, “An original tool for checking energy performance and certification of buildings by means of Artificial Neural Networks,” *Applied Energy*, vol. 120, pp. 125–132, 2014.

[125] F. Khayatian, L. Sarto, and G. Dall’O’, “Application of neural networks for evaluating energy performance certificates of residential buildings,” *Energy and Buildings*, vol. 125, pp. 45–54, 2016.

[126] M. Beccali, G. Ciulla, V. Lo Brano, A. Galatioto, and M. Bonomolo, “Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy,” *Energy*, vol. 137, pp. 1201–1218, 2017.

[127] S. Kalogirou and M. Bojic, “Artificial neural networks for the prediction of the energy consumption of a passive solar building,” *Energy*, vol. 25, no. 5, pp. 479–491, 2000.

[128] S. Kalogirou, G. Florides, C. Neocleous, and C. Schizas, “Estimation of daily heating and cooling loads using artificial Neural Networks,” in *Proceedings of CLIMA 2000 International Conference*, no. September. Naples:

Cyprus University of Technology, 2001, pp. 1–11. [Online]. Available: http://ktisis.cut.ac.cy/bitstream/10488/883/3/C41-CLIMA2001.pdf

[129] Ö. A. Dombayci, "The prediction of heating energy consumption in a model house by using artificial neural networks in Denizli-Turkey," *Advances in Engineering Software*, vol. 41, no. 2, pp. 141–147, 2010.

[130] A. Kialashaki and J. R. Reisel, "Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks," *Applied Energy*, vol. 108, pp. 271–280, 2013.

[131] D. Antanasijević, V. Pocajt, M. Ristić, and A. Perić-Grujić, "Modeling of energy consumption and related GHG (greenhouse gas) intensity and emissions in Europe using general regression neural networks," *Energy*, vol. 84, pp. 816–824, 2015.

[132] A. H. Neto and F. A. S. Fiorelli, "Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption," *Energy and Buildings*, vol. 40, no. 12, pp. 2169–2176, 2008.

[133] D. Popescu, F. Ungureanu, and A. Hernández-Guerrero, "Simulation models for the analysis of space heat consumption of buildings," *Energy*, vol. 34, no. 10, pp. 1447–1453, 2009.

[134] C. Deb, L. S. Eang, J. Yang, and M. Santamouris, "Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks," *Energy and Buildings*, vol. 121, pp. 284–297, 2016.

[135] T. Olofsson and S. Andersson, "Long-term energy demand predictions based on short-term measured data," *Energy and Buildings*, vol. 33, no. 2, pp. 85–91, 2001.

[136] B. B. Ekici and U. T. Aksoy, "Prediction of building energy consumption by using artificial neural networks," *Advances in Engineering Software*, vol. 40, no. 5, pp. 356–362, 2009.

[137] S. Paudel, M. Elmtiri, W. L. Kling, O. L. Corre, and B. Lacarrière, "Pseudo dynamic transitional modeling of building heating energy demand using artificial neural network," *Energy and Buildings*, vol. 70, pp. 81–93, 2014.

[138] A. E. Ben-Nakhi and M. A. Mahmoud, "Cooling load prediction for buildings using general regression neural networks," *Energy Conversion and Management*, vol. 45, no. 13-14, pp. 2127–2141, 2004.

[139] Z. Hou, Z. Lian, Y. Yao, and X. Yuan, "Cooling-load prediction by the combination of rough set theory and an artificial neural-network based on data-fusion technique," *Applied Energy*, vol. 83, no. 9, pp. 1033–1046, 2006.

[140] R. Yokoyama, T. Wakui, and R. Satake, "Prediction of energy demands using neural network with model identification by global optimization," *Energy Conversion and Management*, vol. 50, no. 2, pp. 319–327, 2009.

[141] C. W. Yan and J. Yao, "Application of ANN for the prediction of building energy consumption at different climate zones with HDD and CDD," *Proceedings of the 2010 2nd International Conference on Future Computer and Communication, ICFCC 2010*, vol. 3, no. Cdd, pp. 286–289, 2010.

[142] M. A. Biswas, M. D. Robinson, and N. Fumo, "Prediction of residential building energy consumption: A neural network approach," *Energy*, vol. 117, pp. 84–92, 2016.

[143] M. Aydinalp, V. I. Ugursal, and A. S. Fung, "Modeling of the appliance, lighting and space-cooling energy consumption in the residential sector using neural networks," *Applied Energy*, vol. 71, no. 2, pp. 87–110, 2002.

[144] M. A. Azadeh and S. Sohrabkhani, "Annual electricity consumption forecasting with Neural Network in high energy consuming industrial sectors of Iran," in *Proceedings of the IEEE International Conference on Industrial Technology*, vol. 49, no. 8. IEEE, aug 2006, pp. 2166–2171.

[145] A. Azadeh, S. F. Ghaderi, and S. Sohrabkhani, "Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors," *Energy Conversion and Management*, vol. 49, no. 8, pp. 2272–2278, 2008.

[146] A. Kialashaki and J. R. Reisel, "Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States," *Energy*, vol. 76, pp. 749–760, 2014.

[147] Q. Li, Q. Meng, J. Cai, H. Yoshino, and A. Mochida, "Applying support vector machine to predict hourly cooling load in the building," *Applied Energy*, vol. 86, no. 10, pp. 2249–2256, 2009.

[148] Z. Hou and Z. Lian, "An application of support vector machines in cooling load prediction," in *2009 International Workshop on Intelligent Systems and Applications, ISA 2009*, vol. 2, no. 2. IEEE, 2009, pp. 1–4.

[149] B. Dong, C. Cao, and S. E. Lee, "Applying support vector machines to predict building energy consumption in tropical region," *Energy and Buildings*, vol. 37, no. 5, pp. 545–553, 2005.

