Real-time Energy Use Predictions at the Early Architectural Design Stages with Machine Learning

Greig Paterson

2017

Submitted in partial fulfilment of the requirements for the degree of

Doctor of Engineering

The Bartlett

University College London

I, Greig Robert Paterson confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

....

Machines take me by surprise with great frequency

Alan Turing (1950)

Abstract

It has been argued that traditional building energy simulation methods can be a slow process, which often fails to integrate into the design process of architects at the early design stages. Furthermore, studies have shown that the actual energy consumption of buildings once built and in operation is often far greater than the energy consumption predictions made during design.

The difficulty of simulating real-world systems, such as the stock market or buildings, is the lack of understanding of the complex, non-linear and random interactions that take place. This is in part due to the involvement of people, whose behaviour is difficult to predict. An alternative to simulating complex systems with mathematical models is an approach based on real-world data, where system behaviour is learned through observations. Display Energy Certificates (DECs) are a source of observed building 'behaviour' in the UK and machine learning, a subset of artificial intelligence, can predict global behaviour in complex systems.

In view of this, this thesis presents research that explores a method to predict and communicate the operational energy use of buildings in real-time as early design and briefing parameters are altered interactively. As a demonstrative case, the research focuses on school design in England. Artificial neural networks, a machine learning technique, were trained to predict thermal (gas) and electrical energy use of school designs based on a range of design and briefing parameters. In order to generate data for the artificial neural networks to learn from, a building characteristics dataset was developed which contains real-world data on 502 existing school buildings across England. A product of this research is a user-friendly design tool based on the psychological principles of 'flow', aimed at non-simulation experts, such as architects. The tool is named the 'SEED Tool' (School Early Environmental Design Tool).

Acknowledgements

The research presented here was supported by funding from the UK Engineering and Physical Sciences Research Council (EPSRC) via UCL's EngD Centre in Virtual Environments, Imaging and Visualisation (VEIV) with additional funding and support from AHR (formerly known as Aedas Architects). 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 the Bartlett and AHR/Aedas. Only a few can be mentioned here.

Firstly, I would like to thank my supervisor, Dejan Mumovic, for all the help, support and guidance he offered and for the many conversations we had which started with research and diverted to all sorts of subjects. I suspect he will never know just how important his influence was.

On a similar note, I'd like to thank my industrial supervisor, Judit Kimpian, for welcoming me into AHR, introducing me to some fantastic architecture projects and pushing me to think about my research in a professional context.

I'd like to give a special thank you to Payel Das, for helping with the statistical analyses in this research and giving feedback on the writing of this thesis, and Sung Min Hong, for co-creating the building characteristics database with me. I'd also like to thank the masters students in Environmental Design and Engineering (EDE) at UCL, who assisted in the data collection process, and the professional architects and engineers who tested the design tool that was a product of this research.

Finally, this would not have been possible without the love and support of my family. In particular, I would like to thank my dad, for his unconditional support for all the decisions I have made in my life; my sister, for always being able to make me laugh; and my mum, for her love, encouragement and unique perspective on everything. This doctorate is dedicated to you.

Acronyms

AA	Architecture Association
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASHRAE	American Society of Heating, Refrigerating, and Air-conditioning Engineers
BBC	British Broadcasting Corporation
BIM	Building Information Modelling
BPS	Building Performance Simulation
BRE	Building Research Establishment
BREEAM	Building Research Establishment Environmental Assessment Methodology
BSF	Building Schools for the Future
CAD	Computer Aided Design
CBECS	Commercial Buildings Energy Consumption Survey
CDE	Common Data Environment
CIBSE	Chartered Institution of Building Services Engineers
CIP	Central Information Point
COP	Coefficient of Performance
DEC	Display Energy Certificates

DECC	Department of Energy & Climate Change (HM Government)
DfE	Department for Education
DfES	Department for Education and Skills
DOE	Department of Energy (US Government)
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
EUI	Energy Use Intensity
HEED	Home Energy Efficient Design
HVAC	Heating, Ventilation and Air Conditioning
IBPSA	International Building Performance Simulation Association
ICT	Information and Communications Technology
IES	Integrated Environmental Systems
IPV	Integrated Performance View
IT	Information Technology
LEED	Leadership in Energy & Environmental Design
LiDAR	Light Detection and Ranging
MAPE	Mean Absolute Percentage Error
MIT	Massachusetts Institute of Technology
MSE	Mean Squared Error
NREL	National Renewal Energy Laboratory
NURBS	Non-uniform Rational B-spline

PDA	Passive Design Assistant
PFI	Private Finance Initiative
PVQ	Pre-visit Questionnaire
PI	Performance Indicators
RIBA	Royal Institute of British Architects
RMSE	Root-mean Square Error
SBEM	Simplified Building Energy Models
SEED	School Early Environmental Design
TM	Technical Memorandum
TSB	Technology Strategy Board
UCL	University College London

Contents

List of Figures

List of Tables

For my family

Chapter 1

Introduction

1.1 Background

Environmental responsibility has undeniably moved into the mainstream of our social, economic and political culture. In the UK, the Climate Change Act 2008 (DECC 2008) set a regulatory target to reduce UK carbon emissions by 80% by 2050 against a 1990 baseline. The built environment contributes significantly to the anthropogenic environmental impact, with buildings consuming over 40% of all of the UK's energy use (Carbon Trust 2009). It is the responsibility of the design team to take the appropriate sustainable actions to reduce energy consumption and meet our sustainability aspirations (CIBSE 2004). As such, informing architects during the early design stages based on environmental design reasoning is important (Attia 2012).

In order to set this doctoral research in context, this introductory chapter will expand on the principles of environmental design, outline the architectural design process and discuss the limitations of current design aids available to architects. Following this will be an outline of the building energy use 'performance gap' in the UK, that is, the difference between design predictions and actual building performance, before a machine learning method is introduced as an alternative to current design aids. Finally, the research aims will be presented, together with an outline of the approach taken to achieve them.

1.2 Environmental Design

Overview

Throughout history, the creation and shaping of the built environment has been at the forefront of human endeavour (Nuttgens 1997). Architecture is a part of human history and culture, as well as being an art form in its own right. There is one fundamental difference, however, between architecture and all other forms of art: "it has to be practical as well as attractive," (Nuttgens 1997, p.8).

The first buildings were essentially protection against the elements; simple enclosures that helped maintain a comfortable internal environment by keeping out the rain and wind while sustaining a suitable temperature. Many modern examples of architecture are the antithesis of this. For example, it is now possible to build buildings walled in glass with high internal heat gains in hot arid climates – utilising mechanical means of environmental control. These buildings often rely on cheap energy for space conditioning (Thomas and Garnham 2007). In Reyner Banham's 1960 book *Theory and Design in the First Machine Age*, it was said that mechanical services were the only truly reliable means of controlling internal air quality (Banham 1960). However, despite this claim, there is a common opinion that contemporary buildings are often of poor quality, leading to the term 'sick building syndrome', which relates to a number of phenomena that cause a building to be environmentally uncomfortable and even unsafe. At the very least it is not uncommon for occupants to complain about poor ventilation, inappropriate heating control or overheating of spaces in summer (CIBSE

2004). Furthermore, energy security and the effects of climate change points to mechanisation losing command as the sole means to control internal environmental conditions. As a consequence, environmental design as a discipline within the building industry developed greatly in the latter part of the twentieth century.

Environmental design is the philosophy of using science to design buildings to make best use of their context in order to achieve efficient, healthy and comfortable buildings for occupants while minimising any harmful impact on the wider environment. Low energy design is one aspect of environmental design whereby the building is designed to consume as little energy as possible given the constraints of the design brief. Low energy design forms the setting for this thesis.

Energy and Buildings

The consumption of energy in buildings is necessary for occupant health, comfort and convenience. It is necessary for heating, lighting and electrical equipment. The consumption of energy by buildings in the UK under the current national energy mix results in the emission of CO_2, among other gases and pollutants, and the payment of energy bills. Building systems, such as boilers, tend to increase in capital cost as system capacity increases (Buys and Mathews 2005). Therefore, the reduction of energy use in buildings, such that the occupants remain healthy and satisfied, reduces emissions to the wider environment while also reducing capital and running costs of the building. Some aspects of energy consumption are inherent to occupant activity, such as the use of computers. Other aspects, such as space heating and electrical lighting, can be affected by building design.

Wicked Problems

'Wicked' problems are defined as problems that are difficult to solve because their solution depends on resolving relationships between a host of often contradictory qualitative and quantitative interdependent factors (Rittel, H., W., Webber, M. 1973) – that is, solving one problem (eg. increasing daylight by introducing more glazing) can create another problem (eg. overheating). These problems are characterised as having no global optimum as many design goals conflict with one another. Such problems are often unique, which prevents the effective application of prescriptive or historically determined methods to solve them. Sustainable design decisions need to take into consideration all aspects of environmental design including types of energy consumption (thermal and electrical). In this way, environmental design can be described as being a wicked problem (Pratt and Bosworth 2011).

1.3 The Design Process

RIBA Plan of Work

Since 1963, The Royal Institute of British Architects (RIBA) have provided the RIBA Plan of Work (RIBA 2013), which is a framework for the building design and construction process in the UK. It is widely recognised in the UK construction industry as a model set of procedures for building project administration. The plan of work has evolved through its history and currently divides the process of creating a building into eight stages (Table 1.1). A sustainable overlay (RIBA 2013) also exists to accompany the RIBA Plan of Work, created by Bill Gething (Max Fordham 2014).

Stage	**Core Objectives**
Strategic Definition	Identify client's business case and requirements.
Preparation and Brief	Develop project objectives, including project outcomes, sustainability aspirations, budget, other parameters or constraints and develop initial project brief. Undertake feasibility studies and review of site information.
Concept Design	Prepare concept design, including outline proposals of structural design, building services systems, preliminary costs and project strategies. Agree alterations to brief and issue final project brief.
Developed Design	Prepare developed design, including coordinated and updated proposals for structural design, building services systems, costs and project strategies.
Technical Design	Prepare technical design to include all architectural, structural and building services information as well as specialist subcontractor design and specifications.
Construction	Carry out offsite manufacturing, onsite construction, and resolve design queries from site as they arise.
Handover and Close Out	Handover of building and conclusion of the building contract.
In Use	Undertake in use services and conclude handover strategy.

Table 1.1: RIBA Plan of Work (RIBA 2013)

Concept Design Stage

Early concept designs are hugely important in determining the eventual success and impact of a project. Figure 1.1 shows how the effectiveness (impact on sustainability, running costs and aesthetics etc.) of design decisions diminish from the conceptual to detailed design stages and reduce further into the construction and maintenance stages of a building. Design decisions at the conceptual design stage include defining factors, such as orientation and form. Detailed design development later in the design process, and alterations during maintenance, can refine and elaborate a sound early concept design but can only partly ameliorate a poor one (Eastman 2009).

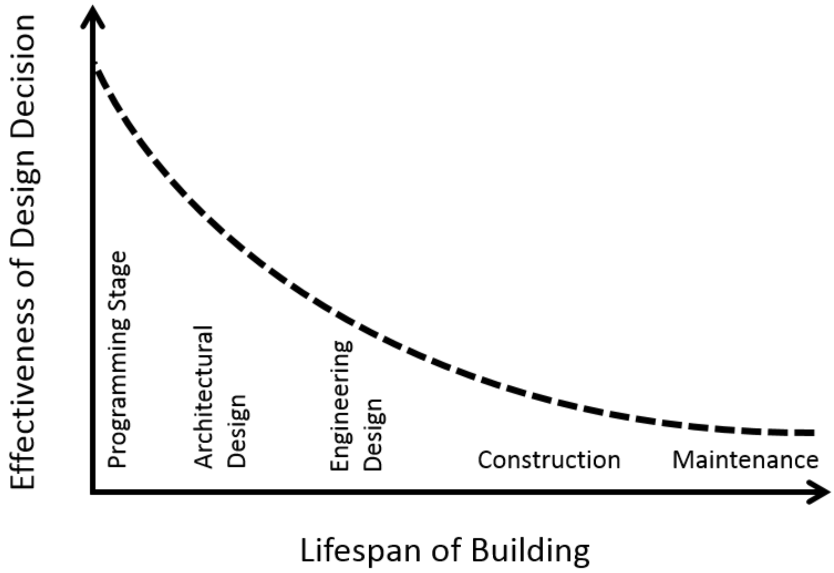


Figure 1.1: The effectiveness of design decisions throughout the lifespan of a building, adapted from Lechner (2001)

Early stage design is exploratory, ill-defined and unpredictable (Attia 2012; Lawson 2006). As a consequence, exploration of the design space during the early design stages is an essential task of the architect (Attia 2012). However, early analysis methods, currently used in the creation of energy efficient buildings, are often ill-suited for the task (Pratt and Bosworth 2011). This is because the design space at the early design stages is "constrained, intermittently populated and information-poor" (Pratt and Bosworth 2011, p.2499). Pratt and Bosworth define information poverty within environmental design as "a lack of predictive information which would give insight into how a design might perform in the ‘real world’" (Pratt and Bosworth 2011, p.2500).

1.4 Design Aids

Overview

Experience and intuition are essential, however, with regards to environmental design, architects should not depend on these aspects alone (Attia 2012). In order to help designers make sustainable design decisions, there are many environmental 'design aids' available. These design aids can largely be grouped into the following categories (Morbitzer 2003):

- Design guidelines / rules of thumb
- Steady state calculation methods
- Correlation-based methods
- Physical modelling
- Building simulation

Given that environmental design problems tend to be 'wicked', as discussed in Section 1.2, rules of thumb, steady state calculations and correlation methods are often inadequate techniques (Morbitzer 2003; Pratt and Bosworth 2011) and physical modelling has the disadvantage of being very costly (Morbitzer 2003). When used correctly, the most powerful and flexible design aid available for the analysis of environmental performance is building simulation (Morbitzer 2003).

Building Simulation

Building simulation, including dynamic thermal simulation, is an approach whereby a mathematical computer model aims to emulate the real physical conditions in a building by representing various energy flow paths and environmental interactions (Clarke 2001). These models can be used to develop predictive information that would address the information poverty of the early design stages, outlined in Section 1.3. Simulation is routinely used in the detailed design stages by engineers and specialist consultants to calculate system loads, verify that performance criteria have been met and document energy code compliance (Ellis et al. 2006). Building simulation is, however, rarely used by architects at the early design stages (Pratt and Bosworth 2011).

Why Architects Reject Building Simulation

It is often found that architects reject simulation, especially at the early stages of design, as they are far removed from the way in which architects think and design (Lawson 2006). The early architectural design process imposes much pressure on designers. There is limited time and resources to create design proposals, and building simulation is often a burden, rather than an aid for design (Morbitzer 2003). Architect and psychologist, Lawson, states that this is because simulation and other building science tools are not 'design' tools but "simply tools of evaluation and give no help at all with synthesis" (Lawson 2006, p.60), which are only used to assess designs after they have been designed: "the computer is certainly acting as a design critic, but rather too late in the process to be constructive" (Lawson 2004, p.76). A major barrier is the time taken to input all the required information, such that the designer can only afford to do it after the major design decisions have been made (Lawson 2004).

Furthermore, the design space is constrained by the fact that commonly used building simulation tools produce static results – it is therefore difficult, given time and economic constraints, to produce a wide range of design options (Pratt and Bosworth 2011). In this way, the design space is sparingly populated because the models are discrete rather than continuous, thus omitting 'in- between solutions' (Pratt and Bosworth 2011).

It is this process that makes many architects describe computational environmental analysis as a rather remote process, far from the way designers work – what is needed instead is a more natural, conversational and immediate feedback process (Lawson 2006). In this way, analysis tools will not be seen as a burden but as a useful tool that makes making informed design decisions easier.

Building simulation is a rapidly evolving industry, as outlined in Section 2.3.1. Many new tools are being developed to cater for the needs of architects. However, as discovered when reviewing early stage design tools (Section 2.3.10), it was found that many of the aforementioned barriers still currently exist.

1.5 The Performance Gap in Building Energy Use

Overview

The *performance gap*, within the context of building energy consumption, is the difference in energy use and carbon emissions between predictions made during design and measured performance once a building is built and in use. In the UK, non-domestic buildings currently consume between 150% and 250% their predicted energy use and carbon emission values (CBxchange 2014). As well as environmental consequences, this also has cost implications and can add over £10/m^2 in unexpected operating costs (CBxchange 2014) to a building.

The performance gap occurs for a number of reasons, including (CBxchange 2014):

- Inaccuracies during the design process
- Design changes
- Poor quality of construction

- Inadequate commissioning
- Systems not operating as intended

Despite current knowledge and emerging research of how to design and deliver sustainable projects, buildings continue to consume energy unsustainably (CBxchange 2014). Furthermore, compliance calculations (in the UK), mandatory by law, do not take 'unregulated energy' aspects, such as swimming pools, lifts, external lighting and server rooms, into account.

CarbonBuzz

CarbonBuzz (2014) is an online RIBA/CIBSE[1] platform that allows users, be they architects, engineers, facility managers or other building stakeholder, to anonymously upload building design and energy data from design through to operation. The dataset is comprised of ~600 buildings from various non-domestic sectors in the UK. Offices and schools comprise the largest contingent at around 40% and 30% of the database respectively. From an audit conducted in April 2013 by the UCL Energy Institute (2013), an analysis of the energy data for office and school buildings was carried out. The results of this study for thermal energy use are shown in Table 1.2 and the results for electricity energy use are shown in Table 1.3.

Sector	**Mean Design Total Thermal Energy Use (kWh/m^2/yr)**	**Mean Actual Total Thermal Energy Use (kWh/m^2/yr)**	**Design Prediction Error (%): 'Performance Gap'**
Offices	46	73	37
Education	57	84	32

Table 1.2: Performance gap – thermal energy use, adapted from the UCL Energy Institute (2013)

[1] Royal Institute of British Architects (RIBA); and Chartered Institution of Building Services Engineers (CIBSE)

Sector	Mean Design Total Electricity Use (kWh/m^2/yr)	Mean Actual Total Electricity Use (kWh/m^2/yr)	Design Prediction Error (%): 'Performance Gap'
Offices	71	121	41
Education	56	106	47

Table 1.3: Performance gap – electricity energy use, adapted from the UCL Energy Institute (2013)

40% of the design data in Tables 1.2 and 1.3 came from energy performance certificates (EPCs), 30% of the design data came from simplified building energy models (SBEMs) and the remaining 30% came from 'full' building energy simulation models (dynamic thermal models). The results show that the prediction errors (performance gap) of the design calculations tend to be as high as 47%. The auditors of the data, the UCL Energy Institute (2013), claimed that there was no marked difference in the performance gap between buildings with design data emanating from SBEMs and those with design data stemming from dynamic thermal models.

1.6 Machine Learning

"A major hindrance in modelling real problems is the lack of understanding of their underlying mechanisms because of complex and nonlinear interactions among various aspects of the problem [...] in many cases, the best solution is to learn system behaviour through observations" (Samarasinghe 2007, p.1-2).

In view of this, an alternative approach at predicting energy consumption to mathematical building physics models (building energy simulation) is to collect large amounts of actual energy and design data and analyse the patterns between the two. A source of actual energy data in the UK are Display Energy Certificates (DECs), as outlined in Section 2.5.2. A method of learning the complex relationships between energy consumption and design and briefing data are artificial neural networks (ANNs). ANNs are machine learning algorithms which are a subset of artificial intelligence. They are inspired by biological neural processes that take place within the brain (Haykin 1999). There are many variations of ANNs, which represent the different ways to abstract inspiration from neuroscience, as outlined in Section 2.4. Their ability to learn, and therefore *generalise*, allows the models to produce predicted outputs for inputs not encountered during their training (learning) process (Haykin 1999).

A number of studies have been carried out using ANNs for building energy use analysis. These include analysing the determinants of energy use in university buildings (Hawkins et al. 2012), predicting building heating demand (Ekici and Aksoy 2009; Kalogirou 2000) and the development of energy benchmarks (Yalcintas and Ozturk 2007) (Section 2.4.5).

1.7 Research Aims

The above discussion has indicated that traditional building energy simulation methods can be a slow process which often fails to integrate into the design process of architects at the early design stages. Furthermore, it has been shown that a performance gap exists where predicted energy consumption of buildings during design is often far lower than the actual energy consumption during operation. In view of this, the following three items are the aims of this research:

1. Develop and analyse a dataset of measured real-world building characteristics
2. Develop a machine learning method that uses real-world data to predict building energy use
3. Specification and development of a tool that enables non-simulation experts to predict energy use in real-time at the early architectural design stages

1.8 Approach

Figure 1.2 shows the work stages undertaken in order to address the research aims. To address Aim 1, a dataset was created of actual energy use and measured building characteristics for 502 existing buildings. The data was collected from the Display Energy Certificate (DEC) scheme and a range of other database and digital map resources. The building characteristics included geometry, fabric, site, services and weather data. Statistical analysis was carried out on the collected dataset to assess the type and strength of relationship between the building characteristics and energy use. This analysis was used to rank the building characteristics in order of most to least influential in preparation for the artificial neural network (ANN) training process.

As a test case, the research presented in this thesis focused on school buildings in England. This is because state schools are public buildings and therefore DEC data, as outlined in Section 2.5.2, was available for many of these buildings.

To address Aim 2, the novel approach of using an ANN method to enable the prediction of energy use in school buildings – using the operational energy and building characteristic data – was then employed. The accuracy of the ANNs were fine-tuned before a statistical analysis of the predictions of the best performing models was carried out. From this analysis, a comparison was able to be made between the energy use patterns shown in the collected data and the ANN predictions. ANNs allow for multivariate analysis, therefore the combined analysis of all building characteristics simultaneously was achievable. This advantage was used to explore more complex relationships between building characteristics and energy use by manipulating the building characteristic ANN inputs and assessing their impact on energy use.

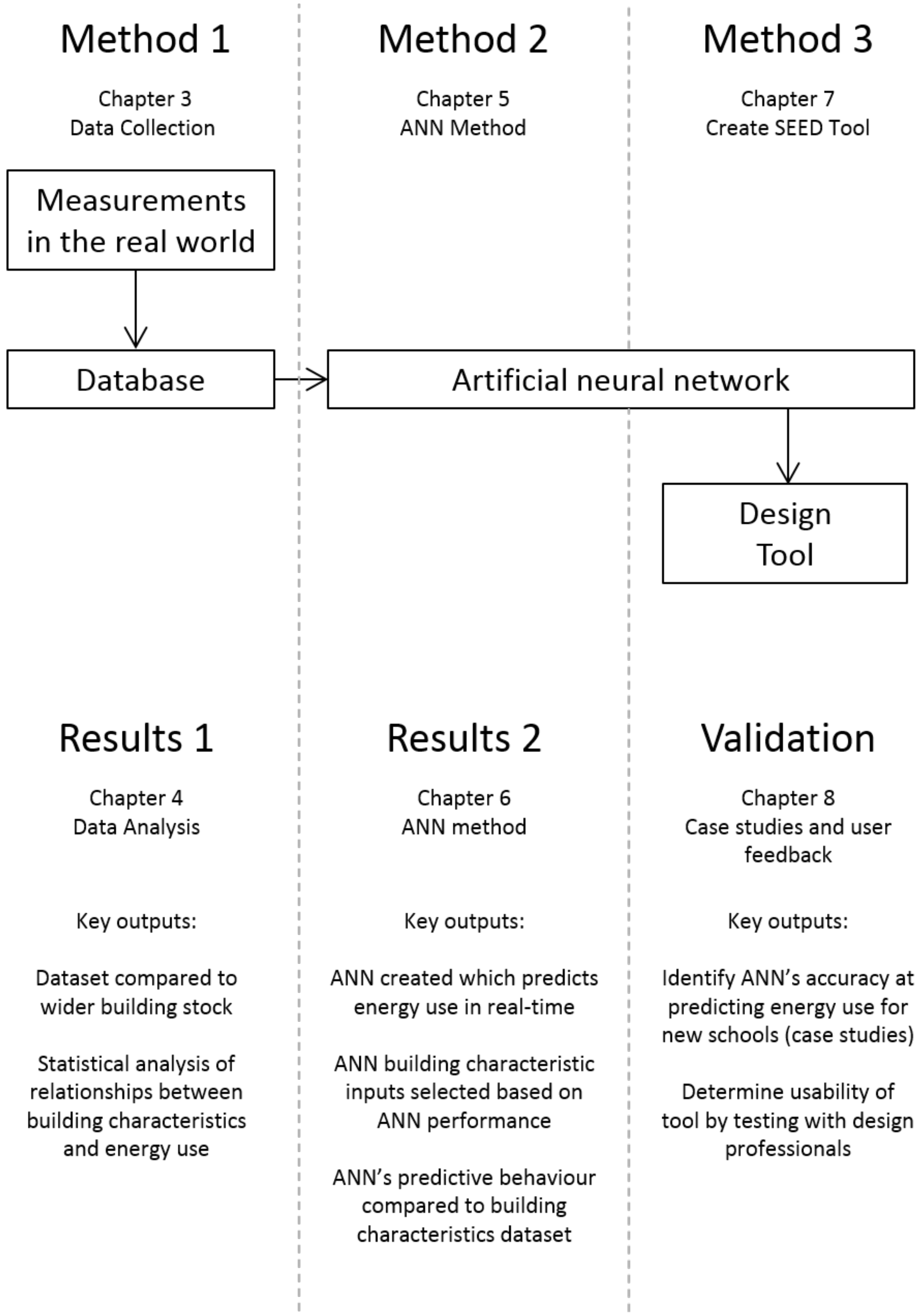


Figure 1.2: Breakdown of Methodology

To address Aim 3, a user-friendly design tool interface was created using the ANN models as the prediction algorithms; this enabled thermal and electricity energy use to be predicted in real-time. The tool was named the SEED Tool (School Early Environmental Design Tool). The SEED Tool's user inputs were based on the building characteristic ANN inputs.

In order to verify Aim 2, four case studies were carried out on recently constructed school buildings in England. The buildings were selected to cover the design and activity patterns of new schools to validate whether the tool can predict energy use in new school building designs. To verify Aim 3, the usability of the SEED Tool was assessed in a set of workshops carried out with professional architects and engineers.

As this research was partly based in industry, the author undertook various activities within a professional architectural practice. These activities are outlined in Appendix A. Appendix B outlines the publications that were produced as a result of this doctorate.

1.9 Thesis Outline

Figure 1.3 displays the structure of this thesis. The sections that follow provide a brief outline of each chapter.

Chapter 1

Introduction

This introductory chapter sets the research in context before outlining the problems with design aids and the energy performance gap. The research aims are then outlined. The chapter concludes with a summary of how the research will be approached.

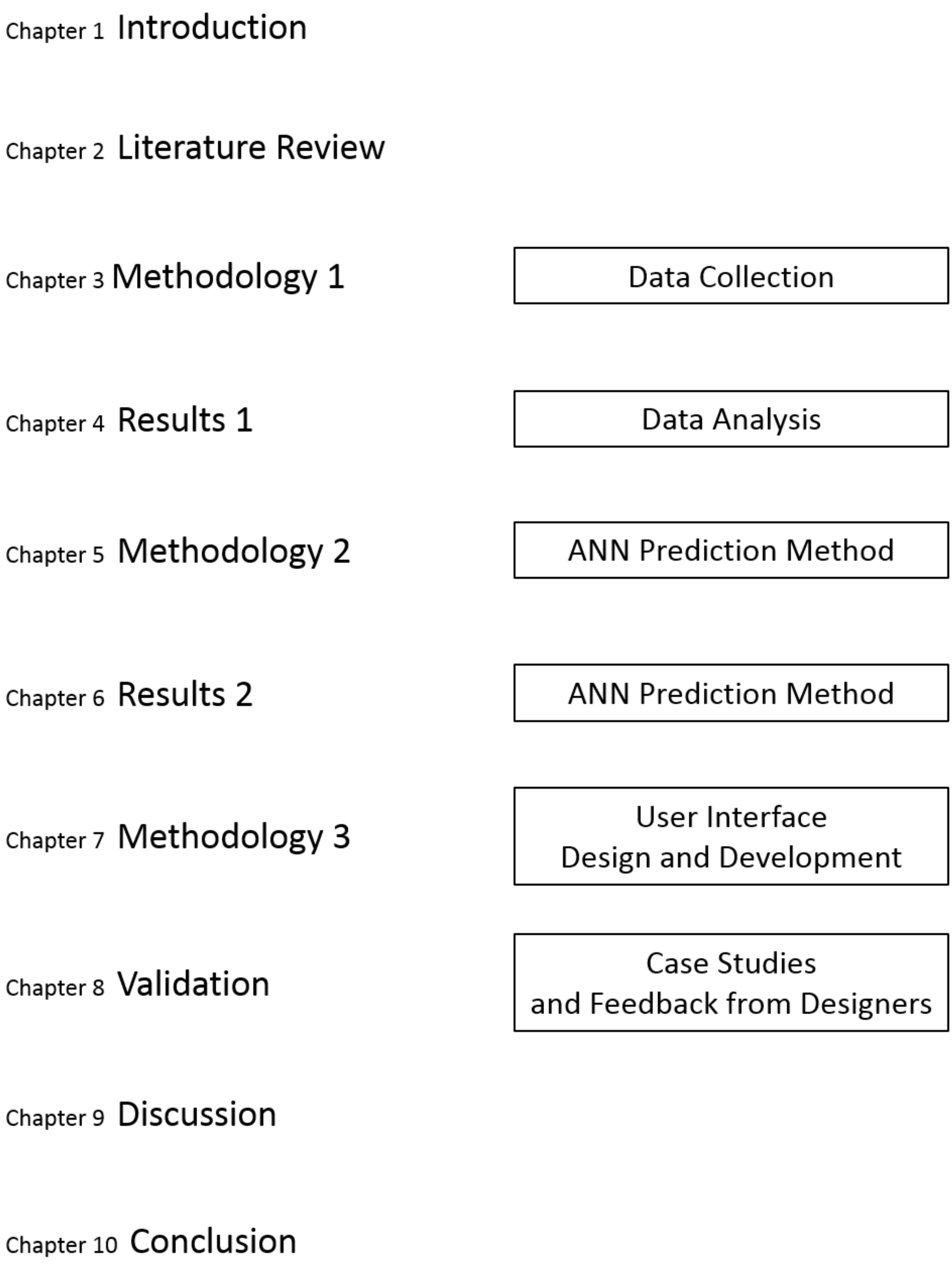


Figure 1.3: Thesis structure

Chapter 2

Literature Review

This chapter is a literature review, focussing on building energy simulation, artificial neural networks (ANNs) and data.

Chapter 3

Method 1: Building Characteristics Dataset

This chapter outlines the methodology for the development of a dataset of actual energy performance and measured building parameters that took place in order to statistically assess energy determinants and provide training data for the ANN method.

Chapter 4

Results 1: Building Characteristics Dataset

This chapter presents the results of the statistical analysis of the building characteristics dataset. As part of this process, the building characteristic parameters are ranked in order of influence on thermal and electricity energy consumption.

Chapter 5

Method 2: ANN Prediction Method

This chapter describes the methodology to design, train and test ANNs to predict the thermal and electricity energy consumption of school buildings in England. The chapter concludes with a description of the methodology to analyse the causal factors of energy use using the ANN models.

Chapter 6

Results 2: ANN Prediction Method

The results of the ANN training process are presented in this chapter, in which building characteristics are selected as ANN input parameters and the ANN performance is detailed. Using the ANN method, the results of global sensitivity and causal analyses are outlined, quantifying the impact each building parameter has on energy consumption.

Chapter 7

Method 3: SEED Tool User Interface Design and Development

This chapter outlines the methodology to create the SEED Tool, including design principles, layout and software development.

Chapter 8

Validation: Case Studies and Feedback From Designers

This chapter is in two main parts. The first part validates the accuracy of the tool at predicting energy use in new schools by inputting data from four case studies. The second part assesses the 'user-friendliness' of the tool by examining the feedback from design professionals who tested the tool interface in a series of workshops.

Chapter 9

Discussion

This chapter discusses the findings of the research within the context of the wider academic and professional landscape.

Chapter 10

Conclusion

This final chapter outlines the principle findings of the research and highlights the contribution to knowledge. The chapter also outlines the limitations of the research and opportunities for future work.

Chapter 2

Literature Review

2.1 Overview

The previous chapter introduced the research and outlined the research aims. This chapter is a literature review, covering the history of school buildings in England, building energy simulation, artificial neural networks and data.

2.2 School Buildings

2.2.1 Overview

The research presented in this thesis focuses on school buildings in England. This is because state schools are public buildings and therefore DEC data, as outlined in Section 2.5.2, is available for many of these buildings. As such, it is important to understand the history of the architecture and teaching philosophy adopted in these buildings.

2.2.2 History of State School Buildings with a Focus on England

It is believed there were schools in England ranging as far back as the Roman conquest (Gillard 2011) and in the centuries that followed, schools existed as part of church-based models and private institutions. In the Middle Ages, wealthy patrons endowed schools, such as the Countess of Suffolk's school at Ewelme (1437) and Eton (1440). Larger schools of this time were modelled on the colleges of Oxford and Cambridge while smaller schools were typically one or two storeys with a schoolmaster's house attached (Historic England 2011).

School buildings for mass education began in the mid-nineteenth century. The School Board for London was set up in 1870 under the terms of the Education Act, making elementary education compulsory for the first time in England and Wales (Steadman 2014). During the Victorian era, until the beginning of the twentieth century, hundreds of schools were built, many of which were in use over a hundred years later (Steadman 2014). These buildings were compact and solidly built (Dudek 2000; Steadman 2014).

The 1918 Education Act raised the school leaving age to fourteen. This period coincided with the building of many grammar and secondary schools which were often modelled on public schools – with quadrangles and playing fields (Historic England 2011). In the 1930s, many school designers began using steel framing for the first time, providing greater design flexibility. Here, the previous neo-Georgian style of architecture was replaced with a more modernist approach. This style tended to have long horizontal glazing in the classrooms, cubic massing and prefabricated systems of construction (Historic England 2011).

In post-war Britain, the modernist architecture philosophy continued, made popular by the Bauhaus pioneers (Dudek 2000). Practicality, daylight and natural ventilation were the drivers and as such the buildings were lightweight, low-rise, amply glazed, open and airy (Dudek 2000; Steadman 2014).

The 1970s saw a rapid growth in the construction of school buildings, largely through a move towards creating more comprehensive schools (Gillard 2011): a schooling system where intake is not based on academic achievement or aptitude. Following the 1970s energy crisis and economic recession, building energy regulations in western countries began to tighten and as such new school designs were focussed on the reduction of energy (Baker 2012). As a consequence, school designs tended to incorporate the more controlled nature of electrical and mechanical systems to provide adequate lighting and thermal conditions (Baker 2012). This resulted in deeper buildings with smaller openings.

In the 1990s and 2000s, there was a desire for a more holistic environmental approach, coinciding with the introduction of BREEAM (Building Research Establishment Environmental Assessment Methodology) in 1990 in the UK (BRE 2015) and LEED (Leadership in Energy & Environmental Design) in 1998 in the USA (US Green Building Council 2015). Building Schools for the Future (BSF) (DfES 2003), dubbed the biggest UK school building programme since the Victorian times, was announced by the then Department for Education and Skills (DfES) in 2004. Many of the schools were funded via private finance initiatives (PFIs). The aim was to rebuild every secondary school in England as deemed necessary and provide facilities fit for the twenty-first century. This often required a change from the layout of traditional classrooms of lines of desks facing a teacher, to 'learning hubs', using ICT[1] equipment and carrying out their own independent research. Some stories emerged about the poor quality and high prices of these buildings (BBC 2011) and the scheme was scrapped in 2010 by the proceeding government.

[1] Information and communications technology (ICT)

2.3 Building Energy Simulation

2.3.1 Background

During the 1950s and 1960s, environmental engineering calculations tended to be carried out by slide rules and desktop electromechanical calculators (Kusuda 1999). Early building simulation applications appeared in the United States in the 1960s, when the US government were evaluating the internal thermal environment of survival shelters during the Cold War (Kusuda 1999). A number of building simulation tools were developed in the 1980s (Hensen 2004), however, it was not until the 1990s that building designers began to be encouraged to explore the possibilities of these tools (Attia 2012) and at the beginning of the 21st century, building simulation as a discipline reached a high level of maturation (Hensen, J. L. M., Roberto Lamberts and Negrao 2002). However, during this time, architects and designers found the tools difficult to use (Punjabi and Miranda 2005) as they failed to integrate into the working process of architects (Gratia and De Herde 2002; Lam et al. 1999; Van Dijk and Luscuere 2002).

Professionally and academically recognised building software tools are registered on the Department for Energy's (DOE) Building Energy Software Tools (BEST) directory (US Department of Energy 2011). Attia and De Herde (2011) reviewed these tools and found that, as of the late 1990s, there has been a steadily increasing number of building performance simulation tools (BPS) available to designers (Figure 2.1). However, as of 2010, of the 389 registered BPS tools, only 35 were designed for architects (Figure 2.1). Furthermore, Attia found that, of the tools designed for architects, only 4 were fit for 'pre-design/informative' purposes (Attia 2012).

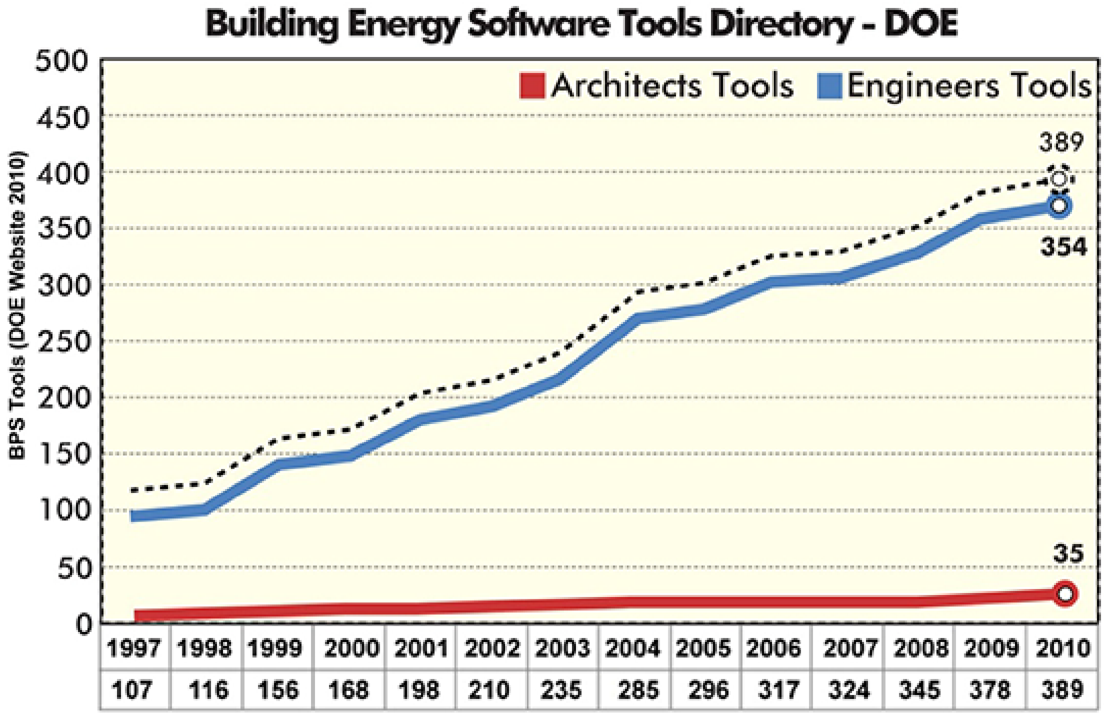


Figure 2.1: Building performance simulation (BPS) tools developed for architects and engineers between 1997 and 2010 (Attia and De Herde 2011)

2.3.2 User Interface

The user interface is the point at which the designer enters design inputs into the model. The user interface influences (CIBSE 1998, 2015):

– The time it takes to describe the building

– The accuracy with which this description is input to the program

– The ability to operate quality assurance procedures

– The ease with which design changes can be analysed

Traditionally, building simulation interfaces were menu-driven and command-line driven (CIBSE 1998) (Figure 2.2). However, since the late 1990s, graphical user interface (GUI) driven inputs were the norm (CIBSE 1998). Figure 2.2 shows an early example of a GUI. GUIs allow the user to interact with the software through graphical icons or other visual indicators. GUIs have steadily evolved with time; Figure 2.3 shows the GUI for IES, a popular simulation tool (IES 2015). GUIs intend to lower the computational skill barrier for users to use the tool and improve the aforementioned list of user interface influences. However, as is shown in Section 2.3.5, contemporary GUIs still often fail in achieving this goal for architects.

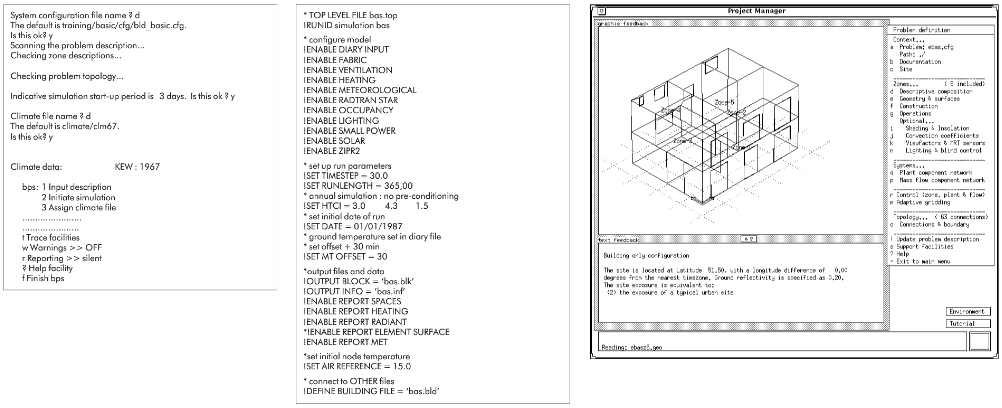


Figure 2.2: Illustrations of a menu-driven interface (left), command-line interface (centre) and early GUI (right) (CIBSE 1998)

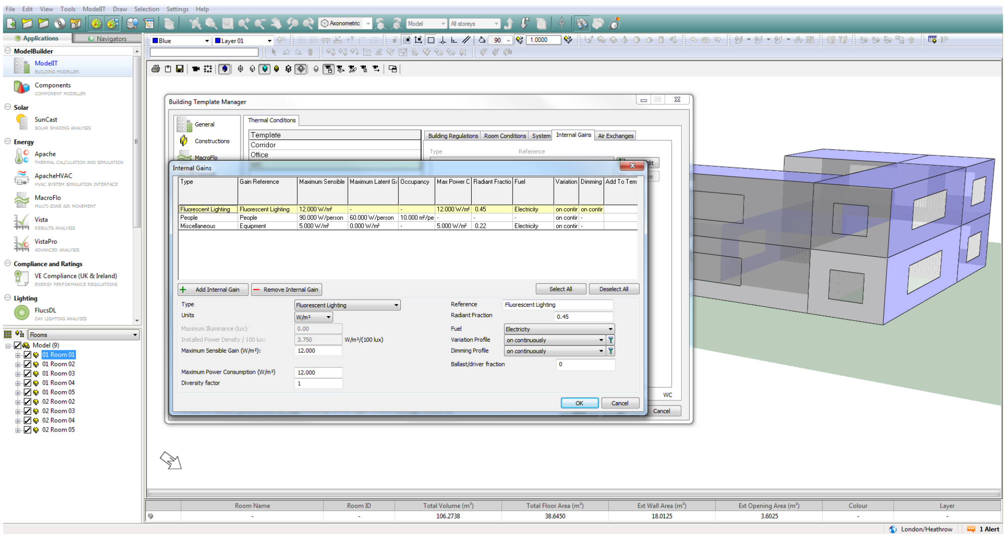


Figure 2.3: IES (2015) user interface

2.3.3 Results Visualisation

There are different ways results can be displayed to the user. Traditionally, this has been in the form of a digital output, tabular output and graphical output (CIBSE 1998) (Figure 2.4). Digital output is cumbersome to analyse (Morbitzer 2003) and therefore rarely used. Tabular data is useful to export for post-processing in other statistical and database managers, such as Excel (Microsoft 2016). Graphical output allows the user to analyse the results using common mathematical graph formats within the tool, such as line graphs, bar charts, scatter plots and radar graphs. Like GUIs, graphical outputs have evolved with time; Figure 2.5 shows the graphical output for IES (2015). Struck et al. (2011) argue that static graphs insufficiently communicate the interaction between system parameters and performance indicators.

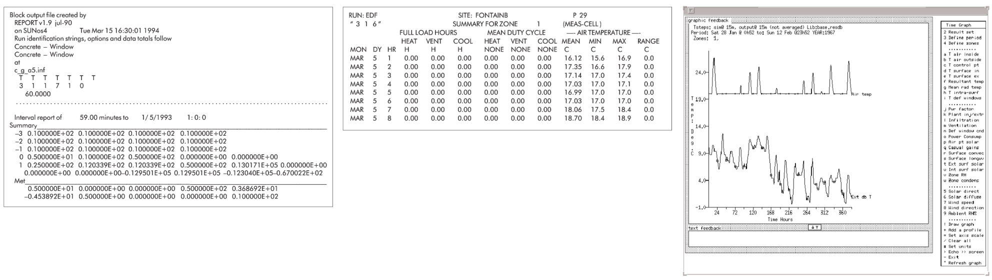


Figure 2.4: Illustrations of a digital output (left), tabular output (centre) and early graphical output (CIBSE 1998)

The Energy Systems Research Unit (ESRU) at The University of Strathclyde (ESRU 2011) developed the Integrated Performance View (IPV) as both an output for the simulation tool ESP-r (Figure 2.6) and also as a wider philosophy for presenting simulation results with other tools. The concept is to automate the results visualisation process – removing the time needed to set up the results visualisations and ensuring no performance parameters are missed – and to visualise a range of results, offering the user a more holistic view of building performance. The IPV concept has been developed by Prazeres (2006) and a sim-

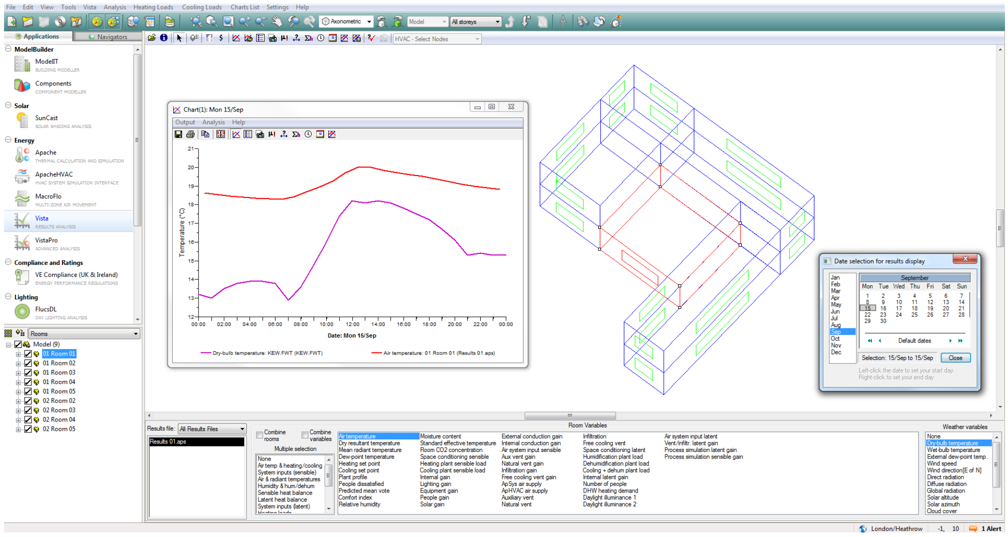


Figure 2.5: Example of an IES (2015) Graphical Output

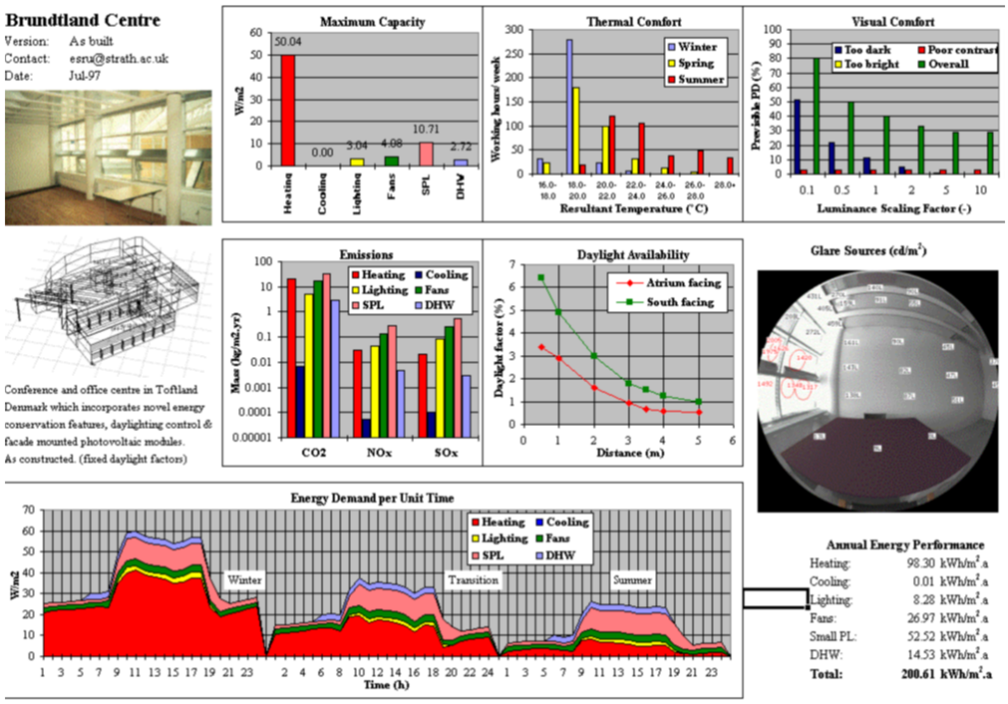


Figure 2.6: Integrated Performance View (IPV) (ESRU 2011), image sourced from Morbitzer (2003)

ilar philosophy has been adopted in Green Building Studio (Autodesk 2014), where Display Energy Certificates (DECs), thermal performance predictions and wind rose data are displayed alongside the geometry model. However, Hamza and DeWilde (2013) claims that the IPV in its various forms suffers from 'information overload', making the results difficult to interpret without an expert.