[150] X. P. Zhang and R. Gu, "Electrical energy consumption forecasting based on cointegration and a support vector machine in China," in *WSEAS Transactions on Mathematics*, vol. 6, no. 12, 2007, pp. 818–883. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.533.9017&rep=rep1&type=pdf

[151] F. Lai, F. Magoulès, and F. Lherminier, "Vapnik's learning theory applied to energy consumption forecasts in residential buildings," *International Journal of Computer Mathematics*, vol. 85, no. 10, pp. 1563–1588, 2008.

[152] Q. Li, P. Ren, and Q. Meng, "Prediction model of annual energy consumption of residential buildings," in *2010 International Conference on Advances in Energy Engineering, ICAEE 2010*. IEEE, 2010, pp. 223–226.

[153] H.-x. Zhao and F. Magoulès, "Parallel Support Vector Machines Applied to the Prediction of Multiple Buildings Energy Consumption," *Journal of Algorithms & Computational Technology*, vol. 4, no. 2, pp. 231–249, 2010.

[154] H. C. Jung, J. S. Kim, and H. Heo, "Prediction of building energy consumption using an improved real coded genetic algorithm based least squares support vector machine approach," in *Energy and Buildings*, vol. 90. Elsevier B.V., 2015, pp. 76–84.

[155] J. Massana, C. Pous, L. Burgas, J. Melendez, and J. Colomer, "Short-term load forecasting in a non-residential building contrasting models and attributes," *Energy and Buildings*, vol. 92, pp. 322–330, 2015.

[156] D. M. Solomon, R. L. Winter, A. G. Boulanger, R. N. Anderson, and L. L. Wu, "Forecasting energy demand in large commercial buildings using support vector machine regression," Tech. Rep., 2011. [Online]. Available: http://academiccommons.columbia.edu/catalog/ac:143154

[157] J. W. Macarthur, A. Mathur, and J. Zhao, "On-line recursive estimation for load profile prediction," *ASHRAE transactions*, vol. 95, pp. 621–628, 1989. [Online]. Available: http://cat.inist.fr/?aModele=afficheN&cpsidt=6935287

[158] L. X. L. Xuemei, L. J.-h. L. Jin-hu, D. L. D. Lixing, X. G. X. Gang, and L. J. L. Jibin, “Building Cooling Load Forecasting Model Based on LS-SVM,” *Asia-Pacific Conference on Information Processing*, vol. 1, pp. 55–58, 2009.

[159] L. Jinhu, L. Xuemei, D. Lixing, and J. Liangzhong, “Applying principal component analysis and weighted support vector machine in building cooling load forecasting,” in *2010 International Conference on Computer and Communication Technologies in Agriculture Engineering*, vol. 1. IEEE, 2010, pp. 434–437.

[160] X. Li, L. Ding, J. Lǔ, G. Xu, and J. Li, “A novel hybrid approach of KPCA and SVM for building cooling load prediction,” in *3rd International Conference on Knowledge Discovery and Data Mining, WKDD 2010*. IEEE, 2010, pp. 522–526.

[161] L. Xuemei, D. Yuyan, D. Lixing, and J. Liangzhong, “Building cooling load forecasting using fuzzy support vector machine and fuzzy C-mean clustering,” in *2010 International Conference on Computer and Communication Technologies in Agriculture Engineering*, vol. 1, 2010, pp. 438–441.

[162] X. Li, L. Ding, and L. Li, “A novel building cooling load prediction based on SVR and SAPSO,” in *2010 International Symposium on Computer, Communication, Control and Automation*, vol. 1, no. 1. IEEE, 2010, pp. 528–532.

[163] Y. M. Zhang and W. G. Qi, “Interval forecasting for heating load using support vector regression and error correcting Markov chains,” in *Proceedings of the 2009 International Conference on Machine Learning and Cybernetics*, vol. 2, no. July, Hebei, 2009, pp. 1106–1110.

[164] H. X. Zhao and F. Magoulès, "Feature selection for predicting building energy consumption based on statistical learning method," *Journal of Algorithms and Computational Technology*, vol. 6, no. 1, pp. 59–77, 2012.

[165] R. K. Jain, K. M. Smith, P. J. Culligan, and J. E. Taylor, "Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy," *Applied Energy*, vol. 123, pp. 168–178, 2014.

[166] R. E. Edwards, J. New, and L. E. Parker, "Predicting future hourly residential electrical consumption: A machine learning case study," *Energy and Buildings*, vol. 49, pp. 591–603, 2012.

[167] X. Jiang, B. Dong, L. Xie, and L. Sweeney, "Adaptive gaussian process for short-term wind speed forecasting," in *Frontiers in Artificial Intelligence and Applications*, vol. 215, 2010, pp. 661–666. [Online]. Available: http://www.ece.tamu.edu/$\sim$le.xie/papers/Xie-AdaptiveGaussian-2010.pdf

[168] E. Grosicki, K. Abed-Meraim, and Y. Hua, "A weighted linear prediction method for near-field source localization," *IEEE Transactions on Signal Processing*, vol. 53, no. 10 I, pp. 3651–3660, 2005.

[169] S. T. Bukkapatnam and C. Cheng, "Forecasting the evolution of nonlinear and nonstationary systems using recurrence-based local Gaussian process models," *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, vol. 82, no. 5, p. 56206, 2010.

[170] Y. Heo, R. Choudhary, and G. A. Augenbroe, "Calibration of building energy models for retrofit analysis under uncertainty," *Energy and Buildings*, vol. 47, pp. 550–560, 2012.

[171] Y. Heo and V. M. Zavala, "Gaussian process modeling for measurement and verification of building energy savings," *Energy and Buildings*, vol. 53, pp. 7–18, 2012.