Given the various forms of visual output available today, Prazeres et al. (2007) argue that contemporary simulation tools still tend to fail in their aim of efficiently and effectively allowing the user to understand how the building is performing. On this note, Hamza and DeWilde (2013) conducted research looking at how to present building simulation results in the 'boardroom', that is, to busy individuals that may not be experts in the field of building physics. Amongst their conclusions, they stated that uncertainties in the models need to be made clear and users need to find a way to link cause and effect in the results. Hamza and DeWilde also concluded that, when being viewed by a non-expert, the results should not provide too much detail. This builds on the mantra of Shneiderman (1996): 'overview first'. Hamza and DeWilde (2013) state that human perception is very sensitive to changes in pictorial positions and therefore animating results may be one way to effectively communicate results. As such, innovative and exploratory forms of visual output, beyond static graphical output, will be introduced in Section 2.3.10.

2.3.4 Tool Complexity

The creation of a model within a detailed thermal simulation program is a non-trivial task (Morbitzer 2003). Andre and Nicolas (1994) claim that in order for a user to be familiar with an advanced simulation tool, daily use of the tool is required – however, it cannot be assumed that architects will use a tool as frequently as this (Morbitzer 2003). Keil et al. (1995) states that the usefulness of a design tool (range of results) will not compensate for the difficulty of use when used by non-experts and will ultimately be rejected. Morbitzer (2003) showed this to be the case for building energy simulation. Morbitzer (2003) states that, if a tool is to be adopted by an architect, it should be intuitive to use, both in the inputting of data and in the viewing of results. Prazeres (2006) conducted research looking at the different preferences for result visualisations of simulation users with different backgrounds and levels of experience. The study found that non-experts preferred intuitive displays while experienced simulation users were more likely to sacrifice intuitive displays in order to maximise screen space and save on computer resources.

Due to the varying needs of different users, different philosophies to the design of user interfaces can be distinguished. Robinson (1994) classifies the two types of simulation philosophies as 'simulation language' and 'simulator' (Figure 2.7). Simulation languages offer more flexibility in the creation of the model (detailed inputs). EnergyPlus (US Department of Energy 2015) is an example of a simulation language. Simulators are typically targeted for the needs of a specific user and simulate a specific range of parameters. The Passive Design Assistant (Arup 2015) is an example of a simulator. The construction of the models in a simulator is faster than a simulation language but simulators offer less flexibility.

Feature	Simulator		Simulation Language
Modelling flexibility	Less	→	More
Duration of model build	Less	→	More
Ease of use	More	←	Less
Time to obtain modelling skills	Less	→	More

Figure 2.7: Comparison between simulators and simulation languages, adapted from Robinson (1994)

2.3.5 Usefulness to Architects

A review of 10 commonly used simulation tools was carried out by Attia and De Herde (2011) in order to gauge their usefulness to architects at the early design stages for net zero energy building design. The tools compared were HEED (UCLA 2015), e-Quest (Hirsch 2009), ENERGY-10 (NREL 2011), Vasari (Autodesk 2015), Solar Shoebox (Troy 2010), Open Studio Plug-in (Alliance for Sustainable Energy 2015), IES Virtual Environment (IES 2015), DesignBuilder (2015), Ecotect (Autodesk 2011) and BEopt (NREL 2015). The researchers commented on each tool in terms of intelligence, usability, interoperability and accuracy.

For usability, the representation of input parameters and simulation outputs were found to be a barrier: the results tables and graphs are often too detailed and complex, providing an overwhelming amount of data. The use of default input values were found to be an advantage when used, however, input quality control is not there, resulting in 'garbage in garbage out' scenarios. In terms of intelligence, it was found that most tools lack in regulation compliant baselines or citable resources – thereby it is difficult for architects to gauge the results of their simulations – it was said that architects would often ask "what to do next based on the simulation results" (Attia and De Herde 2011, p.100). Furthermore, it was found that pre-design decision support is lacking. For interoperability, it was stated that research was needed into the common exchange of data, particularly between design specialisms, at the early stages of design. Accuracy was found to be satisfactory in most tools, however, it was lacking in Ecotect's (Autodesk 2011) thermal engine – a common tool used by architects at the early design stages.

It was concluded that building simulation tools are ultimately used on a post-decision trial and error basis which is "cumbersome, tedious, and costly" (Attia 2012, p.7) to architects thereby forcing the reliance on simulation experts during the early design stages.

Weytjens et al. (2011) conducted research looking at the 'architect-friendliness' of a range of contemporary simulation tools. Despite the recent developments in these tools, they found that no tool was entirely adequate for an architect. The major limitations were the poor visualisation and communication capabilities of the tools, failing to fit in with an architect's workflow and decision-making process. The researchers concluded that major opportunities exist to improve simulation result visualisations in current tools and in the development of new tools that cater to the specific needs of architects. These results correspond with an earlier study carried out by Riether and Butler (2008).

2.3.6 Flow

Flow (Csikszentmihalyi 1990, 1997) is a concept in 'positive' psychology where a person undertaking an activity is fully immersed in a mental state of energised focus, full involvement and enjoyment of the process. This is colloquially known as being 'in the zone', and is commonly associated with playing music, sports and creative activity in the arts or sciences. A state of flow can also be achieved in education, when learning, or in the workplace. Figure 2.8 represents the emotional state a person is in when undertaking a task or activity. This happens on the basis of two factors: the perceived challenge of the task and the skill level of the person undertaking the task.

In order to achieve a state of flow, the following three conditions should be met:

– Goals are clear

– Feedback is immediate

– Balance between challenge of task and skill of participant

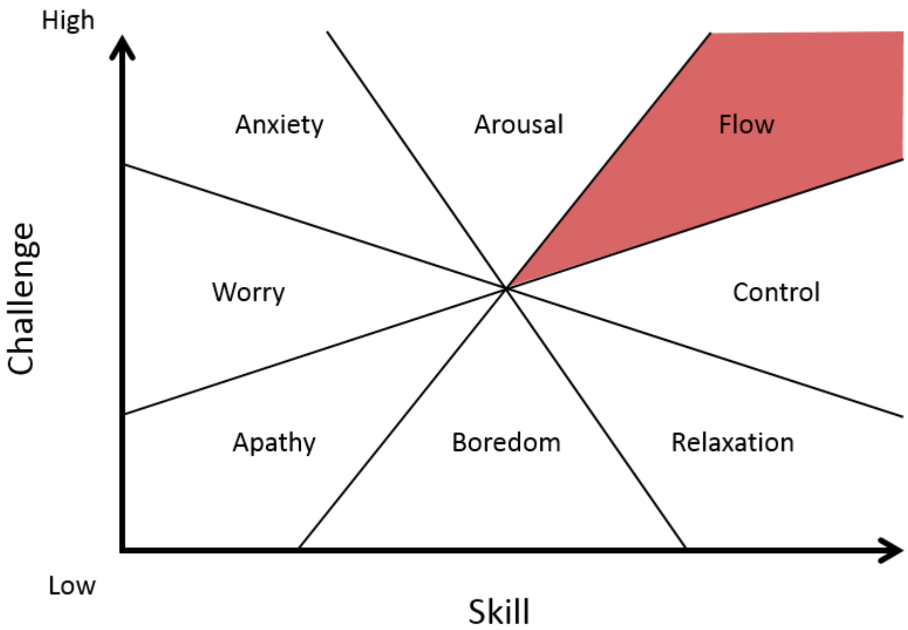


Figure 2.8: Psychological states experienced based on challenge of task and skill of individual, adapted from Csikszentmihalyi (1990, 1997)

Clear goals add direction and structure to the task, avoiding distraction. Immediate feedback gives reinforcement to the individual, helping them to negotiate the task and react and adjust to maintain the flow state. A balance between the challenge of the task and the participant's skill level maintains the participant's confidence in the ability to complete the task. Anxiety can occur when the challenge of a task exceeds the participant's skill level. Keil et al. (1995) states that, for non-frequent users, a computer program which requires too large a skill set at entry level, will result in rejection despite the benefits that the tool offers. This reflects the fact that architects reject overly complex building simulation programs as outlined in Section 1.4.

Therefore, for an architect to not only accept a building simulation tool, but want to use it and experience a state of *flow*, the goals of the task must be clear; the results should be immediate or in real-time; and the tool should be intuitive and user-friendly to use, such that the skill levels required to use the tool match that of an architect (non-simulation expert).

2.3.7 Speed of Results vs Accuracy

Energy modelling tends to contain a trade-off between accuracy of results and speed of simulation process (Li et al. 2015). As such, there are a number of projects in place which aim to reduce the simulation time, without significant loss in accuracy. Different approaches have been used to achieve this. Dobbs and Hencey (2012) proposed an automated process of model complexity reduction, with regards to the thermal structure of the building. Giannakis et al. (2013) proposed methods to simplify the geometry of the models and engage in 'co-simulation ', which involved splitting the building into simpler 'sub-buildings', which are evaluated in parallel and exchange boundary conditions data at each simulation timestep. Geebelen and Neuckermans (2003) proposed a process to alter the known algorithm, radiosity, to optimise the trade-off in speed and accuracy for daylight simulation. The aforementioned studies all produced methods to reduce simulation times, with all researchers stating that the resultant decrease in accuracy was acceptably small. Nevertheless, accuracy was always, to some degree, sacrificed in order to improve the speed of obtaining results.

2.3.8 Uncertainty

The following is a breakdown of the errors associated with prediction models:

– Systematic errors

– Random errors

The systematic errors are the errors inherent within a mathematical model and the random errors are the differences between input parameter values and their true value (Dodge 2003). Systematic errors are due to imperfect calibration of a mathematical model and are consistent with each use of the same model. Random errors include natural variability, such as material properties and building dimensions; occupancy behaviour; and climate. These uncertainties can be substantial (Wit and Augenbroe 2002). Research carried out by Clevenger and Haymaker (2006) estimates that occupancy behaviour alone can affect the outcome of energy predictions by 10-40%, while research has shown that climate change may have a significant impact on future energy consumption (CIBSE 2014). The difficulty of simulating real-world systems, such as buildings, is the lack of understanding of the complex, nonlinear and random interactions that take place (Samarasinghe 2007). This is in part due to the involvement of people, whose behaviour is difficult to predict.

2.3.9 Building Information Modelling

Building information modelling (BIM) is a process involving the central, shared, digital representation of geometry and characteristics of a building. The characteristics include data (information) on aspects such as physical properties and cost of building materials. One aim of BIM is the seamless integration of applications of all building design disciplines within a shared model. This will enable design engineers to conduct analyses, such as energy simulations, on the most up to date designs. This sharing of data and information aims to make the design process more efficient, reducing the need for every design discipline to rebuild individual models after each major design development. Moreover, as the building design evolves, the data from the previous design stages are carried through to the present design stage, again aiming to increase the efficiency of the design process.

BIM development is broken down into levels: Level 0 to Level 3, where (National Building Specification 2014):

– **Level 0 BIM** represents a condition when no digital collaboration between design disciplines occurs and drawings are typically carried out in 2D format.

– **Level 1 BIM** typically represents a condition when a mixture of 3D CAD for concept design, and 2D CAD for detail design are used. Although there is no digital model collaboration between disciplines, sharing of data is carried out from a common data environment (CDE), often managed by the contractor.

– **Level 2 BIM** typically represents a condition when different disciplines own separate 3D models, however, design information is shared through a common file format, which enables each discipline to combine that data with their own in order to make a federated BIM model.

– **Level 3 BIM** is seen as the *holy grail* as it represents the full collaboration between all disciplines by means of using a single, shared project model.

The UK Government asserted its commitment to BIM as part of the Budget announced in March 2016:

"Digital standards in construction – The government will develop the next digital standard for the construction sector – Building Information Modelling 3 – to save owners of built assets billions of pounds a year in unnecessary costs, and maintain the UK's global leadership in digital construction" (HM Treasury 2016, p.127).

Current apprehension about BIM Level 3 revolve around issues with copyright and liability (National Building Specification 2014). However, when BIM Level 3 is reached, data from energy simulations will be able to be passed between models, disciplines and design stages more seamlessly.

2.3.10 Review of Early Stage Environmental Design Tools Aimed at Architects

Overview

As new tools are ever evolving, as outlined in Section 2.3.1, and not comprehensively covered in literature, this section is a review, by the author, of recently developed early stage environmental design tools.

Sefaira Concept

Sefaira Concept (Sefaira 2011) is a simulation tool that aims to aid designers in early design decisions. The software is web-based and carries out its calculations via cloud computing. When beginning a project within Sefaira Concept, the user is asked to locate a site and sketch the boundary on a Google Maps application (Google 2012b). After this stage, a massing model is imported from Google Sketchup (Google 2011) and positioned on the site boundary before entering into the core Sefaira Concept interface (Figure 2.9).

Sefaira allows the user to set up various 'concepts' of each massing model. Within each concept, a range of inputs can be entered, such as construction U-values, building orientation and equipment COPs (coefficient of performance). Multiple design options can be set up and compared in an automated results viewer, with outputs including peak heating loads and projected annual energy usage.

The major advantage of Sefaira Concept is in its use of cloud computing to power each simulation, producing quick analysis depending on the level of detail in the model. Nevertheless, even though it may be true that the computational power achieved in the future can achieve instantaneous results, currently the feedback is staggered rather than instanta-

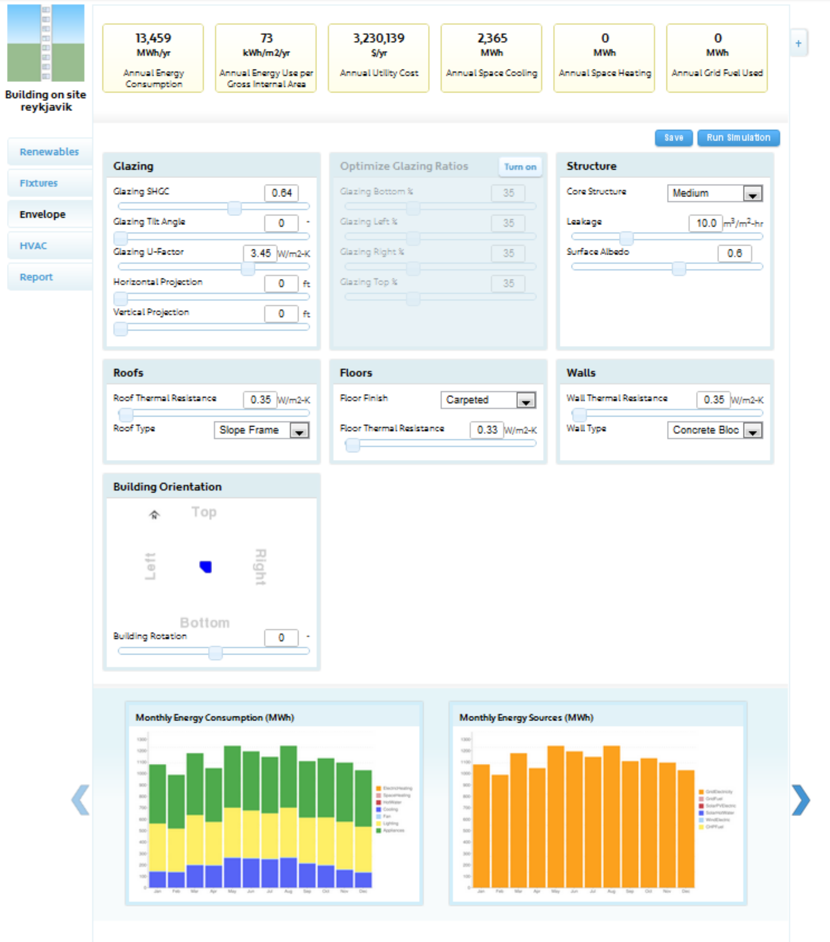


Figure 2.9: Sefaira concept interface (Sefaira 2011)

neous. By linking the tool with the computer aided design modeller Google Sketchup, the user can adapt architectural models and upload various geometry configurations simultaneously and compare each version. However, the inability to alter geometry within the tool itself in an interactive manner means that the user cannot quickly explore alternative forms as they receive feedback from the results. Sefaira have created a real-time plug-in component within Sketchup but at the time of writing, the ability to gain real-time results within their main web-based interface was not possible.

Geco

Geco (Uto 2014) is a downloadable component for the parametric platform Grasshopper (Rutten, D. 2011) which allows for data transfer between Grasshopper and the environmental analysis software Ecotect (Autodesk 2011). The Grasshopper platform is a plug-in graphical algorithm editor, tightly integrated within the 3D modelling environment of Rhinoceros 3D (Robert McNeel and Associates 2014): a commercial 3D NURBS (non-uniform rational b-spline) modeling tool used in architecture and other fields, such as, industrial design, marine design and automotive design. The links between the software are shown in Figure 2.10, with the layout on the computer screen shown in Figure 2.11.

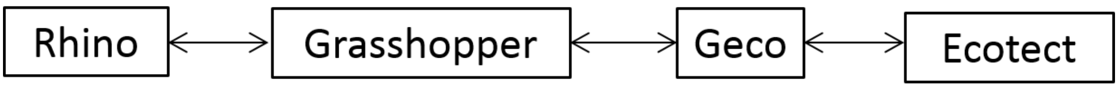


Figure 2.10: Geco Software Links

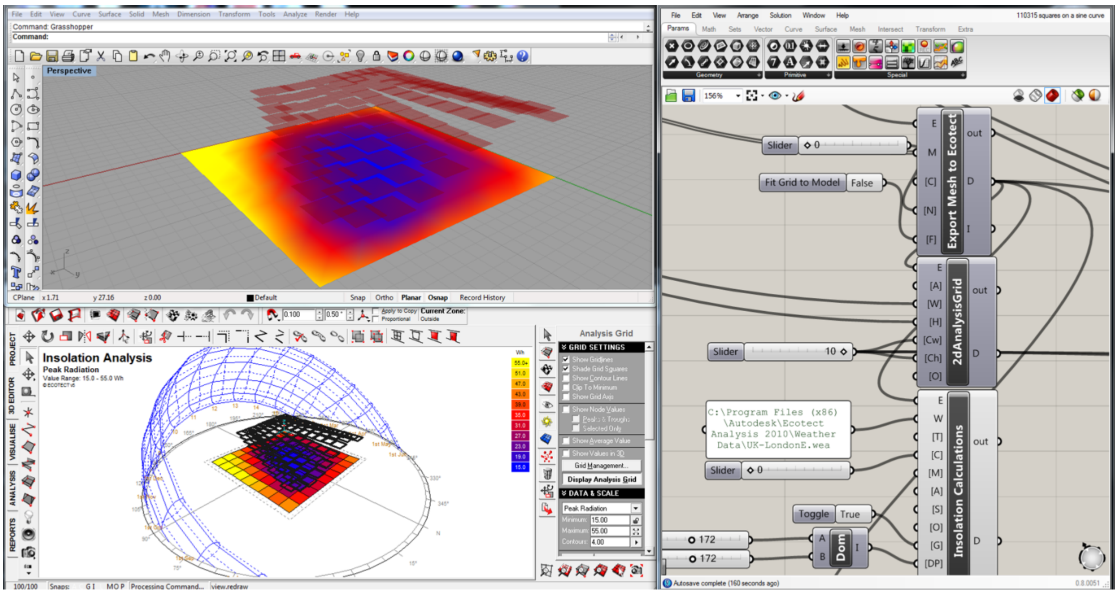


Figure 2.11: Screenshot showing Rhino (top left), Ecotect (bottom left) and Geco components within Grasshopper (right)

Ecotect is often used at the early stages of design to test early environmental design concepts whereas Grasshopper allows the user to parametrically build geometry, displayed in Rhino, based on custom relationships and rules. The Geco components allow the user to set up analysis grids in order to analyse aspects such as daylighting and solar insolation levels. By combining environmental analysis with the parametric nature of Grasshopper, there is the possibility to analyse complex NURB forms with the ability to flexibly alter the geometry. Furthermore, by using the generative capabilities of Grasshopper, it is possible to drive the geometry, based on rules set up to respond to environmental performance.

The flexibility in geometry exploration that this process offers is its greatest asset. A drawback is the computational time that the simulation program, Ecotect, takes to calculate its results when updating geometry. When simple surfaces are altered, the feedback is close to real-time, however, when a degree of complexity is added to the building form, the time it takes for the results to update raises from seconds to minutes to potentially hours given sufficient complexity.

Tall Building Model

The Tall Building Model (AHR 2014)[2] (Figure 2.12) is a cross-disciplinary, early stage concept design tool for tall office buildings in London, UK. The tool was developed by practising designers across a range of architecture and building consultancies. The model has building services, structural and cost functions of a typical tall office building in London built into its system. As geometric and briefing parameters are altered, the model provides instantaneous feedback on aspects such as embodied energy, energy consumption for heating and cooling as well as cost and structural considerations. The tool is embedded within the parametric platform GenerativeComponents (Bentley Systems 2011) and thus parametric

[2] AHR were formally part of Aedas (2014)

relationships and interactivity form the underlying structure of the tool. The environmental predictions are based on linear calculations, derived by the creators, which were generated based on simplified relationships between the geometry, materiality and major building services assumptions. It is through the use of simplified calculations that enables this tool to provide results in real-time to the user at the expense of the accuracy of dynamic thermal simulations. No literature exists for the validation of the accuracy of the energy use predictions of the Tall Building Model, likely due to the exploratory nature of the tool.

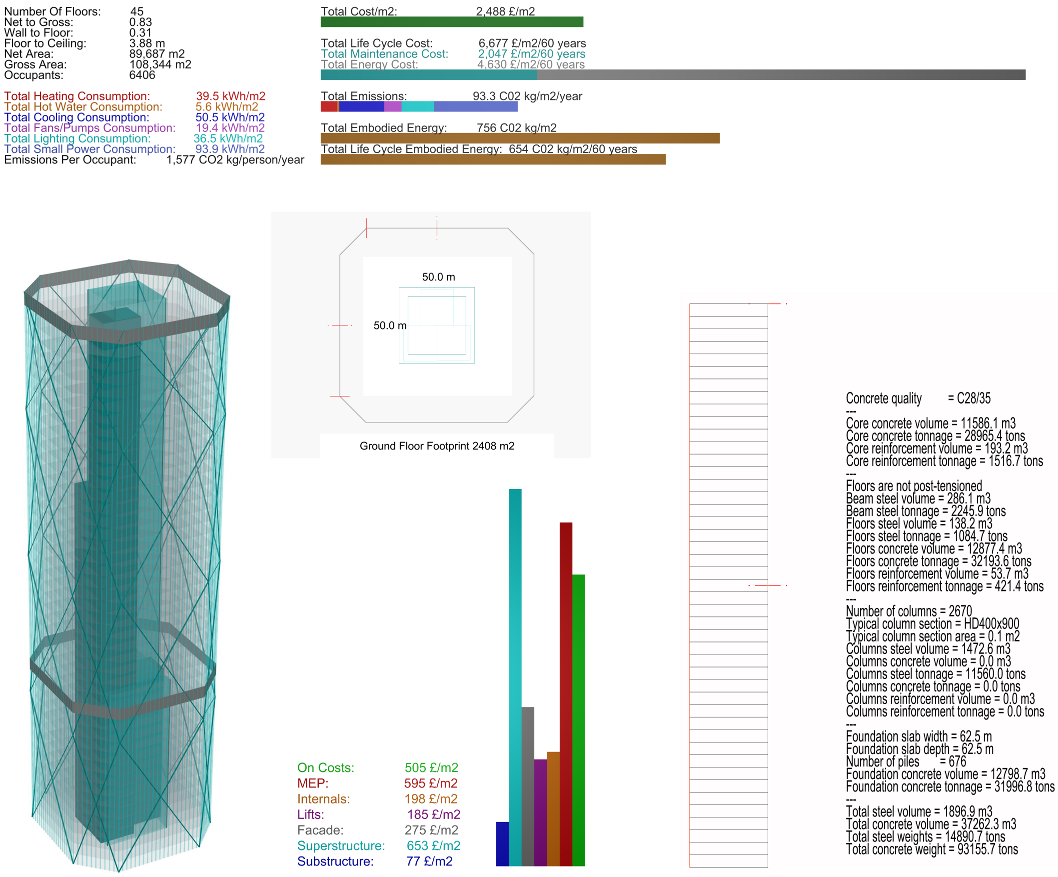


Figure 2.12: Tall Building Model Interface

The model has clear advantages in that it provides feedback to the user in real-time and features such as the ability to 'drag' parameters of the geometry greatly help the user to interactively manipulate performance as well as form. However, the limitations are in the geometry and location constraints. These constraints are mainly down to the fact that the linear equations used to predict performance would need to be revised for different locations; and if the geometric complexity increased, the simplified relationships between the inputs and outputs may no longer remain relevant. With each inclusion of new geometric parameters, new coefficients would need to be calculated.

MIT Design Advisor

Brian Urban (MIT, 2009) developed The MIT Design Advisor, a web-based environmental design tool, designed for architects. The tool (Figure 2.13) was constructed in Java, HTML and JavaScript and includes thermal and lighting calculations. Inputs are restricted in flexibility to basic text (numbers) and scroll menus for ease of use and speed. Side-by-side comparisons, of up to four design options, show graphs of energy consumption; graded colour charts depict comfort zones in the room; 3D perspective images show daylight levels; and a text-based page shows a comprehensive list of inputs and outputs.

Urban claims that the ease of use means the tool can be quickly mastered by non-technical designers, offering them the ability to run through many design options in a single sitting. The emphasis of the tool is on building envelope design. Energy load estimates are based on a library of climate data for 30 global locations. Preliminary validation of the tool was performed by comparing the various outputs with EnergyPlus (US Department of Energy 2015); closed-form calculations, eg. constant surface heat flux equation; and tabular data from literature, eg. ASHRAE[3] standards. The prediction error is stated as being within 15%

[3] American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE)

and therefore the software is recommended to be used as an approximate tool for comparing early building design concepts.

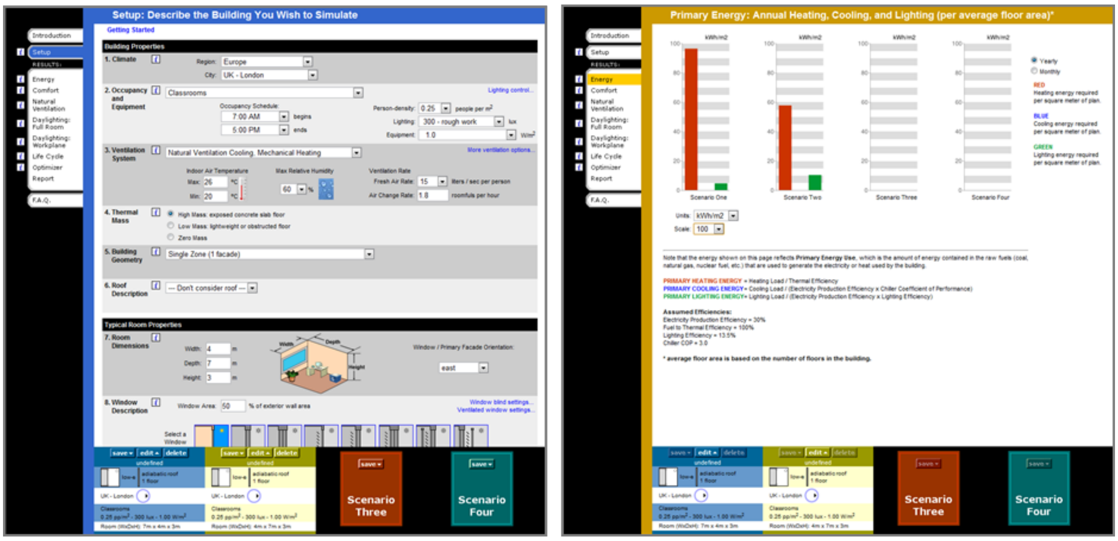


Figure 2.13: MIT Design Advisor input interface (left) and energy consumption results (right)

Real-time Feedback in Analysis Tools

Sanguinetti et al. (2010) at Georgia Institute of Technology undertook research to develop a process for analysing the environmental performance of buildings in real-time. They tested two different techniques – one to gain real-time feedback within a parametric environment, Digital Project (Dassault Systems 2014), and the other to gain real-time feedback within a scripting environment, Rhinoscript (McNeel 2012). In both examples, they linked the geometry modelling environment to a spreadsheet which carried out the calculations – defined as performance indicators (PIs). Four conditions were evaluated: daylight factor, energy consumption, glare index and payback time. The PIs are ranked by the user to align with the preferences of the project. The outputs are then normalised to establish a comparative analysis.

The limitations of this workflow are that it cannot support complex mathematical calculations. Also, it requires an expert user to set up the parametric or scripted environments and define the geometry, parameters, rules and constraints. The parametric nature of the method together with real-time environmental feedback allows the user to design the building by exploring the design space with constant environmental feedback – rather than an evaluation of each design iteration. On working in real-time, it was said that this approach better suits architects than engineers as, unlike engineering problems, architectural problems are commonly ill-defined.

Arup Passive Design Assistant

The development of the Passive Design Assistant (PDA) (Arup 2015; White, A., Holmes, M., Hacker 2012) was led by Arup with financial support from Technology Strategy Board (TSB) (HM Government 2014)[4]. The tool demonstrates the principles of passive (non-mechanical) thermal design. The software models a single cuboid-shaped room and uses an industry-standard calculation method (the CIBSE simple dynamic model). It enables an assessment to be made on internal temperatures within a free-running building or the demand for heating and cooling when the building's environment is mechanically controlled. The design parameters which are able to be altered include basic room dimensions, insulation levels, thermal mass and climate.

The interface (Figure 2.14) aims to be simple enough to enable a non-technical user to understand and learn the influence of design parameters quickly. Results are displayed in graphical form in real-time as parameters are altered. The limitations of the tool are that it cannot model a whole building or single rooms that are more complex than a cuboid form.

[4]Technology Strategy Board is now called Innovate UK (HM Government 2015)

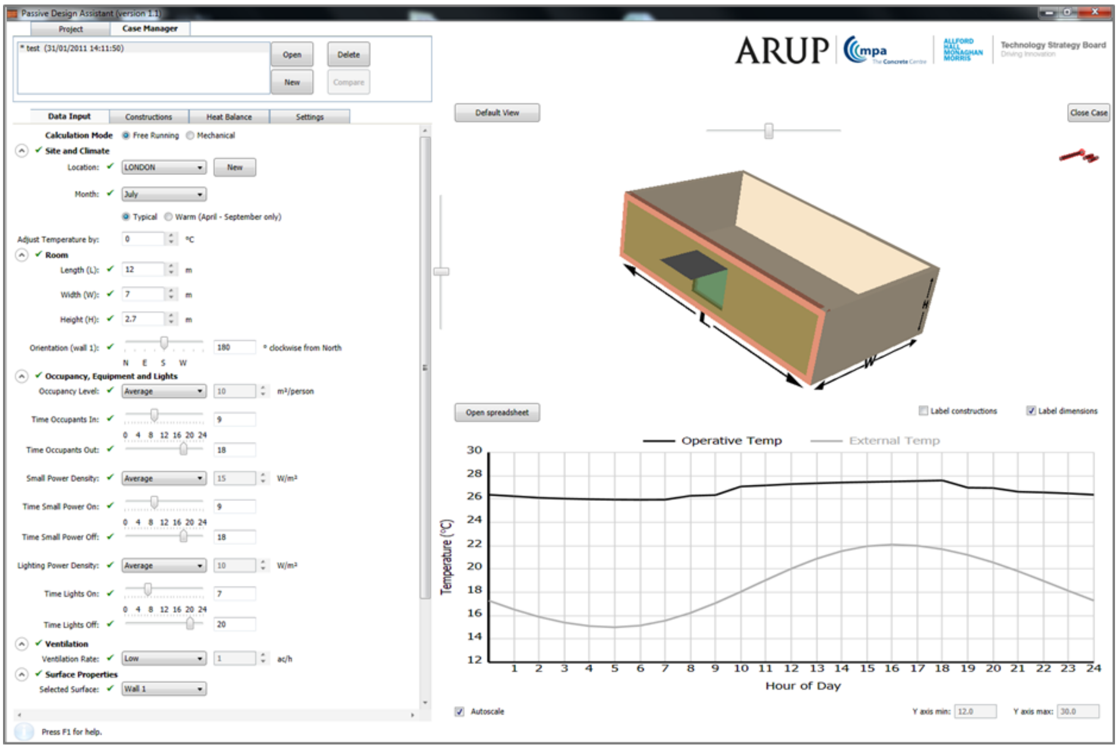


Figure 2.14: PDA Interface

Parametric Energy Model

Attia et al. (2012) and Pratt and Bosworth (2011) present different methods to set up batch runs within EnergyPlus to test the sensitivity of the design space. Pratt and Bosworth (2011) developed a user interface for their research, generating a parametric energy model created as Ruby plugins for Google SketchUp (Google 2011). A separate program to export the material and geometrical data from Sketchup was also created in Ruby in order to ensure the model is able to be successfully formatted for interpretation within EnergyPlus. First, a 'seed' or baseline of the model is created, after which matrices are employed, which allow for translation, rotation, mirroring and scaling of geometry. The parametric energy tool creates the full enumeration of the variations – from every combination of the parameters, a model for simulation is created. Each model is then simulated in EnergyPlus – simulation time can take several hours.

Various visualisation techniques were developed that aimed to promote an understanding of the effects of design parameters on energy performance as well as visualising the design space. Figure 2.15 shows the interface of the tool. The batch-controller in the lower right allows the inputs to be altered. This approach allows the user to visualise the many possible combinations of inputs. The voxel plot in the top right-hand corner visualises the design space. Four input variables and one dependent output are visualised in the voxel plot. Three inputs are shown in Cartesian space, using X, Y and Z coordinates; colour represents the output (eg. $CO_2/m^2/yr$), and time (using animation) represents the fourth input.

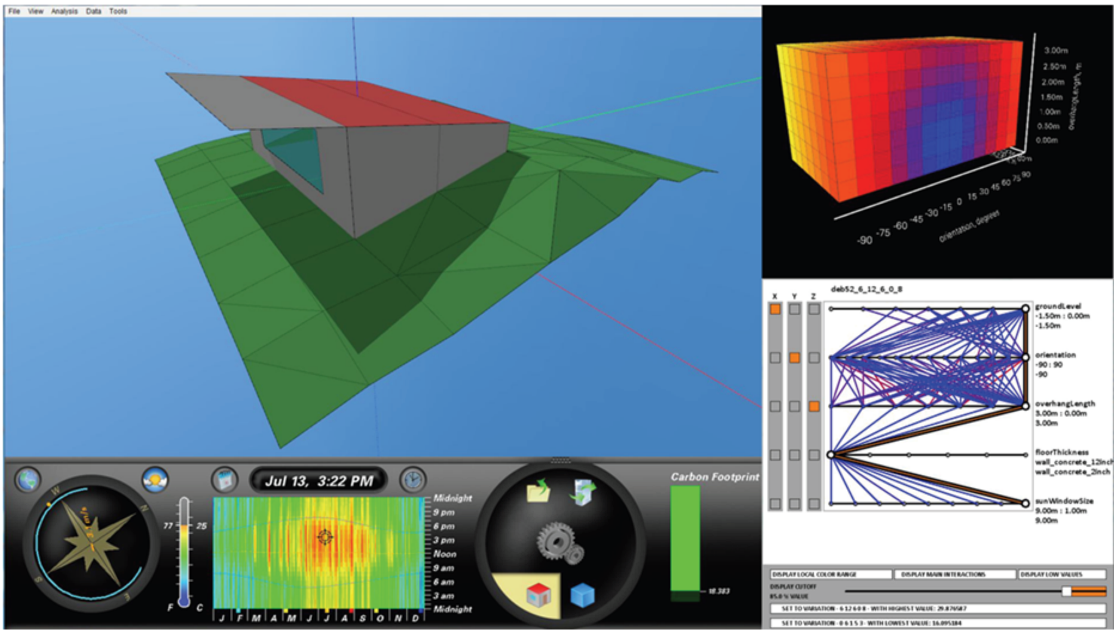


Figure 2.15: Interface showing the parametric model (top left), simulation results (bottom left) voxel-plot of design space (top right) + batch controller (bottom right)

Despite the inputs not being continuous (input combinations are discrete), a sufficient resolution in combinations can offer the designer the ability to explore many subtle variations. A drawback to this method is that it is limited to simple models and therefore the process is largely a proof of concept. However, at the time of writing, work was continuing and more complex buildings were proposed to be tested with this method. A further drawback is that it may take an expert to set up and simulate.

2.4 Artificial Neural Networks

2.4.1 Background

Artificial neural networks (ANNs) are machine learning algorithms: a subset of artificial intelligence. They are inspired by the structure and processes of biological neural networks that take place within the brain (Haykin 1999). Work on artificial neural networks has been motivated from their inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer (Haykin 1999). The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organise its structural constituents (neurons), so as to perform certain computations many times faster than the fastest digital computer in existence today.

ANNs consist of computing cells, referred to as *neurons*, which are simple information-processing units interconnected by synaptic weights. Hidden layers are often introduced to ANNs. These hidden layers are never exposed to the external environment (data) (Samarasinghe, 2007) and enable the system to generate nonlinear and complex relationships by intervening between the input and output neurons (Haykin 1999). Figure 2.16 shows the conceptual structure of an ANN with four inputs, one output and a hidden layer. Typically, ANNs are used to find patterns in data in order to make decisions or predictions. There are, however, many variations in the architecture of ANNs, depending on the application, as introduced in Sections 2.4.3 and 2.4.4.

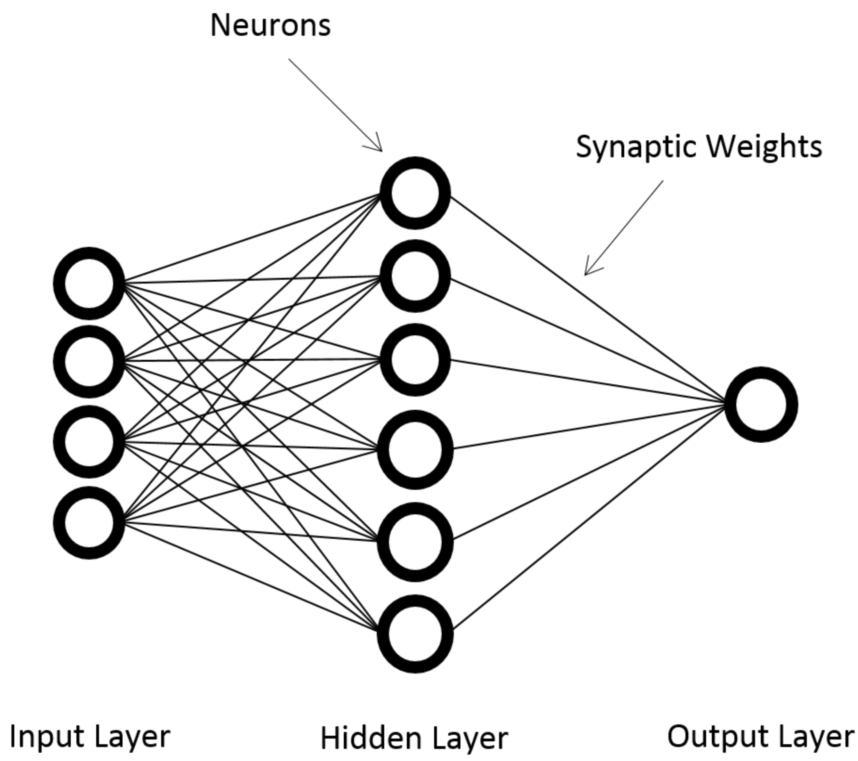


Figure 2.16: Illustration of a three layered artificial neural network

2.4.2 History

Rather than solving logical problems in an 'algorithmic' manner, with a mathematically known outcome, pioneering computer scientists began theorising about whether machines could 'take us by surprise' (Turing 1950). However, the invention of artificial neural networks as a concept began before the advent of computers (Stergiou and Siganos 1996). In 1943, Warren McCulloch and Walter Pitts developed the first conceptual model of an artificial neural network based on their knowledge of neurology. In their paper *A Logical Calculus of the Ideas Immanent in Nervous Activity* (McCulloch and Pitts 1943), the authors described a neuron as a single cell within a network of cells that receives inputs and processes them before generating an output.

Farley and Clark (1954) used computational machines to simulate a network based on Hebbian learning: the theory of neural adaptation during learning, with synapses strengthening or weakening in response to an increase or decrease in their activity (Hebb 1949). Other neural network computational machines were created at a similar time by Rochester et al. (1956). From this, psychologists and engineers began contributing to the progress of artificial neural network simulation. The psychologist Rosenblatt, furthered the field by designing and developing the Perceptron: an algorithm for pattern recognition based on a two-layer computer learning network (Rosenblatt 1958).

During the 1960s and early 1970s, neural networks research suffered a period of little funding (Stergiou and Siganos 1996), partly due to the research of Minsky and Papert (1969) who judged the technique to be 'sterile'. However, the field gained a resurgence during the late 1970s and 1980s (Stergiou and Siganos 1996) with further developments continuing up until the present day. The work of the many computer scientists and researchers in the twentieth century did not aim to accurately describe how the biological brain works; rather, artificial neural networks were designed as computational models based on the brain in order to solve problems (Shiffman 2012).

2.4.3 ANN Variation

There are many variations of ANN which represent the different ways to abstract inspiration from neuroscience. Neural networks derive their usefulness through their parallel distributed structure and their ability to interpolate by *generalisation*. Generalisation refers to the ANN producing predicted outputs for inputs not encountered during the training (learning) process: "these two information-processing capabilities make it possible for neural networks to solve complex (large-scale) problems that are currently intractable" (Haykin 1999, p.2). All neural networks learn from data presented to them, however, they can be broadly classified as either supervised or unsupervised:

Unsupervised Learning

A strategy used when the dataset does not have known outputs. A common application for this is clustering and dimensionality reduction (Duda et al. 2001). The notion of a 'cluster' cannot be precisely defined and therefore is achieved by various techniques, such as identifying dense areas of the data space and identifying statistical distributions. Dimensionality reduction is the process of reducing the number of random variables under consideration.

Supervised Learning

A strategy where the dataset has inputs and corresponding outputs. During the training process, the network receives the inputs, makes a prediction, compares the prediction with the 'correct' output and makes adjustments according to its errors. After training the ANN is then able to predict outputs based on inputs it has not experienced before.

2.4.4 ANN Application

Artificial neural networks are used in a broad range of disciplines, including economics, medical science, engineering and management sectors. The following are examples their application:

- *Pattern Recognition*: the ability to identify regularities in data, for example, facial recognition (Turk and Pentland 1991).
- *Time Series Prediction*: make predictions into the future based on an updating data feed, for example, weather or stock market predictions (Pakdaman Naeini et al. 2010).
- *Signal Processing*: filter out unnecessary noise in the data, for example, in hearing

aid devices (Prasad 2008).

– *Control*: enable the network to manoeuvre around its environment, for example, in robots that move through real, unstructured environments (Brooks 1991) and self-steering cars (Wired 2015).

– *Soft Sensors*: a process where several different measurements are processed together and evaluated as a whole, enabling the prediction of a similar environment with no sensors, for example, predicting atmospheric conditions in a location based on temperature, humidity and other atmospheric conditions in adjacent locations (Chella et al. 2006).

– *Anomaly Detection*: similar to pattern recognition, except alerting the user when an action occurs that lies outwith the pattern, for example, identifying intrusion or an attack on an organisation's computer network (Pradhan et al. 2012).

2.4.5 Examples of Use in the Field of Building Energy Use

Benchmarking

Yalcintas and Ozturk (2007) developed an ANN energy benchmarking model for office buildings in the USA. Data from the Commercial Buildings Energy Consumption Survey (CBECS) was utilised with the weighted energy use intensity (EUI) being used as the benchmarking index. Input variables for the ANN model included descriptions of occupancy, climate and physical properties of the buildings. The model estimated yearly electricity consumption per square meter, EUI. The ANN model was compared with predictions obtained from multiple linear regression models. The ANN model had mean squared errors (MSEs) that varied between 9.60 and 15.25 while the multiple linear regression models had MSE values that varied between 10.24 and 40.43. Therefore it was concluded that ANN models were a better prediction model for this energy benchmarking study.

In a separate study, Yalcintas (2006) created an ANN benchmarking model by collecting data from laboratory, office, school and mixed-use buildings in Hawaii. The model estimated EUI by taking into consideration various input variables, such as operating hours, plug load density, lighting type and equipment efficiencies. The coefficient of correlation for the model was 0.86 for the whole building benchmarking analysis. The use of an ANN benchmark model for estimating energy savings from retrofitting measures was also evaluated. To achieve this, some of the aforementioned model input variables were modified to reflect potential retrofit measures. The ANN model simulated an outcome based on the new inputs. The results of the study indicated that the ANN method was effective as a benchmarking model and can be successfully used to predict energy savings in retrofit projects. The method, however, was not integrated into a usable tool for design professionals and therefore its influence within industry is restricted.

ANNs to Optimise HVAC Systems in Existing Buildings

Research was carried out to investigate the feasibility of using ANNs to optimise various heating, ventilation and air conditioning (HVAC) controls (Ben-Nakhi and Mahmoud 2004; Mahmoud and Ben-Nakhi 2003). In one of their studies, Mahmoud and Ben-Nakhi (2003) tested the feasibility of using general regression neural networks in optimising the thermal energy storage of HVAC systems in public and office buildings. Test buildings of various densities of occupancy and orientation were investigated. The building simulation software ESP-r (ESRU 2011) was used to generate the database to train and test the neural network. Using Kuwait weather data, external air temperature was used as the network input and the cooling load for the following day was used as the output. This research showed that ANNs can be used to accurately predict cooling load profiles. This is significant because their ANN only requires external dry-bulb temperature as its input whereas building simulation software requires many more weather inputs on top of external dry-bulb temperatures, such as relative humidity, direct normal solar intensity, wind direction and wind speed. The reduction in required data, therefore, opens up the opportunity for simple controllers to be created, based on an ANN approach.

Determinants of Energy Use in UK Higher Education Buildings

Using metered energy data and measured building parameters, Hawkins et al. (2012) conducted a study to train an ANN to analyse the determinants of energy use in London university buildings. Data collected included metered gas and electricity figures and a variety of building parameters, such as ventilation strategy, building age, summer and winter temperatures, floor area, occupant activity and glazing type. Occupant activity was shown to be a strong energy use determinant together with ventilation strategy and glazing type. The ANN method had mean absolute percentage errors (MAPEs) of 25% for heating energy use and 34% for electricity energy use. The author concluded that an ANN methodology shows good potential for use in analysing building energy use determinants.

Energy Prediction in Existing Buildings: Real-time Feedback

Yang et al. (2005) investigated the performance of adaptive neural networks when presented with unexpected pattern changes of input data – ultimately leading to the prediction of building energy use in real-time. The input data to the ANN was external dry and wet-bulb temperatures together with the temperature of water leaving the chiller and the output was the chiller electrical demand. Two adaptive ANN models were tested: accumulative training, adding new incoming data to existing data; and 'sliding window' training, which replaced the oldest data with the newest data. The experiments presented by Yang et al. tested their methods with 'real' measured data as it became available in real-time and compared this with 'synthetic' building simulation data. Their results showed that with simulated data, the accumulated and sliding window training methods performed similarly in terms of accuracy and training time, both being acceptably accurate. With the real data, the sliding window training method produced satisfactory results whereas the accumulative method performed poorly. This provides evidence that up to date data is desirable when using 'real' measured data to predict building energy use with ANNs.

ANN as a Design Tool for HVAC Systems

Yalcintas and Akkurt (2005) investigated the use of feedforward, multilayer ANNs to predict the chiller plant power consumption in a mixed use high rise building in a tropical climate. The objectives were to begin research into a generalised ANN model that could be applied to various building sectors, with minimal modifications to the ANN structure, in order to produce a tool for building services engineers that offers faster and simpler analysis of systems compared to traditional statistical and building simulation methods. The average training error for the ANN was 9.7% with a testing error of 10.0%. These predictions were said to be satisfactory, showing that an ANN could form the basis of a useful tool for the modelling of HVAC systems. However, a fully working tool that models building services is yet to be developed. Yalcintas and Akkurt state that this is because certain factors need to be addressed, such as data noise elimination and the identification of ANN architectures for varying applications within building services design.

ANN as a Building Design Tool

Kalogirou (2000) and Ekici and Aksoy (2009) developed separate methods to predict building heating energy demand by using multilayer artificial neural networks with backpropagation in order to develop a design tool. Ekici and Aksoy's incentives were that modelling with traditional building simulation "can be boring and tiring because of complex numerical applications" (Ekici and Aksoy 2009, p.362). A computer program was written in the programming language Fortran (2011) in order to calculate the energy demand and the ANN predictions were compared to these calculations. The inputs of the ANN were glazing-to-wall ratio, orientation and insulation levels, with the output being heating energy consumption. These inputs were based on a simple rectangular planned building. When the ANN response values were compared with the calculated outputs from their computer program, it was seen that the ANN had a prediction accuracy of 94.8–98.5%. These studies concluded that ANNs are capable of predicting building behaviour and could form the basis of a design tool. However, it can be foreseen that as levels of complexity in geometric building form increase (beyond a rectangular plan) the method of creating training data will need to be revisited. Furthermore, no demonstration was made of the user requirements of such a tool in order for it to be successfully adopted as a design aid.

2.5 Data

2.5.1 Big Data

Figure 2.17 shows the growth of the world's capacity to store data from the 1980's to the late 2000's. In 1986, around 1% of the word's data was stored digitally. By 2002, around 50% of the world's data was stored digitally – this was the beginning of the information age (Vastag 2011). By 2007, 96% of the word's data was stored digitally. The total amount of data storage capacity grew from 2.6 billion gigabytes (2.6 exabytes) in 1986 to 295 billion gigabytes in 2007. It is estimated that by the year 2020, the world's accumulated digital data will be 44 trillion gigabytes (44 zettabytes) (Marr 2015).

The notion of big data has arisen in recent years due to the aforementioned abundant availability of digital data (Harvard Magazine 2014). Big data is a broad term for data that is high

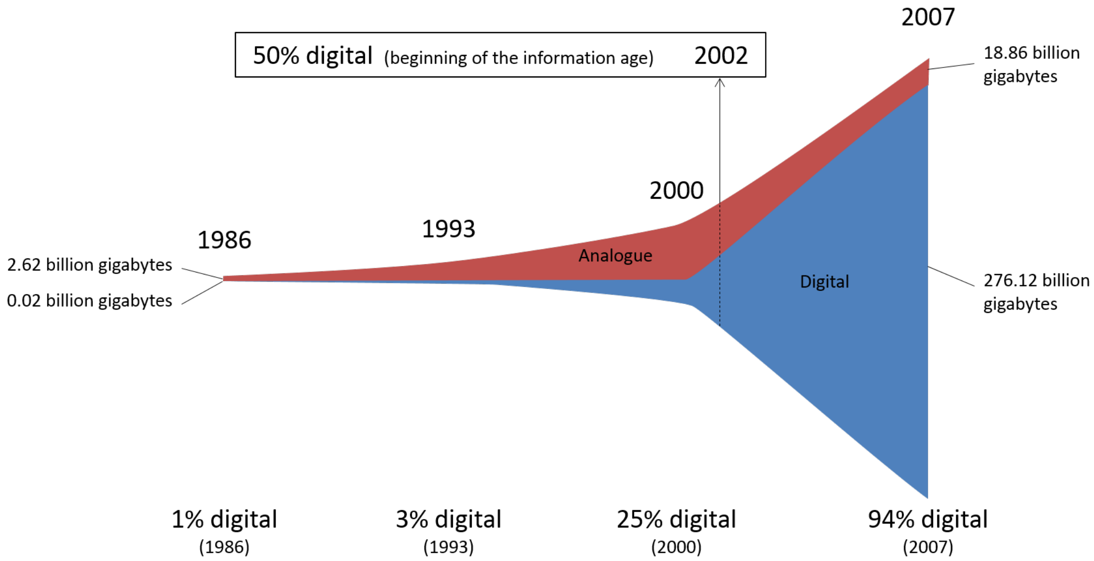


Figure 2.17: World's capacity to store data, adapted from Hilbert and López (2011)

in volume, velocity and variety (Forbes 2013; Gartner 2016), with datasets that are at a size and complexity level that deem traditional statistics and data processing techniques inadequate. As such, innovative forms of information processing are required (Gartner 2016), such as neural networks, to help with tasks such as improving internet search capabilities and identifying the risk of ill health in patients (Google 2016).

2.5.2 Data on Buildings

In the UK, it is mandatory for some public buildings to publicly display how energy efficient they are with a Display Energy Certificate (DEC). The DEC scheme produces ratings of operational energy use, based on a benchmarking methodology developed by CIBSE (2009). Under the scheme, it is currently mandatory for all public buildings with floor areas greater than 1000m^2 (DCLG 2008) to produce a DEC, with the threshold reduced to 500m^2 in 2013 and 250m^2 in 2015 (DCLG 2012, 2015). Section 3.2 outlines the DEC methodology in more detail. The publicly available data collected in the scheme includes thermal and electrical energy intensity (kWh/m^2/yr). In some cases, this data has been inserted into databases, such as CarbonBuzz (2014).

CarbonBuzz (2014), introduced in Section 1.5 ('CarbonBuzz'), is an online RIBA/CIBSE crowdsourcing platform that allows users, be they architects, engineers, facility managers or other building stakeholder, to upload design and energy data for their buildings. The user has the ability to input data anonymously as there may be little incentive for building stakeholders to enter named data, especially if their building performs more poorly than predicted, as is often the case, as shown in Section 1.5. One of the primary developers of CarbonBuzz was the industrial sponsor of this research (AHR 2014) and therefore the database was available to the author. However, significantly more data is required in this platform before techniques, such as machine learning, can be used (Robertson et al. 2015).

In the US, the Commercial Buildings Energy Consumption Survey (CBECS) (US Department of Energy 2015) is a scheme that collects information on the stock of commercial buildings, including building characteristics and energy data. The data is collected by survey of respondents at each building and, when necessary, energy providers. Respondents provide information on building size, activity, types of equipment and conservation measures, as well as energy use and energy source. This data is then augmented with geographic (census region and division) and weather data (including heating and cooling degree days). The resultant CBECS database is used for a variety of purposes, such as policy and building code development, energy use forecasting, benchmarking and building design.

There are some initiatives in the UK, outside the DEC scheme, to collect data relating to the energy use of buildings. Three examples set up by the Department of Energy & Climate Change (DECC)[5] are the Building Energy Efficiency Survey (BEES) (DECC 2013), the Domestic National Energy Efficiency Data-Framework (NEED) (DECC 2015) and the Non-domestic National Energy Efficiency Data-Framework (ND-NEED) (DECC 2014). BEES aims to understand how energy is used in buildings and in addition to energy data, data collected includes building age, number of storeys and main construction material. NEED aims to, in part, create a framework to estimate the saving in energy use following retrofitting measures, such as loft insulation, in domestic buildings. The 'household characteristics' collected in this scheme includes income and tenure. ND-NEED is the non-domestic equivalent of NEED, however, is at an exploratory stage.

There are private organisations that monitor energy patterns of their collaborators, such as Julie's Bicycle (2016), which gathers environmental data on creative industries, such as art exhibitions and outdoor festivals. Despite these programs gathering promising amounts of energy data, their aims are not geared towards the design of new buildings and as such do not collect many details on, for example, building geometry. There are examples of projects that digitally map out the geometry of existing buildings across cities and countries, with data attached to individual buildings. The Waag Society, together with collaborators, developed an interactive map of all buildings in The Netherlands (Wagg Society 2013). The interactive map modelled close to ten million buildings in 2D, which were shaded in accordance with their year of construction. When the user clicks on a building, data, such as age, floor area and function (eg. office, school) are shown. Data on the height and volume of the buildings are not available and therefore calculations of, for example, surface exposure is not possible. The aim of the project, as claimed by the developers, is to demonstrate the power of open data. It can be envisioned that additional data could be added to each building if the model is developed.

[5]DECC became part of the Department for Business, Energy and Industrial Strategy (BEIS) in July 2016

A project which demonstrates a more comprehensive level of detail is the 3D model of the non-domestic building stock of England and Wales by UCL Energy Institute (2014). The project, currently in progress, aims to automate the process of bringing together different data streams, resulting in a 3D model that contains data on energy consumption, building geometry and building activity (including sub-activities within the same building). The pilot study, which focused on non-domestic buildings in Camden, London, UK, was found to be a success, and there are plans to expand to more locations (Evans et al. 2014).

2.6 Summary

This chapter contained four main parts. The first part was a review of the history of state school buildings with a focus on England, showing that the style of architecture and teaching philosophies change with time. The second part was a review of building energy simulation tools. It was shown that there are a range of drawbacks that exist for non-simulation experts, such as architects. These drawbacks include the static nature of the process; confusing results with no context; the fact that there are too many inputs needed to run a simulation; and that no guidance is given as to what inputs are appropriate to use. In response to these barriers, there is an emerging range of early design tools being developed by industry and academia. However, these tools tend to focus on overcoming one particular barrier – such as ease of use or real-time feedback. Furthermore, it was shown that there is a trade-off between accuracy and speed of obtaining results. Further drawbacks of these contemporary tools include the need for specialist training to initially set up and use the tools. This provides evidence for the requirement of a tool that addresses the wide range of barriers that exist, without sacrificing accuracy. As such, a gap in knowledge is the fact that no tool combines ease of use and improved speed of results with increased accuracy.

The next main part of the chapter began by describing what artificial neural networks (ANNs) are, together with giving an overview of their history, variation and application. Examples of ANNs being used in the field of building energy use were then presented. The studies showed that ANNs were a successful method for energy benchmarking purposes and performed better than multiple linear regression models in this area. It was also shown that ANNs can be trained to control HVAC systems with fewer inputs than traditional building simulation methods. A further advantage of using ANNs over traditional simulation methods was their ability to make energy predictions in real-time. It was demonstrated that ANNs have benefits if used to form the basis of a design tool as they can be designed to be simpler (requiring fewer inputs) and produce quicker results than traditional building simulation models. However, further development was said to be needed in order to progress current models beyond simple building geometries. It was shown that energy predictions in existing buildings with ANNs have been tested with real-world data (as well as simulated data), however, there is no evidence of an ANN method, trained with real-world data, being used in a design tool for new building designs. However beneficial these methods are in theory, or when applied by the creators of the ANNs, there was no demonstration of the ANN models being used in industry by building stakeholders, such as building design professionals or facility managers. It can be foreseen there will be technical barriers if managing an ANN model from its source code, without prior experience in computer science. As such, it was shown that, in theory, ANNs are able to form the basis of performance prediction tools, however, there is a gap in knowledge to develop an ANN method for energy use predictions of new buildings that is based on real-world data and create a user-friendly design tool that is able to surpass simple rectangular plan geometry constraints.

The final main part of the chapter introduced the notion of big data and outlined a range of data collection schemes in the building design and construction industry. It was shown that, although many schemes exist that collect high-level data, projects that collect detailed building characteristics tend to be at an exploratory level. As such, the following chapter outlines the data collection process that took place in order to build a training dataset for an artificial neural network method.

Chapter 3

Method 1: Building Characteristics Dataset

3.1 Overview

As part of the literature review, the previous chapter reviewed the history, variation and application of artificial neural networks (ANNs). This chapter outlines the data collection process that took place in order to build a training dataset for the ANN method that was developed for this research. The chapter begins by outlining the measured energy use data source, before presenting the data cleaning process that was necessary to omit potentially erroneous data. The chapter then presents the preparation and data collection process necessary to build a dataset of building characteristics. The resultant dataset is the only one of its kind for school buildings in England. The chapter concludes by outlining the statistical tests carried out in order to rank the various building characteristics in order of influence on thermal and electricity energy use. This chapter is part one of the methodology as outlined in Figure 3.1.

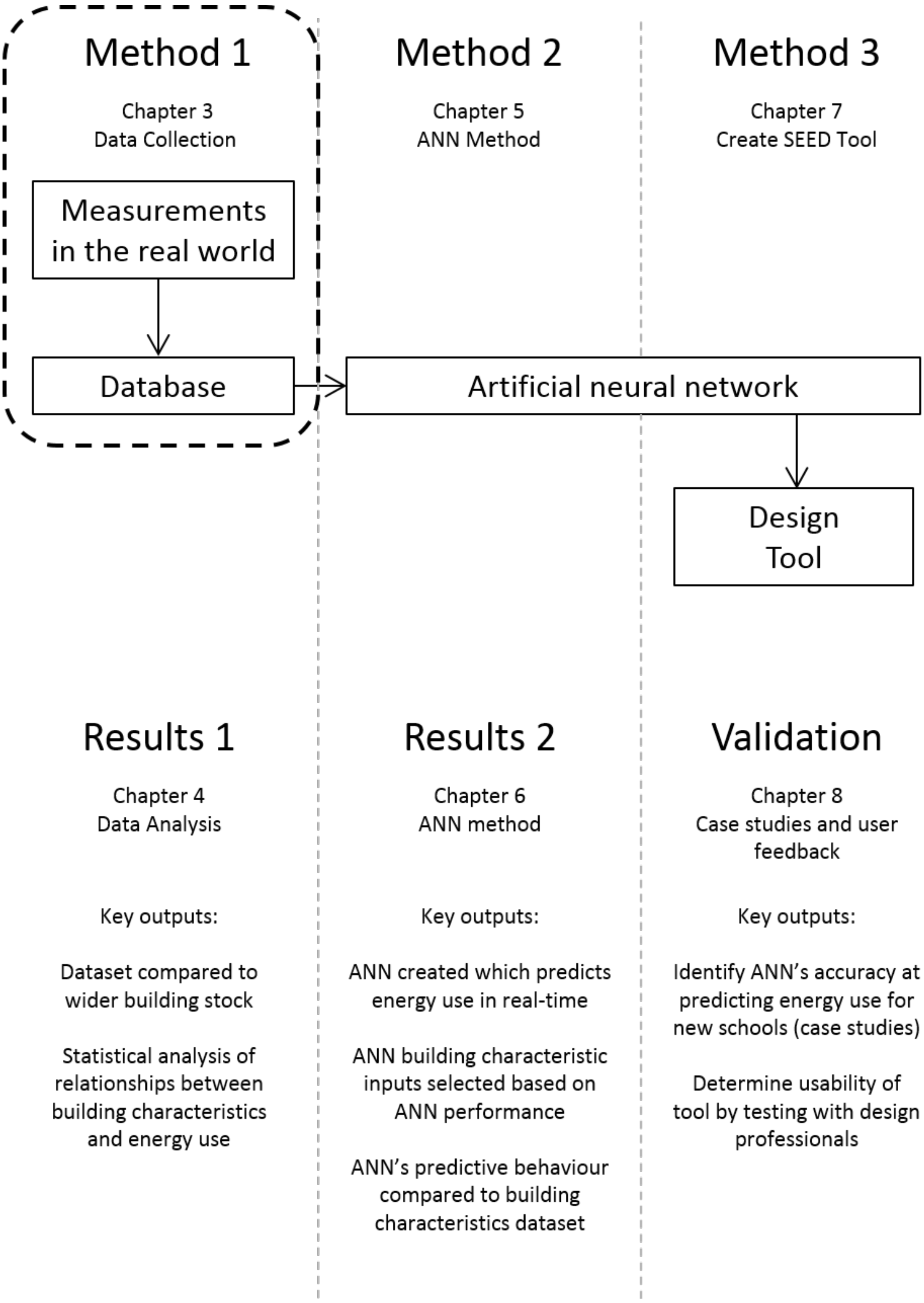


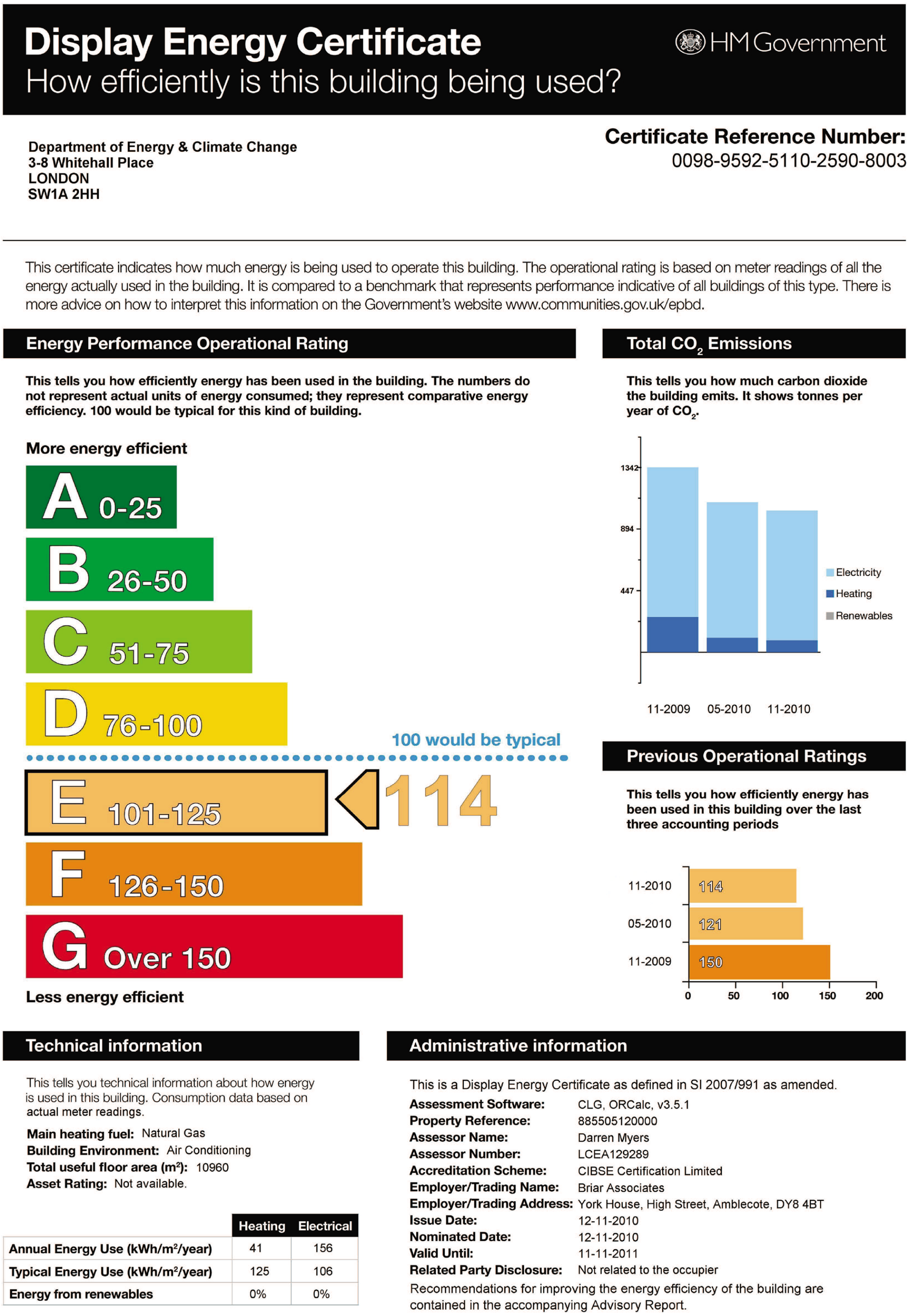
Figure 3.1: Breakdown of Work Stages: Methodology Part 1

3.2 Display Energy Certificate Data

As introduced in Section 2.5.2, the Display Energy Certificate (DEC) scheme was implemented in the UK in 2008 through the Energy Performance of Buildings Regulations to fulfil the requirements of the European Energy Performance of Buildings Directive (EPBD). DECs are certificates that indicate how efficiently an existing building is being used, regarding energy consumption, when it is in operation. The method produces an operational rating for each building, based on the energy benchmarking methodology developed by CIBSE (2009).

Originally, the scheme required non-domestic public buildings greater than 1000m^2 in floor area to produce and display a DEC certificate in a prominent location in the building (DCLG 2008). Figure 3.2 shows an example of a DEC certificate. The recasting of the directive and amendments to the energy performance of buildings regulations saw a lowering of the floor area threshold to 500m^2 in 2013 and 250m^2 in 2015 (DCLG 2012, 2015). Currently, DECs last for one year for buildings with a floor area more than 1000m^2 and ten years for buildings between 250m^2 and 1000m^2.

Information on energy consumption and building characteristics used to produce DECs are stored in the non-domestic energy performance register maintained by Landmark (2013) on behalf of the Department for Communities and Local Governments (DCLG). In September 2012, a dataset of all DEC records lodged until June 2012 was provided to CIBSE by Landmark. The dataset contained 120,253 DEC records, relating to 46,441 different buildings (or sites). The raw data from this dataset was transferred from CIBSE to University College London (UCL) in the form of comma-separated values (CSV) and Microsoft Excel files.



Display Energy Certificate
How efficiently is this building being used?

HM Government

Department of Energy & Climate Change
3-8 Whitehall Place
LONDON
SW1A 2HH

Certificate Reference Number:
0098-9592-5110-2590-8003

This certificate indicates how much energy is being used to operate this building. The operational rating is based on meter readings of all the energy actually used in the building. It is compared to a benchmark that represents performance indicative of all buildings of this type. There is more advice on how to interpret this information on the Government's website www.communities.gov.uk/epbd.

Energy Performance Operational Rating

This tells you how efficiently energy has been used in the building. The numbers do not represent actual units of energy consumed; they represent comparative energy efficiency. 100 would be typical for this kind of building.

More energy efficient

A 0-25
B 26-50
C 51-75
D 76-100
100 would be typical
E 101-125 — 114
F 126-150
G Over 150

Less energy efficient

Total CO_2 Emissions

This tells you how much carbon dioxide the building emits. It shows tonnes per year of CO_2.

Previous Operational Ratings

This tells you how efficiently energy has been used in this building over the last three accounting periods

Technical information

This tells you technical information about how energy is used in this building. Consumption data based on actual meter readings.

Main heating fuel: Natural Gas
Building Environment: Air Conditioning
Total useful floor area (m^2): 10960
Asset Rating: Not available.

	Heating	Electrical
Annual Energy Use (kWh/m²/year)	41	156
Typical Energy Use (kWh/m²/year)	125	106
Energy from renewables	0%	0%

Administrative information

This is a Display Energy Certificate as defined in SI 2007/991 as amended.

Assessment Software: CLG, ORCalc, v3.5.1
Property Reference: 885505120000
Assessor Name: Darren Myers
Assessor Number: LCEA129289
Accreditation Scheme: CIBSE Certification Limited
Employer/Trading Name: Briar Associates
Employer/Trading Address: York House, High Street, Amblecote, DY8 4BT
Issue Date: 12-11-2010
Nominated Date: 12-11-2010
Valid Until: 11-11-2011
Related Party Disclosure: Not related to the occupier

Recommendations for improving the energy efficiency of the building are contained in the accompanying Advisory Report.

Figure 3.2: Example of a DEC Certificate (HM Government 2016)

3.2.1 Energy Data

The annual energy use intensity (EUI) (kWh/m^2/yr) figures for fossil-thermal and electrical energy consumption from the DEC records were used in this research. Fossil-thermal energy relates to combustion fuel for all purposes, such as space heating, water heating and cooking – from here on, 'thermal' will be used in place of 'fossil-thermal'. Electrical energy includes electricity used for all purposes, including lighting and mechanical systems. It should be noted that buildings that use electricity for space heating will be disregarded in this research, as outlined in Section 3.2.2. The prediction of annual thermal and electrical energy consumption of new school buildings is the aim of the artificial neural network (ANN) method. As such, the thermal and electrical energy use intensity data collected from the DECs will form the training 'output' data for the ANNs, as outlined in Section 5.2. Some of the non-energy data in the DEC dataset were utilised in the building characteristics dataset as outlined in Section 3.4.2

3.2.2 Data Cleaning

Analysis of DEC records by Bruhns, H., Jones, P., & Cohen (2011) highlighted the fact that preparation work is required ahead of any analysis, in order to identify and eliminate invalid, erroneous or uncertain records from the raw dataset. The criteria from Bruhns, H., Jones, P., & Cohen (2011) were developed and refined further in this research with assistance from members of the CIBSE Energy Benchmarks Steering Group[1] and in collaboration with Dr Sung Min Hong. The process to select records that were deemed valid was as follows:

– *Remove records with operational ratings[2] that are 200 or 9999.* An operational rating of 200 is a default rating (changing to 9999 in March 2010), given when there is insuf-

[1] CIBSE Energy Benchmarks Group was set up by CIBSE to oversee the development of the energy benchmarks in CIBSE TM46 (CIBSE 2008) that underpin the DEC scheme

[2] The operational rating is used in DECs in the UK as a basis for grading building performance. The rating is derived by dividing the actual energy consumption by adjusted benchmarks and multiplying the ratio by 100

ficient information about energy consumption figures. As of April 2011, these default ratings are no longer allowed.

- *Remove records with operational ratings that are less than 5 or greater than 1000*. These values were deemed practically implausible by an expert in the CIBSE benchmarking steering group, meaning that the building is either vacant or the rating is erroneous.
- *Remove cancelled DECs.* On occasion, DEC assessors may lodge a certificate and later realise it contains a mistake. The assessor may cancel the DEC and replace it with an amended certificate. The 'Report Status' variable in the dataset flags cancelled DECs.
- *Remove records with a total useful floor area that is less than 50m^2.* Very small (school) buildings have the potential to be errors.
- *Remove records where the total annual CO_2 emissions are greater than 100,000 tonnes of CO_2/yr.* DECs with extreme CO_2 emissions were considered extreme outliers.
- *Remove records where the electric energy use intensity (EUI) is 0 kWh/m^2/yr.* It was deemed improbable that an occupied building would not consume electricity. These were therefore deemed to be erroneous.
- *Remove records where the building is electrically heated.* Buildings where electricity is the main space heating source are likely to have characteristically different patterns of energy use from buildings heated by fossil fuels.
- *Remove records where the thermal EUI is 0 kWh/m^2/yr.* Once the previous step of removing electrically heated buildings was carried out, any remaining buildings with no

thermal energy use indicate no heating within the building. Such cases were treated as unlikely and therefore erroneous, especially in the case of school buildings.

– *Remove records where more than one DEC for the same building are lodged within 182 days of each other.* On occasion, a DEC is lodged less than six months after another in order, for example, to report reduced energy use or make a correction. Therefore, all records where this was identified were removed.

Further steps were taken to clean the dataset by amending typing errors and removing duplicate, 'pro-rated'[3] and 'composite'[4] DECs. Lastly, the latest DEC record from each building was extracted for the analyses.

The DEC method provides 29 benchmark categories, within which there are a further 237 building types. These building types are differentiated through the activities occurring within the building. DEC records from primary and secondary schools are found under the 'Schools and seasonal public buildings' category, which contains 26 building-type classifications as shown in Table 3.1. There is a call to refine these inputs, in order to make them less ambiguous (Hong 2014). For example, the building type 'School' could refer to a number of other building types in the category. In order to avoid ambiguity and to distinguish between primary and secondary schools, the building types 'Primary school', 'Secondary school', 'State primary school' and 'State secondary school' were extracted. The reasons for identifying the activity within the building (primary or secondary school), is because it may relate to energy use, as outlined in Section 3.3.4 (Table 3.3).

[3]Pro-rated DECs relate to sites with multiple buildings where consumption is known only for the entire site

[4]A composite methodology is used for mixed use buildings which comprise of different activities that belong to more than one benchmark category

Benchmark Category	**Building Type**
Schools and seasonal public buildings	Community centre
	Community facilities
	Community meeting place
	Creche
	Creche/childcare facility
	Day centre
	Dog racecourse
	Hunting and fishing
	Marina or sailing club
	Nursery or kindergarten
	Pre-school facility
	Primary and secondary teaching establishments
	Primary school
	Private school
	Reserves centre
	School
	Secondary school
	Social clubs
	Special school
	Speedway
	State primary school
	State school
	State secondary school
	Unlicensed club
	Village hall

Table 3.1: Building type categories in the DEC dataset for 'Schools and seasonal public buildings' – building types in bold italic were extracted for this research

3.3 Building Characteristics Survey Preparation

3.3.1 Overview

As outlined in Section 2.5.2, in the US, the Commercial Buildings Energy Consumption Survey (CBECS) (US Department of Energy 2015) is a database that collects information on the stock of commercial buildings, including energy-related building characteristics. In the UK, there are currently no suitable existing databases describing the characteristics of buildings, such as their shape, occupancy levels, site or glazing areas, which may influence the demand for energy. The DEC database provides some information on building characteristics, such as floor area and ventilation strategies, as described in Section 3.4.2. However, this database does not describe many other characteristics which may affect energy use. Therefore, a process to collect building characteristics was put in place. Section 3.4 describes this data collection process in detail and the following sections outline the preparation that took place before the data collection process commenced.

3.3.2 Sample Size

Before collecting building characteristics it was necessary to estimate an adequate sample size in order to provide sufficient training data for the ANNs. There is no agreed method of designing and training ANNs – some resources claim the process to be more of an art than a science (Pyle 2003). However, rules of thumb exist for various aspects of ANN configuration and training, such as estimating an adequate sample size. Abu-Mostafa (2012) proposes the following rule of thumb (Equation 3.1) to estimate a sample size for a learning algorithm.

$$N \geq 10 d_{vc} \tag{3.1}$$

Where N is the number of data samples and d_{vc} is the Vapnik-Chervonenkis (VC) dimension of the model.

The VC dimension is a measure of the complexity of the statistical model – taken as the number of weights in the case of an ANN. Section 5.2 shows the structure of the ANNs used in this research, with weights between the input and hidden layer; weights between the hidden and output layer; and weights between the bias neurons and certain network neurons. The minimum number of hidden neurons in the network is two, as shown in Section 5.3, and the maximum number of input neurons for the thermal energy ANNs (Table 6.1) and electrical energy ANNs (Table 6.2) are both eighteen. As separate ANNs will predict thermal and electrical energy use, as outlined in Section 5.2, both of these models will have one output neuron. Taking the minimal ANN complexity with maximum possible inputs, a single ANN would have eighteen input neurons, two hidden neurons, and one output neuron, with one bias neuron connected to the hidden layer and one bias neuron connected to the output layer. Each network configuration has a total of 41 weights. Therefore, the minimum sample size necessary is taken to be 410 schools.

3.3.3 Selecting Schools

The aim of selecting schools was to represent a geographical spread across England. In order to achieve this, schools in the cleaned DEC dataset were shuffled into a random order to ensure no bias was given to a particular location of the country.

In order to reduce factors that may cause uncertainties and ensure all required data may be collected, a set of criteria was created by which a school was seen as suitable for this research. As such, schools were chosen from the aforementioned randomised dataset and assessed against the following criteria:

– *The school has one main building.* Campus-based schools may have multiple DECs and the possibility of non-typical educational activities, such as swimming pools and were therefore disregarded.

– *Building features are consistent throughout (e.g. age and main construction materials).* Composite schools of varying build ages or main construction materials will likely have a range of performance behaviours due to different materials' thermal properties or different build qualities of constructions built under various building regulation revisions.

– *The facades of the school can be observed using Bing Map's Bird's Eye View (Microsoft 2012) function or Google Street View (Google 2012b).* Facades that cannot be seen in either of these two programmes prohibit the collection of information on these buildings (see Section 3.4.3)

– *The school has pupil numbers data from the Department for Education's (DfE) database.* This ensures all schools in the dataset has a measurement of occupancy numbers (see Section 3.4.3)

If the school passed these criteria, they were deemed suitable for the collection process.

3.3.4 Selecting Building Characteristics

Many factors that make up what a building is, where a building is, and how a building is used influence the way in which a building consumes energy. The factors that influence energy performance can be placed in the following categories (Ratti et al. 2005):

– Climate

– Urban context

– Building design

– Systems

– Occupant behaviour

Climate, or more notably weather, are dependent on where the building is located geographically. Urban context accounts for the built and natural environment surrounding the building. The building design relates to the form and fabric of a building. Systems relates to any systems requiring energy to operate, such as space heating and lighting. Occupant behaviour relates to how occupants interact with the building. There are, however, overlaps in these categories, for example, occupant behaviour can dictate the use of mechanical ventilation systems if present or the opening of windows (building design) if naturally ventilated, owing to the complex and wicked nature of design, as described in Section 1.2.

Taking these categories into consideration and upon a review of literature of energy analysis and theory, the variables in Tables 3.2 and 3.3 were identified as key factors to base the data collection process on. The factors in these tables are by no means comprehensive; they were based on the likelihood of data being available, in line with the nature of the desktop study data collection process, described in Section 3.4.1. Additional factors that influence energy use, such as glazing shading coefficients, were deemed inaccessible through this process.

3.4 Building Characteristics Data Collection

3.4.1 Overview

Different methods to collect data were considered. Site visits offer an effective way to collect detailed information on a building and their occupants. Studies such as The Probe Project (Cohen et al. 2001) undertook this method, which included surveying occupants and undertaking air pressure tests. From 1995 to 2001, The Probe Project published 18 surveys. Innovate UK's Building Performance and Evaluation (BPE) Programme assessed

Category	**Factor**	**Impact on Energy Use**	**Study/Source**
Climate	External temperature	Temperature control (space heating and cooling): fabric heat transfer	CIBSE (2006)
Urban context	Overshadowing by surroundings	Temp. control: insolation on facade, solar gain; electricity: daylight	Ratti et al. (2005)
Building design	Surface to volume ratio	Temp. control: fabric heat transfer	Steadman et al. (2009)
	Building depth	Space heating/electricity: ventilation strategy (see 'Systems' category); electricity: daylight	Steadman et al. (2009)
	Facade orientation	Temp. control: solar gain	Ratti et al. (2005)
	U-value	Temp. control: fabric heat transfer	CIBSE (2006)
	Window to wall ratio	Temp. control: fabric heat transfer, solar heat gain; electricity: daylight	Yang et al. (2008)
	Atria	Space heating/electricity: ventilation strategy (see 'Systems' category); electricity: daylight	CIBSE (2004)
	Thermal mass	Temp. control: heat storage, response times of systems; space heating/electricity: ventilation strategy (see 'Systems' category)	CIBSE (2004)
Building design / Systems	Age	Space heating: fabric thermal performance; electricity: ICT equipment, efficiencies of building services; space heating/electricity: ventilation strategy (see 'Systems' category).	Godoy-Shimizu et al. (2011), Global Action Plan (2006)
Systems	Ventilation strategy	Space heating: ventilation heat loss; electricity: use of mechanical systems	Thomas (2006)
	Controls	Temp. control/electricity: complex controls leads to services and systems being unnecessarily used at times	Innovate UK (2016)

Table 3.2: Building Energy Performance Factors (1 of 2)

Category	Factor	Impact on Energy Use	Study/Source
Occupant behaviour	Number of occupants	Electricity: use of equipment (such as ICT)	Godoy-Shimizu et al. (2011)
	Occupancy hours	Space heating/electricity: extra hours use of systems and services	BRE (1998)
	Type of activity	Electricity: use of equipment (such as ICT)	Global Action Plan (2006)

Table 3.3: Building Energy Performance Factors (2 of 2)

the performance of buildings through detailed monitoring on-site and assessment of design documents that were part of planning permission. The project had a budget of £8 million, with assessors based across a range of academic and industrial organisations, often times within the architectural or engineering practice that designed the buildings being evaluated. In total, 50 buildings were assessed. It is evident that a site visit based method of collecting data is unsuitable. The target sample size for this research (410), a outlined in Section 3.3.2, far exceeds the number of buildings studied in the aforementioned studies and the time and resources required to undertake such research make it infeasible.

As such, a desktop study style approach was considered more suitable. This method includes using digital map and surveying data; online databases; and auxiliary data from the DEC dataset. In this way, data on hundreds of schools were able to be collected with less time and resources that site visits would demand.

It should be noted that attempts were made to collect additional data by contacting local councils and head teachers directly. It was hoped that these groups may be able to provide information, at varying detail, on building services, construction materials, facilities and specialist activities. However, due to the lack of feedback and bureaucratic process of gaining such information, data was unable to be collected via this method. Nonetheless, some of the aforementioned desired information, such as building services, was able to be collected by the desktop approach, as described in the following sections.

The following sections describe the process to collect available building characteristic data that is likely to impact on building energy use, as outlined in Tables 3.2 and 3.3 in the previous section.

3.4.2 DEC Building Characteristics

As previously mentioned, the DEC dataset provides additional information, other than energy use figures and ratings. Table 3.4 lists the key data fields within the dataset that were collected to form part of the wider building characteristics dataset. The following sections will provide more detail on the collection of these fields.

Floor Area

The total floor represents the total useful floor area (TUFA). This is the same as the gross internal floor area (GIA) that is often used by industry. The measurement is taken as the area to the internal face of the external walls in all enclosed spaces (including untreated areas), adhering to the following (Department for Communities and Local Government 2008):

– The area of sloping surfaces such as staircases, galleries, raked auditoria, and tiered terraces are taken as their area on plan

– Areas that are not enclosed, such as open floors and balconies, are excluded

Field	**Outputs/units**
Total floor area	m^2
Occupancy level (hours)	Standard
	Extended (number of hours also provided)
Internal environment	Air Conditioning
	Heating and Natural Ventilation
	Heating and Mechanical Ventilation
	Mixed-mode with Natural Ventilation
	Mixed-mode with Mechanical Ventilation
	Natural Ventilation Only
	Mechanical Ventilation Only
Building type category	Primary school
	Secondary school
	State primary school
	State secondary school

Table 3.4: Key (non-energy) fields in the DEC dataset

Ventilation Strategy

The internal environment is the primary environmental conditioning strategy of a building, broken down into seven categories as shown in Table 3.4. Due to the unclear differences between 'Mixed-mode with Natural Ventilation' and 'Mixed-mode with Mechanical Ventilation' (confirmed by conversions with an approved DEC assessor), these categories were combined to 'Mixed-mode' and were assumed to have heating. Furthermore, due to the relatively small numbers of mixed-mode buildings and the fact that there were no air conditioned buildings in the collected building characteristic dataset, as outlined in Section 4.2.3 (Table 4.11), these categories were combined with mechanical ventilation to form buildings with some degree of mechanical ventilation. Therefore, two categories for ventilation strategy emerged:

– Natural ventilation

– Mechanical ventilation

Occupancy Hours

The 'occupancy level' field identifies whether a building is operating at 'standard' or 'extended' occupancy hours. Standard occupancy hours for schools in the DEC scheme uses the default of 1400 hours per annum as set out in TM46 (CIBSE 2008). Schools marked as having extended hours are in operation more than 1400 hours per year. The hours per annum figure for these cases are provided. As the majority of schools in the building characteristics dataset were classed as having standard hours (see Section 4.2.3, Table 4.10), 1400 hours effectively becomes a categorical data field, therefore it was not deemed useful to treat this data as being continuous. As a result, occupancy hours was treated as categorical data, with the following occupancy hours categories forming inputs within the building characteristics dataset:

– Standard hours

– Extended hours

Phase of education

Phase of education relates to the type of activities taking place within the building: primary school activities or secondary school activities. Primary schools refer to primary, infant and junior schools (age range ~4-11) and secondary schools refer to secondary schools, academies and sixth form colleges (age range ~11-18). As mentioned in Section 3.2.2, the building types that formed the cleaned DEC dataset were 'Primary school', 'Secondary school', 'State primary school' and 'State secondary school'. These groups were refined to form the following phase of education categories within the building characteristics dataset:

- Primary school
- Secondary school

3.4.3 Non-DEC Building Characteristics

Number of Pupils

Number of pupils in each school were extracted from the Department for Education's (DfE) data, research and statistics database (DfE 2011). The data is for full-time equivalent pupils which is calculated as the number of part-time pupils divided by 2, plus the number of full-time pupils. This was deemed to give a more accurate number of pupils than a simple total of all pupils.

Year of Construction

There were two methods to collect the year the school was built. The first method was to refer to the school's website. If the website did not provide the year the school was built, the construction year was approximated using historical map software (EDINA 2012a) (see Figure 3.3). This process involved identifying the most recent historical map where the school building does not exist on the site and identifying the oldest historical map where the school does appear on the site. An average of the two years was then calculated to approximate the year of construction. In the example in Figure 3.3, the most recent historical map where the school does not exist on the site is 1975 and the oldest historical map where the school does exist is 1984. In this case, the year of construction was estimated as being 1980.

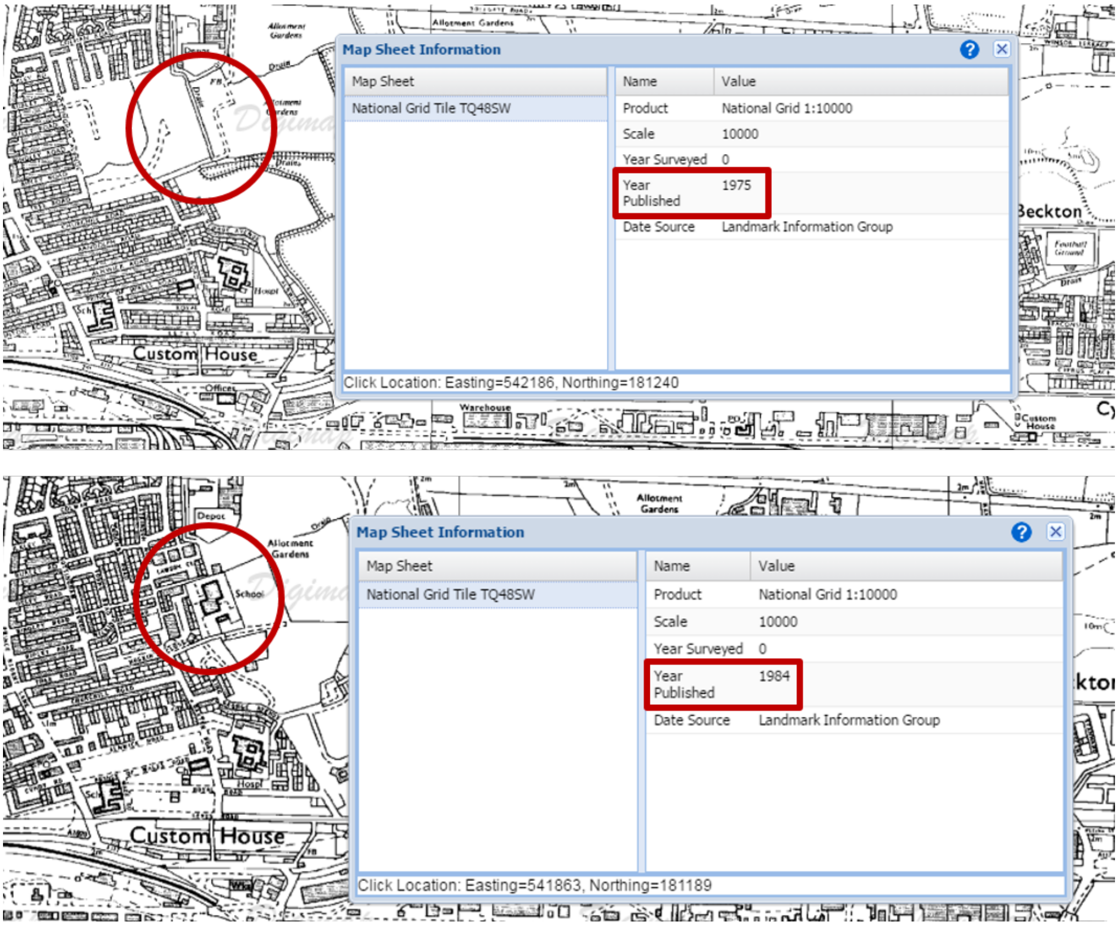


Figure 3.3: Digimap historical maps (EDINA 2012a)

Weather

As the DEC monitoring period for each individual school varied, heating and cooling degree days for the monitoring period of each school were obtained from the Central Information Point (CIP) file (Department for Communities and Local Government 2008).

Geometry

The following measurements were taken for each building to help describe the geometry of the building. Some of these measurements were used to derive other parameters, as discussed in the 'Derived Parameters' section (see section 3.4.3: Derived Parameters).

– Total perimeter (m)

– Exposed perimeter (m)

– Building footprint area (m^2)

– Orientation correction factor (^{o})

– North, south, east and west facade length (m)

– Number of storeys

Building Footprint and Roof Area

The building footprint area is the area of the building that makes contact with the ground. This data along with an approximation of roof area was gathered to help describe the geometry of the buildings in order to derive ratios, as shown in 'Derived Parameters' section below. The footprint area was measured using the area measurement tool from EDINA (2012b) as seen in Figure 3.4. The shape of some roofs in the dataset were flat, while others were pitched. The constraints in available tools meant that it was difficult to measure the area of pitched roof accurately. As such, roof areas were simplified and taken to be equal to the building footprint area. This was based on the assumption that all external walls were straight and orthogonal to the ground.

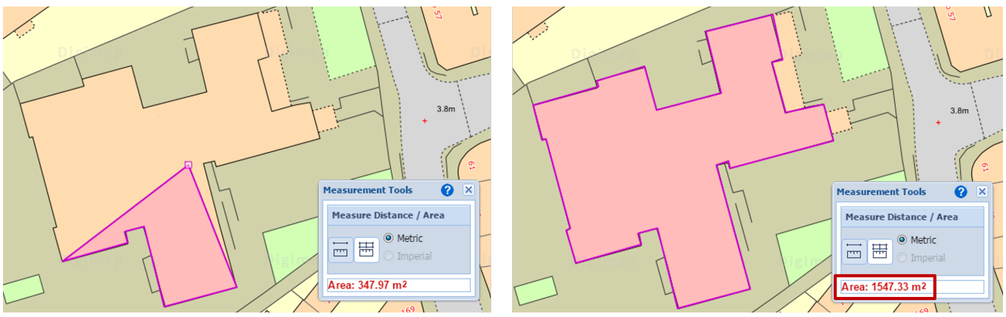


Figure 3.4: Measuring the building footprint area (EDINA 2012b)

Orientation

The general orientation (Figure 3.5) outlines the boundaries at which all future terms of north, south, east and west are determined (such as south facade length). The orientation correction factor (Figure 3.6) is the angle at which the external walls differ from absolute north, south, east and west. This measurement was made in Google Earth (Google 2012a). The minimum angle this can be is -45^{o} (anti-clockwise rotation) and the maximum angle is 45^{o} (clockwise rotation).

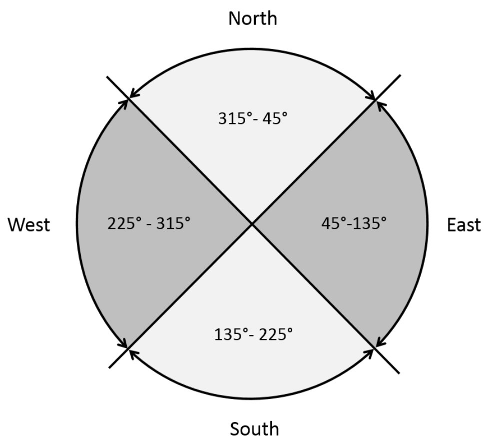


Figure 3.5: General orientation

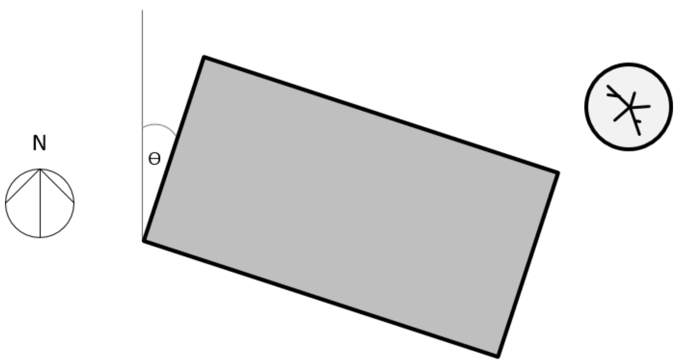


Figure 3.6: Orientation correction factor

Perimeter and Facade Lengths

The perimeter of the building and length of each facade on different general orientations were gathered to help describe the geometry of the buildings in order to derive ratios, as shown in the 'Derived Parameters' section below. The total perimeter of the building was measured together with the exposed perimeter using a distance measuring tool from EDINA (2012b) (Figure 3.7). The exposed perimeter is the total perimeter minus the perimeter shared with other buildings (see Figure 3.8).

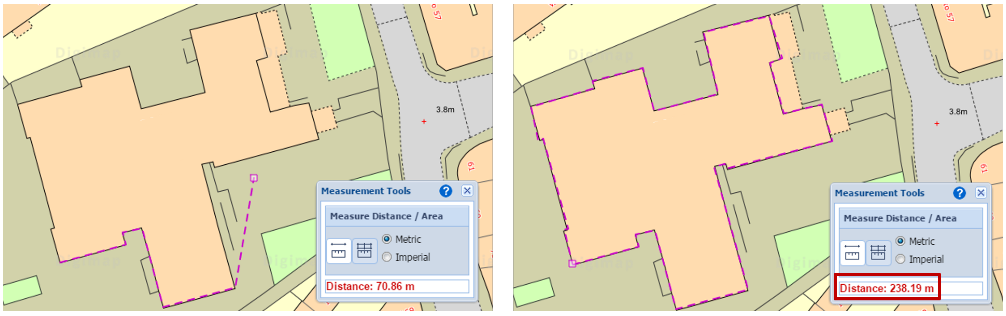


Figure 3.7: Measuring the building perimeter (EDINA 2012b)

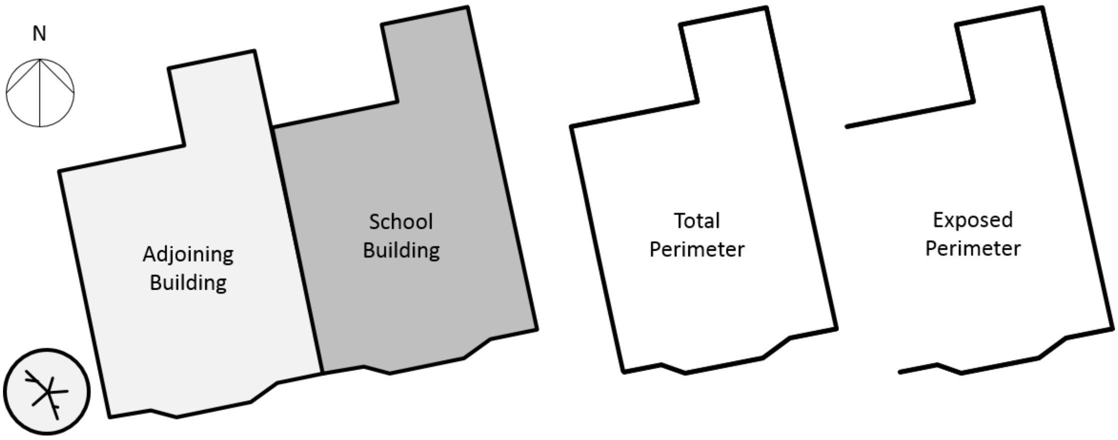


Figure 3.8: Total perimeter vs exposed perimeter

The facade length of each general orientation (north, south, east and west) is the cumulative length of external wall on each general orientation (see Figure 3.9). This data was measured using the aforementioned distance measuring tool from EDINA (2012b).