[172] Y. Zhang, Z. O'Neill, T. Wagner, and G. Augenbroe, "An inverse model with uncertainty quantification to estimate the energy performance of an office building," *13th Conference of the International Building Performance Simulation Association*, pp. 614–621, 2013. [Online]. Available: http://www.ibpsa.org/proceedings/BS2013/p_1410.pdf

[173] H. Y. Noh and R. Rajagopal, "Data-driven forecasting algorithms for building energy consumption," in *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, vol. 8692. San Diego: SPIE, 2013, p. 86920T.

[174] B. Lewis, I. Smith, M. Fowler, and J. Licato, "The robot mafia: A test environment for deceptive robots," in *28th Modern Artificial Intelligence and Cognitive Science Conference*, 2017, pp. 189–190.

[175] P. Rastogi, E. Polytechnique, and F. D. Lausanne, "Gaussian-Process-Based Emulators for Building Performance Simulation," in *Building Simulation 2017: The 15th International Conference of IBPSA*. San Francisco: IBPSA, 2017. [Online]. Available: https://infoscience.epfl.ch/record/252858/files/BS2017_448.pdf

[176] M. C. Burkhart, Y. Heo, and V. M. Zavala, "Measurement and verification of building systems under uncertain data: A Gaussian process modeling approach," *Energy and Buildings*, vol. 75, pp. 189–198, 2014.

[177] M. Manfren, N. Aste, and R. Moshksar, "Calibration and uncertainty analysis for computer models - A meta-model based approach for integrated building energy simulation," *Applied Energy*, vol. 103, pp. 627–641, 2013.

[178] A. Srivastav, A. Tewari, and B. Dong, “Baseline building energy modeling and localized uncertainty quantification using Gaussian mixture models,” *Energy and Buildings*, vol. 65, pp. 438–447, 2013.

[179] A. Tsanas and A. Xifara, “Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools,” *Energy and Buildings*, vol. 49, pp. 560–567, 2012.

[180] S. Papadopoulos, E. Azar, W.-L. Woon, and C. E. Kontokosta, “Evaluation of tree-based ensemble learning algorithms for building energy performance estimation,” *Journal of Building Performance Simulation*, vol. 1493, pp. 1–11, 2017.

[181] H. Deng, D. Fannon, and M. J. Eckelman, “Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECS microdata,” *Energy and Buildings*, vol. 163, pp. 34–43, 2018.

[182] Z. Wang, Y. Wang, R. Zeng, R. S. Srinivasan, and S. Ahrentzen, “Random Forest based hourly building energy prediction,” *Energy and Buildings*, vol. 171, pp. 11–25, 2018.

[183] Z. Li, Y. Han, and P. Xu, “Methods for benchmarking building energy consumption against its past or intended performance: An overview,” pp. 325–334, 2014.

[184] S. Papadopoulos, E. Azar, W. L. Woon, and C. E. Kontokosta, “Evaluation of tree-based ensemble learning algorithms for building energy performance estimation,” *Journal of Building Performance Simulation*, vol. 11, no. 3, pp. 322–332, 2018.

[185] X. Gao and A. Malkawi, "A new methodology for building energy performance benchmarking: An approach based on intelligent clustering algorithm," *Energy and Buildings*, vol. 84, pp. 607–616, 2014.

[186] M. Santamouris, G. Mihalakakou, P. Patargias, N. Gaitani, K. Sfakianaki, M. Papaglastra, C. Pavlou, P. Doukas, E. Primikiri, V. Geros, M. N. Assimakopoulos, R. Mitoula, and S. Zerefos, "Using intelligent clustering techniques to classify the energy performance of school buildings," *Energy and Buildings*, vol. 39, no. 1, pp. 45–51, 2007.

[187] I. Gath and A. Geva, "Unsupervised optimal fuzzy clustering," *IEEE Transactions on pattern analysis and machine*, vol. 11, no. 7, pp. 773–780, 1989.

[188] N. Gaitani, C. Lehmann, M. Santamouris, G. Mihalakakou, and P. Patargias, "Using principal component and cluster analysis in the heating evaluation of the school building sector," *Applied Energy*, vol. 87, no. 6, pp. 2079–2086, 2010.

[189] S. P. Pieri, I. Tzouvadakis, and M. Santamouris, "Identifying energy consumption patterns in the Attica hotel sector using cluster analysis techniques with the aim of reducing hotels' CO2 footprint," *Energy and Buildings*, vol. 94, pp. 252–262, 2015.

[190] R. Arambula Lara, G. Pernigotto, F. Cappelletti, P. Romagnoni, and A. Gasparella, "Energy audit of schools by means of cluster analysis," *Energy and Buildings*, vol. 95, pp. 160–171, 2015.

[191] Z. Yu, B. C. Fung, F. Haghighat, H. Yoshino, and E. Morofsky, "A systematic procedure to study the influence of occupant behavior on building energy consumption," *Energy and Buildings*, vol. 43, no. 6, pp. 1409–1417, 2011.

[192] S. Petcharat, S. Chungpaibulpatana, and P. Rakkwamsuk, "Assessment of potential energy saving using cluster analysis: A case study of lighting systems in buildings," *Energy and Buildings*, vol. 52, pp. 145–152, 2012.

[193] J. Yang, C. Ning, C. Deb, F. Zhang, D. Cheong, S. E. Lee, C. Sekhar, and K. W. Tham, "k-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement," *Energy and Buildings*, vol. 146, pp. 27–37, 2017.

[194] S. Jalori and T. A. Reddy, "A new clustering method to identify outliers and diurnal schedules from building energy interval data," *ASHRAE Transactions*, vol. 121, pp. 33–44, 2015.