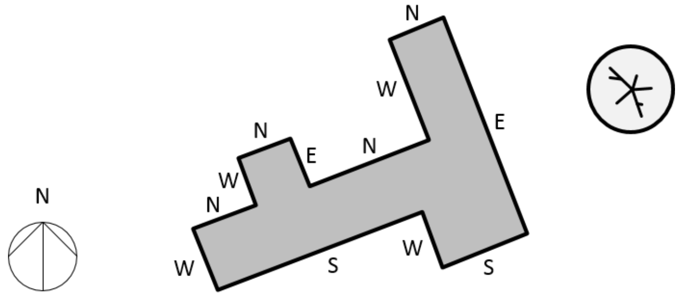


Figure 3.9: Orientation of each external wall

Building Height

The height of buildings were gathered to help describe the geometry of the buildings in order to derive ratios, as shown in the 'Derived Parameters' section below. Two methods were explored to collect accurate height data.

The first method looked to utilise the Geographic Information System (GIS) database from Landmap (2012). The database contains geological data spanning the UK, including terrain and building height data. The building heights were measured using light detection and ranging (LiDAR) technology. From the downloaded Landmap dataset, individual buildings were identified and heights were collected using ArcGIS software (Esri 2012) (Figure 3.10). However, some of the height data was found to be questionable. When dividing the building height by number of floors, some school buildings were said to have floor-floor heights of ~8m which raised suspicion, and upon inspection of satellite images (Microsoft 2012), (Google 2012b), it was evident that the data was erroneous. Similar uncertainties were found in some single storey schools with a sports hall attached. The Landmap data indicated that the sports hall height was lower than that of the rest of the one storey building. This data was deemed erroneous as the sports halls clearly had a greater height than the rest of the school (based on common sense and on inspection of satellite images).

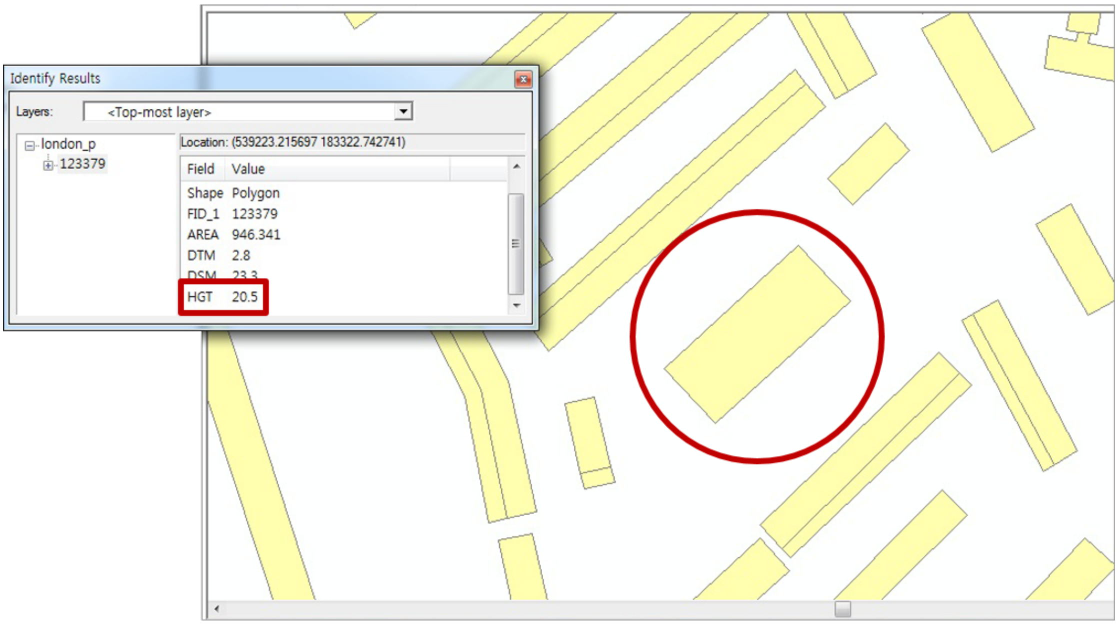


Figure 3.10: Measuring building height (Esri 2012)

As a result of this uncertainty, an alternative method to estimate building height was explored. The second method involved multiplying the number of floors in the building by the average floor-floor height of schools in England. The average storey height of schools in the England was taken to be 3.62m: a figure sourced from the Non-Domestic Building Stock (England and Wales) project by Steadman P., Bruhns H.R. (2000). The number of storeys in each building were counted upon visual inspection, using Bing Map's bird's eye view (Microsoft 2012) which offers four points of aerial view, equally spaced around a 360-degree rotation of the site (see Figure 3.11). More complex buildings, with a varying number of floors in different parts of the building, were addressed by taking the average of the maximum and minimum number of floors in the building. The maximum and minimum number of floors were only recorded if a considerable proportion of the building had a different number of floors and did not take into account small, possibly unheated, spaces. Therefore, spaces such as porches did not affect the average number of floors. It should be noted that there were limitations in using this method to accurately describe the height of a building. Variations in different storey heights in different buildings, for example, Victorian buildings and more modern buildings, and variations in different storey heights within the same building, such as classrooms and sports halls, were not accounted for.

Figure 3.11: Example of Bing Map's bird's eye view's four viewing angles around a building (Microsoft 2012)

Glazing

The glazing percentage on the north, south, east and west facing facades were collected by comparing the area of glazing to the area of facade on each general orientation (Figure 3.5). This process was carried out by capturing images of each facade orientation using Bing Map bird's eye view or Google street view. These images were then imported into an in-house programme created in Processing (2014) by Dr David Hawkins. The programme allows the users to draw two different colours of polygons on top of images. Blue polygons are drawn over the whole of the facade, on each orientation. Red polygons are drawn over glazed areas within the overall facade (see Figure 3.12). The programme then calculates the percentage of the facade area (blue) that that is glazed (red).

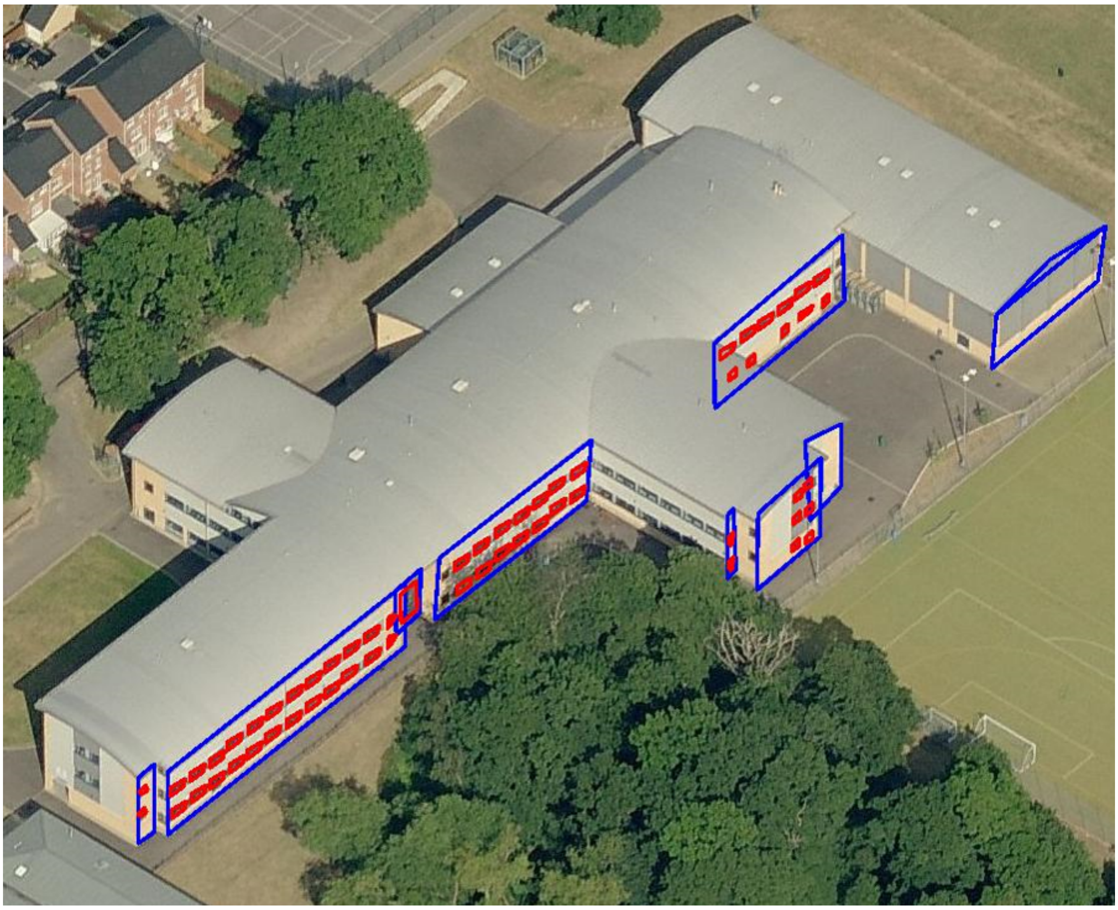


Figure 3.12: Processing code extracting glazing percentage on southern facade orientations

Building Adjacency

In order to account for significant solar and wind shading, it was noted if the majority of each orientation had an obstruction directly adjacent to it, such as a building or a line of trees. Through visual inspections on Google Earth (Google 2012a) and Bing Maps bird's eye view (Microsoft 2012), if an adjacent object was the height of the school building away or closer and the same height of the building or taller (Figure 3.13), it was deemed to be an obstruction if this occurred for over 50% of the facade general orientation.

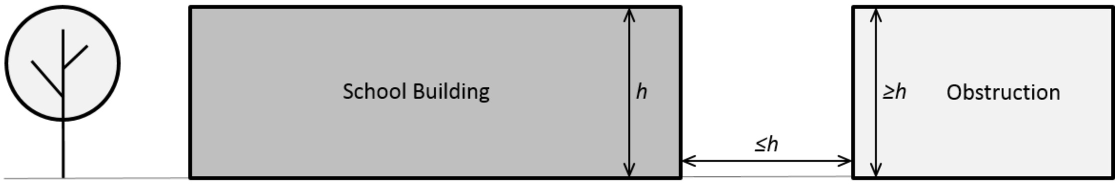


Figure 3.13: Building adjacency

External Building Materials

The primary external building materials for external walls and roofs were noted upon visual inspections on Google Earth (Google 2012a) and Bing Maps bird's eye view (Microsoft 2012). For example, if brickwork was the predominant material for external walls, this was noted. Similarly, if ceramic tiles was the predominant material for roof, this was also be noted.

Building Features

Additional building features that may impact on the environmental performance of the school, such as wind-catchers or solar thermal panels, were gathered. This was achieved by visual inspection of Bing maps (Microsoft 2012) and Google Earth (Google 2012a).

Derived Parameters

It was necessary to derive a number of parameters from the collected building characteristics in order to generate a set of ratios which further describe the buildings. The building volume was derived by multiplying the building height with the building footprint area. The exposed external wall area was derived by multiplying the exposed perimeter by the building height. The exposed surface area is the exposed external wall area plus the roof area. The facade area on each general orientation was calculated by multiplying the facade lengths on each general orientation by the building height. The glazed areas on each facade orientation were derived by multiplying the glazed percentage on each facade orientation with the facade area on each general orientation. As mentioned, these parameters were used, with some of the previously described building characteristics, to derive the following ratios:

– Plan depth ratio = building volume / exposed external wall area

– Surface exposure ratio = exposed surface area / building volume

– North glazing ratio = glazed area on the north facade / total floor area

– South glazing ratio = glazed area on the south facade / total floor area

– East glazing ratio = glazed area on the east facade / total floor area

– West glazing ratio = glazed area on the west facade / total floor area

Omitted Data

The following data was collected but ultimately omitted from any analyses:

– Primary external roof material

– Primary external wall material

– Building features

Due to lack of diversity, it was deemed necessary to omit primary external materials. It was found that brickwork dominated the external wall materials and the roofing materials were mostly split between ceramic tiles and waterproof felt polymer. There were lesser numbers of, for example, concrete, timber and render for external walls and metal, slate and concrete for roofs. The number of buildings with these less common materials were as low as ~1% of the dataset, and were therefore deemed too small to be categories within the ANN method. No schools were seen to have additional environmental building features, such as wind-catchers or solar thermal panels

3.4.4 Removal of Outliers

Upon the completion of the data collection process, energy use outliers were removed. Machine learning algorithms are sensitive to the range and distribution of the training data. Outliers in the training data can 'mislead' the training process of a neural network and can result in less accurate models (Brownlee 2013). Therefore, a process to remove outliers was undertaken on the energy use figures. Energy use data 1.5 times the interquartile range below the lower quartile and above the upper quartile were used as a boundary for identifying outliers. Data points identified as outliers were removed. Outliers were identified from the data using interquartile ranges to account for the possibility of skewed distributions. The outlier removal procedure was carried out on the thermal and electricity energy use figures separately.

3.5 Kruskal-Wallis Analysis

The Kruskal-Wallis test is a nonparametric version of the one-way analysis of variance test (ANOVA). It was used on the gathered data to determine how influential each input was on the thermal and electricity energy consumption. The Kruskal-Wallis method was chosen as results from continuous data can be compared with categorical data.

For each of the continuous input parameter states, the values were ordered from the lowest to the greatest value and then split into four equally-sized groups. The categorical inputs are naturally grouped. The Kruskal-Wallis method compares the median outputs of the groups in each input to determine if the samples come from the same population. That is, determining if a significant change in energy consumption output occurs as the value of each input changes, indicating how influential an input is on the output. The method ranks the data by ordering the data from smallest to largest across all groups and calculating the test statistic (Equation 3.2).

$$H = \frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{m_j} - 3(N+1) \tag{3.2}$$

Where H is the Kruskal-Wallis test statistic, N is the total number of observations across all groups, k is the number of groups, j is the group number, m is the number of observations in group j and R is the sum of the ranks from the jth sample.

The p-value is the probability of observing a test statistic (Equation 3.2) as extreme as the one that was actually observed. The null hypothesis is the default position that there is no relationship between two measured phenomena. Small p-values, $p < 0.05$ (Stigler 2008), cast doubt on the null hypothesis. That is, a p-value of 0.05 or lower has a 95% confidence level or higher that the input is influencing the output. The p-values are found from a chi-squared distribution table or Kruskal-Wallis test statistic table, such as those outlined by Gibbons and Chakraborti (2003, p.368).

3.6 Summary

This chapter outlined the data collection process that took place in order to build a training dataset for the artificial neural network method – the training process is presented in Chapter 5. The chapter began by outlining the available DEC data, before presenting the data cleaning process that is necessary to omit erroneous data from the raw DEC dataset. The chapter then presented the preparation and data collection process necessary to build a dataset of building characteristics. The resultant dataset, a product of the methodology in this chapter, is the only one of its kind for school buildings in England. The chapter concluded by outlining the statistical tests that will be carried out on the collected dataset in order to rank the various building characteristics in order of influence on thermal and electricity energy consumption. This process will be taken into account when introducing the inputs sequentially into the ANN model, as outlined in Chapter 5. The following chapter will present the dataset and results of the statistical analyses described in this chapter.

Chapter 4

Results 1: Building Characteristics Dataset

4.1 Overview

The previous chapter outlined the process to collect and analyse a building characteristics dataset. In this chapter, the dataset and results of the statistical analyses are presented. The chapter begins by presenting the distributions of the energy use and building characteristics data. The chapter concludes by analysing the relationships between the building characteristics and thermal and electrical energy use. This process involves the analysis of scatter plots together with the results of a Kruskal-Wallis analysis. The Kruskal-Wallis analysis ranks the building characteristics in order of influence on thermal and electricity energy consumption. This ranking will form the basis of the input group ordering in the ANN training methodology, as described in the following chapter. This chapter is part one of the results as outlined in Figure 4.1.

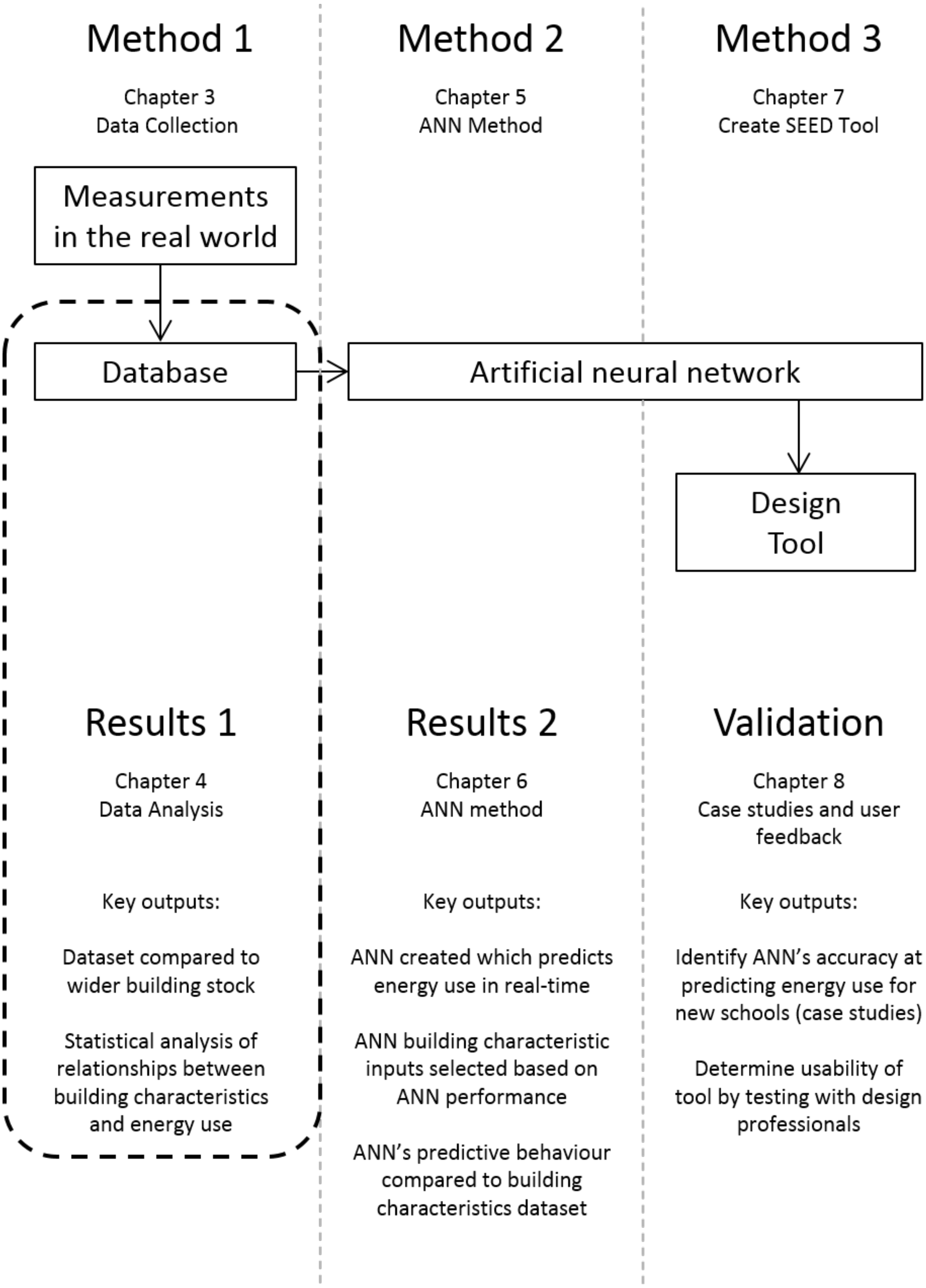


Figure 4.1: Breakdown of Work Stages: Results Part 1

4.2 Data Distribution

4.2.1 Overview

As shown in Table 4.1, there were 10,144 schools in the 'cleaned' DEC dataset for England. In the academic year 2012/13, there were 20,065 state-funded schools in England (DfE 2013). The 'cleaned DEC dataset' sample therefore represents approximately 51% of the state schools in England. The final building characteristics dataset is comprised of 502 schools[1]. This number surpasses the target to collect data on 410 schools, as described in Section 3.3.2.

Dataset	N
Cleaned DEC dataset	10,144
Initial building characteristic dataset	588
Building characteristic dataset with outliers removed	502

Table 4.1: Number of schools in datasets in England

Figure 4.2 shows the locations, across England, of the schools in the building characteristic dataset. It can be seen from this that a spread of schools across many geographical regions of England made up the dataset. Table 4.2 shows a comparison of the number of schools in each location between the building characteristics dataset and the cleaned DEC dataset. The percentage of buildings in each location differ by 8% or less between the two datasets, demonstrating that the distribution of schools across England in the building characteristics dataset is statistically similar to the overall stock.

[1] Section 3.4.4 outlines the outlier removal process

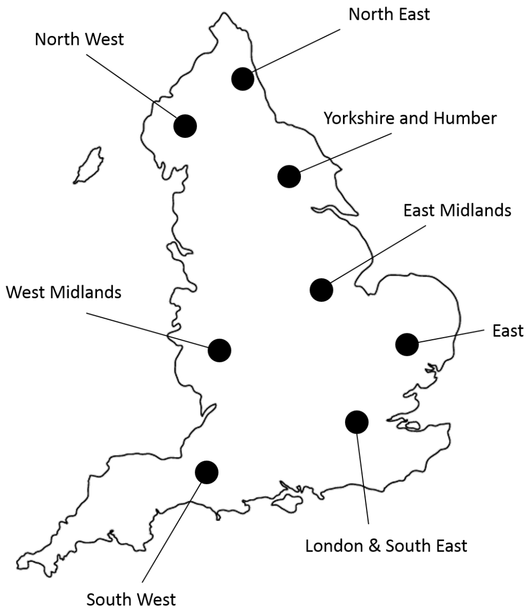


Figure 4.2: Location of schools in building characteristics dataset across England

Location	Building characteristics dataset		Cleaned DEC dataset	
	N	%	N	%
London and South East	139	28	2809	28
South West	71	14	794	8
East	22	4	1196	12
West Midlands	35	7	1164	11.5
East Midlands	68	14	631	6
Yorkshire and Humber	47	9	1184	11.5
North East	65	13	646	6
North West	55	11	1720	17
Total	502	100	10144	100

Table 4.2: Number of schools in building characteristics dataset across locations of England

4.2.2 Energy Use

Thermal Energy

Table 4.3 shows the spread of thermal energy use intensity across the building characteristics dataset. For comparison, figures for the cleaned DEC dataset are also provided. It can be seen that the maximum and minimum values for the building characteristic dataset are less extreme than the DEC dataset. This is due, in part, to the removal of outliers in the building characteristic dataset, as outlined in Section 3.4.4. The median of the building characteristics database is similar to the DEC database; the two medians differ by 2kWh/m^2/yr (1.5% of the cleaned DEC dataset median). The upper and lower quartiles from the building characteristics database and DEC dataset are also similar; the lower quartiles differ by 6kWh/m^2/yr (5.8% of the cleaned DEC dataset lower quartile) and the upper quartiles are the same value. This demonstrates that, despite the differences in overall range, the distribution in the building characteristics dataset is statistically similar to the overall stock. It should be noted that the minimum value for the cleaned DEC dataset (2kWh/m^2/yr) appears too low to be a functioning, heated, building. The difficulty of removing possible errors such as this in the DEC data cleaning process is the allocation of non-arbitrary lower and upper kWh/m^2/yr thresholds for thermal energy use. Accordingly, this issue was raised with the CIBSE Energy Benchmarks Steering Group who assisted with the DEC data cleaning process in this thesis, as outlined in Section 3.2.2.

	N	**Thermal EUI (kWh/m^2/yr)**				
		Min	1st Quartile	Median	3rd Quartile	Max
Building characteristics dataset	502	47	109	132	162	246
Cleaned DEC dataset for schools	10,144	2	103	130	162	837

Table 4.3: Statistics of thermal energy use of schools in England

Electrical Energy

Table 4.4 shows the spread of electricity energy use intensity across the building characteristics dataset. For comparison, figures for the cleaned DEC dataset are also provided. It can be seen that the maximum and minimum values for the building characteristic dataset are less extreme than the DEC dataset. As with the previously discussed thermal energy use figures, this is partly due to the removal of outliers in the building characteristic dataset, as outlined in Section 3.4.4. The median of the building characteristics database is similar to the DEC database; the two medians differ by 3kWh/m^2/yr (6.7% of the cleaned DEC dataset median). The upper and lower quartiles from the building characteristics database and DEC dataset are also similar; the lower quartiles differ by 1kWh/m^2/yr (2.7% of the cleaned DEC dataset lower quartile) and the upper quartiles differ by 3kWh/m^2/yr (5.5% of the cleaned DEC dataset upper quartile). This demonstrates that, despite the differences in overall range, the distribution in the building characteristics dataset is statistically similar to the overall stock. As with the thermal energy use figures, it should be noted that the minimum value for the cleaned DEC dataset (1kWh/m^2/yr) appears too low to be a functioning building. The reasoning for this was given in the previous section ('Thermal Energy') and the issue was raised with the CIBSE Energy Benchmarks Steering Group who assisted with the DEC data cleaning process in this thesis, as outlined in Section 3.2.2.

	N	**Electricity EUI (kWh/m^2/yr)**				
		Min	1st Quartile	Median	3rd Quartile	Max
Building characteristics dataset	502	13	38	48	58	91
Cleaned DEC dataset for schools	10,144	1	37	45	55	191

Table 4.4: Statistics of electricity energy use of schools in England

4.2.3 Building Characteristics

Final Dataset Summary

Tables 4.5 and 4.6 summarise the building characteristics that will form the inputs of the ANN method including the ranges for the continuous data and categories for the categorical data. The following sections will discuss the distributions of this data in more detail.

Geometry

Figure 4.3 shows the distributions of collected geometry data. Floor areas range from 861m^2 to 15,396m^2. The distribution is skewed towards smaller floor areas, with the majority of schools having a floor area of around 1000-2000m^2. This is likely due to there being more primary schools than secondary schools in the building characteristics dataset and across England in general as described in the following section (Table 4.9). Table 4.7 shows the mean floor areas of primary and secondary schools. It is shown that primary schools tend to have less floor area than secondary schools. Figure 4.4 shows scatter plots of pupil numbers and pupil density against floor area. As expected, as schools increase in size (area), pupil numbers tend to increase. The data also shows that larger schools tend to have a lower density of pupils.

Figure 4.3 also shows that the surface exposure distribution is concentrated between a ratio of 0.2 (less exposed) to 0.6 (more exposed) with a small number of schools having surface exposures above this range. The building depth ratios range from ~2 (less deep) to ~11 (more deep). The distribution is skewed towards a depth ratio of ~5. The orientation correction is approximately uniformly distributed with a small bias towards zero. This implies that the buildings are approximately randomly orientated, with a small overdensity of buildings with facades that face absolute N,S,E,W.

Parameter	**Data Type**	**Data Range/ Categories**	**Description Summary**
Floor Area	Continuous	861-15396m^2	Gross internal area (GIA)
Surface Exposure Ratio	Continuous	0.1725 - 0.8457	Exposed surface area / building volume
Building Depth Ratio	Continuous	2.1145 - 11.4932	Building volume / exposed external wall area
Orientation Correction	Continuous	-45 - +45^o	Angle at which the external walls differ from absolute north, south, east and west. Positive angle for clockwise orientations
Number of Pupils	Continuous	54 - 2013	Part-time pupils divided by 2, plus the number of full-time pupils
Phase of Education	Categorical	[Primary], [Secondary]	Primary schools or secondary schools/sixth form colleges
Ventilation Strategy	Categorical	[Nat. vent], [Mech. vent]	Natural ventilation only or existence of mechanical ventilation to some degree
Year of Construction	Continuous	1828 - 2010	Year the school was built
Glazing Ratio on Northern Facades	Continuous	0.0014 - 0.1313	Glazed area on the northern facades/total floor area
Glazing Ratio on Southern Facades	Continuous	0 - 0.1734	Glazed area on the southern facades/total floor area
Glazing Ratio on Eastern Facades	Continuous	0 - 0.1349	Glazed area on the eastern facades/total floor area
Glazing Ratio on Western Facades	Continuous	0 - 0.1341	Glazed area on the western facades/total floor area
Occupancy hours	Categorical	[Standard], [Extended]	Standard or extended occupancy hours

Table 4.5: List of collected building characteristics data (1 of 2)

Parameter	Data Type	Data Range/ Categories	Description Summary
Adjacency of Northern Facades	Categorical	[Not obstructed], [Obstructed]	Obstructed if a building or tree is within 1 x the height of the building from the majority of the facade orientation
Adjacency of Southern Facade	Categorical	[Not obstructed], [Obstructed]	See adjacency of northern facades
Adjacency of Eastern Facades	Categorical	[Not obstructed], [Obstructed]	See adjacency of northern facades
Adjacency of Western Facade	Categorical	[Not obstructed], [Obstructed]	See adjacency of northern facades
Heating Degree Days	Continuous	1519.9 - 2843.3	Heating degree days during the DEC monitoring period (to be utilised within the thermal ANNs only)
Cooling Degree Days	Continuous	73.9 - 457.1	Cooling degree days during the DEC monitoring period (to be utilised within the electrical ANNs only)

Table 4.6: List of collected building characteristic data (2 of 2)

	Mean Floor Area (m^2)	
	Primary	**Secondary**
Building characteristics database	1951	8310
Cleaned DEC dataset for schools	1824	7878

Table 4.7: Mean floor areas of primary and secondary schools

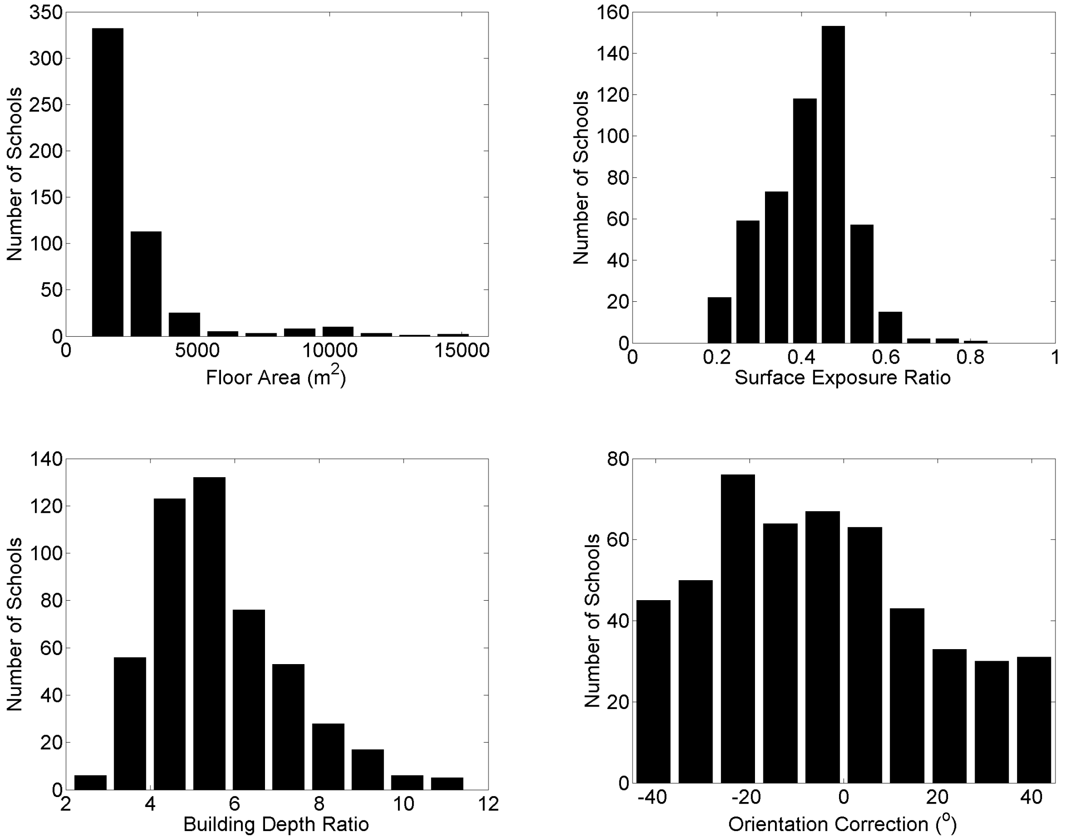


Figure 4.3: Distributions of collected geometry data

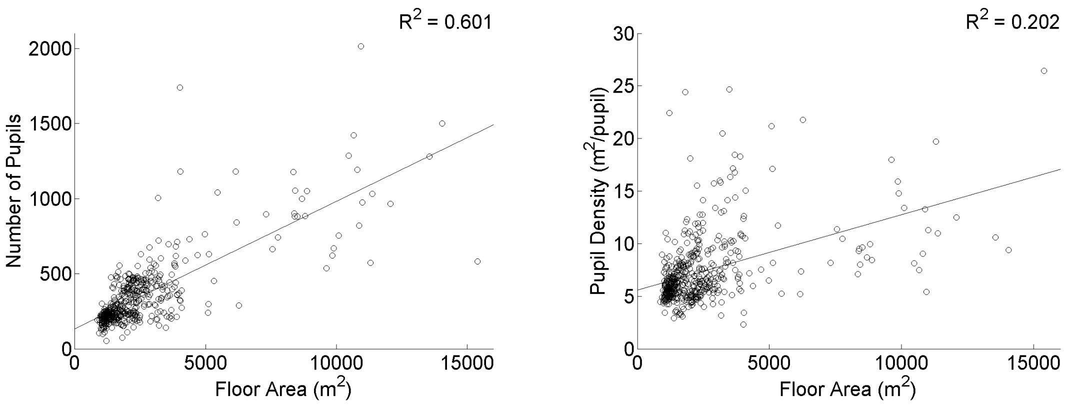


Figure 4.4: Scatter plots showing pupil numbers (left) and pupil density (right) against floor area

Activity

Figure 4.5 shows the distribution of collected pupil number data. The numbers range from 54 to 2,013 pupils, with the distribution skewed towards fewer pupil numbers, concentrating at around 100-500 pupils before tailing off considerably to higher pupil numbers. This is likely due to there being more primary than secondary schools in the dataset, as described below; primary schools tend to have lower numbers of pupils, as indicated in Table 4.8.

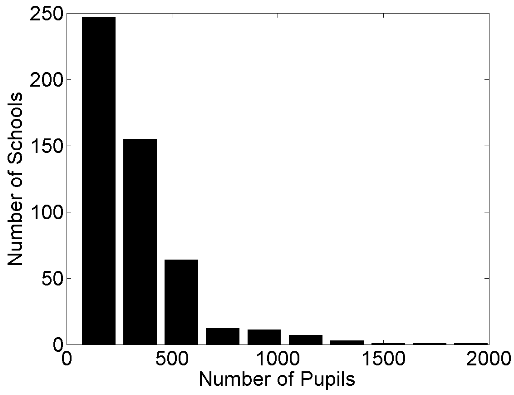


Figure 4.5: Distribution of collected pupil number data

	Primary	**Secondary**
Mean number of pupils	293	911

Table 4.8: Mean number of pupils in the building characteristics dataset

Table 4.9 shows the breakdown of primary and secondary schools in the building characteristics dataset and the cleaned DEC school dataset. 92% of the building characteristics dataset is compiled of primary schools. This figure is within 7% of the proportion in the cleaned DEC dataset, showing that the proportion of primary and secondary schools in the collected building characteristics dataset is similar to the proportion across England.

	Primary	Secondary
Numbers in building characteristics dataset	461	41
Percentage	92%	8%
Numbers in cleaned DEC school dataset	8625	1519
Percentage	85%	15%

Table 4.9: School type breakdown

Table 4.10 shows the breakdown of occupancy hours in the building characteristics dataset and the cleaned DEC school dataset. The majority of the schools in the building characteristics dataset have 'standard'[2] school hours. 30% of the buildings in the building characteristics dataset have 'extended'[3] hours, which includes after hours activities. This figure is within 6% of the proportion in the cleaned DEC dataset, showing that the occupancy hours in the collected building characteristics dataset is similar to that of schools across England.

	Standard Hours	Extended Hours
Numbers in building characteristics dataset	352	150
Percentage	70%	30%
Numbers in cleaned DEC school dataset	7731	2413
Percentage	76%	24%

Table 4.10: Occupancy hours breakdown

Construction Year

Figure 4.6 shows the distribution of collected construction year data. The year in which the schools in the dataset were built range from the 1800s to 2010. There is a small peak at

[2] Standard hours are 1400 hours per annum as per the CIBSE TM46 (CIBSE 2008) definition for Schools and Seasonal Public Buildings

[3] Extended hours are more than 1400 hours per annum as per the CIBSE TM46 (CIBSE 2008) definition for Schools and Seasonal Public Buildings

the end of the nineteenth century, coinciding with the Education Act, making elementary education compulsory for the first time in England, as outlined in Section 2.2.2. However, the distribution is mainly skewed towards buildings built between the 1950s and the 2000s, peaking in the 1970s. As outlined in Section 2.2.2, this period of development was due to post-war construction; rapid growth of comprehensive schools in the 1970s; and the Building Schools for the Future (BSF) programme in the 2000s.

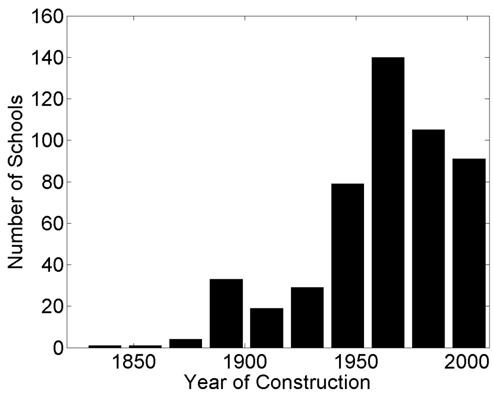


Figure 4.6: Distribution of collected construction year data

Services

Table 4.11 compares the breakdown of ventilation strategies in the building characteristics dataset with the wider cleaned DEC dataset. The majority (89%) of schools in the building characteristics dataset are complied of naturally ventilated buildings; this figure is similar (within 5%) to the proportion in the cleaned DEC dataset. The building characteristics dataset had zero air conditioned buildings, which is comparable with the wider DEC dataset which had close to 0% (21 from 10,144 schools) air conditioned schools. Due to the small number of buildings with mixed-mode and mechanical ventilation, these buildings were combined to represent buildings with mechanical services, as shown in Table 4.12. Table 4.12

also shows that secondary schools are more likely to have mechanical ventilation than primary schools.

	Natural Ventilation	**Mixed-mode**	**Mechanical Ventilation**	**Air Conditioning**
Numbers in building characteristics dataset	446	26	30	0
Percentage	89%	5%	6%	0%
Numbers in cleaned DEC school dataset	9502	334	287	21
Percentage	94%	3%	3%	~0%

Table 4.11: Ventilation strategy comparison

	Primary	**Secondary**	**All**
Number of buildings with some form of mechanical services (ventilation)	45	11	56
Percentage	10%	27%	11%

Table 4.12: Ventilation strategy breakdown for the building characteristics dataset

Glazing

Figure 4.7 shows the distribution of glazing ratio data. Higher glazing ratios equate to higher proportions of glazing to solid walls (see Section 3.4.3). The north, south, east and west glazing ratios have similar distributions, which are skewed towards ratios of 0.01 to 0.05. There tends to be fewer schools with higher glazing ratios on all orientations.

Site

Table 4.13 shows the breakdown of the proportion of N,S,E,W facades that are obstructed. As outlined in Section 3.3, the presence of facade obstructions were collected to, in part,

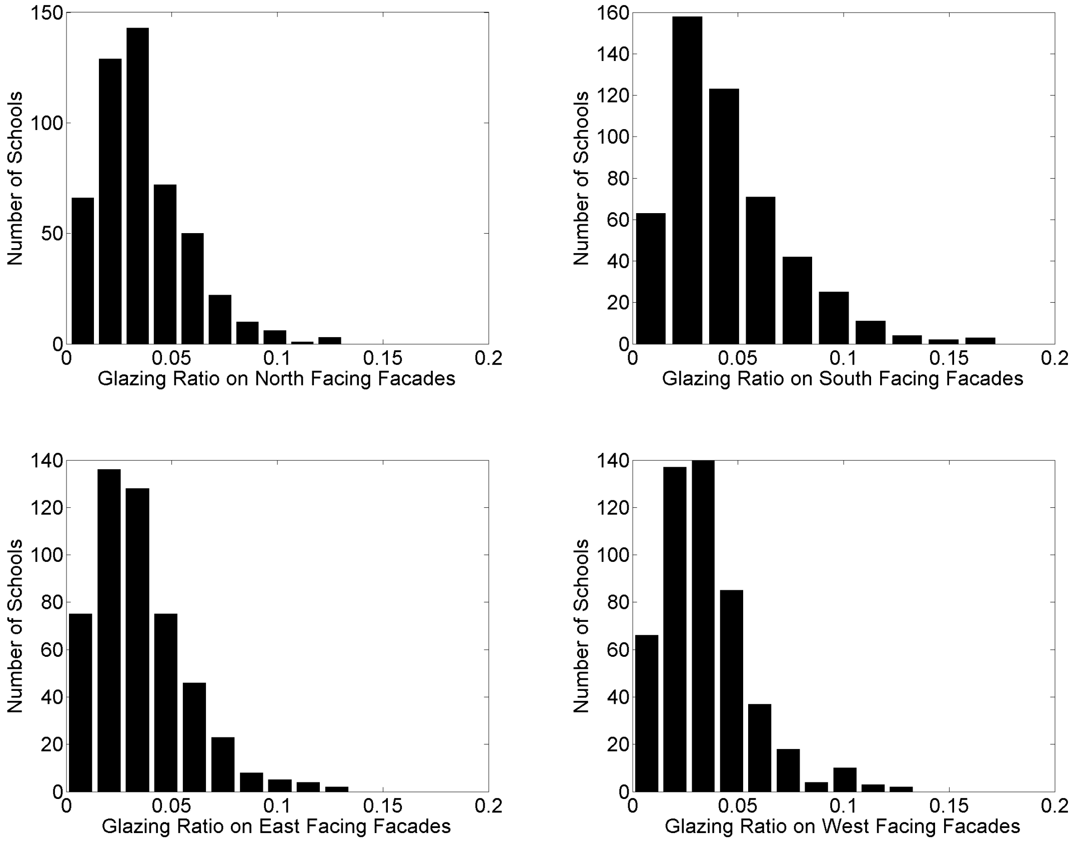


Figure 4.7: Distribution of collected glazing ratio data

	Obstructed on north facades	**Obstructed on south facades**	**Obstructed on east facades**	**Obstructed on west facades**
No.	55	65	62	85
Percentage	11%	13%	12%	17%

Table 4.13: Facade adjacency breakdown in building characteristics dataset

take into account the obstruction of solar gain. North facades, in the UK, receive the least solar gain and were found to be obstructed the least: 11% of facades in the dataset. West facades receive solar gain in the afternoon and were obstructed the most: 17% of facades in the dataset. East facades receive solar gain in the morning; 12% of the buildings in the dataset were obstructed to the east. South facades tend to receive the most solar gain; 13% of the buildings in the dataset were obstructed to the south.

Weather

Figure 4.8 shows the distribution of degree days. The heating and cooling degree days both have normal distributions. The heating degree days are centred around 2100 degree days. In the UK (excluding Scotland), the CIBSE TM46 energy benchmarking methodology is based on the average UK climate, with 2,021 heating degree days with 15.5^{o}C as the base temperature (CIBSE 2008). The latest standardised figures for the UK are 2,463 heating degree days (Vilnis Vesma 2016). This indicates that the most common heating degree days in the building characteristics dataset are similar to national averages. Cooling degree days are centred around 250 degree days. The latest standardised figures for the UK are 213 cooling degree days. The higher cooling degree days in the building characteristics dataset compared to the national average is likely due to the larger proportion of schools in the building characteristics dataset being located in London and the South East (Table 4.2), which tends to have warmer summers than many of the other regions in Figure 4.2.

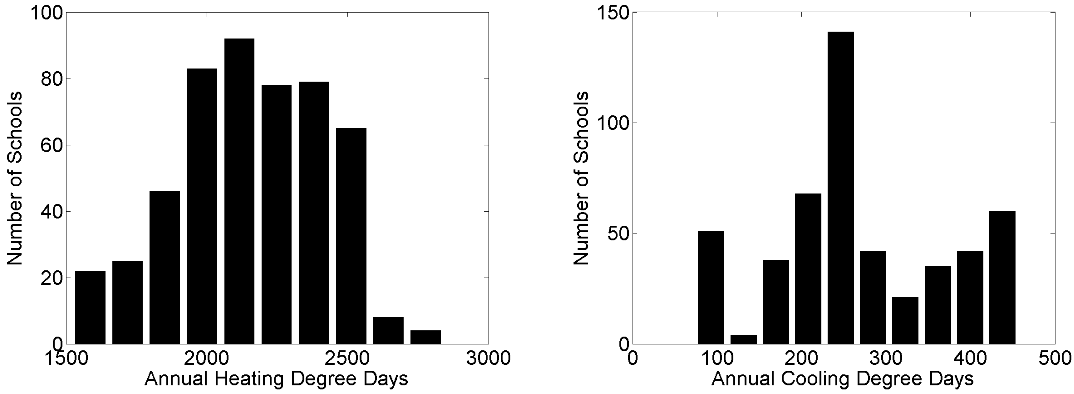


Figure 4.8: Distribution of collected degree day data

4.3 Relationships Between Building Characteristics and Energy Use Intensity

4.3.1 Thermal Energy Use Intensity

Overall

The p-value results of the Kruskal-Wallis analysis for thermal energy use intensity are shown in Table 4.14. Using a p-value threshold of 0.05 (Stigler 2008) as outlined in Section 3.5, building characteristics can be categorised as being influential to the thermal energy use intensity with a 95% confidence level. Furthermore, the building characteristics are ranked from most influential to thermal energy use intensity to least influential. The most influential inputs, in descending order, are building depth ratio; surface exposure ratio; construction year; ventilation strategy; glazing ratio on southern, western, eastern and northern facades; phase of education; floor area; and adjacency on northern facades. The ordering of the inputs from most influential to least influential will be taken into account when introducing the inputs sequentially into the ANN model, as described in the following chapter.

No.	**Parameter**	**Parameter Type**	**p-value**	**p-value < 0.05**
1	Building depth ratio	Geometry	2.358×10^{-8}	Yes
2	Surface exposure ratio	Geometry	3.239×10^{-6}	Yes
3	Construction year	Construction year	5.043×10^{-4}	Yes
4	Ventilation strategy	Services	2.708×10^{-3}	Yes
5	Glazing ratio on south facades	Glazing	3.062×10^{-3}	Yes
6	Glazing ratio on west facades	Glazing	5.042×10^{-3}	Yes
7	Glazing ratio on east facades	Glazing	6.134×10^{-3}	Yes
8	Glazing ratio on north facades	Glazing	1.929×10^{-2}	Yes
9	Phase of education	Activity	2.240×10^{-2}	Yes
10	Floor area	Geometry	2.366×10^{-2}	Yes
11	Adjacency on north facades	Site	2.751×10^{-2}	Yes
12	Adjacency on west facades	Site	1.677×10^{-1}	No
13	Adjacency on south facades	Site	1.766×10^{-1}	No
14	Orientation correction	Geometry	2.734×10^{-1}	No
15	Heating degree days	Weather	4.735×10^{-1}	No
16	Number of pupils	Activity	5.533×10^{-1}	No
17	Adjacency on east facades	Site	7.056×10^{-1}	No
18	Occupancy hours	Activity	9.096×10^{-1}	No

Table 4.14: Building characteristics dataset p-values for thermal energy use intensity according to the Kruskal-Wallis analysis (no. 1: most influential, no.18: least influential)

The following sections describe the results, with reference to the building science of various factors as outlined in Section 3.3.4. It should be noted that the coefficient of determination (R^2) values tend to be small (<0.5) for the results in this analysis. This is in part due to the noise in the real-world data and also because the R^2 value is an indicator of a linear correlation, not a general correlation. Furthermore, in fields that involve human behaviour, such as the operation of buildings, low R^2 values can be expected (Frost 2013). The benefit of the Kruskal-Wallis (p-value) results is that they show general correlations (for continuous and categorical data), and the benefit of the coefficient of determination is that it shows the direction of the correlation (for continuous data).