[195] Z. Ma, P. Cooper, D. Daly, and L. Ledo, "Existing building retrofits: Methodology and state-of-the-art," pp. 889–902, dec 2012.

[196] F. Kern, P. Kivimaa, and M. Martiskainen, "Policy packaging or policy patching? The development of complex energy efficiency policy mixes," *Energy research & social science*, vol. 23, pp. 11–25, 2017.

[197] L. Tobias, *Retrofitting Office Buildings to Be Green and Energy-Efficient: Optimizing Building Performance, Tenant Satisfaction, and Financial Return*. Urban Land Institute, 2010.

[198] O. Pombo, B. Rivela, and J. Neila, "The challenge of sustainable building renovation: Assessment of current criteria and future outlook," *Journal of Cleaner Production*, vol. 123, pp. 88–100, 2016.

[199] J. Hou, Y. Liu, Y. Wu, N. Zhou, and W. Feng, "Comparative study of commercial building energy-effi ciency retro fit policies in four pilot cities in China," *Energy Policy*, vol. 88, pp. 204–215, 2016.

[200] A. Costa, M. M. Keane, P. Raftery, and J. O'Donnell, "Key factors methodology—A novel support to the decision making process of the building energy manager in defining optimal operation strategies," *Energy and Buildings*, vol. 49, pp. 158–163, 2012.

[201] E. Abel and A. Elmroth, *Buildings and Energy - a systematic approach.* Formas, 2007, vol. 6, no. 2007. [Online]. Available: http://lup.lub.lu.se/record/8056305

[202] E. Asadi, M. G. Da Silva, C. H. Antunes, and L. Dias, "Multi-objective optimization for building retrofit strategies: A model and an application," *Energy and Buildings*, vol. 44, no. 1, pp. 81–87, 2012.

[203] C. Diakaki, E. Grigoroudis, and D. Kolokotsa, "Towards a multi-objective optimization approach for improving energy efficiency in buildings," *Energy and Buildings*, vol. 40, no. 9, pp. 1747–1754, jan 2008.

[204] J. S. Gero, N. D'Cruz, and A. D. Radford, "Energy in context: A multicriteria model for building design," *Building and Environment*, vol. 18, no. 3, pp. 99–107, jan 1983.

[205] S. Pohekar and M. Ramachandran, "Application of multi-criteria decision making to sustainable energy planning—A review," *Renewable and Sustainable Energy Reviews*, vol. 8, no. 4, pp. 365–381, 2004.

[206] J. K. W. Wong and H. Li, "Application of the analytic hierarchy process (AHP) in multi-criteria analysis of the selection of intelligent building systems," *Building and Environment*, vol. 43, no. 1, pp. 108–125, 2008.

[207] D. Kolokotsa, C. Diakaki, E. Grigoroudis, G. Stavrakakis, and K. Kalaitzakis, "Decision support methodologies on the energy efficiency

and energy management in buildings," *Advances in Building Energy Research*, vol. 3, no. 1, pp. 121–146, 2009.

[208] H. Ren, W. Gao, and W. Zhou, "Multi-criteria evaluation for the optimal adoption of distributed residential energy systems in Japan," *Energy Policy*, vol. 37, no. 12, pp. 5484–5493, 2009.

[209] M. Jaggs and J. Palmer, "Energy performance indoor environmental quality retrofit - a European diagnosis and decision making method for building refurbishment," *Energy and Buildings*, vol. 31, no. 2, pp. 97–101, feb 2000.

[210] F. Flourentzou and C. A. Roulet, "Elaboration of retrofit scenarios," *Energy and Buildings*, vol. 34, no. 2, pp. 185–192, feb 2002.

[211] A. Kaklauskas, E. K. Zavadskas, and S. Raslanas, "Multivariant design and multiple criteria analysis of building refurbishments," *Energy and Buildings*, vol. 37, no. 4, pp. 361–372, 2005.

[212] S. Gou, V. M. Nik, J. L. Scartezzini, Q. Zhao, and Z. Li, "Passive design optimization of newly-built residential buildings in Shanghai for improving indoor thermal comfort while reducing building energy demand," *Energy and Buildings*, vol. 169, pp. 484–506, 2018.

[213] S. Carlucci, G. Cattarin, F. Causone, and L. Pagliano, "Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II)," *Energy and Buildings*, vol. 104, pp. 378–394, 2015.

[214] W. Yu, B. Li, H. Jia, M. Zhang, and D. Wang, "Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design," *Energy and Buildings*, vol. 88, pp. 135–143, 2015.

[215] K. McCusker and S. Gunaydin, "Research using qualitative, quantitative or mixed methods and choice based on the research," *Perfusion*, vol. 30, no. 7, pp. 537–542, 2015.

[216] G. K. F. Tso and K. K. W. Yau, "Predicting electricity energy consumption : A comparison of regression analysis , decision tree and neural networks," *Energy*, vol. 32, no. 9, pp. 1761–1768, 2007.

[217] Y.-S. Park and S. Lek, "Artificial Neural Networks: Multilayer Perceptron for Ecological Modeling," in *Developments in Environmental Modelling*. Wiley Online Library, 2016, pp. 123–140.

[218] M. Ghiassi, H. Saidane, and D. Zimbra, "A dynamic artificial neural network model for forecasting time series events," *International Journal of Forecasting*, vol. 21, no. 2, pp. 341–362, 2005.

[219] C. Harpham and C. W. Dawson, "The effect of different basis functions on a radial basis function network for time series prediction: a comparative study," *Neurocomputing*, vol. 69, no. 16, pp. 2161–2170, 2006.

[220] H. Leung, T. Lo, S. Member, and S. Wang, "Prediction of Noisy Chaotic Time Series Using an Optimal Radial Basis Function Neural Network," *IEEE Transactions on Neural Networks*, vol. 12, no. 5, pp. 1163–1172, 2001.