Geometry

Floor area, surface exposure ratio and building depth ratio all have p-values that are less than 0.05 and are therefore deemed by this analysis as being influential on thermal energy use intensity for the buildings in the collected dataset. Figure 4.9 shows scatter plots of thermal energy use intensity against these parameters. Surface exposure has a weak positive correlation (R^2 = 0.071), suggesting that as the buildings become more exposed, they tend to consume more thermal energy per square metre. This is likely due to fabric heat loss in that a building that has more of its surface exposed, relative to its volume, the more fabric heat loss it incurs; therefore, in order to keep the internal temperatures at an adequate level, more thermal energy is required (Steadman et al. 2009). Building depth has a weak negative correlation (R^2 = 0.073), suggesting that as the buildings become deeper, they tend to consume less thermal energy per square metre. This is likely due to the close relationship between building depth ratio and the aforementioned surface exposure ratio, as a building with a deep plan is more likely to be less exposed and therefore will incur less fabric heat loss. Furthermore, deeper buildings are more likely to have mechanical ventilation (Steadman et al. 2009), which tend to incur less ventilation heat loss than naturally ventilated buildings and therefore require less thermal energy per square metre (Thomas 2006). The weak negative correlation for floor area (R^2 = 0.024) suggests that as the buildings increase in floor area, there is a trend to consume less thermal energy per square metre. It was previously shown that as floor area increases, pupil density decreases (Figure 4.4), therefore the decrease in thermal energy use intensity as floor area increases may be due to fewer occupants, per unit of area, using domestic hot water services while also requiring smaller cooking loads proportionally. Furthermore, larger buildings and buildings with smaller pupil densities may have more spaces used for activities other than teaching, such as wide corridors and sports facilities, which require less heating.

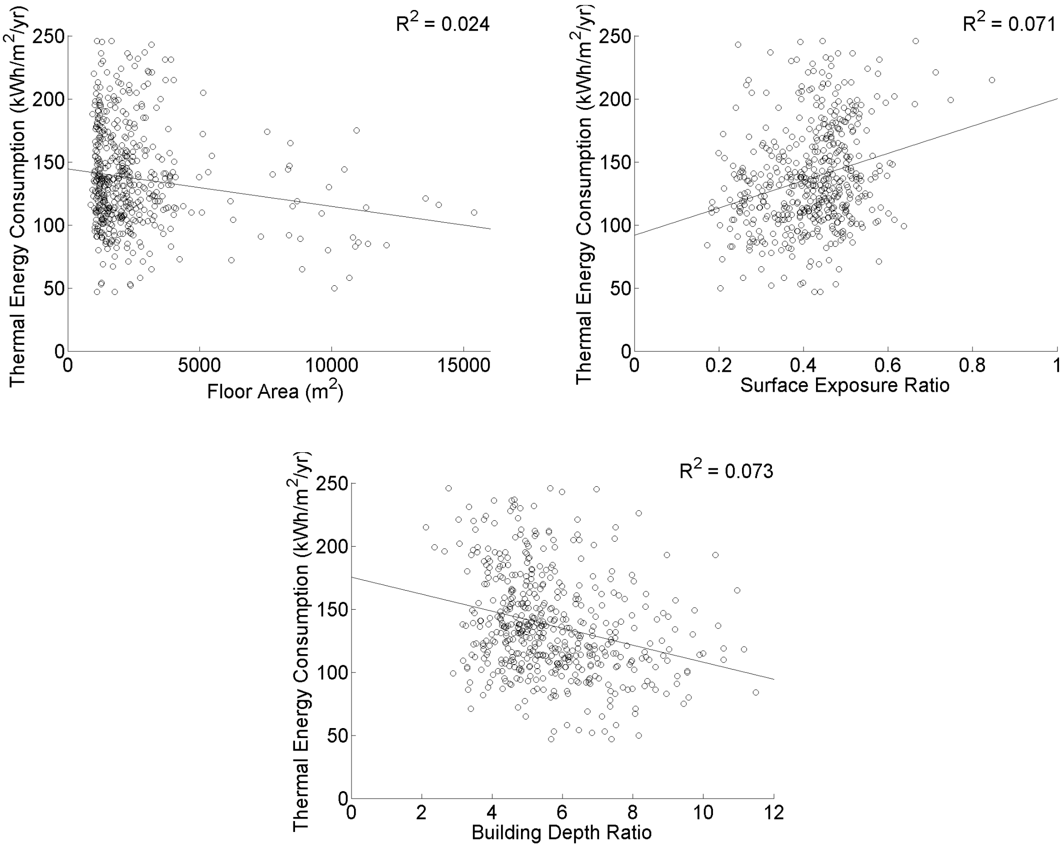


Figure 4.9: Scatter plots showing thermal energy use intensity against collected geometry data

Activity

The p-value for number of pupils is greater than 0.05 and is therefore deemed by this analysis not to significantly influence thermal energy use intensity for the buildings in the collected dataset. Figure 4.10 is a scatter plot of thermal energy use intensity against collected pupil number data. Despite the p-value being greater than 0.05 and weak trend (R^2 = 0.004), there is a slight tendency for thermal energy use intensity to decrease as pupil numbers increase. This may be due to the fact that as pupil numbers increase, pupil density tends to decrease (Figure 4.4). The relationship between pupil numbers and thermal energy use intensity may therefore be linked to pupil density as described in the previous section ('Geometry').

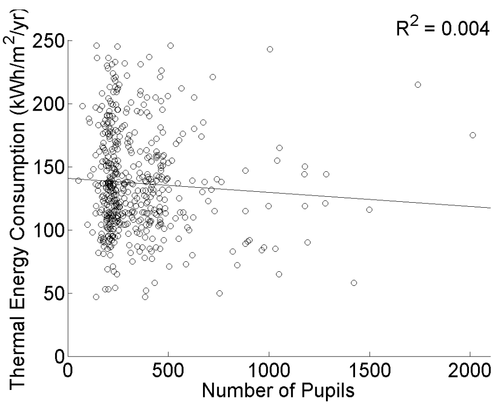


Figure 4.10: Scatter plot showing thermal energy use intensity against collected pupil number data

Figure 4.11 shows how thermal energy use intensity depends on the remaining collected activity data. For phase of education, the 1st and 3rd quartile and median for secondary schools are all lower than their respective figures in primary schools, suggesting that primary schools tend to consume more thermal energy per square metre than secondary schools. This corresponds with the p-value result for phase of education which is less than 0.05 and therefore deemed by this analysis as being influential on thermal energy use intensity for the buildings in the collected dataset. This is likely due to the fact that secondary schools tend to be larger than primary schools (Figure 4.7) and therefore relates to the floor area parameter. As previously discussed (Section 'Geometry'), larger schools are more likely to

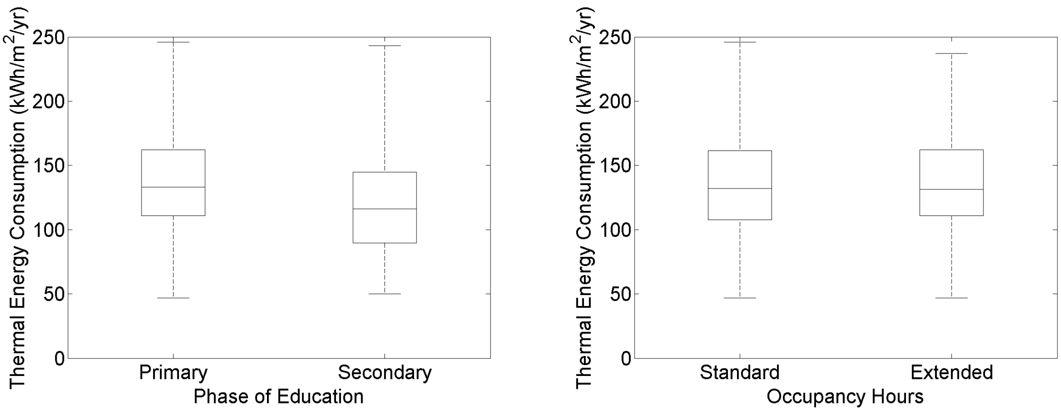


Figure 4.11: Box plots showing how thermal energy use intensity depends on collected activity data

have more spaces used for activities other than teaching, such as wide corridors and sports facilities, which require less heating. The link between floor area, pupil density and thermal energy use intensity was also described in the previous section ('Geometry').

Construction Year

Construction year has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on thermal energy use for the buildings in the collected dataset. Figure 4.12 is a scatter plot of thermal energy use intensity against collected construction year data. There is a weak negative correlation (R^2 = 0.020), suggesting that older buildings tend to consume more thermal energy per square metre than newer school buildings. The energy efficiency requirements of building regulations, which have become gradually more stringent over recent decades, are likely to have reduced the demand for heating in buildings which were erected more recently (Global Action Plan 2006; Godoy-Shimizu et al. 2011).

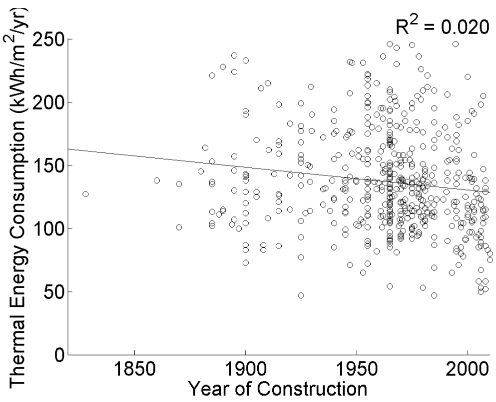


Figure 4.12: Scatter plot showing thermal energy use intensity against collected construction year data

Services

Ventilation strategy has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on thermal energy use intensity for the buildings in the collected dataset. Figure 4.13 shows how thermal energy use intensity depends on the collected ventilation strategy data. The median and upper quartile for mechanically ventilated buildings are lower than the respective values in naturally ventilated buildings, indicating that naturally ventilated buildings tend to consume more thermal energy per square metre than mechanically ventilated buildings. This is likely because mechanically ventilated buildings tend to be more sealed and may use heat recovery systems, while, by their nature, naturally ventilated buildings are less sealed and therefore incur greater ventilation heat losses, requiring more heating energy (Thomas 2006).

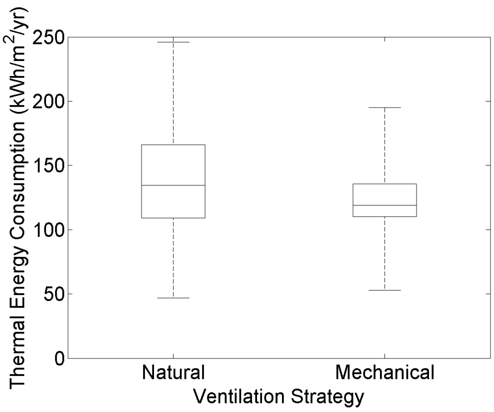


Figure 4.13: Box plot showing how thermal energy use intensity depends on collected ventilation strategy data

Glazing

Glazing ratios on north, south, east and west facades all have p-values that are less than 0.05 and are therefore deemed by this analysis as being influential on thermal energy use intensity for the buildings in the collected dataset. Figure 4.14 shows scatter plots of thermal energy use intensity against collected glazing ratio data. All glazing ratios have a weak positive correlation – R^2 = 0.018 (north), R^2 = 0.026 (south), R^2 = 0.037 (east), R^2 = 0.033 (west) – suggesting that as glazing proportions increase on all facade orientations, buildings tend to consume more thermal energy per square metre. An increase in glazing tends to result in an increase in solar heat gain, however, glazing almost always has poorer thermal insulation properties than external walls. Therefore, the increased fabric heat loss that occurs with an increase in glazing is likely to offset any beneficial solar heat gain.

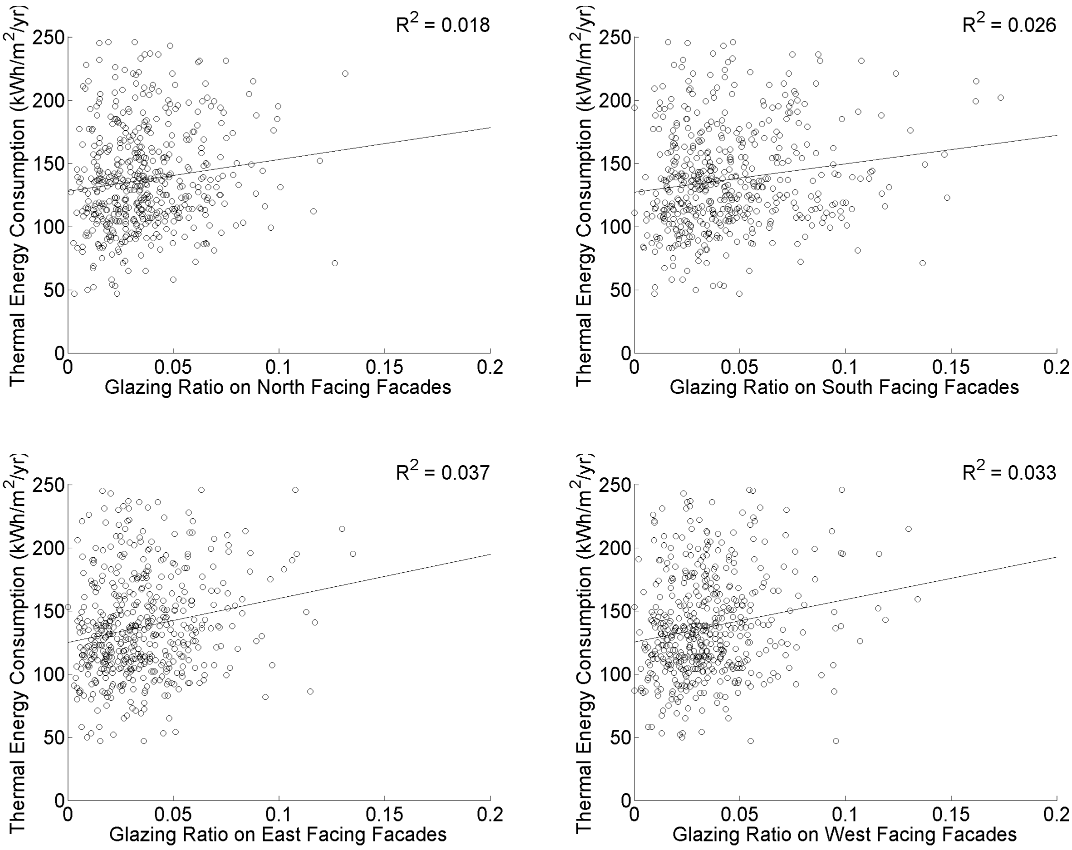


Figure 4.14: Scatter plots showing thermal energy use intensity against collected glazing ratio data

Site

Adjacency on south, east and west facades have p-values that are greater than 0.05 and are therefore deemed by this analysis not to significantly influence thermal energy use intensity for the buildings in the collected dataset. Adjacency on north facades has a p-value that is less than 0.05 and is therefore deemed as influential on thermal energy use intensity. Figure 4.15 shows how thermal energy use intensity depends on the collected facade adjacency data.

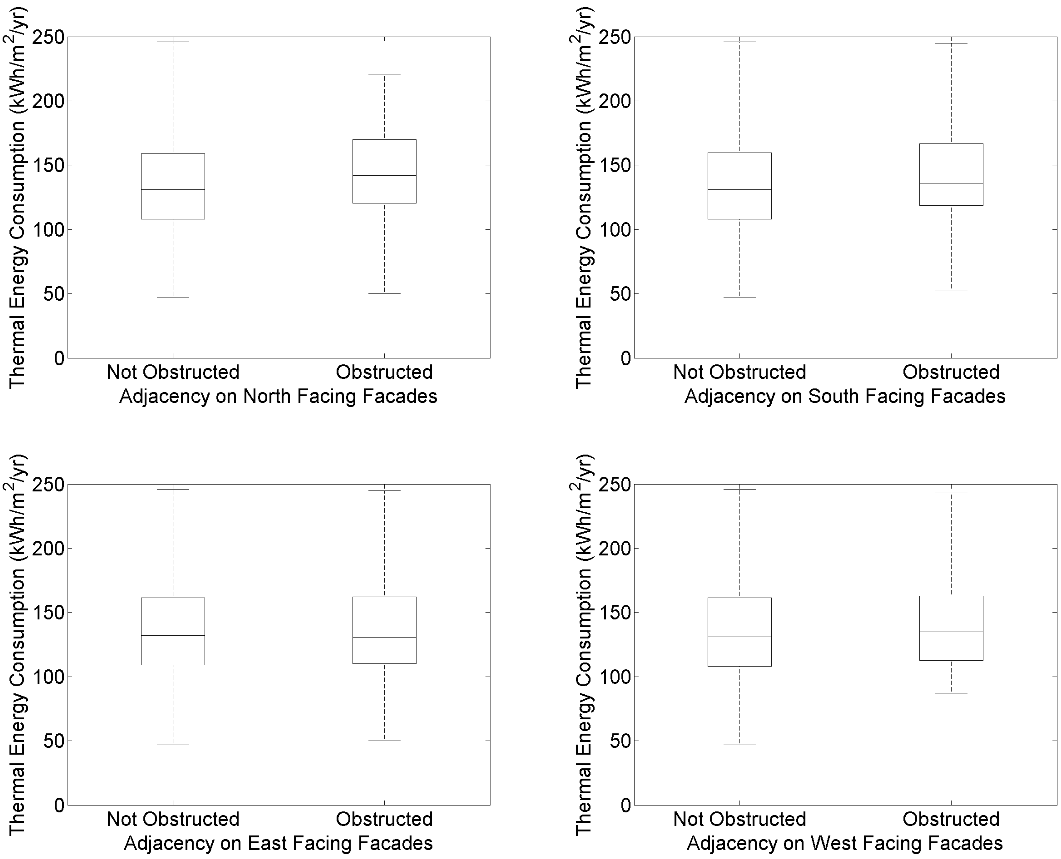


Figure 4.15: Box plots showing how thermal energy use intensity depends on collected facade adjacency data

For the most influential facade adjacency, north, the median, lower quartile and upper quartile for obstructed northern facades are greater than the respective figures in non-obstructed northern facades, indicating that buildings in which the northern facades are obstructed tend to consume more thermal energy per square metre. It was expected that buildings with obstructed facades would consume more thermal energy for space heating due to the obstruction of solar radiation falling on the facades (Ratti et al. 2005). However, north facades generally let in diffuse light which does not contribute towards solar heat gain. These results represent correlations, which may mean that there are unforeseen characteristics common amongst buildings with obstructions on north facades that influence thermal energy use.

Furthermore, that fact that building adjacency on south, west and east facades did not significantly impact thermal energy use may be because of related aspects such as cloud cover or the fact that other building characteristics are more dominant.

Weather

Figure 4.16 is a scatter plot of thermal energy use intensity against collected heating degree day data. The results are very scattered (R^2 = 0.004) and the p-value is greater than 0.05. This parameter is therefore deemed by this analysis not to significantly influence thermal energy use intensity for the buildings in the collected dataset. Heating degree days were expected to affect space heating because of their relationship with fabric heat loss (CIBSE 2006). The fact that this characteristic did not affect thermal energy use is likely due to the poor operation of heating systems (Hong 2014) and also because of the relative similarity of external temperatures in England – if the study expanded to Scotland, with typically lower external temperatures, or indeed internationally, it would be expected that heating degree days would be more influential on thermal energy use.

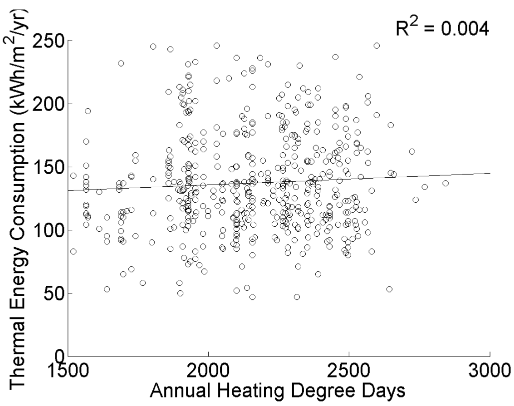


Figure 4.16: Scatter plots showing thermal energy use intensity against collected heating degree day data

4.3.2 Electrical Energy Use

Overall

The p-value results of the Kruskal-Wallis analysis for electricity energy use intensity are shown in Table 4.15. As with the thermal energy results, using a p-value threshold of 0.05 (Stigler 2008), building characteristics can be categorised as being influential or not influential to the electricity energy use intensity with a 95% confidence level. Furthermore, the building characteristics are ranked from most influential to electricity energy use intensity to least influential. The most influential inputs, in descending order, are construction year; phase of education; glazing ratio on southern facades; floor area; glazing ratio on northern facades; and number of pupils. The ordering of the inputs from most influential to least influential will be taken into account when introducing the inputs sequentially into the ANN model, as described in the following chapter.

The following sections describe the results, with reference to the building science of various factors as outlined in Section 3.3.4. It should be noted that the coefficient of determination (R^2) values tend to be small (<0.5) for the results in this analysis. As mentioned in Section 4.3.1, this is in part due to the noise in the real-world data; the fact that the R^2 value is an indicator of a linear correlation, not a general correlation; and because fields that involve human behaviour, such as the operation of buildings, can expect to have low R^2 values (Frost 2013). As previously mentioned, the benefit of the Kruskal-Wallis (p-value) results is that they show general correlations (for continuous and categorical data) and the benefit of the coefficient of determination is that it shows the direction of the correlation (for continuous data).

No.	**Parameter**	**Parameter Type**	**p-value**	**p-value < 0.05**
1	Construction year	Construction year	3.005×10^{-13}	Yes
2	Phase of education	Activity	1.952×10^{-7}	Yes
3	Glazing ratio on south facades	Glazing	1.133×10^{-4}	Yes
4	Floor area	Geometry	7.484×10^{-4}	Yes
5	Glazing ratio on north facades	Glazing	1.502×10^{-2}	Yes
6	Number of pupils	Activity	4.205×10^{-2}	Yes
7	Adjacency on west facades	Site	5.887×10^{-2}	No
8	Building depth ratio	Geometry	7.870×10^{-2}	No
9	Ventilation strategy	Services	1.690×10^{-1}	No
10	Adjacency on east facades	Site	2.553×10^{-1}	No
11	Glazing ratio on west facades	Glazing	2.612×10^{-1}	No
12	Glazing ratio on east facades	Glazing	2.786×10^{-1}	No
13	Surface exposure ratio	Geometry	3.180×10^{-1}	No
14	Orientation correction	Geometry	5.513×10^{-1}	No
15	Cooling degree days	Weather	6.712×10^{-1}	No
16	Adjacency on north facades	Site	8.295×10^{-1}	No
17	Occupancy hours	Activity	8.981×10^{-1}	No
18	Adjacency on south facades	Site	9.001×10^{-1}	No

Table 4.15: Building characteristics dataset p-values for electricity energy use according to the Kruskal-Wallis analysis (no. 1: most influential, no.18: least influential)

Geometry

Floor area has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy use intensity for the buildings in the collected dataset. Surface exposure and building depth both have p-values that are greater than 0.05 and are therefore deemed by this analysis not to significantly influence electricity energy use intensity for the buildings in the collected dataset. Figure 4.17 shows scatter plots of electricity energy use intensity against collected geometry data. Floor area has a weak positive correlation (R^2 = 0.016), suggesting that as the buildings increase in floor area, they tend to consume more electrical energy. This may be because larger school buildings are more likely to be secondary schools (see Table 4.7). Secondary school buildings are more likely to make greater use of information communication technology (ICT) and electrical equipment in laboratories (Global Action Plan 2006). Despite building depth ratio falling slightly below the 95% confidence level in its influence on electrical energy use intensity, there is a weak positive trend (R^2 = 0.013), suggesting that deeper buildings tend to consume more electrical energy per square metre than more shallow buildings. Deeper buildings tend to receive less daylight into central areas and therefore require more artificial lighting than shallower buildings (Steadman et al. 2009). Furthermore, deeper buildings are more likely to require mechanical ventilation (Steadman et al. 2009). Increased electricity demand for these services and systems explains the tendency for deeper buildings requiring more electrical energy per square meter.

Activity

Pupil number data has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy consumption. Figure 4.18 is a scatter plot of electrical energy use intensity against collected pupil numbers. There is a weak positive correlation (R^2 = 0.047), indicating that as pupil numbers increase, the electricity energy use intensity tends to increase. This may be because schools with higher pupil numbers are more likely to be secondary schools. Secondary school buildings are more likely to consume more electrical energy as previously discussed and outlined in the following set of results.

Phase of education has a p-value which is less than 0.05 and is therefore deemed by this

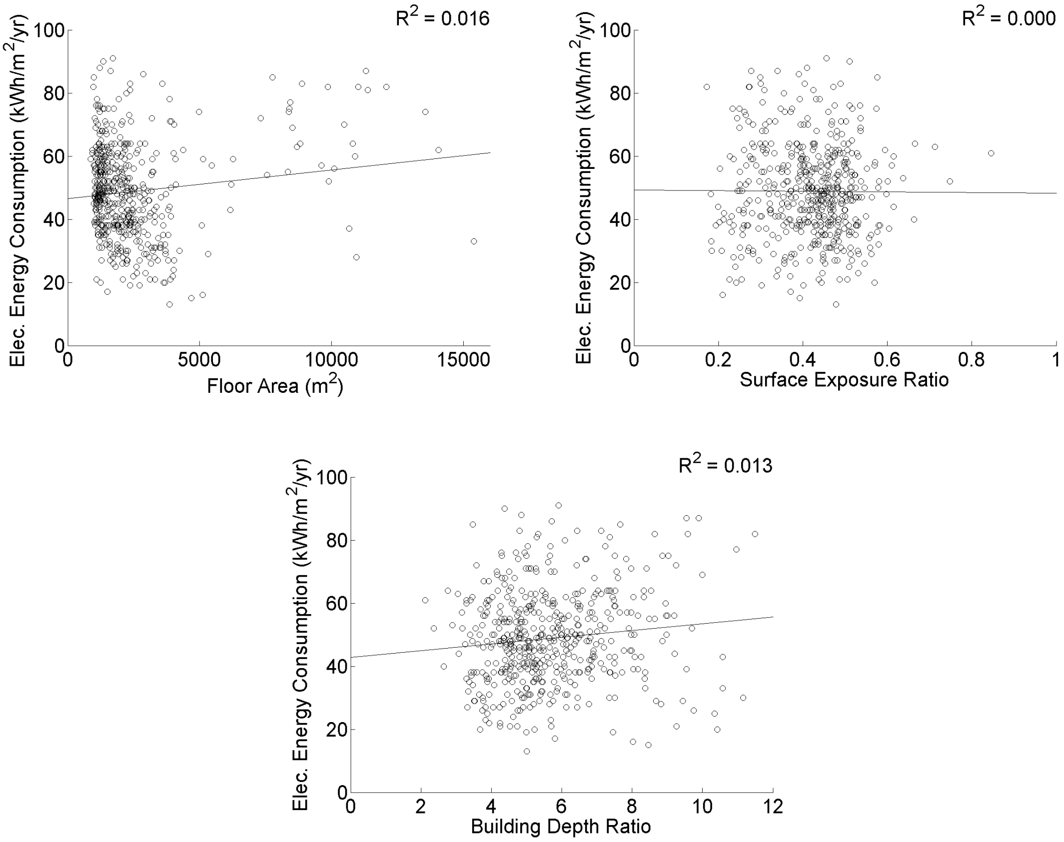


Figure 4.17: Scatter plots showing electricity energy use intensity against collected geometry data

analysis as being influential on electricity energy use intensity for the buildings in the collected dataset. Occupancy hours has a p-value that is greater than 0.05 and is therefore deemed by this analysis not to significantly influence electricity energy use intensity for the buildings in the collected dataset. Figure 4.19 shows how electricity energy use intensity depends on phase of education and occupancy hours. The 1st and 3rd quartiles and median for secondary schools are all higher than their respective figures in primary schools, indicating that secondary schools tend to consume more electrical energy than primary schools. As previously mentioned, this may be explained by secondary school being more likely to make greater use of ICT and electrical equipment in laboratories than primary schools (Global

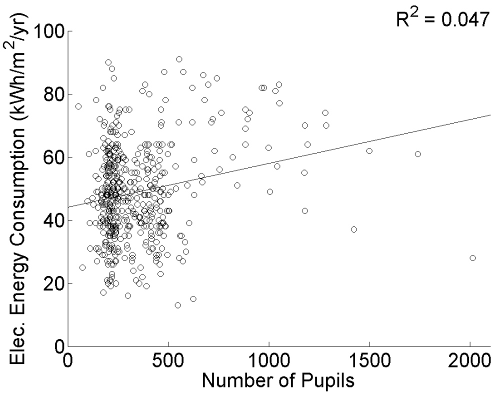


Figure 4.18: Scatter plot showing electricity energy use intensity against collected pupil number data

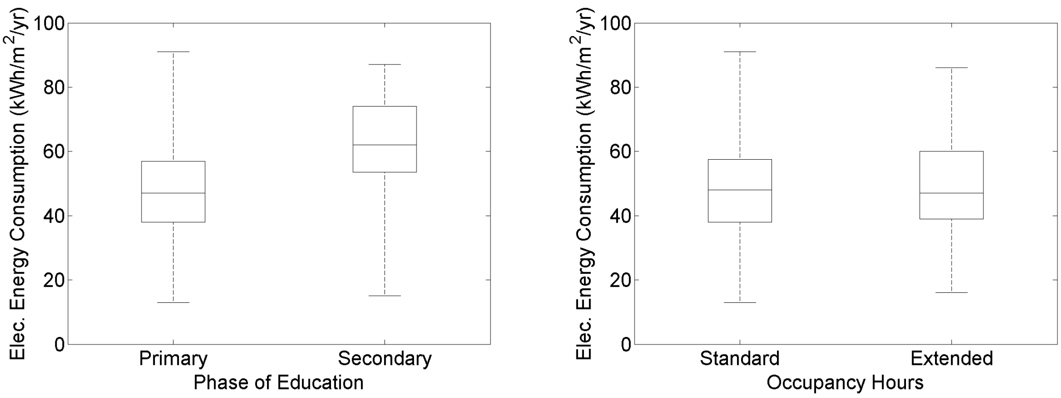


Figure 4.19: Box plots showing how electricity energy use intensity depends on collected activity data

Action Plan 2006). Despite the high p-value, the 1st and 3rd quartiles for extended hours are slightly higher than their respective figures in standard hours, indicating a small increase in electrical energy use intensity with longer occupancy hours. Buildings with longer occupancy hours are likely to be running electrical systems, such as artificial lighting, for longer periods of time and therefore are likely to consume more electrical energy (BRE 1998).

Construction Year

The p-value result for construction year is less than 0.05 and therefore is deemed by this analysis as being influential on electricity energy use intensity for the buildings in the collected dataset. Figure 4.20 is a scatter plot of electricity energy use intensity against collected construction year data. There is a weak positive correlation (R^2 = 0.085), suggesting that newer buildings tend to consume more electrical energy than older school buildings. This may be because newer buildings are more likely to contain more building services and may also be designed to accommodate a greater density of ICT equipment (Global Action Plan 2006; Godoy-Shimizu et al. 2011).

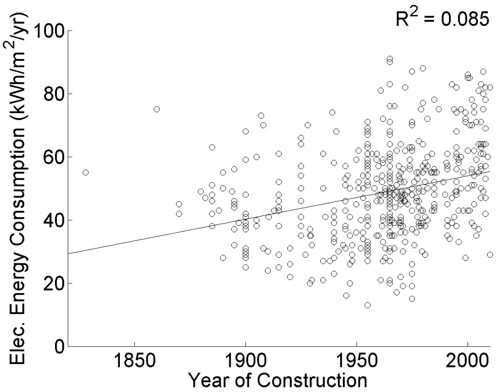


Figure 4.20: Scatter plot showing electricity energy use intensity against collected construction year data

Services

The p-value for ventilation strategy is greater than 0.05 and is therefore deemed by the Kruskal-Wallis analysis not to significantly influence electricity energy use intensity for the buildings in the collected dataset. Figure 4.21 shows how electricity energy use intensity depends on the collected ventilation strategy data. Despite the Kruskal-Wallis result, the median and upper quartile of mechanically ventilated buildings are higher than the corresponding values in naturally ventilated buildings suggesting that mechanically ventilated buildings tend to consume more electricity energy per square metre than naturally ventilated buildings. This would be expected due to the electricity required to run such systems (Thomas 2006).

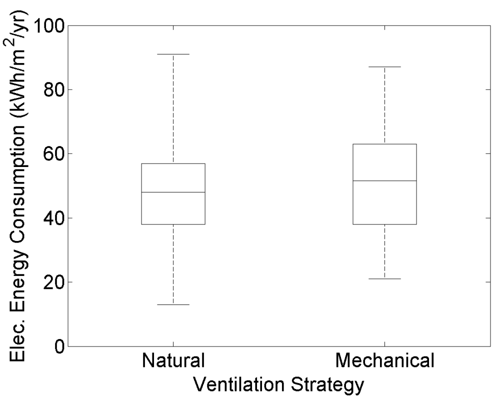


Figure 4.21: Box plot showing how electricity energy use intensity depends on collected ventilation strategy data

Glazing

Glazing ratios on east and west facades have p-values that are greater than 0.05 and are therefore deemed by this analysis not to be influential on electricity energy use for the buildings in the collected dataset. Glazing ratios on north and south facades have p-values that are less than 0.05 and are therefore deemed by this analysis as being influential on electricity energy use for the buildings in the collected dataset. Figure 4.22 shows scatter plots of electricity energy use intensity against collected glazing ratio data. The influential glazing orientations have weak negative correlations – R^2 = 0.016 (north), R^2 = 0.031 (south) – suggesting that as glazing proportions increase, buildings tend to consume less electrical energy. This is likely because an increase in glazing allows more natural light into the building and therefore reduces electrical energy use through a reduction in artificial lighting usage (Yang et al. 2008).

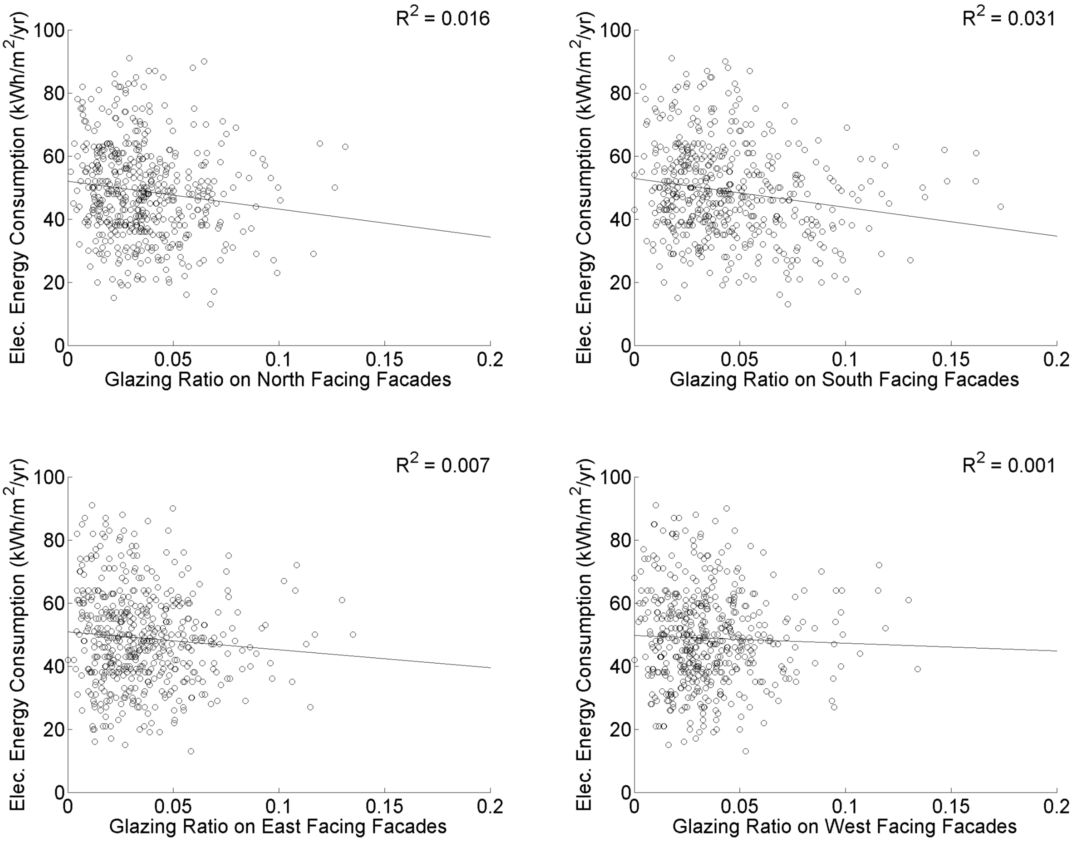


Figure 4.22: Scatter plots showing electricity energy use intensity against collected glazing ratio data

Site

Figure 4.23 shows how electricity energy use intensity depends on the collected facade adjacency data. Adjacencies on all orientations have p-values that are greater than 0.05 and are therefore deemed by the Kruskal-Wallis analysis not to significantly influence electricity energy use intensity for the buildings in the collected dataset. Building adjacencies were expected to affect artificial lighting, in that overshadowing from adjacent buildings or other obstructions reduce daylight (Ratti et al. 2005). The fact that these characteristics did not greatly affect electrical energy use may be related to aspects such as cloud cover or the fact that artificial lighting tends not to be used during the day in perimeter spaces.

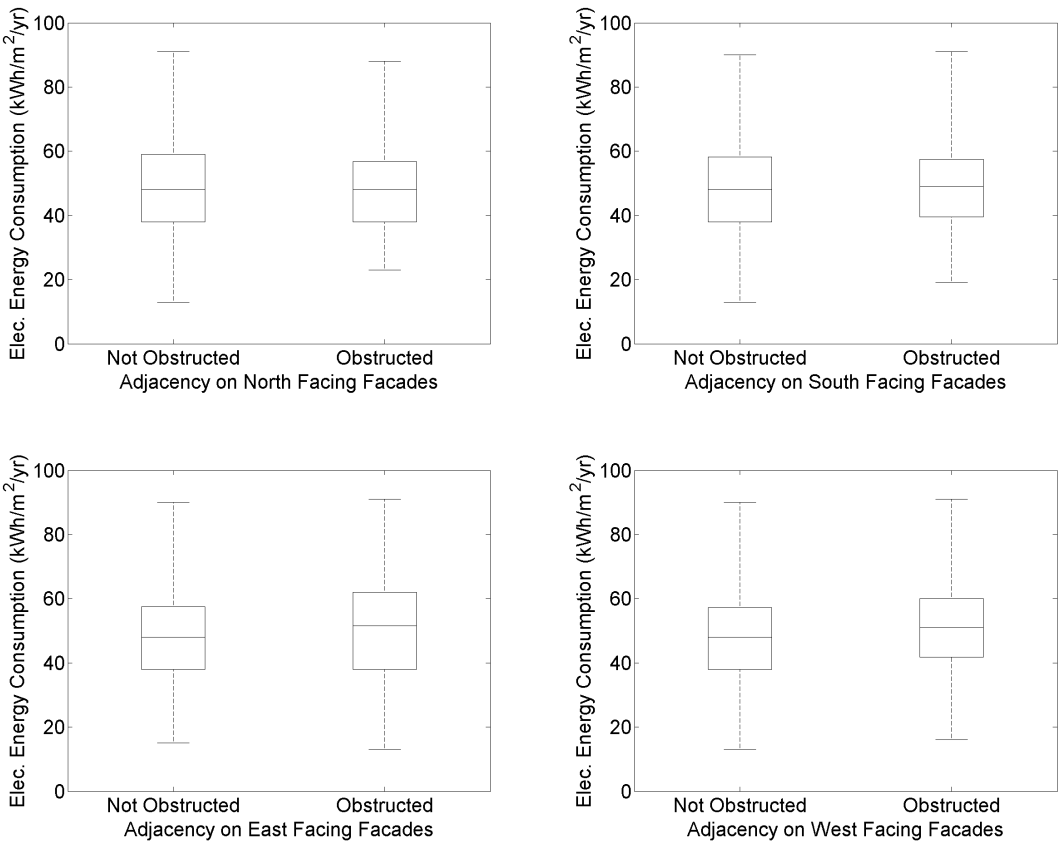


Figure 4.23: Box plots showing how electricity energy use intensity depends on collected facade adjacency data

Weather

Figure 4.24 is a scatter plot of electricity energy use intensity against collected cooling degree day data. The data points are very scattered (R^2 = 0.000), corresponding with the p-value result that is greater than 0.05. Therefore cooling degree days are deemed by this analysis not to significantly influence electricity energy use intensity for the buildings in the collected dataset. Cooling degree days would be expected to affect electricity use of schools with mechanical cooling because they indicate when mechanical cooling may be required. Unsurprisingly, as there were no air conditioned buildings in the dataset, this characteristic did not affect electrical energy use.

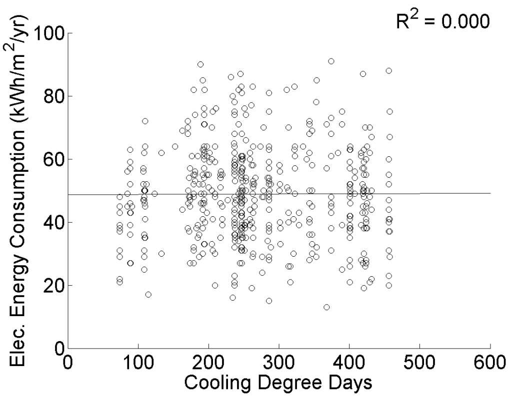


Figure 4.24: Scatter plots showing electricity energy use intensity against collected cooling degree day data

4.4 Summary

In this chapter, the dataset collected for this research was statistically analysed. The chapter began by presenting the distributions of the collected energy use data. It was shown that the distribution of the collected energy use figures for thermal and electricity energy use were statistically similar to that of the wider English school building stock. The distributions for the building characteristics were then presented and discussed. The chapter concluded by analysing the relationships between the building characteristics and thermal and electrical energy consumption. This process involved the analysis of scatter plots together with the results of a Kruskal-Wallis analysis. The building characteristics had weak correlations with energy use, however, the patterns shown were largely in line with building physics principles. The Kruskal-Wallis analysis ranked the building characteristics in order of influence on thermal and electricity energy consumption. This ranking will form the basis of the input group ordering in the ANN training methodology, as described in the following chapter.

Chapter 5

Method 2: ANN Prediction Method

5.1 Overview

In the previous chapter, the building characteristics dataset was statistically analysed. This chapter describes the process to design, train and test artificial neural networks (ANNs) in order to best predict the thermal and electricity energy consumption of school building designs in England. The aforementioned building characteristics dataset is used to train the ANNs. The chapter begins by outlining the architecture of the ANNs used in this research before detailing the training process. Statistical analysis that took place with the resultant ANNs are then outlined in order to compare their outputs with the energy use data from the building characteristics dataset. The chapter concludes by describing causal strength analyses carried out to further understand the energy determinants of school buildings. The overall aim is to create a model that predicts energy use of school building designs based on a set of building characteristic inputs. This is part two of the methodology as outlined in Figure 5.1.

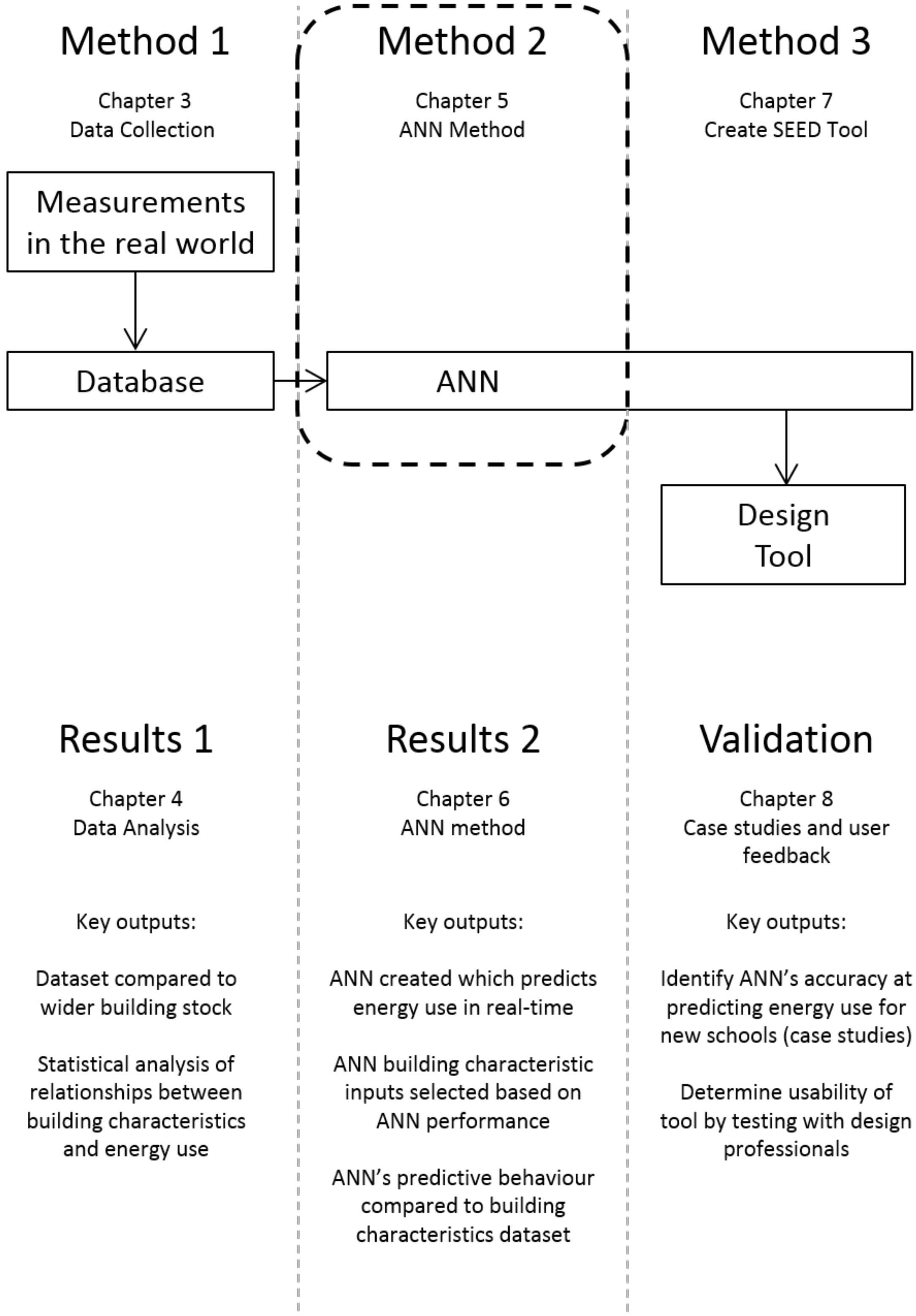


Figure 5.1: Breakdown of Work Stages: Methodology Part 2

5.2 Artificial Neural Network Architecture

An introduction to ANNs was given in Section 2.4, together with examples of their variation and application. MATLAB (Mathworks 2013) was used to create the ANNs in this research. Feedforward multilayer perceptron networks were used, each comprised of an input layer, a hidden layer and an output layer – Figure 5.2 shows the conceptual structure of this network. *Feedforward* relates to the fact that, once trained, information only moves forward through the network, from the input layer, through the hidden layer, to the output layer. Two ANN models were constructed: one with thermal energy consumption as an output and one with electrical energy consumption as an output. The number of potential input neurons was eighteen and the number of output neurons was one. The final number of input and hidden neurons were determined as a result of the analysis outlined in Section 5.3. Each neuron in the input layer represents a variable in the building characteristics dataset, and the single neuron in the output layer represents energy consumption: one model predicting thermal energy use and another predicting electrical energy use. Figure 5.3 shows a simplified example of the structure of an ANN predicting thermal energy consumption.

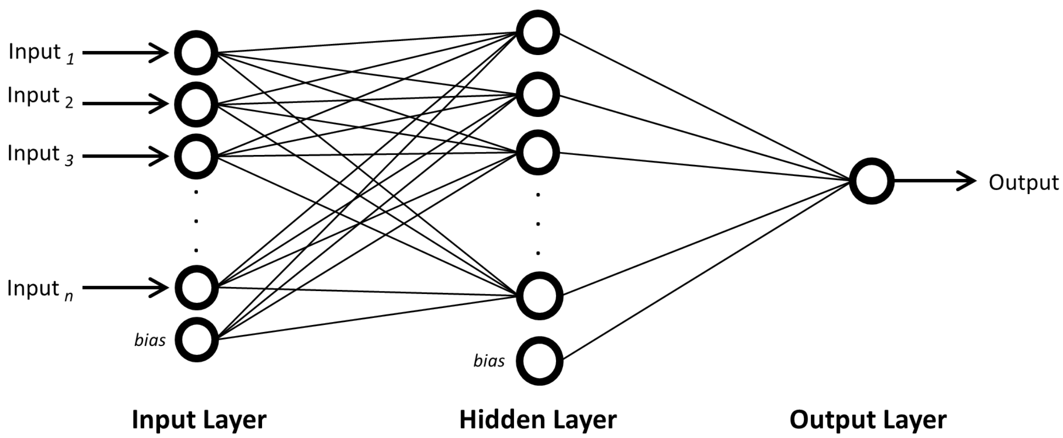


Figure 5.2: Architecture of the multilayer feedforward ANN

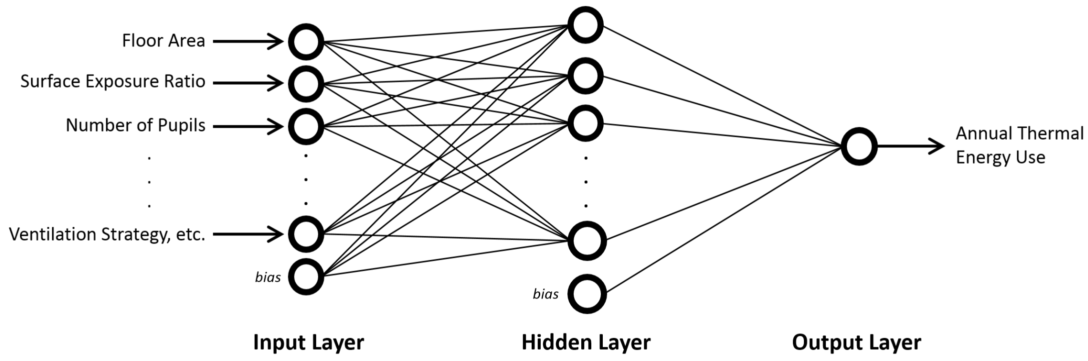


Figure 5.3: Simplified example of an ANN predicting thermal energy consumption

Each neuron in the input layer is comprised of continuous or categorical data, as listed in Tables 4.5 and 4.6 from Section 4.2.3. The input data was normalised to values between -1 and 1 to generalise the calculation processes within the neural network. Continuous input neurons were a floating number between -1 and 1 and categorical (binary) input neurons were 1 when activated and -1 when not. It can be seen from Figures 5.2 and 5.3 that each layer feeds forward to the next layer: input layer to the hidden layer and the hidden layer to the output layer, forming a parallel information-processing system. The middle layer is referred to as the 'hidden layer' as it is never exposed to the external environment (data) (Samarasinghe 2007). The hidden layer helps the system to generate nonlinear and complex relationships by intervening between the input and output layers (Haykin 1999); a single hidden layer was deemed sufficient for this application (Fausett 1994).

Each neuron is connected to each neuron in the next layer by synaptic weights. These weights hold a random value at the beginning of the training process (Beale et al. 2013). During this training process, the synaptic weights of the network are modified to attain a response from the network that closely matches the actual (target) outputs after a number of iterations (Haykin 1999) as described in the following section.

5.3 Training and Testing

The building characteristics dataset was split into three groups: training (80% of the dataset), validation (10% of the dataset) and testing (10% of the dataset). The process of splitting the dataset into these three groups is described in detail in the following section ('K-Fold Cross Validation').

A Levenberg-Marquardt backpropagation process (Beale et al. 2013), a supervised training technique, with early stopping, was used to train the network. The training process involved fine tuning the network weights so that predicted ANN outputs match the target training dataset outputs with minimal error. As previously mentioned, all of the network weights are initially random. At the beginning of training, the ANN chooses a sample at random from the training dataset. Each neuron in the input layer then transmits its data to the hidden layer after being weighted (multiplied) by the input-hidden layer weights. Each hidden neuron sums all of this weighted data before sending it through a nonlinear activation function. This process is visualised in Figure 5.4. The activation function used in this study was a hyperbolic tangent sigmoid transfer function (tan-sigmoid function) (Equation 5.1) which enables a continuous weighted output from the hidden layer rather than an 'on' / 'off' scenario. The tan-sigmoid function is visualised in Figure 5.5. Bias neurons, which have a fixed value of 1 and are weighted (see Figure 5.4), allows the activation function to be translated (shifted), improving learning (Sarle 2002).

$$y = \frac{2}{1 + e^{-2x}} - 1 \tag{5.1}$$

Where y is the product of the tan-sigmoid function and x is the value of the summation as shown in Figure 5.4.

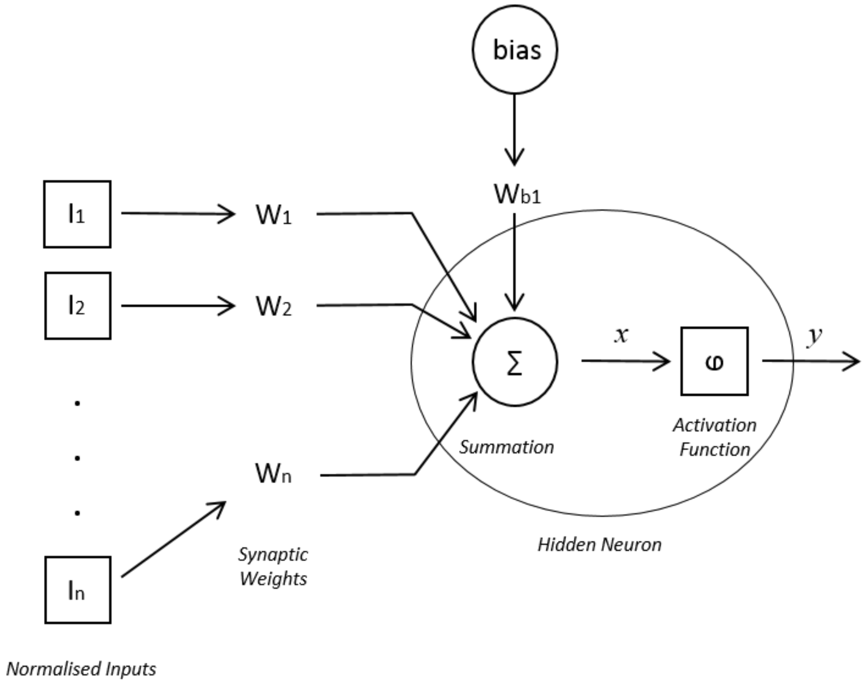


Figure 5.4: Data processing between the input layer and one hidden neuron in the neural network

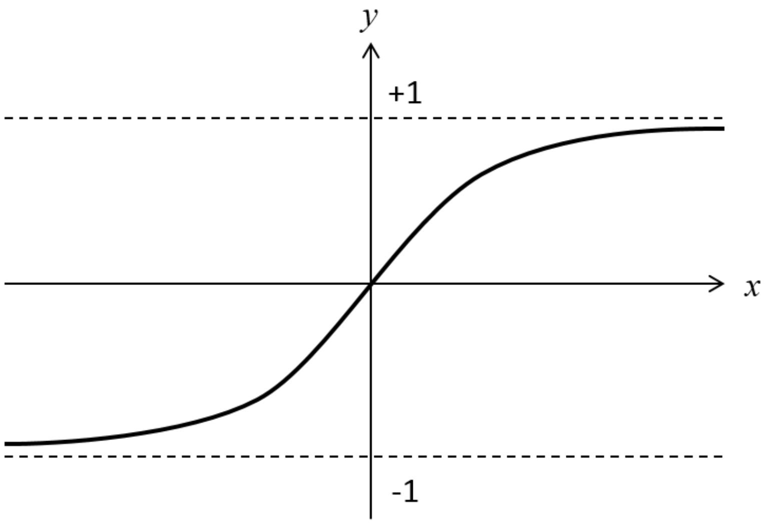


Figure 5.5: Tan-sigmoid function curve

Once each hidden neuron has processed its data in the aforementioned manner, each neuron in the hidden layer transmits its data to the output layer after being weighted (multiplied) by the hidden-output layer weights. The output neuron sums all of this weighted data before sending the data through a linear transfer function to produce the ANN's predicted output. The ANN's predicted output is compared to the target output of the training dataset and a process of backpropagation is then carried out to fine tune the network. This process adjusts the weights between the output and hidden layers and the weights between the input and hidden layers in order to minimise the prediction error, enabling the ANN outputs to closely match the training (target) outputs (Samarasinghe 2007). This process is iterated many times using different samples from the training dataset. In conceptual terms, this supervised process can be viewed as the ANN having a teacher which has knowledge of the environment (input-output data). This training process is carried out iteratively with the aim of teaching the ANN to emulate the teacher as closely as possible.

After each iteration, the MSE (Equation 5.2) of the validation set is recorded. Unlike the training dataset, the validation set does not affect the backpropagation process. The training is stopped when the validation error increases for six iterations, the default indication of divergence within MATLAB (Mathworks 2013). This early stopping technique ensures the algorithm will not overlearn and will be able to best generalise when presented with new inputs. When this condition is achieved, the teacher may be dispensed of and the ANN be allowed to react to the environment without being supervised as it has learned the global behaviour of the system. Thus, when the training process is over, the ANN can predict outputs when presented with new inputs it has never experienced (Haykin 1999).

$$\text{Mean square error (MSE)} = \frac{1}{n}\sum_{n}^{i}(\hat{Y}_i - Y_i)^2 \tag{5.2}$$

Where Y_i and $\hat{Y}_i$ are the target and predicted outputs respectively for the training, validation or testing data configuration i and n is the total number of configurations in the training, validation or testing datasets.

K-Fold Cross Validation

Section 3.3.2, Equation 3.1, described the minimum number of data samples (schools) required for the minimum complexity of ANN used in this research. The complexity of an ANN can be taken to be the number of weights in the network. As described below, the hidden neurons in the ANNs are increased to find an ANN architecture that performs the best. Therefore, due to the limited number of school samples (502) compared with the maximum possible complexity of ANN, k-fold cross validation (Mitchell, T. 1997) was adopted. The benefit of k-folding is that all the data is utilised for training, testing and validation. Before training, the 502 input patterns and corresponding outputs were randomly shuffled and then split in 10 equal[1] sections or 'folds' (see Figure 5.6). The first of the 10 folds was used for the testing dataset, the second for the validation dataset (which relates to early stopping as explained in the previous section) and the remaining 8 folds were used for the training dataset. This process is repeated 10 times, each time using a different fold for testing, the adjacent fold for validation and the remaining data for training.

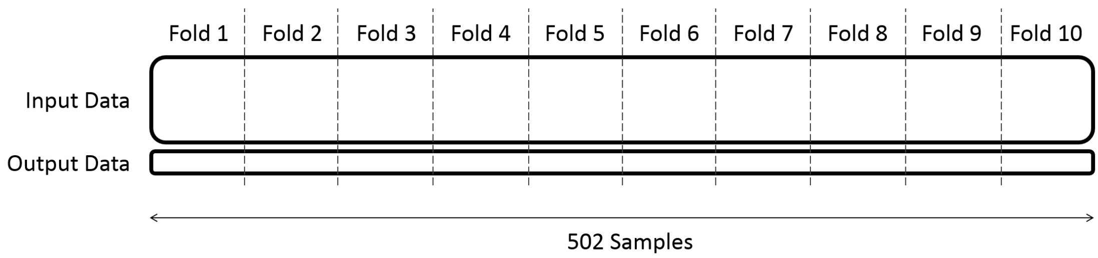


Figure 5.6: Representation of the dataset being split into 10 'folds'

[1] As 502 (school samples) is not a product of 10, the final fold contained 2 more schools (remainder) than the other folds

For each of these 10 folds, the number of hidden layer neurons were altered between 2, 4, 8, 16, 32 and 64. 100 runs were performed for each hidden neuron configuration, with the initial synaptic weights randomised each time. For each fold, the ANN with the lowest mean-squared error (MSE) (Equation 5.2) for the testing dataset was saved and the generalisation errors determined retrospectively. The generalisation errors of the ANN were evaluated in terms of the root-mean squared error (RMSE) (Equation 5.3) and the mean absolute percentage error (MAPE) (Equation 5.4) for the testing dataset. The overall ANN performance was established as the average of the minimum generalisation errors achieved for all 10 folds.

$$\text{Root-mean square error (RMSE)} = \sqrt{\sum_{n}^{i} \frac{(\hat{Y}_i - Y_i)^2}{n}} \text{ (kWh/m}^2\text{/yr)} \tag{5.3}$$

$$\text{Mean absolute percentage error (MAPE)} = \frac{\sum_{n}^{i} \frac{|\hat{Y}_i - Y_i|}{Y_i}}{n} \text{ (\%)} \tag{5.4}$$

Where Y_i and $\hat{Y}_i$ are the target and predicted outputs respectively for the testing data configuration i and n is the total number of configurations in the testing dataset.

Committee Machine

In machine learning, there is the possibility that differently trained models, such as ANNs, converge to different local minima on the error surface and that the overall performance can be improved by combining the outputs of various models (Haykin 1999). Through this process, a complex computational task is distributed among a committee of 'experts' (ANN models). "The expectation is that the differently trained experts converge to different local minima on the error surface, and overall performance is improved by combining the outputs" (Haykin 1999, p.375). The combined set of models is referred to a committee machine (Haykin 1999).

As such, after training, the best performing ANN from each of the 10 folds, presented in the previous section, were utilised. The resultant ANN model was constructed of these 10 individual ANNs for thermal energy consumption predictions and 10 ANNs for electricity energy consumption predictions. In the final committee machine, the 10 ANNs in the thermal energy model and 10 ANNs in the electricity energy model all receive the same inputs and make individual predictions. Through the process of ensemble averaging (Haykin 1999), the mean of the 10 ANN predictions for thermal energy use form the first committee output and the mean of the 10 ANN predictions for electricity energy use form the second committee output (Equation 5.5). See Figure 5.7 for an illustration of this process. Figure 5.8 shows a visual representation of the committee machines created in this research, highlighting the many connections between the neurons – the neuron in the centre of these two committee machines represent the single prediction for thermal and electricity energy use.

$$\hat{z} = \frac{\sum_n^i z_i}{n} \tag{5.5}$$

Where $\hat{z}$ is the committee output for thermal or electricity use, z is the individual ANN output for each thermal or electrical energy use model i and n is the number of ANNs (ten) in each committee machine.

5.3.1 Addition Analysis

In order to assess the correct number of inputs to include in the ANN analysis – that is, which inputs produce the least generalisation errors – input sets were cumulatively added to the network and the mean minimum generalisation errors across all 10 folds were calculated. As ANNs are multivariate algorithms, and some inputs are *supportive* rather than having a direct influence on energy use (such as orientation correction), it was deemed useful to group the inputs into sets of common characteristics. Table 5.1 outlines the input sets.

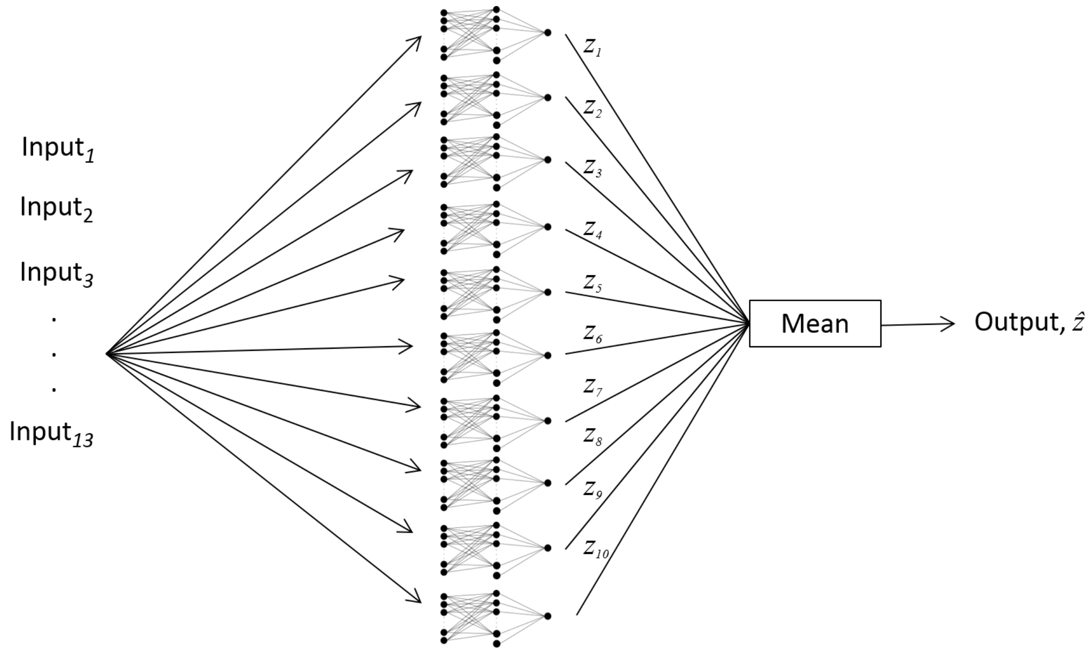


Figure 5.7: Committee machine process

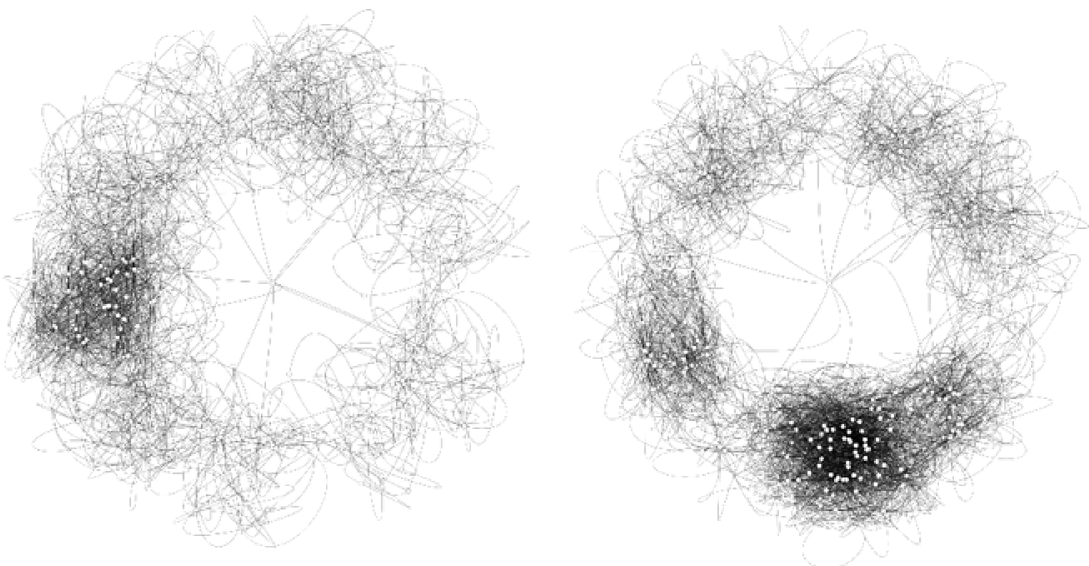


Figure 5.8: Visual representation of the thermal (left) and electricity (right) energy use ANN committee machines showing all the connections between the neurons

Input set	**Building characteristic**
Geometry	Building depth ratio
	Surface exposure ratio
	Floor area
	Orientation correction
Activity	Occupancy hours
	Phase of education
	Number of pupils
Services	Ventilation strategy
Glazing	Glazing ratio on north facing facades
	Glazing ratio on south facing facades
	Glazing ratio on east facing facades
	Glazing ratio on west facing facades
Construction year	Year of construction
Site	Adjacency on north facing facades
	Adjacency on south facing facades
	Adjacency on east facing facades
	Adjacency on west facing facades
Weather	Heating degree days (thermal ANNs only)
	Cooling degree days (electrical ANNs only)

Table 5.1: ANN training input sets

The ordering of the input sets – that is, the order in which the input sets are cumulatively introduced to the ANNs during training – are based on the Kruskal-Wallis analyses results outlined in the previous chapter: Table 4.14 for thermal energy consumption and Table 4.14 for electricity energy consumption.

The input set ordering for ANNs predicting thermal energy consumption are as follows:

– Input Set 1: Geometry

– Input Set 2: Construction year

– Input Set 3: Services

– Input Set 4: Glazing

– Input Set 5: Activity

– Input Set 6: Site

– Input Set 7: Weather

The input set ordering for ANNs predicting electricity energy consumption are as follows:

– Input Set 1: Construction year

– Input Set 2: Activity

– Input Set 3: Glazing

– Input Set 4: Geometry

– Input Set 5: Services

– Input Set 6: Site

– Input Set 7: Weather

5.4 Global Sensitivity Analysis

In order to ascertain how well the ANN method predicts reality, a dataset of pseudo school buildings will be generated and simulated by the best performing ANNs, as determined from

Section 5.3.1, and compared with the analysis of the building characteristics dataset in Section 4.3. The comparison will be between the trends (R^2 values) of energy use against building characteristics and influence of building characteristics on energy use (Kruskal-Wallis analysis).

In order to generate the aforementioned dataset of simulated school buildings, a sensitivity analysis will be carried out using the ANN models. A sensitivity analysis is the study of how the variation in output of a mathematical model can be apportioned to variations in its inputs (Saltelli, A., Chan, K., Scott 2000). They can be useful in identifying key input parameters that affect the model outputs. In a local sensitivity analysis, a single input is varied a small percentage around a baseline (Saltelli, A., Chan, K., Scott 2000). As each input variable is adjusted separately, interactions between the inputs are not taken into account. In a global sensitivity analysis, the inputs are varied simultaneously over their entire range. Monte Carlo methods (Metropolis and Ulam 1949) can be used to carry out global sensitivity analyses.

5.4.1 Monte Carlo Method

Monte Carlo methods are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The Monte Carlo analyses in this research were carried out in MATLAB (Mathworks 2013). Probability distribution curves were generated for each of the continuous inputs and the probabilities of each category of the categorical inputs were calculated. 500 data points for each input were randomly generated from the aforementioned distribution curves and probabilities creating 500 pseudo school configurations. Using the best performing ANN models, as derived from the process outlined in Section 5.3.1, these 500 configurations were fed into the ANN models and the predictions for thermal and electricity energy consumption were recorded. Thermal and electricity energy consumption were assessed separately with the same input configurations.

5.4.2 Kruskal-Wallis Analysis

As described in Section 3.5, the Kruskal-Wallis test is a nonparametric version of the one-way analysis of variance test (ANOVA). It was used on the data generated by the Monte Carlo method to determine how influential each input was on the predicted thermal and electricity energy use outputs.

For each of the continuous input parameters' 500 states, the values were ordered from the lowest to the greatest value and then split into 4 equal groups. The categorical inputs are naturally grouped. The Kruskal-Wallis method compares the median outputs of the groups in each input to determine if the samples come from the same population. That is, determining if a significant change in energy consumption output occurs as the value of each input changes, indicating how influential an input is to the output. The method ranks the data by ordering the data from smallest to largest across all groups and calculating the test statistic (Equation 3.2).

As outlined in Section 3.5, the p-value is the probability of observing a test statistic as extreme as the one that was actually observed. The null hypothesis is the default position that there is no relationship between two measured phenomena. Small p-values, $p < 0.05$ (Stigler 2008), cast doubt on the null hypothesis. That is, a p-value of 0.05 or lower has a 95% confidence level or higher that the input is influencing the output. The p-values are found from a chi-squared distribution table or Kruskal-Wallis test statistic table, such as those outlined by Gibbons and Chakraborti (2003, p.368).

5.5 Causal Strength Analysis

In order to understand more complex relationships between building characteristics and energy use, a study was conducted that tested the change in output as the inputs were altered. The best performing ANN models, as derived from the process outlined in Section 5.3.1, were used in this causal analysis. The causal strength method isolates individual inputs at a time and determines the impact each input has on energy use. The approach has similarities to a sensitivity analysis and follows a similar approach to those taken by Baxt (1992) as described by Sarle (2000). Thermal and electricity energy consumption were assessed separately. The process was as follows:

1. A Monte Carlo simulation was carried out, as described in Section 5.4.1 (500 simulations), and the mean of the 500 outputs was recorded. This was called the base case.

2. For each continuous input at a time, the normalised values of the input were set to their 90th percentile value. For each binary input at a time, the normalised values of the input were set to 1.

3. As each input is separately fixed to their upper value, a Monte Carlo simulation of all other inputs was run.

4. The mean result for each set of Monte Carlo simulations were recorded for each input that was fixed.

5. For each continuous input at a time, the normalised values of the input were set to their 10th percentile value. For each binary input at a time, the normalised values of the input were set to -1.

6. As each input is separately fixed to their lower value, a Monte Carlo simulation of all other inputs was run.

7. The mean result for each set of Monte Carlo simulations were recorded for each input that was fixed.

8. Output 1: the change in output between the fixed lower and fixed upper values of each input were compared against the base case output.

9. Output 2: the directional change in output was compared with the base case output.

Note: to simplify the results – glazing ratios on north, south, east and west facing facades were altered together. Orientation correction was not included in this analysis as it is a *supportive* input rather than a determinant of energy (see Section 3.4.3 'Geometry')

5.6 Summary

This chapter described the process to design and train artificial neural networks (ANNs) in order to best predict the thermal and electricity energy consumption of school building designs in England. The process of cumulatively adding input groups to the ANN method was outlined to create ANNs that use the specific inputs that maximise accuracy – inputs that, when added to the ANN, increase errors, will be rejected. A global sensitivity analysis and causal strength analysis were then outlined. The aim of these sets of analyses is to compare the ANN behaviours to the collected building characteristics dataset and to allow for a deeper understanding of the influence each building characteristic input had on the energy use outputs. The results of these analyses are described in the following chapter.

Chapter 6

Results 2: ANN Prediction Method

6.1 Overview

The previous chapter described the process to design and train artificial neural networks (ANNs) in order to best predict the thermal and electricity energy use of school building designs in England. The results of this process, together with the global sensitivity and causal analyses are outlined in this chapter. This chapter is part two of the results as outlined in Figure 6.1.

6.2 Prediction Performance: Addition Analysis

6.2.1 Thermal Energy Use Intensity

Table 6.1 gives the generalisation errors for the thermal energy use addition analysis. As the input sets increase, more inputs are added to the analysis cumulatively. When input set 1 (geometry) is introduced, the ANN MAPE is 24.2%. The MAPE steadily falls as the next four input sets are added, reaching the lowest error (22.9%) as the activity input set is introduced. As the final two sets are added (site and weather) the errors steadily increase.

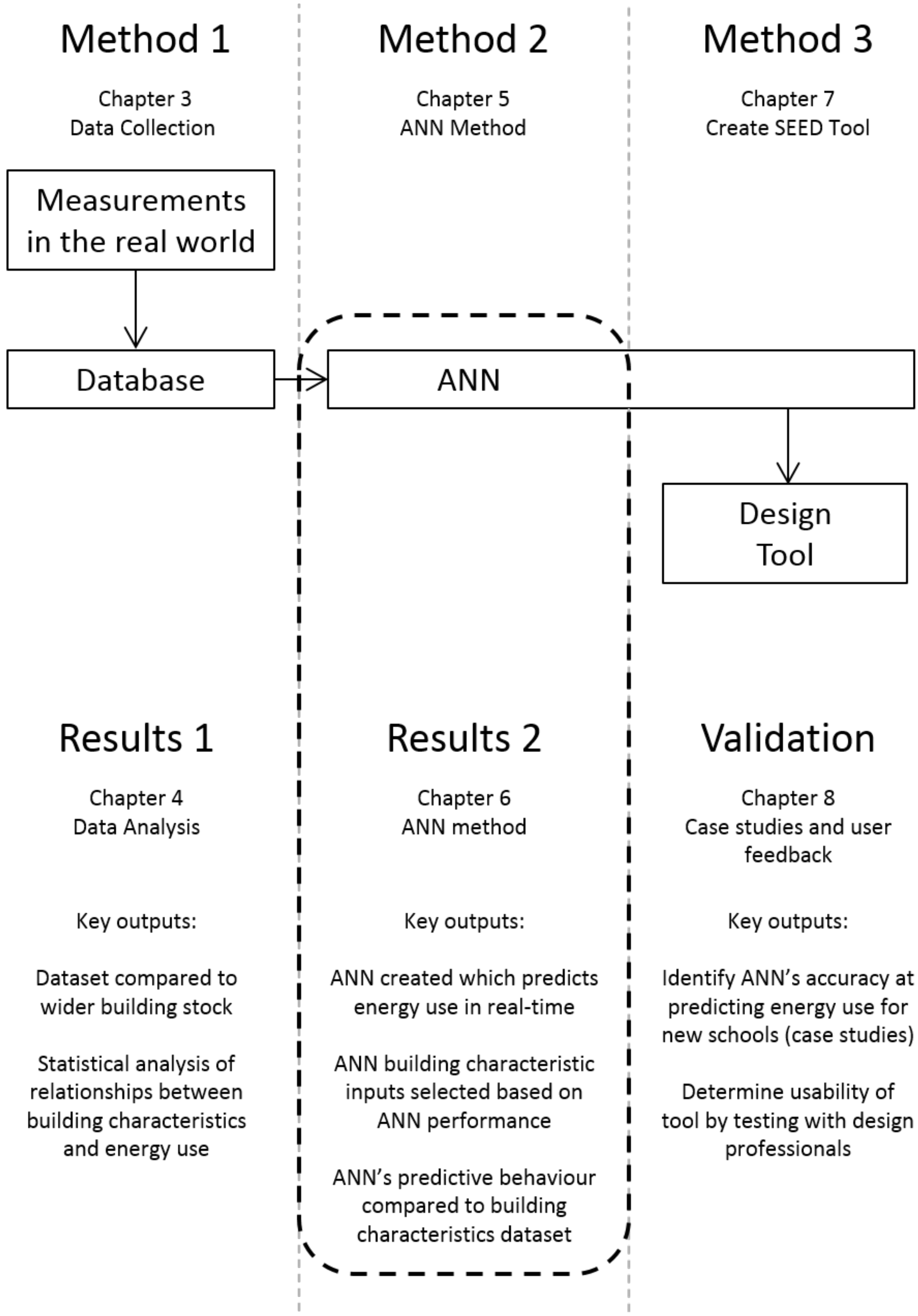


Figure 6.1: Breakdown of work stages: results part 2

Input Set	**Input Set 1**	**Input Set 2**	**Input Set 3**	**Input Set 4**	**Input Set 5**	**Input Set 6**	**Input Set 7**
Geometry	4	4	4	4	4	4	4
Construction Year		1	1	1	1	1	1
Services			1	1	1	1	1
Glazing				4	4	4	4
Activity					3	3	3
Site						4	4
Weather							1
Total Input Neurons	4	5	6	10	13	17	18
RMSE (kWh/m^2/yr)	37.1	37.0	36.7	36.3	36.1	36.3	37.0
MAPE (%)	24.2	23.9	23.9	23.2	22.9	23.8	24.1

Table 6.1: Thermal energy use ANNs – number of input neurons and ANN mean minimum errors for each input set

As more inputs were added, the ANN prediction errors tended to decrease. This is in line with the building physics principles and environmental studies outlined in Tables 3.2 and 3.2 (Section 3.3.4). The errors did, however, increase when site (building adjacency) and weather (heating degree day) inputs were added. The building adjacency inputs were expected to affect solar gain, in that overshadowing from adjacent buildings or other obstructions reduce solar gain and therefore affect space heating requirement (Ratti et al. 2005). However, as shown in Section 4.3.1 ('Site'), when adjacency was statistically analysed in the collected building characteristics dataset, it largely did not influence thermal energy use, and therefore these ANN results are representative of the wider building stock's behaviour. As mentioned in Section 4.3.1 ('Site'), building adjacency may not have affected thermal energy use that greatly because of related aspects such as cloud cover or the fact that other building characteristics are more dominant. Heating degree days were expected to affect space heating because of its relationship with fabric heat loss. However, as shown in Section 4.3.1

('Weather'), when the collected heating degree days were statistically analysed, they were shown not to influence thermal energy use, and therefore these ANN results are also representative of the wider building stock's behaviour. As discussed in Section 4.3.1 ('Weather'), the fact that heating degree day inputs did not affect thermal energy use is likely due to the poor control of heating systems (Hong 2014) and also because of the relative similarity of external temperatures in England – if the study expanded to Scotland, with typically lower external temperatures, or indeed internationally, it would be expected that heating degree days would be more influential on thermal energy use.

As input set 5 achieved the lowest errors, this ANN input configuration is the final design for the prediction of thermal energy use and will be used throughout the remainder of this research.

6.2.2 Electricity Energy Use

Table 6.2 gives the generalisation errors for the electricity energy use addition analysis. As previously mentioned, as the input sets increase, more inputs are added to the analysis cumulatively. When set 1 (construction year) is introduced, the ANN MAPE is 25.4%. The MAPE steadily falls as the next four input sets are added, reaching the lowest error (22.5%) as input set 5 (services) is introduced. As the final two sets are added (site and weather) the errors steadily increase.

As more inputs were added, the ANN prediction errors tended to decrease. This is in line with the building physics principles and environmental studies outlined in Tables 3.2 and 3.2 (Section 3.3.4). The errors did, however, increase when site (building adjacency) and weather (cooling degree days) inputs were added. The building adjacency inputs were expected to affect artificial lighting, in that overshadowing from adjacent buildings or other

Input Set	**Input Set 1**	**Input Set 2**	**Input Set 3**	**Input Set 4**	**Input Set 5**	**Input Set 6**	**Input Set 7**
Construction Year	1	1	1	1	1	1	1
Activity		3	3	3	3	3	3
Glazing			4	4	4	4	4
Geometry				4	4	4	4
Services					1	1	1
Site						4	4
Weather							1
Total Input Neurons	1	4	8	12	13	17	18
RMSE (kWh/m^2/yr)	13.3	13.1	13.1	12.5	12.1	12.7	12.8
MAPE (%)	25.4	25.5	24.9	23.5	22.5	23.5	23.6

Table 6.2: Electricity energy consumption – number of input neurons and ANN mean minimum errors for each input set

obstructions reduce daylight (Ratti et al. 2005). However, as shown in Section 4.3.2 ('Site'), when adjacency was statistically analysed in the collected building characteristics dataset, it did not influence electricity energy use, and therefore these ANN results are representative of the wider building stock's behaviour. As described in Section 4.3.2 ('Site'), building adjacency may not have affected electricity energy use because of related aspects such as cloud cover or the fact that lighting tends not to be used during the day in perimeter spaces. Cooling degree days would be expected to affect electricity use in mechanically cooled buildings. However, as discussed in Section 4.3.2 ('Weather'), the fact that cooling degree days did not improve the accuracy of the ANN was due to the fact that no air conditioned buildings were part of the ANN training dataset, as shown in Section 4.2.3 ('Services'), Table 4.11.

As input set 5 achieved the lowest errors, this ANN input configuration is the final design for the prediction of electrical energy use and will be used throughout the remainder of this research.

6.3 Global Sensitivity Analysis

6.3.1 Thermal Energy Use

This section details the results of the sensitivity analysis for the ANN predictions of thermal energy use intensity, carried out on the dataset generated from the Monte Carlo method, outlined in Section 5.4. The p-value results of the Kruskal-Wallis analysis for thermal energy use intensity are shown in Table 6.3. Using the p-value threshold of 0.05 (Stigler 2008) as outlined in Section 5.4.2, inputs can be categorised as being influential on the energy use intensity outputs with a 95% confidence level. Furthermore, the input parameters were ranked from most influential to energy use intensity to least influential. The most influential inputs, in descending order, are surface exposure ratio, construction year, ventilation strategy, building depth ratio, number of pupils, glazing ratio on east facades, occupancy hours, phase of education, floor area and glazing ratio on west facades.

The following sections describe the results. For clarity, the data generated by the Monte Carlo method will be referred to as 'ANN Monte Carlo' data. As outlined in Section 5.4, in order to ascertain how well the ANN method predicts reality, the results of this ANN study will be compared with the results of the building characteristics dataset analysis from Section 4.3.1.

Geometry

Floor area, surface exposure ratio and building depth ratio all have p-values that are less than 0.05 and are therefore deemed by this analysis as being influential on thermal energy use intensity. Figure 6.2 shows scatter plots of thermal energy use intensity against ANN Monte Carlo geometry inputs. Surface exposure has a weak positive correlation (R^2 = 0.362), indicating that as the buildings become more exposed, they tend to consume more

No.	Parameter	ANN Monte Carlo Inputs		Building Characteristics Dataset	
		p-value	**p-value < 0.05**	**p-value**	**p-value < 0.05**
1	Surface exposure ratio	2.263×10^{-36}	Yes	3.239×10^{-6}	Yes
2	Construction year	8.282×10^{-17}	Yes	5.043×10^{-4}	Yes
3	Ventilation strategy	1.016×10^{-8}	Yes	2.708×10^{-3}	Yes
4	Building depth ratio	2.008×10^{-8}	Yes	2.358×10^{-8}	Yes
5	Number of pupils	4.791×10^{-6}	Yes	5.533×10^{-1}	No
6	Glazing ratio on east facades	3.450×10^{-4}	Yes	6.134×10^{-3}	Yes
7	Occupancy hours	4.528×10^{-4}	Yes	9.096×10^{-1}	No
8	Phase of education	4.541×10^{-3}	Yes	2.240×10^{-2}	Yes
9	Floor area	5.813×10^{-3}	Yes	2.366×10^{-2}	Yes
10	Glazing ratio on west facades	3.896×10^{-2}	Yes	5.042×10^{-3}	Yes
11	Glazing ratio on north facades	1.321×10^{-1}	No	1.929×10^{-2}	Yes
12	Orientation correction	5.726×10^{-1}	No	2.734×10^{-1}	No
13	Glazing ratio on south facades	8.464×10^{-1}	No	3.062×10^{-3}	Yes

Table 6.3: ANN Monte Carlo input p-values for thermal energy use according to the Kruskal-Wallis analysis (no. 1: most influential, no.18: least influential); for comparison, the building characteristic dataset results are also presented

thermal energy per square metre. Building depth has a weak negative correlation (R^2 = 0.052), indicating that as the buildings become deeper, they tend to consume less thermal energy per square metre. Floor area has a weak negative correlation (R^2 = 0.032), suggesting that as the buildings increase in floor area, they tend to consume less thermal energy per square metre. The trends for these geometry parameters are similar to the trends found in the building characteristics dataset, outlined in Section 4.3.1 ('Geometry').

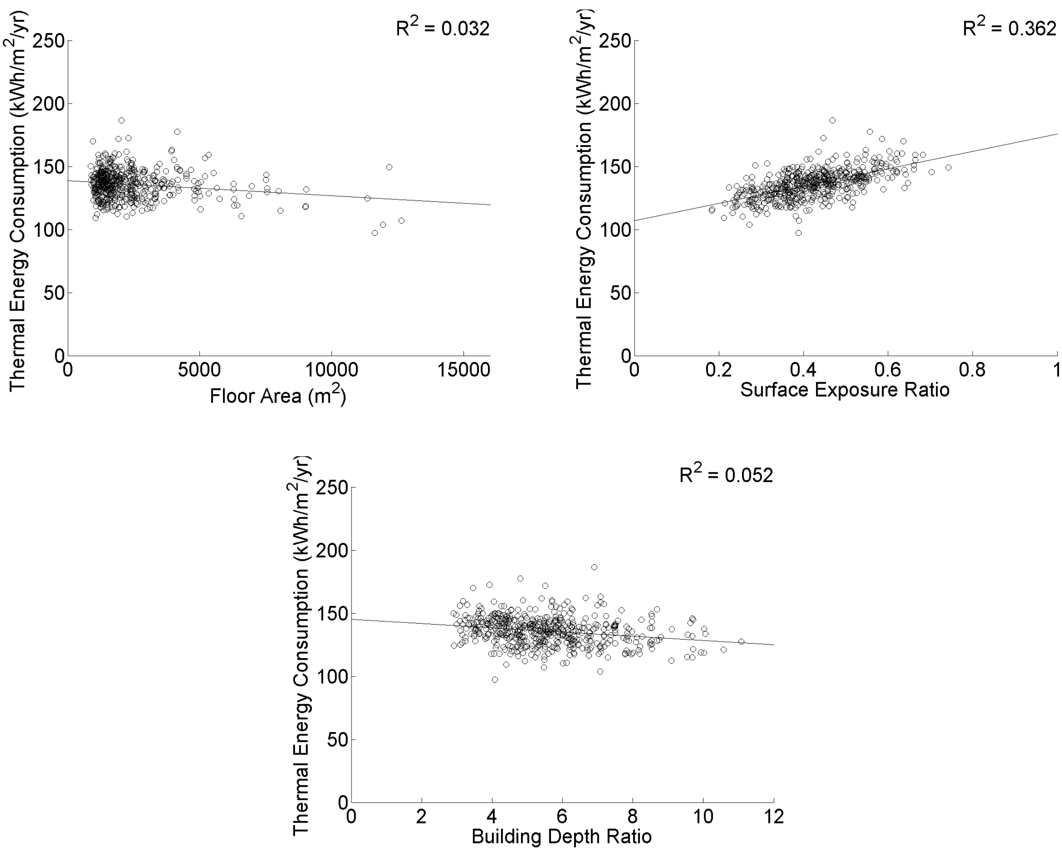


Figure 6.2: Scatter plots showing thermal energy use intensity against ANN Monte Carlo geometry inputs

Activity

Figure 6.3 is a scatter plot of thermal energy use intensity against ANN Monte Carlo pupil number inputs. Unlike the results from the building characteristics dataset, the p-value is less than 0.05, and therefore deemed by this analysis as being influential on thermal energy use. Furthermore, there is a weak positive correlation (R^2 = 0.063), indicating that buildings with more pupils tend to consume more thermal energy per square metre. It was suggested in Section 4.3.1 ('Activity') that it may not be pupil numbers alone that affects thermal energy use intensity, but pupil density. The relationship between pupil density and thermal energy use is analysed in more detail in Section 6.4.1.

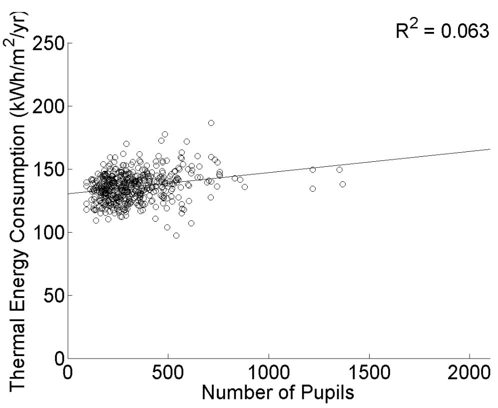


Figure 6.3: Scatter plots showing thermal energy use intensity against ANN Monte Carlo pupil number inputs

Phase of education has a p-value that is less than 0.05, therefore, the Kruskal-Wallis analysis for both the ANN study and building characteristics dataset (Section 4.3.1) showed that phase of education was influential to thermal energy use. Figure 6.4 shows how thermal energy use intensity depends on the ANN Monte Carlo phase of education and occupancy hours inputs. The 1st and 3rd quartile and median figures for secondary schools are all lower than their respective figures in primary schools suggesting that primary schools tend to consume more thermal energy per square metre than secondary schools: a trend also seen in the building characteristics dataset. Occupancy hours has a p-value that is less than 0.05, therefore, unlike the building characteristics dataset analysis, the ANN study deems this parameter as being influential on thermal energy use intensity. The 1st and 3rd quartile and median figures for schools with extended hours are all greater than their respective figures in schools operating under standard hours, suggesting that longer occupancy hours results in the consumption of more thermal energy per square metre.

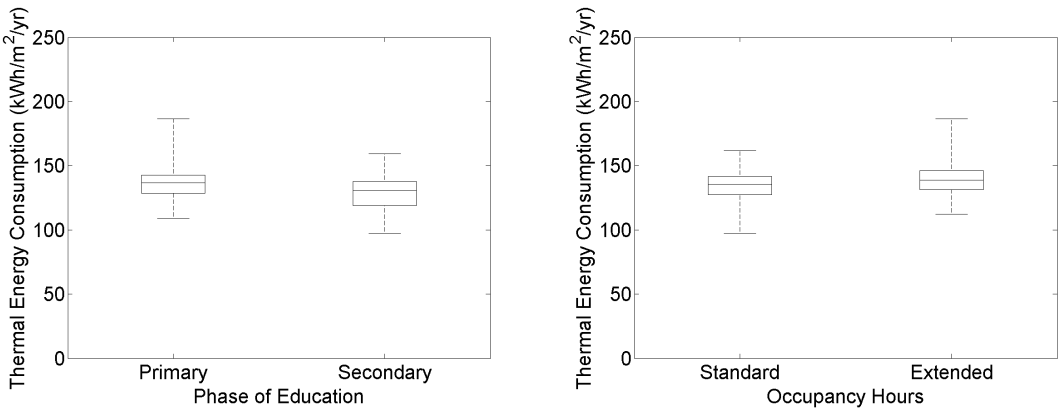


Figure 6.4: Box plots showing how thermal energy use intensity depends on ANN Monte Carlo activity inputs

Construction Year

Construction year has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on thermal energy use intensity for school buildings in England – corresponding with the results from the building characteristics dataset which also found this parameter as being influential. Figure 6.5 shows a scatter plot of thermal energy use intensity against ANN Monte Carlo construction year inputs. Moreover, reflecting the results from the building characteristics dataset, there is a weak negative correlation (R^2 = 0.160), suggesting that older buildings tend to consume more thermal energy than newer school buildings.

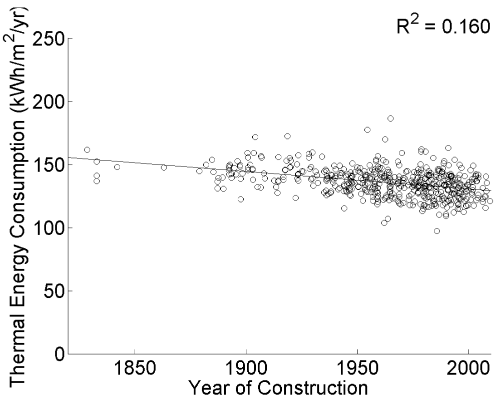


Figure 6.5: Scatter plot showing thermal energy use intensity against ANN Monte Carlo construction year inputs

Services

Ventilation strategy has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on thermal energy use intensity. Figure 6.6 shows how thermal energy use intensity depends on the ANN Monte Carlo ventilation strategy inputs. The 1st and 3rd quartile and median figures for mechanically ventilated buildings are all lower than their respective figures in naturally ventilated buildings, suggesting that mechanically ventilated schools tend to consume less thermal energy per square metre than naturally ventilated schools. The Kruskal-Wallis analysis for both the ANN Monte Carlo study and building characteristics dataset (Section 4.3.1) showed the ventilation strategy as being influential on thermal energy use, with both analyses showing similar thermal energy trends for this parameter.

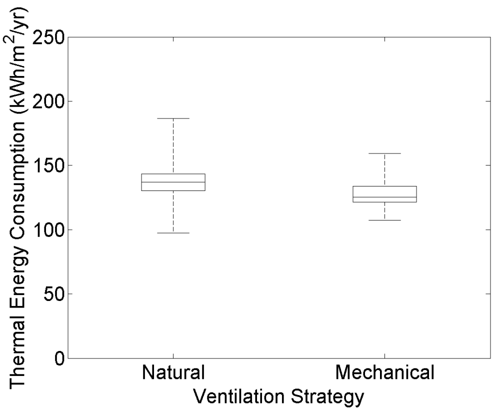


Figure 6.6: Box plot showing how thermal energy use intensity depends on ANN Monte Carlo ventilation strategy inputs

Glazing

Glazing ratios on north and south orientations have p-values that are greater than 0.05 and glazing ratios on east and west orientations have p-values that are less than 0.05. This analysis, therefore, deems glazing proportions on east and west orientations as being more influential on thermal energy use than glazing proportions on north and south orientations. Figure 6.7 shows scatter plots of thermal energy use intensity against ANN Monte Carlo glazing ratio inputs. The more influential glazing orientations have weak positive correlations – R^2 = 0.033 (east), R^2 = 0.012 (west) – suggesting that as glazing proportions increase, buildings tend to consume more thermal energy. These trends reflect the results found in the building characteristics dataset, however, the analysis of building characteristics dataset found glazing proportions on all orientations, not just east and west, as being influential, with a weak trend of greater thermal energy use values as glazing proportions increase. This suggests that the ANN failed to model the behaviour of glazing ratio on all orientations. As such, to simplify the manipulation of glazing ratios, all glazing ratios were altered in unison in the causal strength analysis (Section 6.4.1) to assess the global behaviour of these input parameters when altered together.

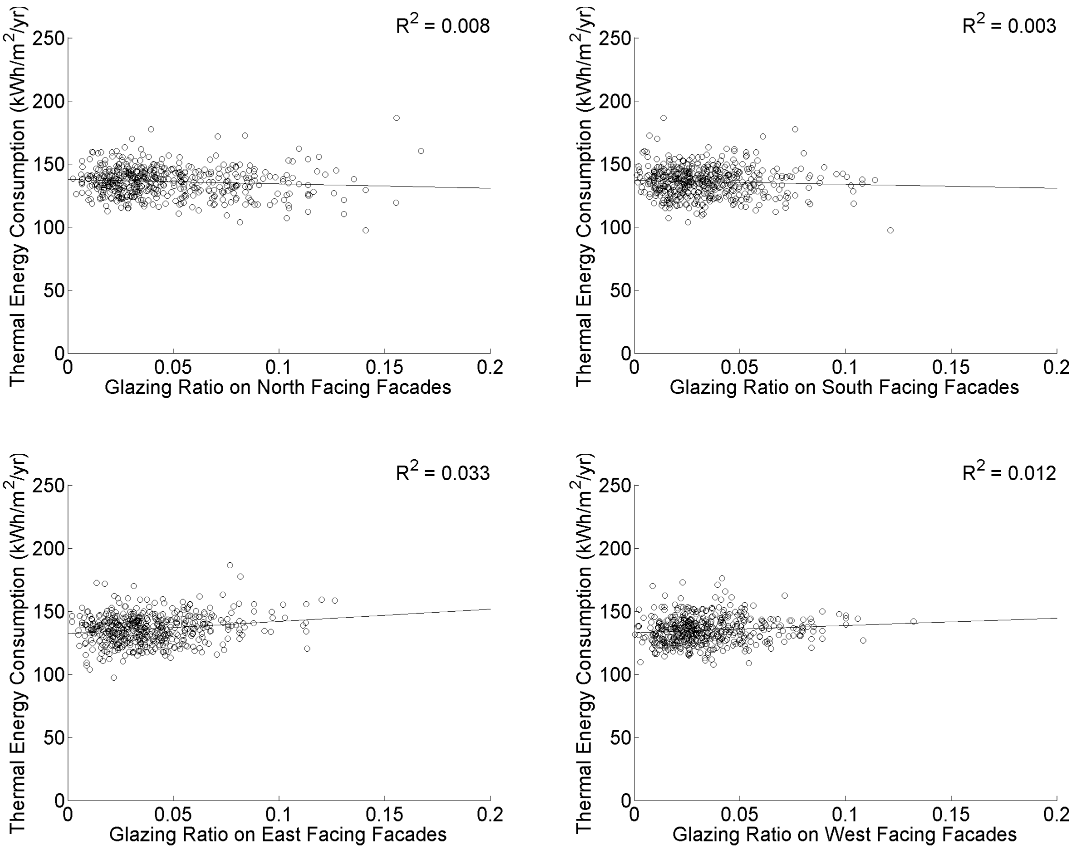


Figure 6.7: Scatter plots showing thermal energy use intensity against ANN Monte Carlo glazing ratio inputs

6.3.2 Electricity Energy Use

This section details the results of the sensitivity analysis for the ANN predictions of electricity energy use intensity, carried out on the dataset generated from the Monte Carlo method, outlined in Section 5.4. The p-value results of the Kruskal-Wallis analysis for electricity energy use intensity are shown in Table 6.4. Using the p-value threshold of 0.05 (Stigler 2008), inputs can be categorised as being influential on the energy use intensity outputs with a 95% confidence level. Furthermore, the input parameters were ranked from most influential to energy use intensity to least influential. The most influential inputs, in descending order, are construction year, number of pupils, phase of education, glazing ratio on east facades, floor area, ventilation strategy, surface exposure ratio, glazing ratio on south facades, occupancy hours and glazing ratio on west facades.