[221] B. Park, C. J. Messer, and T. Urbanik II, "Short-term freeway traffic volume forecasting using radial basis function neural network," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1651, no. 1651, pp. 39–47, 1998.

[222] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and regression trees.* Routledge, 2017.

[223] V. F. Rodriguez-Galiano, J. A. Luque-Espinar, M. Chica-Olmo, and M. P. Mendes, “Feature selection approaches for predictive modelling of groundwater nitrate pollution: An evaluation of filters, embedded and wrapper methods,” *Science of the Total Environment*, vol. 624, pp. 661–672, may 2018.

[224] R. Rawbone, *Doing a Successful Research Project—Using Qualitative or Quantitative Methods:*. Macmillan International Higher Education, 2015, vol. 65, no. 2.

[225] D. B. Owen, M. Abramowitz, and I. A. Stegun, *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. Courier Corporation, 1965, vol. 7, no. 1.

[226] T. Chen and C. Guestrin, “XGBoost: A scalable tree boosting system,” in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, vol. 13-17-Augu. ACM, 2016, pp. 785–794.

[227] P. Rastogi, “On the sensitivity of buildings to climate: the interaction of weather and building envelopes in determining future building energy consumption,” Ph.D. dissertation, Ecole Polytechnique Fédérale de Lausanne, 2016. [Online]. Available: https://infoscience.epfl.ch/record/220971/files/EPFL_TH6881.pdf

[228] Angeliki Xifara and Athanasios Tsanas, “Energy efficiency Data Set,” pp. 1–2, 2012. [Online]. Available: http://archive.ics.uci.edu/ml/datasets/Energy+efficiency

[229] U.S. Department of Energy, “Commercial Reference Buildings,” 2015. [Online]. Available: https://www.energy.gov/eere/buildings/commercial-reference-buildings

[230] G. Chinazzo, P. Rastogi, and M. Andersen, "Assessing robustness regarding weather uncertainties for energy-efficiency-driven building refurbishments," *Energy Procedia*, vol. 78, pp. 931–936, 2015.

[231] P. Rastogi and M. Andersen, "Incorporating Climate Change Predictions in the Analysis of Weather-Based Uncertainty," *Proceedings of SimBuild*, vol. 6, no. 1, 2016.

[232] I. M. Sobol, "Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates," *Mathematics and computers in simulation*, vol. 55, no. 1-3, pp. 271–280, 2001.

[233] A. Saltelli, "Sensitivity analysis for importance assessment," *Risk analysis*, vol. 22, no. 3, pp. 579–590, 2002.

[234] K. Deb, "Multi-objective optimization," in *Search Methodologies*. Boston: Springer, 2013, pp. 403–449.

[235] F. Hutter, H. H. Hoos, and K. Leyton-Brown, "Sequential model-based optimization for general algorithm configuration," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 6683 LNCS, no. Chapter 40. Springer, 2011, pp. 507–523.

[236] Communities and Government Local: London, "Performance Testing of Buildings BD 2535," Department for Communities and Local Government, London, UK, Tech. Rep., 2013. [Online]. Available: https://www.bipsolutions.com/docstore/pdf/20548.pdf

[237] C. Koo, T. Hong, M. Lee, and H. Park, "Development of a new energy efficiency rating system for existing residential buildings," *Energy Policy*, vol. 68, pp. 218–231, 2014.

[238] Building Research Establishment (BRE), "Building Standards Division National Calculation Methodology (NCM) Modelling Guide for Non-Domestic Buildings in Scotland," Tech. Rep., 2015. [Online]. Available: http://www.gov.scot/bsd

[239] S. M. Hong, "Benchmarking the energy performance of the UK non-domestic stock : a schools case study," Ph.D. dissertation, 2015.

[240] G. Went, "EPC minimum standards update," Lennons Solicitors, Tech. Rep., 2018. [Online]. Available: http://www.lennonssolicitors.co.uk/2018-epc-minimum-standards-update/

[241] H. Bruhns, "Identifying Determinants of Energy Use in the UK nondomestic Stock," in *Improving Energy Efficiency in Commercial Buildings Conference*. Frankfurt: Citeseer, 2008, pp. 10–11. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.588.365&rep=rep1&type=pdf

[242] A. Ng, "Machine Learning and AI via Brain Simulations," 2013. [Online]. Available: http://www.youtube.com/watch?v=n1ViNeWhC24%5Cnpapers3://publication/uuid/FD4F0FE0-BB23-431D-8840-6808135CC089

[243] Arbnco, "arbn consult." [Online]. Available: https://arbnco.co.uk/arbn-consult/

[244] Y. Lu, "Industry 4.0: A survey on technologies, applications and open research issues," *Journal of Industrial Information Integration*, vol. 6, pp. 1–10, 2017.

[245] W. Yi and A. P. Chan, "Critical review of labor productivity research in construction journals," *Journal of Management in Engineering*, vol. 30, no. 2, pp. 214–225, 2014.

[246] S. Azhar, I. Ahmad, and M. K. Sein, "Action research as a proactive research method for construction engineering and management," *Journal of Construction Engineering and Management*, vol. 136, no. 1, pp. 87–98, 2010.

[247] L. Blaxter, C. Hughes, and M. Tight, *How to Research Trends*, 4th ed. Maidenhead: McGraw-Hill Education (UK), 2010.

APPENDIX A

Detailed Results for Tuning Machine Learning Model

The detail of tuning each ML model discussed in Chapter 4 is presented here. Some models have several parameters, so the brute force search includes thousands of train-test models. Therefore, it is not possible to present the list of all results in this paper. However,Tables A.1 to A.6 demonstrates the parameters for the best models predicting energy loads of datasets processed with EnergyPlus and Ecotect. In each table the best model is highlighted with light blue colour.

In order to reduce the time complexity of tuning ANN model, the number of epochs was fixed at 500 and the other parameters were optimised. Then the optimal number of propagations was separately obtained using the best parameters. As shown in the Figures A.1 (a) and (b)

Table A.1: Detail of optimising SVM for both datasets.

EPlus Data		Ecotect Data		SVM Parameters	
Heat RMSE	Cool RMSE	Heat RMSE	Cool RMSE	C	Gamma
14.318	9.785	0.677	1.622	10,000	1
18.988	9.774	0.654	1.667	1000	1
15.720	9.261	0.660	1.756	1,000,000	0.1
15.313	10.302	0.978	1.842	1,000,000	1
21.626	8.763	0.815	2.048	100,000	0.1
31.415	9.452	2.108	2.636	10,000	0.1
43.719	17.833	2.627	3.365	10,000	0.01
60.974	31.658	3.304	3.886	1	0.1
60.974	31.658	3.304	6.550	1	0.01

Table A.2: Detail of optimising RF for both datasets.

EPlus Data		Ecotect Data		RF Parameters		
Heat RMSE	Cool RMSE	Heat RMSE	Cool RMSE	Bootstrap	Max features	No. of estimators
12.873	9.894	0.568	1.585	False	sqrt	600
12.720	9.693	0.576	1.605	False	sqrt	400
14.556	10.734	0.604	1.612	True	sqrt	200
13.334	10.214	0.502	1.658	False	log2	1000
14.551	9.691	0.476	1.683	True	auto	600
14.584	9.600	0.478	1.691	True	auto	800
24.189	13.727	0.536	1.814	False	auto	1000
14.199	10.995	0.616	1.604	True	sqrt	400

Table A.3: Detail of optimising GBRT for both datasets.

EPlus Data		Ecotect Data		GBRT Parameters						
Heat RMSE	Cool RMSE	Heat RMSE	Cool RMSE	Learning rate	Max depth	max features	Min sample leaf	Min sample split	No. estimators	Sub sample
13.157	7.402	0.388	0.677	0.15	8	None	1	100	1500	1
11.534	6.667	0.366	0.893	0.15	3	None	1	2	1500	1
12.914	6.297	0.399	1.033	0.25	3	sqrt	1	2	1500	1
10.721	8.855	0.514	1.261	0.1	8	sqrt	1	2	2000	1
13.257	9.608	0.523	1.578	0.01	13	sqrt	1	2	1250	0.9
17.843	8.654	3.77	3.895	0.01	8	sqrt	200	100	500	1
22.775	9.856	8.732	8.524	0.001	13	sqrt	200	100	1250	0.7
26.221	15.625	10.054	9.725	0.25	3	sqrt	1000	100	1750	1
35.518	21.196	10.003	9.726	0.1	8	sqrt	1000	1000	1000	0.9
46.991	24.279	9.996	9.720	0.1	3	sqrt	1000	2	1000	0.8
49.515	24.542	9.996	9.722	0.1	3	None	1000	100	1500	0.7
21.578	11.642	10.422	9.746	0.15	13	None	500	1000	1000	0.8

Table A.4: Detail of optimising XGBoost for both datasets.

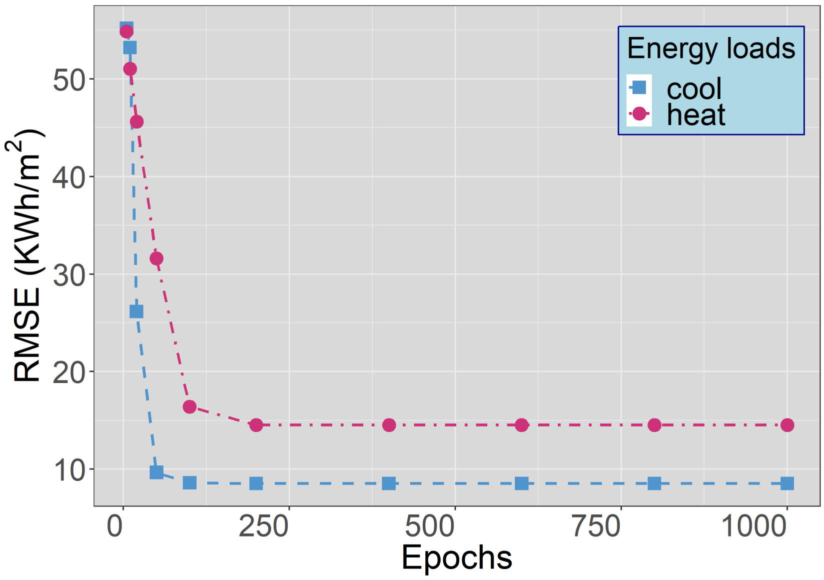
EPlus Data		Ecotect Data		XGBoost Parameters					
Heat RMSE	Cool RMSE	Heat RMSE	Cool RMSE	Portion of features	Learning rate	Max depth	Min child weight	No. estimator	Sub sample
10.909	8.145	0.303	0.401	0.6	0.1	8	1	1750	0.9
11.616	9.002	0.300	0.452	0.6	0.1	13	1	750	0.7
12.273	8.048	0.323	0.573	0.38	0.1	8	1	1250	0.8
12.436	8.18	0.329	0.804	0.6	0.01	13	1	1750	1
11.302	6.270	0.413	1.131	0.6	0.1	3	1	2000	0.7
10.387	6.382	0.409	1.115	0.6	0.1	3	3	2000	0.9
13.738	9.982	0.306	0.443	0.5	0.1	13	1	1750	0.8
16.030	12.706	0.337	0.557	0.4	0.5	13	3	1000	0.7
20.003	10.434	0.304	0.433	0.1	0.1	8	1	10000	0.8
23.821	14.138	0.343	0.567	0.1	0.25	13	3	1000	0.7
26.266	16.581	0.365	0.578	0.1	0.5	13	3	1500	0.8
57.263	35.554	9.459	10.412	0.6	0.01	3	1	200	0.7

Table A.5: Detail of optimising GP for both datasets.