The following sections describe the results. As previously mentioned, the data generated by the Monte Carlo method will be referred to as 'ANN Monte Carlo' data. As outlined in Section 5.4, in order to ascertain how well the ANN method predicts reality, the results of this ANN study will be compared with the results of the building characteristics dataset analysis from Section 4.3.2.

Geometry

Figure 6.8 shows scatter plots of electricity energy use intensity against ANN Monte Carlo geometry inputs. Floor area has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy use intensity, reflecting the building characteristics dataset analysis in Section 4.3.2. The trend again reflects the building characteristics dataset analysis in having a weak positive correlation (R^2 = 0.116), suggesting that as the buildings increase in floor area, they consume more electrical energy per square metre. Unlike the results shown in the building characteristics dataset analysis, surface exposure has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy use. The trend is negative but very weak (R^2 = 0.004), suggesting that more exposed buildings tend to consume slightly less electrical energy per square metre. Building depth ratio has a p-value that is greater than 0.05 and is therefore deemed by this analysis not to significantly influence electricity energy use intensity, reflecting the results from the building characteristics dataset.

No.	Parameter	ANN Monte Carlo Inputs		Building Characteristics Dataset	
		p-value	**p-value < 0.05**	**p-value**	**p-value < 0.05**
1	Construction year	2.084×10^{-12}	Yes	3.005×10^{-13}	Yes
2	Number of pupils	5.524×10^{-12}	Yes	4.205×10^{-2}	Yes
3	Phase of education	1.637×10^{-4}	Yes	1.952×10^{-7}	Yes
4	Glazing ratio on east facades	3.389×10^{-3}	Yes	2.786×10^{-1}	No
5	Floor area	4.199×10^{-3}	Yes	7.484×10^{-4}	Yes
6	Ventilation strategy	1.390×10^{-2}	Yes	1.690×10^{-1}	No
7	Surface exposure ratio	3.039×10^{-2}	Yes	3.180×10^{-1}	No
8	Glazing ratio on south facades	3.377×10^{-2}	Yes	1.133×10^{-4}	Yes
9	Occupancy hours	3.407×10^{-2}	Yes	8.981×10^{-1}	No
10	Glazing ratio on west facades	3.726×10^{-2}	Yes	2.612×10^{-1}	No
11	Building depth ratio	5.564×10^{-2}	No	7.870×10^{-2}	No
12	Orientation correction	3.364×10^{-1}	No	5.513×10^{-1}	No
13	Glazing ratio on north facades	5.037×10^{-1}	No	1.502×10^{-2}	Yes

Table 6.4: ANN Monte Carlo input p-values for electricity energy use according to the Kruskal-Wallis analysis (no. 1: most influential, no.18: least influential); for comparison, the building characteristic dataset results are also presented

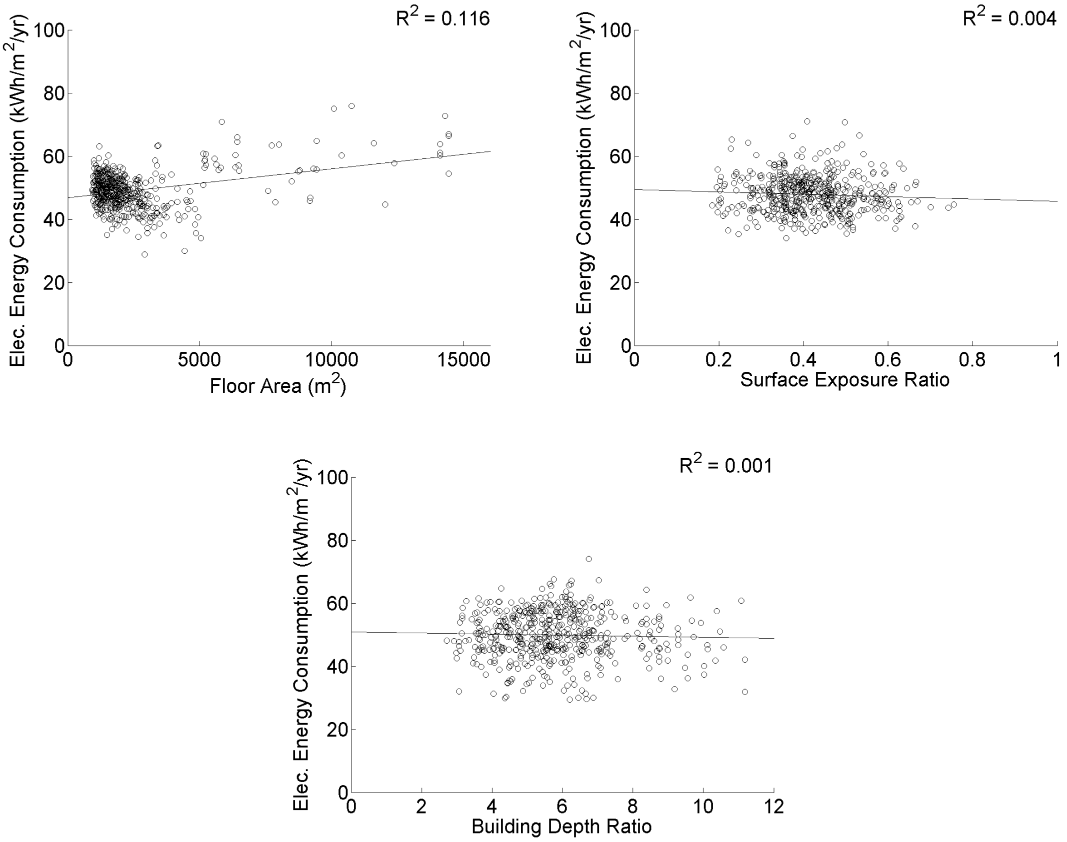


Figure 6.8: Scatter plots showing electricity energy use intensity against ANN Monte Carlo geometry inputs

Activity

Figure 6.9 is a scatter plot of electricity energy use intensity against ANN Monte Carlo pupil number inputs. The p-value is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy use intensity. There is a weak positive correlation (R^2 = 0.099), suggesting that buildings with more pupils tend to consume more energy per square metre. These results reflect the analysis on the building characteristics dataset.

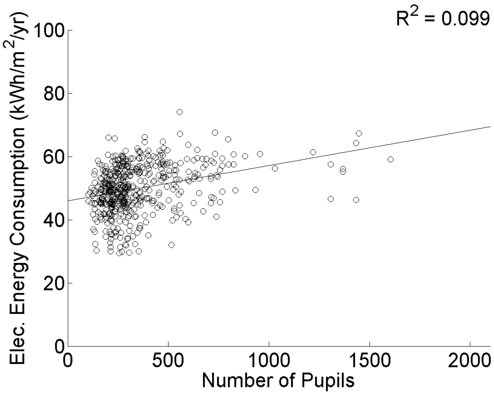


Figure 6.9: Scatter plot showing electricity energy use intensity against ANN Monte Carlo pupil number inputs

Figure 6.10 shows how electricity energy use intensity depends on the remaining ANN Monte Carlo activity inputs. Phase of education has a p-value that is less than 0.05 and is therefore deemed by this analysis as being influential on electricity energy use, corresponding with the results of the building characteristics dataset analysis. The 1st and 3rd quartile and median figures for secondary schools are all higher than their respective figures in primary schools suggesting that secondary schools tend to consume more electrical energy per square metre than primary schools, reflecting the trend shown from the building characteristics dataset. Unlike the analysis of the building characteristics dataset, the occupancy hours input has a p-value that is less than 0.05 in the ANN Monte Carlo analysis and is therefore deemed by this study as being influential on electricity energy use. Despite the 1st quartile figure being lower, the median and 3rd quartile figures are greater in schools with extended hours compared to the respective figures in schools with standard hours. This suggests that schools with extended hours tend to consume slightly more electrical energy per square metre than schools with standard hours.

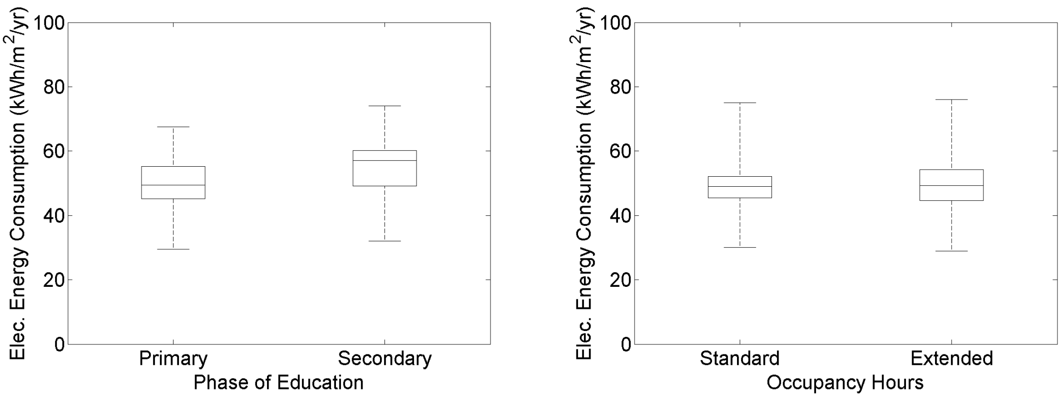


Figure 6.10: Box plots showing how electricity energy use intensity depends on ANN Monte Carlo activity inputs

Construction Year

The Kruskal-Wallis analysis of both the ANN study and building characteristics dataset showed that year of construction was influential to electrical energy use as both studies had p-values that were less than 0.05. Figure 6.11 is a scatter plot of electricity energy use intensity against ANN Monte Carlo construction year inputs. There is a weak positive correlation (R^2 = 0.103), suggesting that newer buildings tend to consume more electrical energy than older school buildings, reflecting the results from the building characteristics dataset.

Services

The Kruskal-Wallis analysis of the building characteristics dataset deemed ventilation strategy not to be influential on electrical energy use intensity, however, the Kruskal-Wallis analysis for the ANN study showed this parameter to be influential. Figure 6.12 shows how electricity energy use intensity depends on the ANN Monte Carlo ventilation strategy inputs. The 1st and 3rd quartile and median figures for mechanically ventilated buildings are all greater than their respective figures in naturally

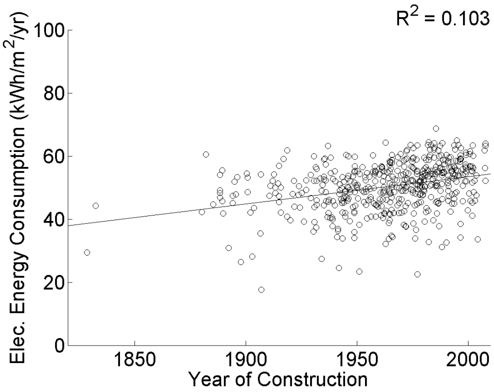


Figure 6.11: Scatter plot showing electricity energy use intensity against ANN Monte Carlo construction year inputs

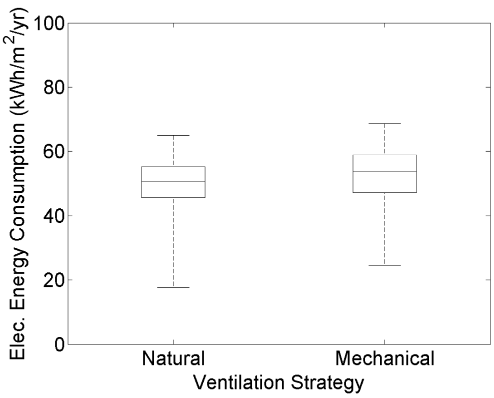


Figure 6.12: Box plot showing how electricity energy use intensity depends on ANN Monte Carlo ventilation strategy inputs

ventilated buildings suggesting that mechanically ventilated schools tend to consume more electrical energy than naturally ventilated schools – a trend that was shown in the building characteristics dataset box plot.

Glazing

The Kruskal-Wallis analysis for the ANN Monte Carlo study showed glazing ratios on south, east and west orientations to be influential on electricity energy use intensity, whereas the Kruskal-Wallis analysis of the building characteristics database deemed the glazing ratios on north orientations to be influential. Figure 6.13 shows scatter plots of electricity energy use intensity against the ANN Monte Carlo glazing ratio inputs. South and east glazing ratios have weak negative correlations – R^2 = 0.016 (south), R^2 = 0.032 (east) – suggesting that as glazing proportions increase on south and east facade orientations, buildings tend to consume less electrical energy. West glazing ratios have a weak positive correlation (R^2 = 0.0.018), suggesting that as glazing proportions increase on east facade orientations, buildings tend to consume more electrical energy. The data points for north glazing ratios are very scattered (R^2 = 0.001). The building characteristics dataset scatter plots showed that as glazing proportions increased on all orientations, school buildings tended to consume less electrical energy. This suggests that the ANN failed to model the behaviour of glazing ratios on all orientations. As such, to simplify the manipulation of glazing ratios, all glazing ratios were altered in unison in the causal strength analysis (Section 6.4.2) to assess the global behaviour of these input parameters when altered together.

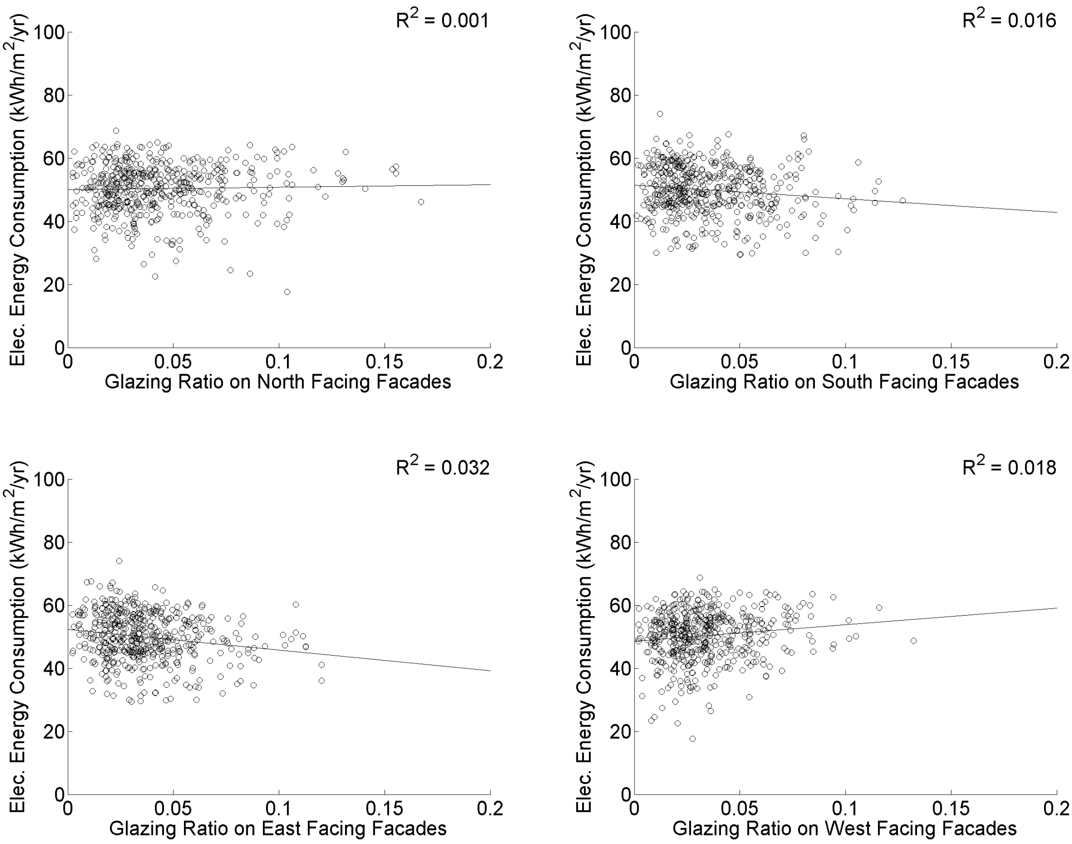


Figure 6.13: Scatter plots showing electricity energy use intensity against ANN Monte Carlo glazing ratio inputs

6.4 Causal Strength Analysis

6.4.1 Thermal Energy Use

Figure 6.14 shows the absolute changes in thermal energy use intensity (ANN output) across the predefined range of each input when compared with the base case output values. Larger changes in output indicate a greater influence of the input on the output. The results show that at 12.1%, surface exposure has the most influence on thermal energy use intensity. Year of construction is the second most influential, with a 9.3% change in output. At 8.1%, ventilation strategy is the third most influential input. All other inputs have a less than

5% change in output across their predefined ranges or categories with floor area having the least influence. The order of influence on thermal energy use from this analysis matches the precise order of the Kruskal-Wallis analysis of the ANN Monte Carlo dataset (Section 6.3.1), excluding glazing ratio as all glazing ratio orientations were combined and altered in unison in the causal analysis.

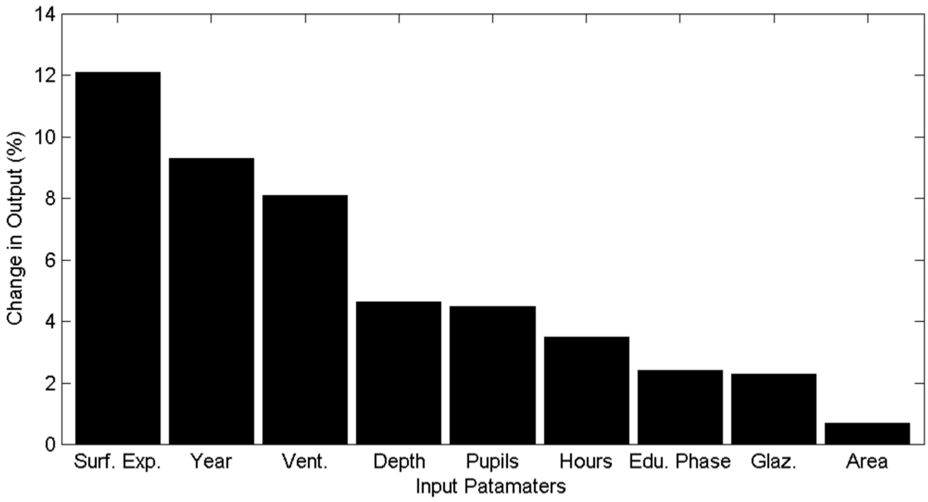


Figure 6.14: Thermal energy consumption – causal strengths of input parameters

Figure 6.15 shows the directional impact the input parameters had on thermal energy use intensity (ANN output), that is, as the inputs are altered an indication of whether they reduce or increase thermal energy consumption is shown. A positive change indicates an increase in energy consumption per square metre and a negative change indicates a reduction in energy consumption per square metre. The results are compared to the building characteristics (Section 4.3.1) and ANN Monte Carlo (Section 6.3.1) trends.

The results show that when surface area is increased the output increases by 4.8% and reduces by 7.3% when surface exposure is decreased. This is in line with the building char-

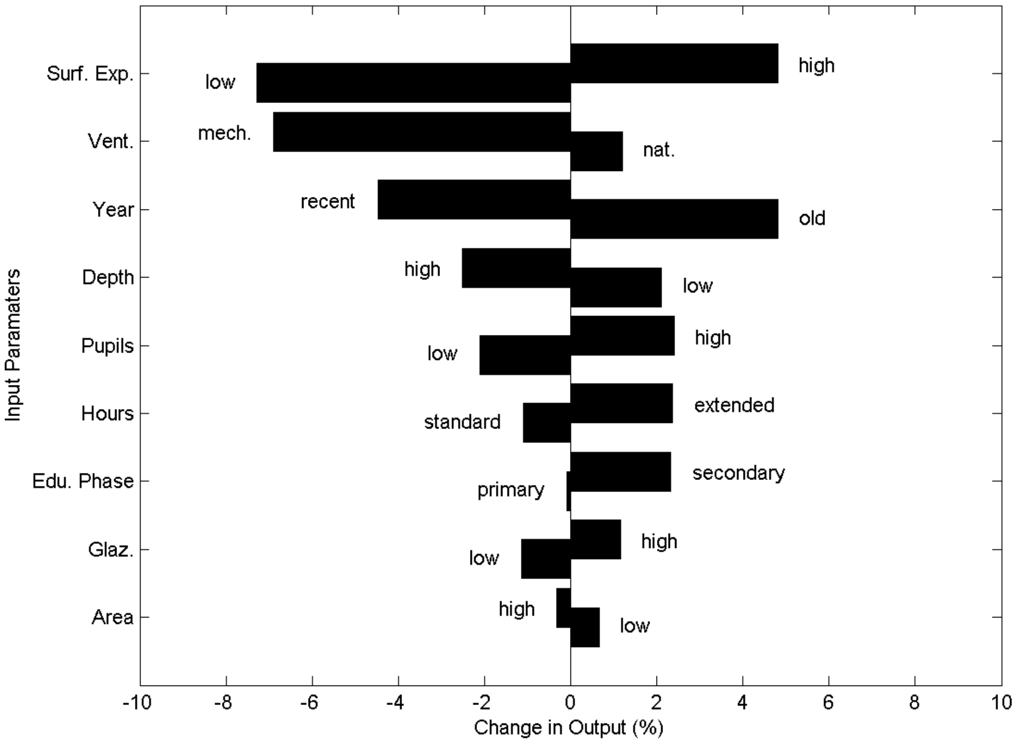


Figure 6.15: Thermal energy consumption – directional impact of input parameters

acteristics dataset and ANN Monte Carlo trends. Other inputs that followed similar trends to the building characteristics dataset and ANN Monte Carlo analyses were ventilation strategy, construction year, building depth ratio, phase of education and floor area. With standard occupancy hours, the output decreased by 1.1% and with extended occupancy hours, the output increased by 2.4%. This shows that with extended hours, schools tend to consume more thermal energy per square metre. This is in line with the trend in the ANN Monte Carlo analysis. This shows that the ANN model has picked up a pattern in the occupancy hours parameter despite there not being a clear impact when analysed in the building characteristics dataset. As shown in Section 6.3.1 ('Glazing'), the ANN failed to model the behaviour of glazing ratio on all orientations. As such, to simplify the manipulation of glazing ratios, all glazing ratios were altered in unison in the causal strength analysis to assess the global behaviour of these input parameters when altered together. The results show that the thermal energy use intensity output increases by 1.2% when glazing is increased and reduces by 1.1% when glazing is reduced. This is in line with the trends shown on all orientations when glazing ratios were analysed in the building characteristics dataset and, in turn, provides evidence that the glazing ratio orientations should be altered together when incorporated into the SEED Tool to ensure the input behaves in a similar manner to that of the building stock. When number of pupils are increased the output increases by 2.4% and when number of pupils are decreased the output decreases by 2.1%. This is in line with the ANN Monte Carlo analysis, however, the analysis of the building characteristics dataset showed there to be no strong trend with pupil numbers. As expected and as shown in Figure 4.4 (Section 4.2.3, 'Geometry'), pupil numbers are correlated to floor area: as floor area increases, pupil numbers tend to increase. The causal strength analysis is useful, as it enables the analysis of individual parameters as all other parameters remain at a baseline level. Altering pupil numbers while keeping floor area at a baseline level, resulted in changes to pupil density. A building with increased pupil numbers and a baseline floor area resulted in an increase in pupil density. A building with more pupils per square meter is, therefore, likely to consume more thermal energy per square metre because of the increased domestic hot water and cooking loads. Furthermore, buildings with smaller pupil densities may have more spaces used for activities other than teaching, such as wide corridors and sports facilities, which require less space heating.

6.4.2 Electricity Energy Use

Figure 6.16 shows the absolute changes in electricity energy use intensity (ANN output) across the predefined range of each input when compared with the Monte Carlo base case output values. Larger changes in output indicate a greater influence of the input on the output. The results show that at 32.6%, floor area has the most influence on electricity energy use intensity. Number of pupils is the second most influential input, with a 17.9% change in output. Phase of education and construction year are the third and fourth most influential inputs with a 16.6% and 12.8% change in output respectively. All other inputs have a less than 6% change in output across their predefined ranges or categories with surface exposure having the least influence. The four most influential inputs and four least influential inputs to electrical energy use intensity were the same parameters to that of the four most influential and four least influential parameters in the Kruskal-Wallis analysis of the ANN Monte Carlo dataset (Section 6.3.2), excluding glazing ratio as all glazing ratio orientations were combined and altered in unison in the causal analysis.

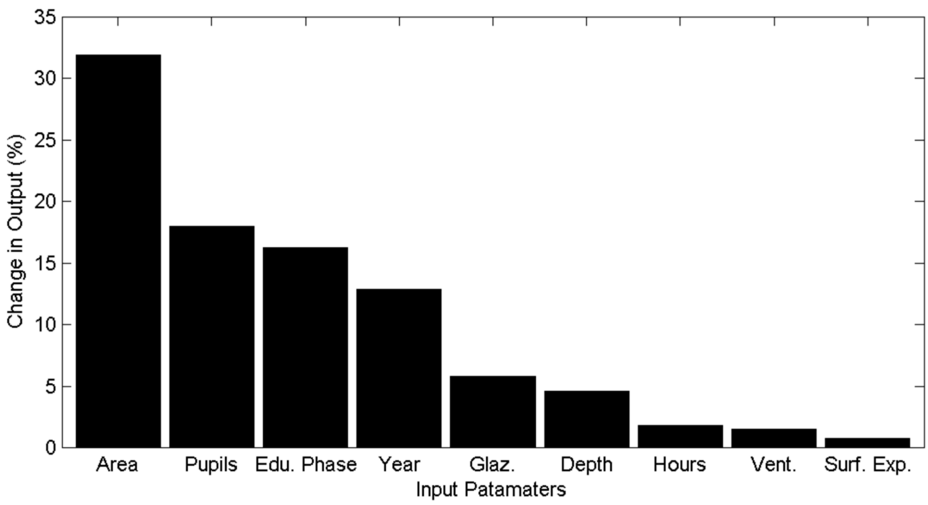


Figure 6.16: Electricity energy consumption – causal strengths of input parameters

Figure 6.17 shows the directional impact the input parameters had on electricity energy consumption (ANN output), that is, as the inputs are altered an indication of whether they reduce or increase electricity energy consumption is shown. A positive change indicates an increase in energy consumption per square metre and a negative change indicates a reduction in energy consumption per square metre. The results are compared to the building characteristics (Section 4.3.2) and ANN Monte Carlo (Section 6.3.2) trends.

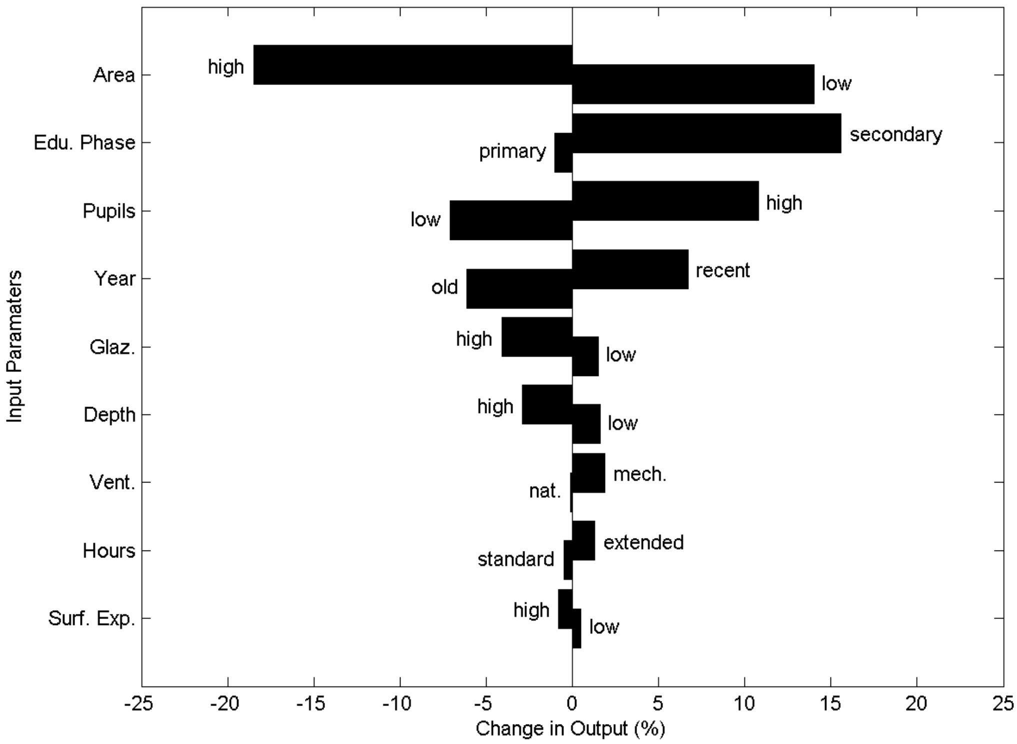


Figure 6.17: Electricity energy consumption – directional impact of input parameters

The results show that when the model is set to be a secondary school the output increased by 15.6% and decreased by 1.0% when the model is set to be a primary school. This is in line with the building characteristics dataset and ANN Monte Carlo trends. Other inputs that followed similar trends to the building characteristics dataset and ANN Monte Carlo analyses were number of pupils, year of construction and ventilation strategy. When floor area is increased the electricity energy consumption output decreases by 18.5% and increases by 14.0% when floor area is decreased. As previously mentioned, the causal strength analysis is useful, as it enables the analysis of individual parameters as all other parameters remain at a baseline level. As shown in Figure 4.4 (Section 4.2.3, 'Geometry'), floor area is correlated to pupil numbers: as floor area increases, pupil numbers tend to increase. Both the statistical analysis of the building characteristics dataset and the ANN Monte Carlo global sensitivity analysis showed that as floor area increased, electrical energy use per square meter tended to increase. It was suggested that this is likely due to larger buildings tending to be secondary schools, which make greater use of ICT and electrical laboratory equipment. However, as the causal analysis was able to isolate floor area, and test the effects when only this parameter was altered, the results showed that electricity use intensity decreased as floor area increased. Altering floor areas while keeping pupil numbers (and phase of education) at a baseline level, resulted in changes to pupil density. In this case, a building with a large floor area and baseline pupil numbers resulted in a reduction in pupil density. A building with fewer pupils per square meter is, therefore, likely to consume less electrical energy as there will be fewer laptops and other individual electrical equipment used, explaining the reduction in electrical energy use intensity. This highlights the benefits of the multivariate approach inherent in the ANN method. As shown in Section 6.3.2 ('Glazing'), the ANN failed to model the behaviour of glazing ratios on all orientations. As such, to simplify the manipulation of glazing ratios, all glazing ratios were altered in unison in the causal strength analysis to assess the global behaviour of these input parameters when altered together. The results show that the electrical energy use intensity output decreases by 4.1% when glazing is increased and increases by 1.5% when glazing is reduced. This is in line with the trends shown on all orientations when glazing ratios were analysed in the building characteristics dataset and, in turn, provides evidence that the glazing ratio orientations should be altered together when incorporated into the SEED Tool to ensure the input behaves in a similar manner to that of the building stock. With standard occupancy hours, the output decreased by 0.5% and with extended occupancy hours, the output increased by

1.3%. This shows that with extended hours, schools tend to consume more electrical energy per square metre. This is in line with the trend in the ANN Monte Carlo analysis; the building characteristics dataset analysis also indicated a small trend in the same direction despite the Kruskal-Wallis analysis showing occupancy hours as not having a significant influence on electrical energy use. The Kruskal-Wallis analysis of both the ANN study and building characteristics dataset deemed that building depth had little influence on electrical energy use. The building characteristics dataset scatter plot and the ANN causal analysis, however, did show a slight trend towards deeper buildings consuming less electrical energy. Based on principles of building physics, such a correlation is difficult to explain, as deeper buildings generally have less availability of natural light and natural ventilation to central areas and are therefore expected to consume more electricity due to an increased use of artificial lighting and mechanical ventilation. The results represent correlations, which perhaps means that there are characteristics common between the deeper buildings in this research, that influence electricity use. Finally, the results show that when surface exposure is increased the electricity energy consumption output reduces by 0.8% and increases by 0.5% when surface exposure is decreased. This is in line with the trend in the ANN Monte Carlo analysis. As with the occupancy hours parameter, this shows that the ANN model has picked up a pattern in surface exposure despite there not being a clear impact when analysed in the building characteristics dataset.

6.5 Summary

The analysis of cumulatively adding input groups to the ANN method showed, for both thermal and electricity energy consumption predictions, that geometry, construction year, ventilation strategy, glazing and activity based inputs produced the lowest errors. Site and weather based inputs were disregarded for both thermal and electricity energy consumption

predictions as the inclusion of these inputs increased the generalisation errors in the ANN method. The global sensitivity and causal analyses allowed a deeper understanding of the influence each input had on the outputs. The results of these analyses were described and compared with the statistical results from the building characteristics dataset.
The main findings of this chapter included:

– The mean absolute percentage error (MAPE) for the thermal energy use ANN was 22.9%

– The MAPE for the electricity energy use ANN was 22.5%

– Both the thermal and electrical energy ANN models performed with increasing accuracy as more inputs were added up until site (building adjacency) and weather (heating and cooling degree days). As such, site and weather inputs were omitted from the ANN models.

– The behaviour of the ANN inputs largely corresponded with the statistical trends found in the building characteristics dataset – this indicates that the ANNs were able to learn the relationships between the building characteristics and energy use despite the weak correlations (R^2 values) displayed when the building characteristics dataset was statistically analysed.

– The causal strength analysis showed pupil density to be a determinant in energy use when altering floor area and pupil numbers independently of each other

– The ANNs failed to model the behaviour of glazing ratio on all orientations for both thermal and electrical energy use. As such, to simplify the manipulation of glazing ratios, all glazing ratios were altered in unison in the causal strength analyses to assess the global behaviour of these input parameters when altered together. By doing this, glazing ratio behaved in a similar manner to the trends shown on all orientations when glazing ratio was analysed in the building characteristics dataset and in turn provided evidence that the glazing ratio orientations should be altered together when incorporated into the SEED Tool.

The following chapter presents the design and development of the SEED Tool, using the ANNs and inputs analysed in this chapter.

Chapter 7

Method 3: SEED Tool User Interface Design and Development

7.1 Overview

The previous chapter outlined the results of the artificial neural network (ANN) analysis and determined the final ANN inputs for the SEED Tool. This chapter outlines the design and development of the SEED Tool user interface, using the ANN and inputs analysed in the previous chapter. The SEED Tool was developed in accordance with the conditions of the UCL Doctoral Centre for Virtual Environments, Interaction and Visualisation (VEIV) to produce academic research with an industrial application. The first part of this chapter describes and explains the layout and user function design of the user interface. The second part of the chapter defines the computation that was necessary to develop the user interface, including generating the inputs and simulating the ANNs with the tool. Finally, the strategy to disseminate the tool will be outlined. This is part three of the methodology as outlined in Figure 7.1.

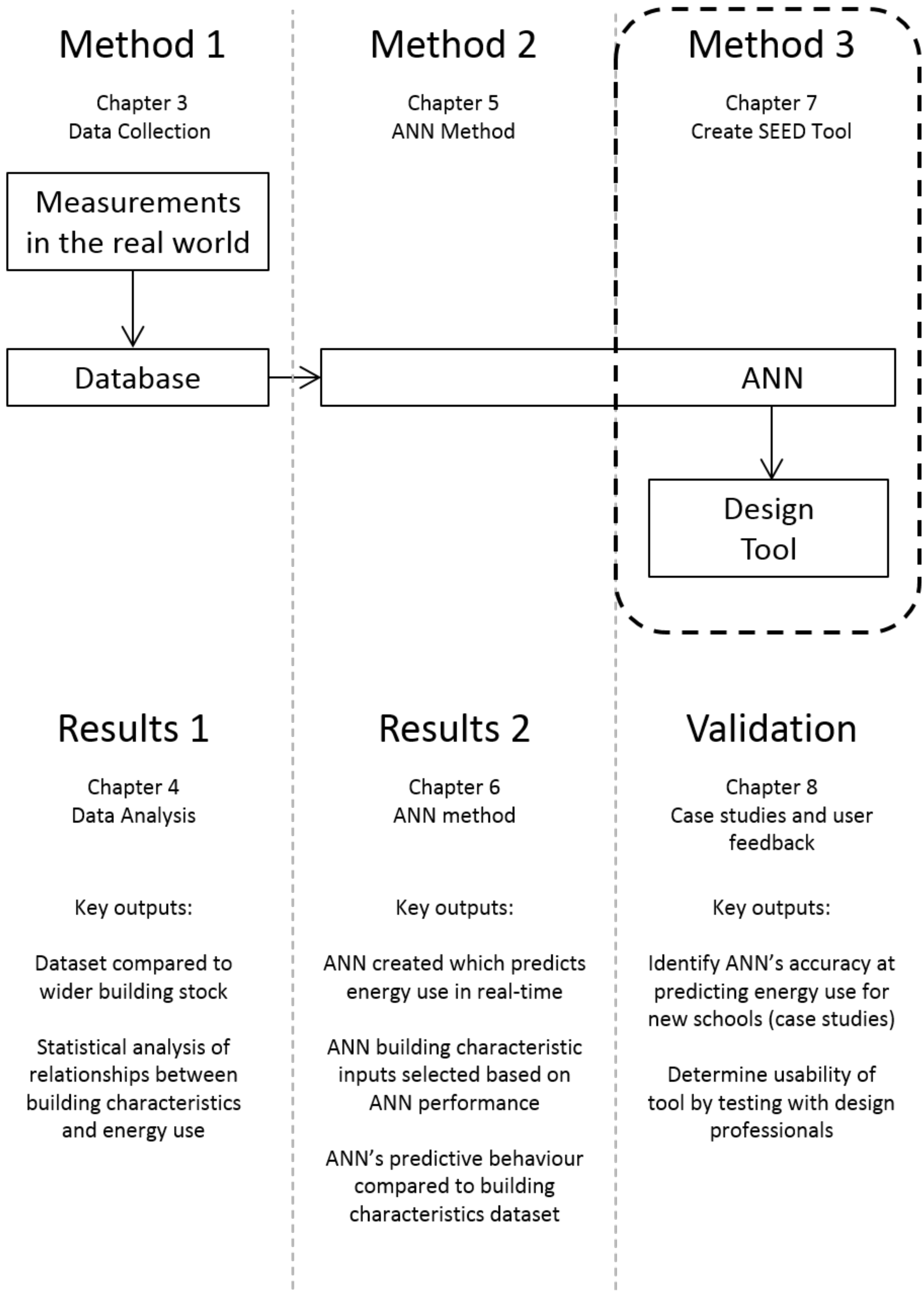


Figure 7.1: Breakdown of work stages: methodology part 3

7.2 Interface Design

7.2.1 Design Principles

As described in Section 1.4, architects tend to reject energy simulation tools as they are too complex and timely to use. Section 2.3.6 also outlined the different psychological states experienced when undertaking a task (Figure 2.8). In order for architects to be in a state of 'flow' when using a design tool – that is, in a mental state of energised focus, full immersement and enjoyment of the process – the task in which they are participating in must contain these conditions (as described in Section 2.3.6):

– Goals are clear

– Feedback is immediate

– Balance between challenge of task and skill of participant

As such, three aspects formed the basis of the SEED Tool. Firstly, the results are to be in clear view from the start of the user experience with energy benchmarks (goals) so the user knows what typical energy use figures are for school buildings in England. The 'goal' is, ultimately, left to the designer to decide – they may wish, for example, to better the benchmarks. Secondly, the results (feedback) are communicated in real-time (immediate) as the user alters the inputs. Thirdly, ensure the tool is user-friendly (lowering the challenge) to the 'skill set' of non-simulation experts, such as architects.

Section 2.3.4 introduced two philosophies for interface design by Robinson (1994): simulator and simulation language (Figure 2.7). Where a simulation language relates to an interface that offers full flexibility to the user and a simulator relates to a purpose-designed interface that models a specific range of parameters. The philosophy of the SEED Tool is to be a simulator.

Section 2.3.3 introduced the concept of an integrated performance view (IPV) whereby a range of results are displayed in one window. The interface of the SEED Tool will follow this principle and expand it to include the inputs as well as the results (outputs). That is, all of the functions of the tool will be displayed in one window to aid the user to gain a holistic result while allowing them to easily associate the input parameters that produce the energy use outputs.

Tool Concept

The tool is named the SEED Tool (School Early Environmental Design Tool). The metaphor relates to the fact that a sound early design concept is essential for the eventual success of a building – similar to the conditions required for the germination process of a seed before it flourishes into a tree. The form of a tree, like a building design, cannot be precisely predicted from the offset, however, careful nurturing during its early existence can enable it to develop and have a long and successful life. As mentioned in Section 1.3, detailed design development later in the building design process can refine and elaborate a sound early concept design but can only partly ameliorate a poor one (Eastman 2009).

7.2.2 Interface Design

Overview

Figure 7.2 shows the welcome screen users first experience and Figure 7.3 shows the SEED user interface. The aim of the interface is to follow the design principles outlined in the previous section – in short, be intuitive, fast and user-friendly for architects and non-simulation experts. The following sections describe and explain each part of the interface.

Figure 7.2: SEED Tool welcome screen

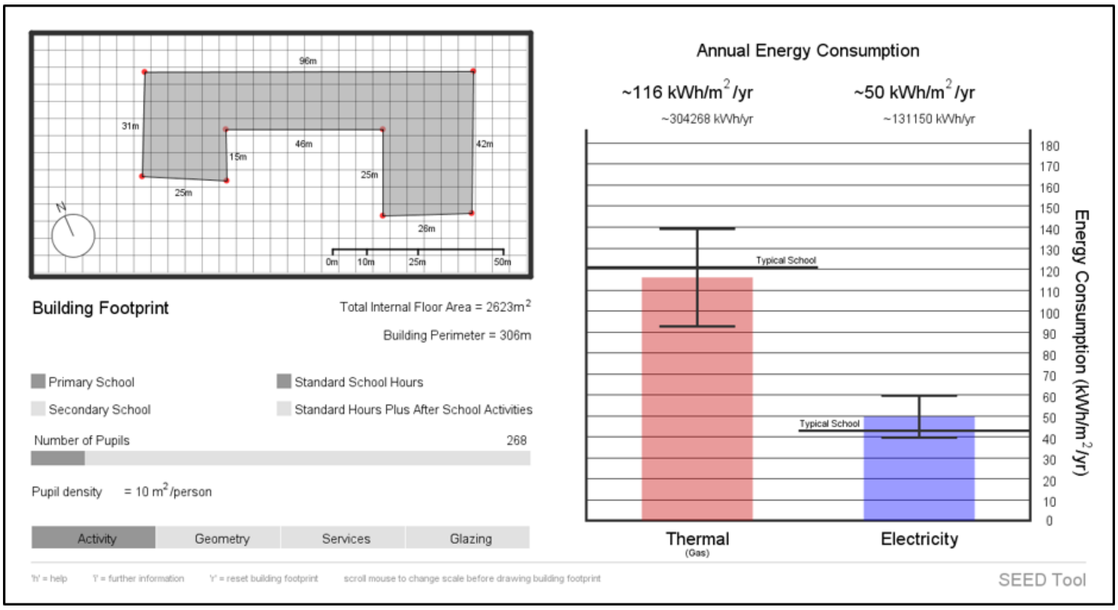


Figure 7.3: SEED Tool user interface

Drawing the Building Geometry

Figure 7.4 highlights the section of the interface dedicated to drawing the geometry of the building footprint. The 'canvas' is the area in the top left-hand side of the interface where the user can draw. The building footprint, the part of the building that makes contact with the ground, is drawn in 2D in plan.

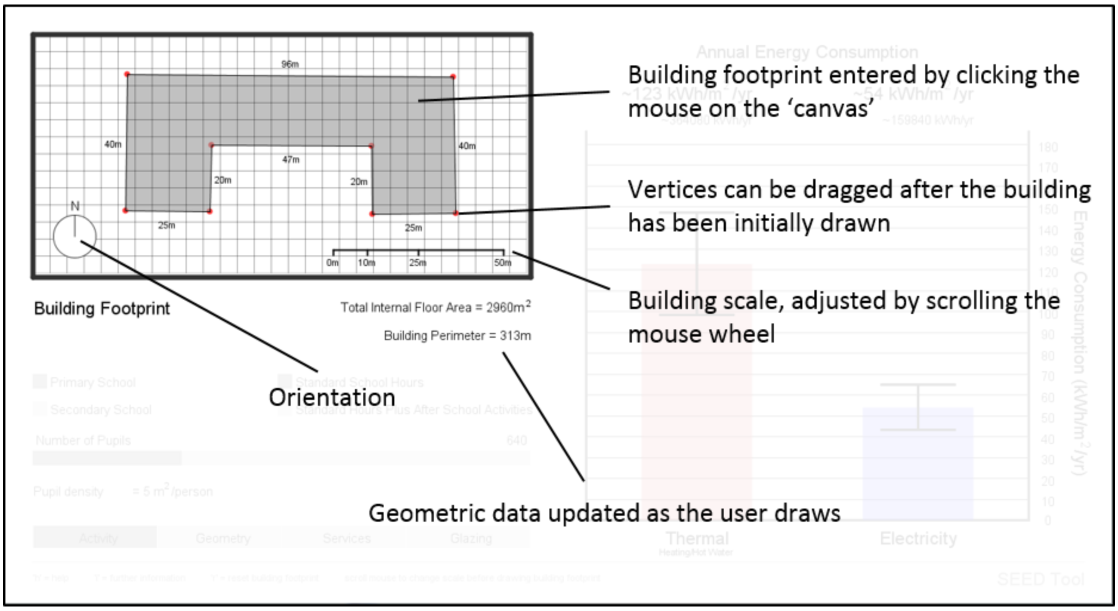


Figure 7.4: SEED Tool user interface: canvas

Prior to drawing the building, the scale of the canvas can be increased or decreased by scrolling the wheel of the mouse. The user can view the scale in the lower right-hand side of the canvas. The building footprint is drawn by clicking and dropping vertices, much like any ubiquitous computer aided design (CAD) programme, influenced by the principles of Ivan Sutherland's pioneering SKETCHPAD (Sutherland 1963). The geometry created is a closed polygon of light grey tone, with the last entered vertex joining the first vertex, therefore always creating a two-dimensional shape. As the user draws the geometry, the length of the wall being drawn is shown, in metres, adjacent to the latest vertex. When the user wishes to finish drawing the building footprint they may press 'ENTER' on the keyboard or make an action as if they were placing the latest vertex on top of the first. When the shape is complete, it turns a darker shade of grey, intuitively letting the user know that an action has been completed. Once complete, the length of each external building wall is shown in meters adjacent to each corresponding wall. Also, after the footprint has been drawn, the shape can be altered by clicking on vertices and dragging them to the desired location. The current orientation of the canvas is shown in the lower left-hand side of the canvas. This can be altered as outlined in the following section. Outside of the canvas to the lower right, are two pieces of information: the building perimeter length and total internal floor area. The building perimeter is the summation of external wall lengths. The total internal floor area is the area of the building footprint multiplied by the number of storeys in the building. Selecting the number of storeys is outlined in the following section. The underlying calculations that take place in order for the ANN to receive inputs and produce results will be outlined in Section 7.3.

Inputs

Figure 7.5 highlights the section of the interface dedicated to inputting design and briefing data. This data is contained within the lower left portion of the user interface. Categorical data is displayed in a tick box format and continuous data is displayed in a slider format. The aim is to have everything in one window without overloading the user with information; therefore tabs in the lower left of the window call-up tick boxes and sliders relating to 'Activity', 'Geometry', 'Services' and 'Glazing', while remaining on the same overall window. Table 7.1 shows details of the tool inputs. The data ranges for continuous data inputs and categories for categorical data inputs are based on the ranges of the data collected in Chapter 3[1], rounded and truncated where necessary to appear *cleaner* to the user.