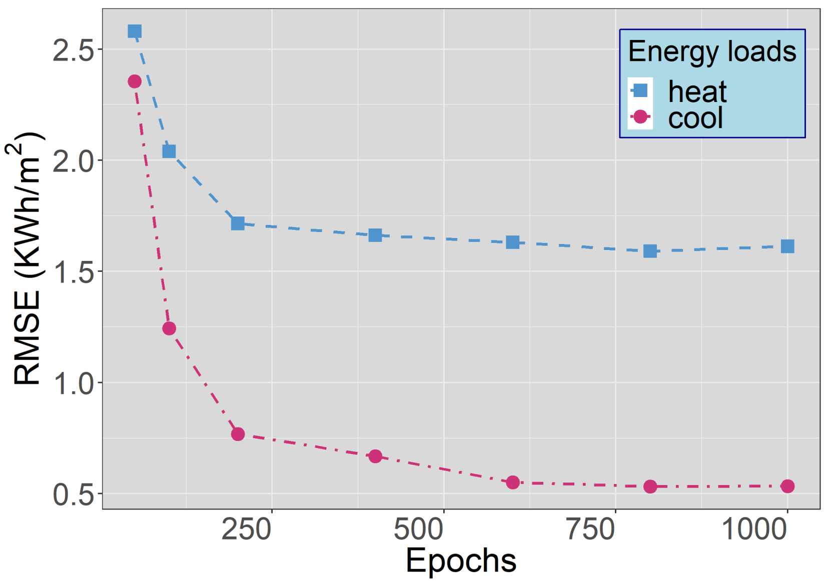
Ecotect Data		GP Parameters		
Heat RMSE	Cool RMSE	Alpha	Kernel	No. restarts
1.382	2.279	1e-08	Mattern	2
1.381	2.383	1e-12	RBF	4
8.472	2.332	1e-8	RBF	2
8.471	2.333	1e-10	RBF	0
1.383	3.138	1e-4	Mattern	0
4.440	4.238	1e-6	RBF	4

Table A.6: Detail of optimising ANN for both datasets.

EPlus Data		Ecotect Data		ANN Parameters				
Heat RMSE	Cool RMSE	Heat RMSE	Cool RMSE	Activation	Batch size	No. hidden layers	No. neurons	Optimiser
30.456	12.103	0.492	1.829	Logistic	10	1	2N	lbfgs
30.675	15.847	0.781	1.711	Tanh	10	1	2N	lbfgs
14.631	9.973	0.884	3.389	Tanh	1	2	N, 2N	adam
17.337	9.376	1.052	3.308	Tanh	10	3	3N, 2N, N	lbfgs
14.068	9.754	2.616	3.388	Tanh	1	1	2N	adam
41.157	18.079	4.476	6.645	Relu	1	2	N, 2N	adam
27.573	13.994	10.005	9.73	Logistic	10	3	3N, 2N, N	adam
51.323	26.502	14.453	15.968	Relu	auto	1	N	adam
49.118	25.223	6.401	7.010	Identity	1	2	N, N/2	adam
80.052	57.114	23.506	25.482	Logistic	10	2	3N, N/2	adam



(a)



(b)

Figure A.1: RMSE of ANN model predicting energy loads for (a) EPlus and (b) Ecotects datasets against number of epochs.

APPENDIX B

Non-domestic Building Records Distribution

Table B.1 presents the distribution of buildings in different weather locations for the data collected from arbn consult platform. The first column, “Type”, shows the usage type of buildings. The next 12 columns present the number of building in each specific climate region. Column “area” presents the variation of buildings area in m^2.

Table B.1: Distribution of non-domestic building records considering usage type and location.

Type	Number of buildings in each weather*												Area (m^2)
	BIR	CAR	GLA	LEE	LON	MAN	NEW	NOR	NOT	PLY	SOU	SWI	
Retail and Financial/Professional services	120	400	290	432	651	492	185	89	98	128	104	134	6 – 50411
Restaurant and Cafes	16	41	16	24	102	60	20	9	14	13	12	20	14 – 3725
Offices and Workshop businesses	92	64	47	33	417	80	34	21	21	18	15	34	4 – 130751
General and Special Industry	35	1	67	25	60	10	8	2	13	5	2	15	32 – 17471
Storage or Distribution	63	10	8	5	48	2	17	0	11	5	7	10	13 – 51778
Hotels	1		2	3	3	1	1	0	0	0	0		470 – 6942
Other (education, health, public)	3	17	9	9	25	12	7	6	4	2	6	3	85 – 25300
Average BER for each weather	94	106	116	107	107	103	109	117	114	108	111	110	

* BIR: Birmingham, CAR:Cardiff, GLA: Glasgow, LEE: Leeds, LON: London, MAN: Manchester, NEW; Newcastle, NOR: Norwich, NOT: Nottingham, PLY: Plymouth, SOU: Southampton, SWI: Swindon

APPENDIX C

Calculating Features for Retrofit-specific Energy Modelling

Here, the the details of calculated features for modelling non-domestic buildings energy performance, are presented. The features are retrieved from the '.inp' output files processed with SBEM software.

DHW_Dem: The sum of the product of systems' electric equivalent efficiencies and associated hot water demand for a single day. Normalised by total area including unconditioned zones.

$$DHW\_Dem = \frac{\sum zone\ DHW\ demand}{\sum area} \qquad (litters/m^2 day) \tag{C.1}$$

U_Trans: Weighted U-Value for external glazing. The sum of the product of glazing areas' associated glass U-Value. Normalised by total glazing surface area.

$$U\_trans = \frac{\sum(window\ area \times glass\ u\ value)}{\sum window\ area} \tag{C.2}$$

ST_ExW: Weighted solar transmittance ratio for external glazing. The sum of the product of glazing areas' associated GLASS total solar transmittance coefficient. Normalised by total glazing surface area.

$$ST\_ExW = \frac{\sum(window\ area \times glass\ total\ solar\ transmittivity)}{\sum window\ area} \tag{C.3}$$

U_Opaq: Weighted U-Value for opaque external surfaces adjusted by heat electric equivalent efficiency. It is calculated by the sum of the quotient of HVAC-level aggregation of the product of wall area and associated construction U-Value and the heat electric equivalent efficiency.

$$U\_Opaq = \frac{\sum(external\ wall\ area \times wall\ u\_value)}{\sum external\ wall\ area} \tag{C.4}$$

LPD: Lighting power density is defined as the installed lighting power, in wattages, in a building space divided by the space area in square meters or square feet.

$$LPD = \frac{\sum wattage\ of\ lighting}{\sum area} \qquad (W/m^2) \tag{C.5}$$

SFP_Vent: The collective air handling unit's effective specific fan power (SFP) weighted by area served by mechanical ventilation, representing the power necessary to deliver 1 litre of fresh air per second (W/l/s).It is calculated by the quotient of the product of serviced area by the associated HVAC's SFP and the sum of all mechanically ventilated areas.

$$SFP\_Vent = \frac{\sum zone\ sfp\ termial\ unit \times area\ with\ fan\ coil\ system}{\sum zone\ area} \tag{C.6}$$

IHG: The internal heat gains from equipment, lighting and occupants adjusted by the associated HVAC's heat electric equivalent efficiency. It is calculated by the quotient of the product of the sum of occupant gains, waste heat from equipment and waste heat from lighting, and the associated HVAC's efficiency (heff) and normalised by heated area.

$$IHG = \sum \frac{heated\ zone\ gain\ (occgains + eqgains + lgains)}{heff} \times \frac{1}{\sum heated\ zone\ area} \qquad (W/m^2) \tag{C.7}$$

ICO: Internal conduction is the heat transfer from conditioned to unconditioned building zones is calculated for one unit of area in unit time. It is calculated by the quotient of the product of the sum of area of component under analysis and wall heat transfer coefficient normalised by area.

$$ICO = \frac{\sum adjacent\ area \times heat\ coefficient \times temp\ diff}{\sum\ zone\ area} \qquad (W/m^2) \tag{C.8}$$

ECS: It is the cooling system efficiency of the abstract conditioning system, and calculated as the quotient of the product the sum of zone areas and cooling source efficiency, and the sum of all cooled areas.

$$ECS = \frac{\sum\ cool\ zone\ area \times\ cool\ efficiency}{\sum\ zonearea} \tag{C.9}$$

EHS: It is the heating system efficiency of the abstract conditioning system, and calculated as the quotient of the product the sum of zone areas and heat source efficiency, and the sum of all heated areas.

$$EHS = \frac{\sum\ heat\ zone\ area \times\ heat\ efficiency}{\sum\ zonearea} \tag{C.10}$$

APPENDIX D

Details of the Case Study Building Characteristics

The case study building, Graham Hill, has been subjected to several retrofits over the last twenty years. Table D.1 summarises the thermal properties of different layers of the envelope parts for the building at its latest status. These include external walls, stud partitions (separate spaces where no load-bearing wall is present), load-bearing internal envelopes, flat roof, internal floors and glazing. All external envelopes and glazing remain without renovation since construction.

Table D.1: Envelope and glazing properties of Graham Hill eighth floor

Envelopes and glazing	External Wall				Internal Partitions (Stud)		Internal Partitions (Brick)			Flat Roof				Raised Exposed Floor			Single Glazing
Layers	Plasterboard	Concrete	Cavity	Concrete	Plasterboard	Plasterboard	Plasterboard	Brickwork	Plasterboard	Tiles	Cavity	Concrete	Bitumen	Carpet	Screed	Concrete	C6MM
Specific heat capacity $(J/(kg.tK))$	8400	1000	NA	1000	100		1000	800	100	1000	NA	1000	1000	2500	840	1000	8400
Thermal conductivity $(W/m.K)$	0.16	0.51	0.51	0.51	0.21		0.16	0.62	0.16	0.05	NA	1.13	0.50	0.06	0.41	1.13	1.06
Density $(kg/m^3))$	950	1400	1400	1400	900		600	1700	600	380	2000	1700	14	160	1200	2000	8400
Resistance (m^2K/W)	0.031	0.019	0.30	0.042	0.0619		0.813	0.169	0.813	0.01	0.8	0.1	0.005	0.833	0.122	0.089	0.006
Thickness (cm)	0.5	1	10	5	1.3		1.3	1.05	1.3	0.01	80	10	0.5	5	5	10	0.6
Surfaces	Outside		Inside		Inside		Inside			Outside		Inside		inside			Out/In
Emissivity	0.9		0.9		0.9		0.9			0.9		0.9		0.9			
Solar absorptance	0.5		0.5		0.55		0.55			0.5		0.5		0.55			0.9
Thermal Performance																	
U-Value(W/m^2K)	1.77				2.65		1.69			1.7034				0.798			5.561
Thermal mass$(kJ/(m^2K))$	17.99				11.7		79.2			3.8				70.4			5.7
Mass(kg/m^2)	118.75				23.4		194			212				260			0.78
Thermal bridging$((W/m^2K))$	0.117				0.035		0.169			0.17				0.08			0.82