[1] With the exception of orientation – the calculation to convert the orientation in the user interface to orientation correction factor and glazing ratios on facade orientations (ANN inputs) are outlined in the Section 7.3

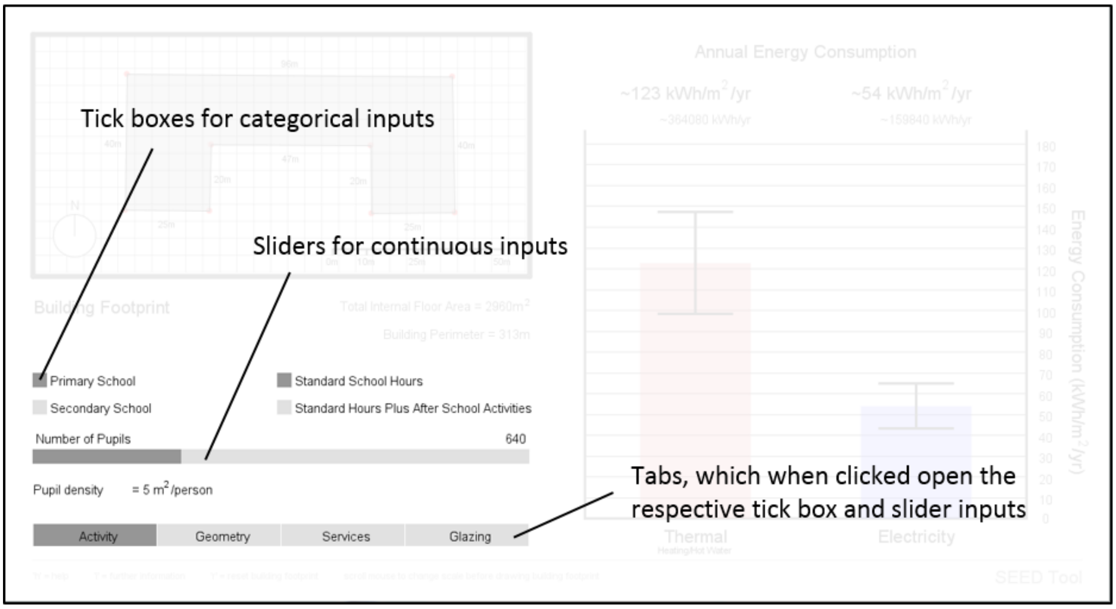


Figure 7.5: SEED Tool user interface: inputs

Tab	Inputs	Data Type	Data Range / Category
Activity	Phase of education	Categorical	[Primary school], [Secondary school]
	Occupancy hours	Categorical	[Standard school hours], [Standard hours plus after school activities]
	Number of pupils	Continuous	60 - 2000
Geometry	Orientation	Continuous	-180 – +180^{o}
	Number of floors	Categorical	[1], [2], [3], [4]
Services	Ventilation strategy	Categorical	[Natural ventilation], [Mechanical ventilation]
Glazing	Glazing percent on all wall orientations	Continuous	5 – 75%

Table 7.1: SEED Tool inputs

Constraining the user to tick boxes and sliders performs two functions. Firstly, it reduces the skill level required to input data, that is, the user can be confident that any input they make is 'reasonable' and in line with other school buildings in England. The intention being to encourages the user to 'play' with the tool and test different options without the threat of 'garbage-in garbage-out' scenarios. This is in line with the third condition to achieve a state of 'flow' as outlined in Section 7.2.1, ie. lowering the skill level required by the user. Secondly, sliders and tick boxes allow the ANN to receive a change in input with each user action, therefore being able to 'animate' the results as the user alters the inputs. This is in line with the second condition to achieve a state of 'flow': immediate feedback. These seven inputs together with the building footprint comprise all of the user inputs to the model. This small amount of data required by the user aims to encourage architects to use the tool without rejecting it due to complexity.

Additional information is derived from some of the input data and presented to the user. In the 'Activity' and 'Geometry' tabs, pupil density (m^2/person) is provided and in the 'Glazing' tab, north facing glazing area, south facing glazing area, east facing glazing area and west facing glazing area (m^2) is shown. An example of this (pupil density) is shown in Figure 7.5.

The underlying calculations that take place in order for the ANN to receive inputs and produce results will be outlined in Section 7.3.

Energy Use Outputs

Figure 7.6 highlights the section of the interface dedicated to displaying the energy use outputs. Two outputs are shown on a bar graph: a red bar for thermal energy consumption and a blue bar for electricity energy consumption. The values of the bar graph are in kWh/m^2/yr so that the user can compare their design with other designs, other school buildings in England and energy benchmarks, as discussed in the following paragraph. Two values are shown at the top of the graph: the values of the two bar graphs (kWh/m^2/yr), in larger font to highlight the link between them and the bar graph, and the absolute energy consumption (kWh/yr), for both thermal and electricity energy consumption. The error bars on the bar graph are the generalisation errors in the two ANNs. Therefore, the thermal error bar expands 22.9% above and below the output on the thermal energy use bar graph and the electricity energy use error bar expands 22.5% above and below the output on the electricity energy use bar graph. The error bars aim to reinforce the fact that absolute precision in the final building performance is not achievable in energy prediction tools (Wit and Augenbroe 2002) and would be misleading to the (non-simulation expert) user if presented as such. Furthermore, given the early stage of the project and small number of inputs, there are an inextricably large number of variables between this model and a constructed school building, relating back to the seed analogy (Section 7.2.1, 'Tool Concept').

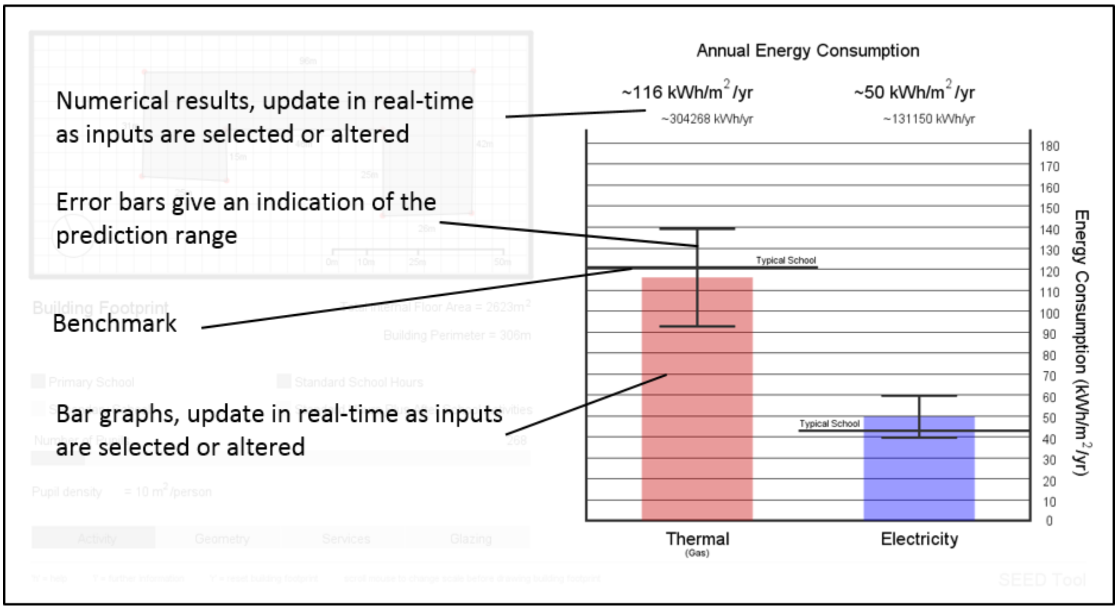


Figure 7.6: SEED Tool user interface: energy use outputs

Energy benchmarks are shown on the results graph. Benchmark figures for thermal and electricity energy are given for primary and secondary schools, depending on what school type is chosen by the user. The benchmarks were sourced from research carried out by Hong et al. (2014). These benchmark figures were chosen because of a study carried out by Bruhns, H., Jones, P., & Cohen (2011) which gave rise to concerns over how accurately the CIBSE TM46 benchmarks (CIBSE 2008) convey the building stock today. The study found a trend towards higher electricity consumption and lower thermal energy use in many benchmark categories. Hong et al. (2014) addressed these concerns by conducting statistical analyses on approximately 14,000 primary and secondary schools in England. The benchmarks used in the SEED Tool are the medians from Hong's study. Table 7.2 shows the benchmarks used.

Phase of Education	**Thermal Energy Use ($kWh/m^2/yr$)**	**Electrical Energy Use ($kWh/m^2/yr$)**
Primary	121	43
Secondary	111	50

Table 7.2: Energy benchmarks for schools in England (Hong et al. 2014)

The energy use outputs are displayed on the same page as the building characteristic inputs for a number of reasons. Having the results visible, with benchmarks, from the start of the user experience sets out a clear target or *goal* for the user. This is in line with the first condition to achieve a state of 'flow' (clear goal) as outlined in Section 7.2.1. The inclusion of sliders, and the ability to manipulate and drag the geometry of the building, results in the user being able to 'animate' the results and learn the relationships between the inputs and outputs by the acceleration of change in the results as the design space is explored. Displaying the thermal and electricity energy use figures adjacent to one another helps the user tackle 'wicked' problems of design as outlined in Chapter 1 (Section 1.2) whereby solving one problem, for example, reducing thermal energy use, can create another problem, such as increasing electricity consumption. By having both outputs side by side, it allows the user to find a holistic solution to their design.

The underlying calculations that take place in order for the ANN to receive inputs and produce results will be outlined in Section 7.3.

7.2.3 Supplementary Information

The tool has various pieces of supplementary information to aid the user. Figure 7.7 highlights the 'information bar' that runs the length of the bottom of the interface. The information bar displays the keyboard shortcuts for the SEED Tool: 'h' to bring up the help screen; 'r' to reset the building footprint; and 'i' to bring up extra information and annotate parts of the interface.

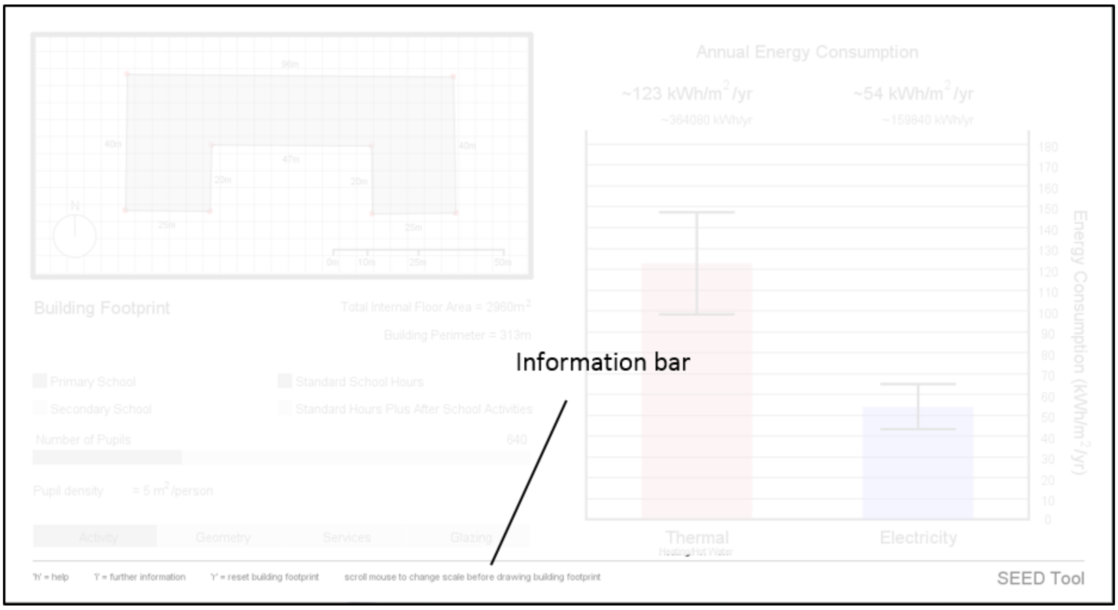


Figure 7.7: SEED Tool user interface: information bar

Resetting the building footprint ('r') deletes the current drawing of the building in the canvas, allowing the user to begin drawing a fresh building. When 'i' on the keyboard is held, the error bars on the bar graphs are annotated with the words 'prediction range', this is to aid non-technical users who may not be aware of the mathematical meaning of error bars (as shown to be the case in Section 8.3.8). The general orientation (north, south, east or west) of each external wall is shown adjacent to each external wall in the building footprint. A link to a video of a lecture (Architecture Association 2014) the author gave at the Architecture Association (AA) in London is shown in the information bar. This is for users who want to know more about the methodology adopted to create the tool. The lecture was primarily to an audience of architects – the target user of the tool.

Warnings are provided to alert the user when one or more inputs fall outside the typical input ranges of school buildings in England, that is, when the ANN input parameters exceed the range of the building characteristics dataset, outlined in Section 4.2.3. Users are not allowed to stray from typical input ranges as multilayer networks do not have the ability to accurately extrapolate beyond the training data range (Beale et al. 2013). When a warning occurs, the results vanish and the information bar turns red. The aim is to intuitively alert the user that they need to make alterations to their model. With each warning there is a corresponding *tip*, guiding the user on how to alter the inputs to get back to an acceptable value. Figure 7.8 shows an example of a *warning* and corresponding *tip*.

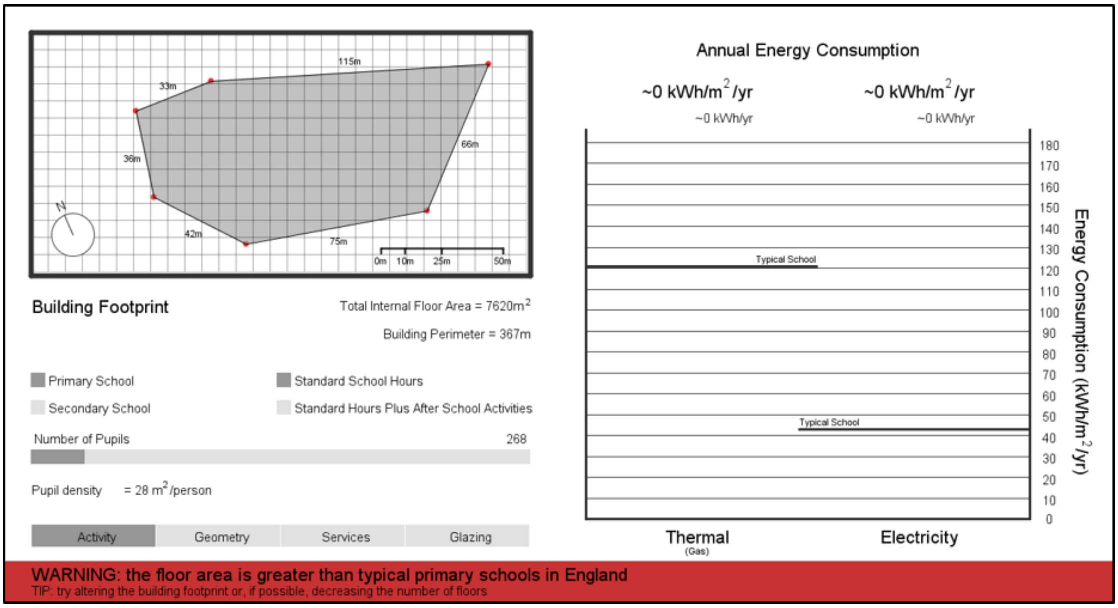


Figure 7.8: SEED Tool user interface: example of a warnings and tip

7.3 Interface Development

7.3.1 Overview

The previous section presented the design philosophy and layout of the SEED Tool's user interface; this section will outline the calculations and computation that was required to build and operate the tool.

7.3.2 Software Overview

The development of the tool was in two main software stages. First, the structure of the committee of ANNs for predicting thermal and electricity energy consumption were derived in MATLAB as outlined in Chapter 5. The structure of the ANNs were in the form of synaptic weights between the input neurons and the hidden neurons; the synaptic weights between the hidden neurons and the output neurons; and the synaptic weights between the bias neurons and the hidden and output neurons. These weights were exported from MATLAB as comma separated values (CSV) files.

The second main stage in the tool development was the creation of the user interface in Processing programming environment (Processing 2014). Processing is an open source, Java-based, programming language which specialises in image creation, animation and interaction. Where MATLAB was used to create the artificial neural networks, Processing forms the human-computer interaction environment from which the users of the SEED Tool are exposed to. The synaptic weights were imported to the processing code from the aforementioned CSV files. The structure of the ANNs were built in processing with the synaptic weights connecting each layer. Through this process, the ANN predictions are identical to the original MATLAB ANNs and there is no need to access MATLAB from within the Processing environment.

Figure 7.9 shows a high level diagram, highlighting the process of the ANN receiving inputs generated by the user and producing energy use outputs to the interface. Figure 7.10 and 7.11 show the code structure for the SEED Tool. The overall structure is split into two main sections. The first part, Figure 7.10, shows the process of the code receiving inputs from the user and generating normalised inputs for the ANNs; this is described in Section 7.3.3. The second part, Figure 7.11, shows the process of the ANNs receiving normalised inputs and making energy use predictions; this is described in Section 7.3.5.

7.3.3 Input Generation

Building Footprint

The building footprint, outlined in Section 7.2.2, is a *simple* polygon. A simple polygon is a two-dimensional shape consisting of straight, non-intersecting line segments. If the

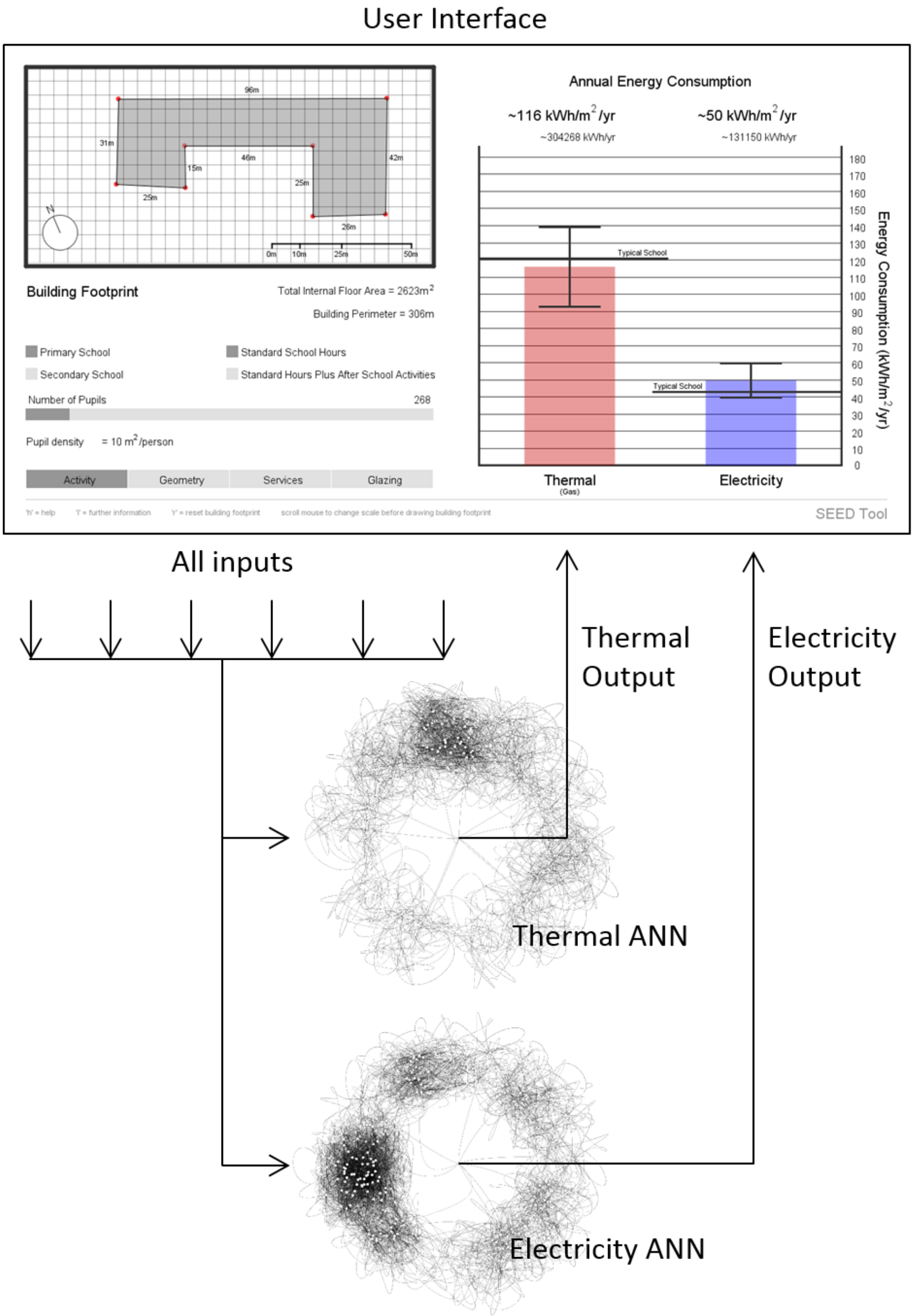


Figure 7.9: Visualisation of ANNs interacting with SEED Tool interface

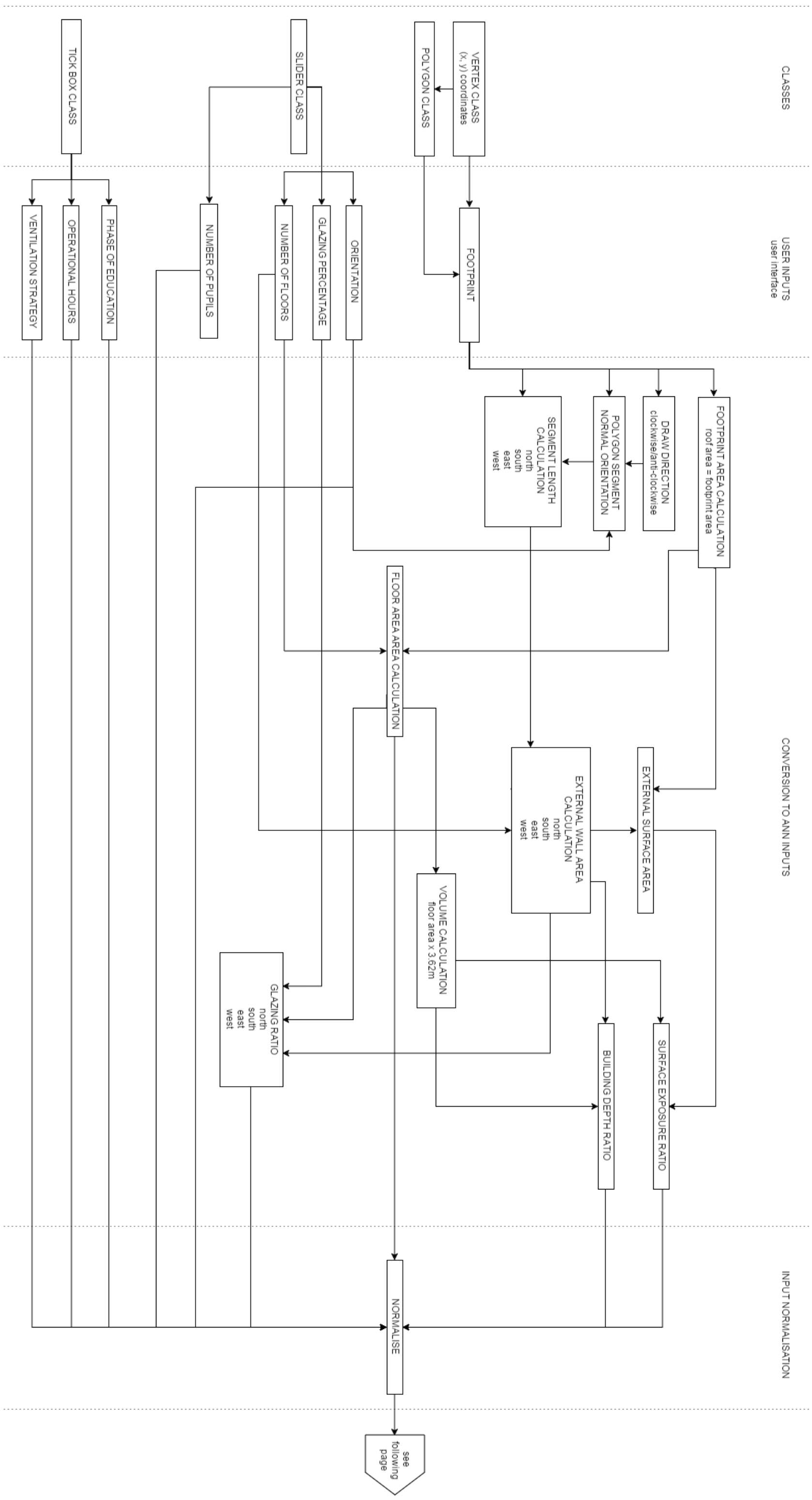


Figure 7.10: Code structure (1 of 2): input generation

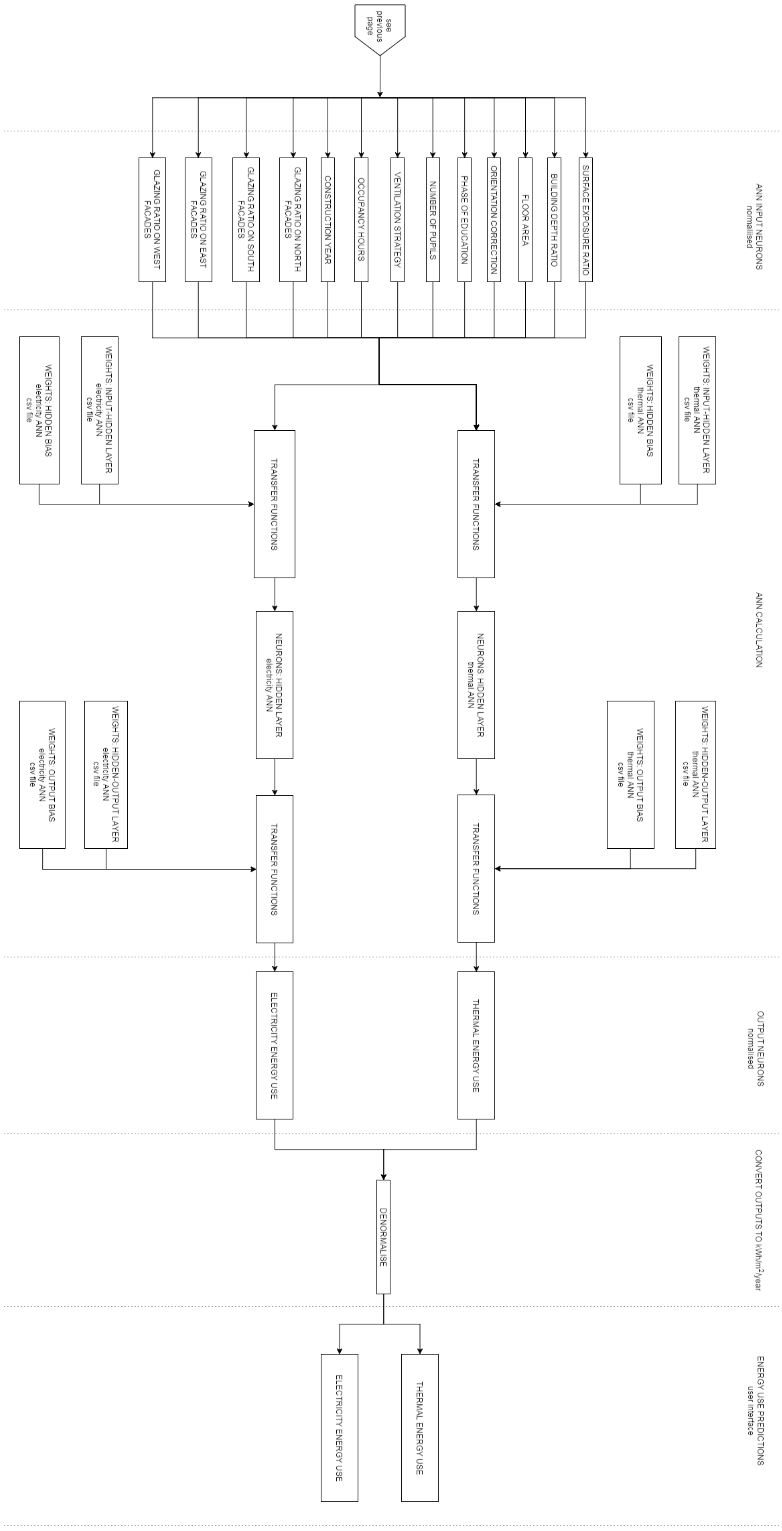


Figure 7.11: Code structure (2 of 2): ANN creating outputs

segments intersect, for example in a figure of eight configuration, the polygon is *complex*. A simple polygon also has the following properties:

- The shape forms an enclosed region (with a measurable area)
- Line segments meet only at their endpoints, called vertices ('corners')
- Two segments meet at each vertex
- The number of segments always equals the number of vertices

From here on, the term polygon or building footprint refers to a simple polygon. Figure 7.12 shows an example of a polygon with indexed vertices.

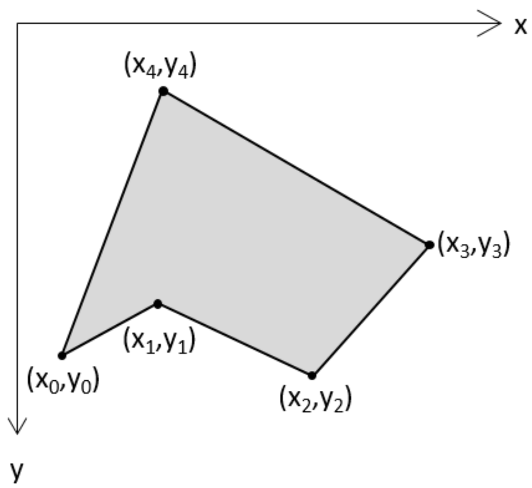


Figure 7.12: Simple Polygon

The building footprint is constructed of an ArrayList of vertices (corners of the building). An ArrayList stores a varying number of objects. It was chosen over an array, as items (vertices) can be added and removed – thereby it can be resized dynamically. This means any number of external walls and corners can be drawn. The vertices are coded as PVectors. A PVector is a code class which describes a two or three-dimensional vector. In the case of the two-dimensional footprint, the PVectors are composed of *x,y* coordinates for the vertices.

As can be seen in Figure 7.10, the building footprint serves a number of purposes, contributing to the formation of a number of inputs for the ANN model. In order for the building footprint to be useful, a number of geometric calculations take place.

Footprint Area Calculation

Calculating the area of the building footprint polygon is necessary to then calculate the total floor area and the surface area of the building. In order to calculate the area of the drawn footprint, the 'shoelace formula', otherwise known as the 'surveyor's area formula' (Braden 1986), is utilised (Equation 7.1). The formula can be used to calculate the area of any simple polygon, including convex and concave shapes.

$$A = \frac{1}{2}|\sum_{i=1}^{n} x_i(y_{i+1} - y_{i-1})| \tag{7.1}$$

Where A is the area of the polygon, n is the number of vertices of the polygon and (x, y) are the coordinates for each vertex i.

Draw Direction: Clockwise/Anti-clockwise

Determining the direction the building footprint (polygon) is drawn – that is, clockwise or anti-clockwise – is necessary in order to determine the orientation of each external wall (polygon segment). Figure 7.13 shows a polygon drawn in an anti-clockwise direction.

A polygon can be described by n vertices, ordered:

$$(x_0, y_0), (x_1, y_1), (x_2, y_2), ...(x_n, y_n)$$

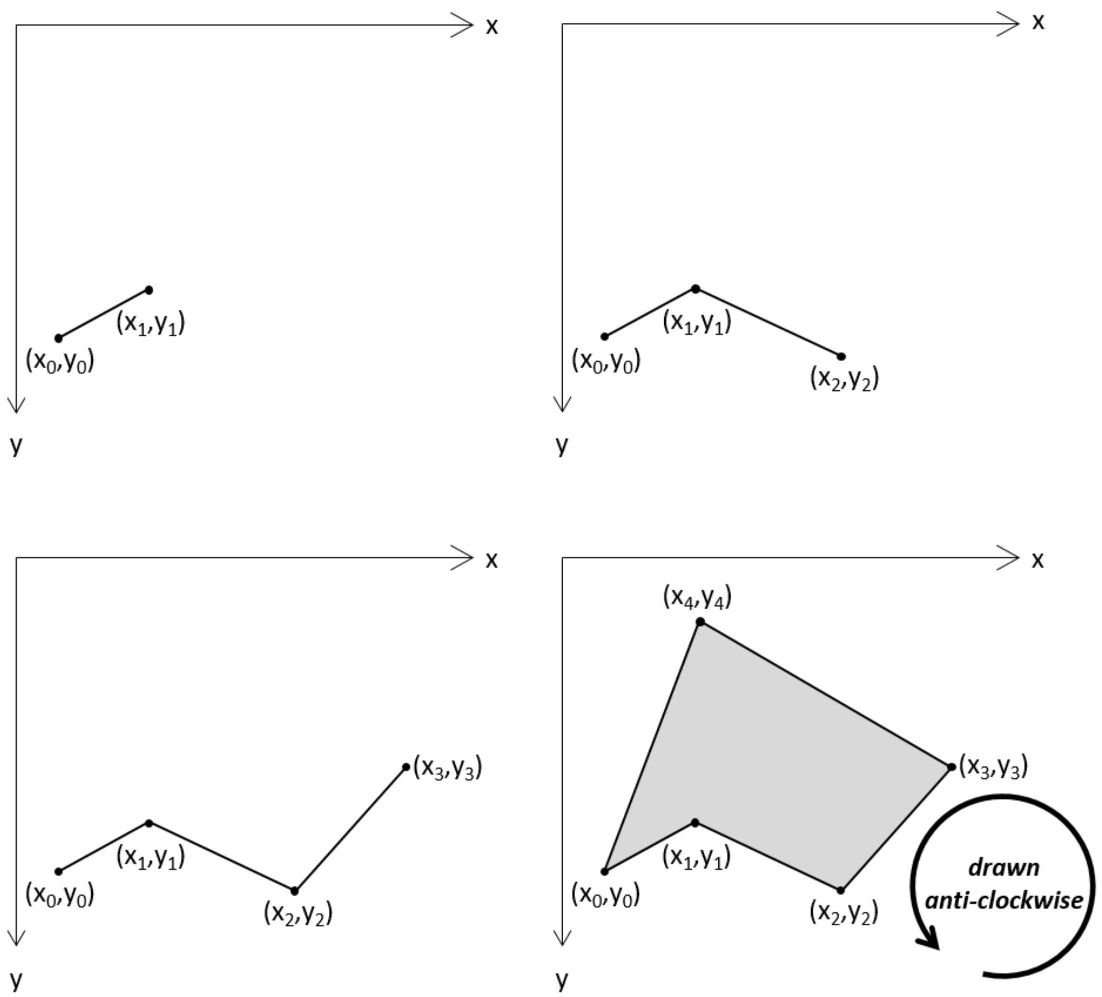


Figure 7.13: Draw direction of polygon on 2D plane

The draw direction is identified using the following equation (Equation 7.2):

$$d = \sum (x_{i+1} - x_i)(y_{i+1} + y_i) \tag{7.2}$$

Where d is the direction product of the equation and i is the index of the coordinates x, y.

If the product of Equation 7.2 is negative, the polygon was drawn in a clockwise direction and if the product of the equation is positive, the polygon was drawn in an anti-clockwise direction. Note: in the case of the *last* vertex, where $i = n$, the *next* vertex is the *first* vertex: $i + 1 = 0$. It should also be noted that the interpretation of the results of this equation is based on using the coordinate system of the Processing language, in which the positive y-axis points down (see Figure 7.12). This differs from the standard orientated Cartesian coordinate system where the positive y-axis points up.

Polygon Segment Normal Orientation

For each segment of the polygon, separate ArrayLists are stored for the normal orientation, length (described in the following section) and corresponding vertices (as previously described). Figure 7.14 visually describes the segment normal orientation. In order to determine a segment's normal orientation, the *atan2* Processing function is utilised. The function calculates the angle from the positive x-axis to a specified point. The draw direction, as described in the previous section, determines the outside direction of the external wall, that is, the direction that orientates the segment normal from the segment (wall) to the outside of the building rather than the inside of the building (see Figure 7.14). This calculation is able to classify each wall as facing a general direction of north, south east or west (see Table 7.3).

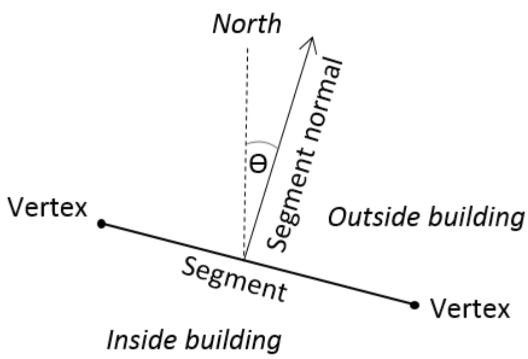


Figure 7.14: Segment Normal Orientation

Segment Length Calculation

The *dist* Processing function calculates the distance between two points. The lengths of each segment were calculated using the corresponding vertices as the required inputs for the *dist* function and these segment lengths were stored in an ArrayList in the same order as the corresponding segment normal orientation ArrayList. Calling each segment by index number, the segment lengths were further grouped into north, south east and west orientations. These smaller groups were themselves ArrayLists. Table 7.3 shows how the *general* orientations are identified – this coincides with the general orientation (Figure 3.9) outlined in Section 3.4.3 ('Geometry'). From this information, the lengths of external wall on each general orientation was calculated as well as the total building perimeter.

External Wall *General* Orientation	**Segment Normal Orientation**		
North	$\geq 315^{o}$	&	$<45^{o}$
South	$\geq 135^{o}$	&	$<225^{o}$
East	$\geq 45^{o}$	&	$<135^{o}$
West	$\geq 225^{o}$	&	$<315^{o}$

Table 7.3: External Wall General Orientation

Additional Geometry Calculations

The following describes the additional geometry calculations that took place in order to calculate a number of the ANN inputs outlined in Section 3.4:

– Floor area = building footprint area * number of storeys

– Volume = floor area * 3.62

– Surface area = (building perimeter * number of storeys * 3.62) + roof area

– External wall area = building perimeter * number of storeys * 3.62

- North facing wall area = total length of north facing walls * number of storeys * 3.62
- South facing wall area = total length of south facing walls * number of storeys * 3.62
- East facing wall area = total length of east facing walls * number of storeys * 3.62
- West facing wall area = total length of west facing walls * number of storeys * 3.62
- North facing glazing area = North facing wall area * glazing percentage
- South facing glazing area = South facing wall area * glazing percentage
- East facing glazing area = East facing wall area * glazing percentage
- West facing glazing area = West facing wall area * glazing percentage

Note: 3.62m is the average storey height for school buildings (Steadman P., Bruhns H.R. 2000) as outlined in Section 3.4.3 ('Geometry'), and the roof area is taken to be the same as the building footprint area as outlined in Section 3.4.3 ('Geometry').

Sliders and Tick Boxes

The slider and tick box graphical user interface (GUI) components were created using a Processing library built by Schlegel (2015). Figure 7.15 shows an example of a slider and tick boxes. Sliders were used for continuous data and non-binary data and tick boxes were used for binary inputs. Where sliders directly represent ANN inputs, for example 'number of pupils', the data produced by the slider requires to be normalised (see following section) before being fed into the ANN algorithm as described in Section 7.3.4. All tick boxes are in sets of two with only one being able to be selected at any one time. The tick boxes produce a value of '1' when the first box is selected and '2' when the second box is selected. This data is normalised to a binary input of '-1' when 'off' (tick box output = '1') and '1' when 'on' (tick box output = '2').

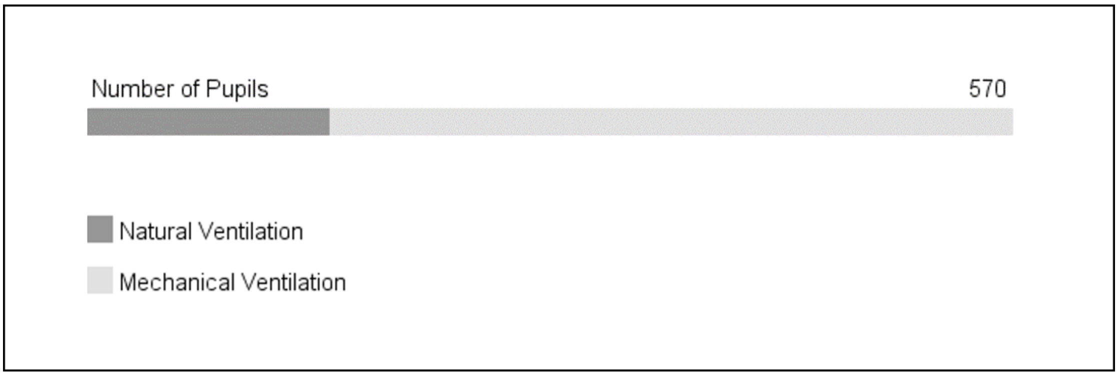


Figure 7.15: Example of slider (top) and tick boxes (bottom)

7.3.4 Normalisation

Chapter 5, Section 5.2, described the use of normalisation for ANN input and output data. In order to simulate the ANN in the Processing environment, the input data must be normalised in the same way. Equation 7.3 shows the *feature scaling* method required to normalise the input data generated by the user inputs.

$$X' = a + \frac{(X - \mathrm{X_{min}})(b - a)}{\mathrm{X_{max}} - \mathrm{X_{min}}} \tag{7.3}$$

Where X' is the normalised input value, X is the original input value, $\mathrm{X_{min}}$ and $\mathrm{X_{max}}$ are the minimum and maximum input values in the collected dataset respectively (Tables 4.5 and 4.6), a is the lower (-1) and b is the upper (1) input values of the normalised range.

7.3.5 Output Generation

Import ANN Weights

As mentioned, the weights that make up the neural networks were exported from MATLAB in the form of 2D matrix CSV files. These files are stored in Processing's 'data' folder: where all data files loaded in a Processing programme must be located in order to be used. The process to import the CSV files was as follows:

- Load the CSV files from the 'data folder' using the *loadStrings()* function
- Determine the matrix dimensions in the imported file
- Create an array based on the matrix dimensions
- Parse the values into the 2D array

Artificial Neural Network Simulation

Chapter 5 details the artificial neural network method, visualised in Figure 7.11. It should be noted that a committee of machines are used to predict thermal energy use and electricity use. Therefore, the process outlined in Figure 7.11 is carried out in effect 10 times for thermal energy predictions and 10 times for electricity energy predictions, each with a different ANN architecture (number of weights and weight values). The mean value for each of the two aforementioned ANN committee machines are taken to be the energy use predictions, as outlined in Section 5.3.

Denormalisation

The outputs generated by the ANN are required to be denormalised in order to present values to the user in kWh/m^2/yr. The method to achieve this, shown in Equation 7.4, is similar to the normalisation equation described in Section 7.3.4.

$$Y = \mathrm{Y}_{\min} + \frac{(Y' - a)(\mathrm{Y}_{\max} - \mathrm{Y}_{\min})}{b - a} \tag{7.4}$$

Where Y is the denormalised output value, Y' is the normalised output value, $\mathrm{Y}_{\min}$ and $\mathrm{Y}_{\max}$ are the minimum and maximum output values in the collected dataset respectively

(Tables 4.3 and 4.4), a is the lower (-1) and b is the upper (1) output values of the normalised range.

7.3.6 Dissemination

In order to run a Processing Source Code file, where the SEED Tool was created, a user must have Processing installed, including all libraries relating to the code they wish to run. It also allows the user to copy and edit the source code, compromising intellectual property. Currently, the SEED Tool is disseminated by exporting the programme as a 'Java Application' (for Windows) from Processing Version 2.1.1. The Java runtime (JRE) is embedded with the exported application. This ensures users are not required to install software on their machine in order to run the application. When the application is exported, a folder is created for the application containing a Windows Batch File; a folder containing all libraries as Executable Jar Files; and a replication of the Processing data folder. The user double clicks on the Windows Batch File to run the tool. A Windows Batch File is a script file consisting of a series of commands which, when opened, are executed by the command line interpreter. Executable Jar Files are Java Archive 'package files' containing additional data (in this case Processing libraries) needed to run the main programme. The data folder contains all of the ANN weights in CSV format.

The aforementioned process enables the SEED Tool to run on Windows only. In order for the tool to be used across multiple operating systems, a recommended future development would be to create a web-based version of the programme. One method, which would enable the SEED Tool to be embedded in a website efficiently, without the need to download the application and its related folders and files, would be to transfer the source code to JavaScript, as discussed in Section 10.5.

7.4 Summary

This chapter outlined the design and development of the user interface for the SEED Tool. The first part of the chapter described and explained the layout and user function design of the user interface. The second part of the chapter defined the computation that was necessary to develop the user interface, including generating the inputs and simulating the ANN method with the tool. Finally, the strategy to disseminate the tool was outlined.

The following chapter is a validation of the accuracy and usability of the SEED Tool by carrying out case studies with new school buildings and testing the tool in workshops with professional architects and engineers.

Chapter 8

Validation: Case Studies and Feedback From Designers

8.1 Overview

The previous chapter outlined the design and development of the SEED Tool user interface. This chapter is a validation of the accuracy and usability of the SEED Tool. The chapter is broken into two main parts: case studies and user workshops. The first main part, case studies, assesses the accuracy of the ANN algorithm at predicting new building designs by inputting data from four recently constructed school buildings (2004-2010) and comparing the ANN predictions with actual metered energy figures. The second main part outlines a set of workshops that were set up to test the usability of the tool. The workshops involved a number of design professionals testing the software and completing a questionnaire. This chapter is the final part of the main work stages, validation, as outlined in Figure 8.1.

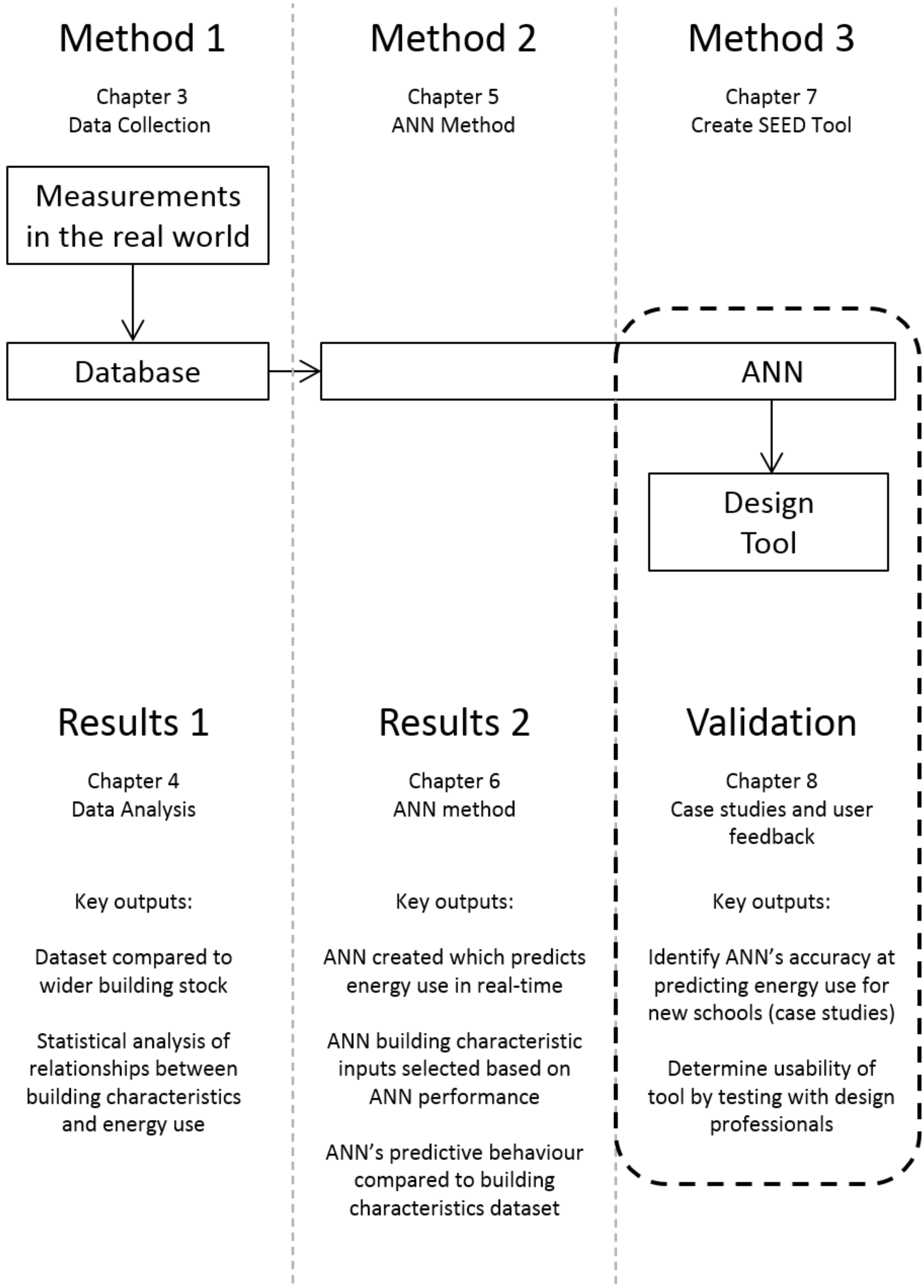


Figure 8.1: Breakdown of work stages: validation

8.2 Case Studies

8.2.1 Overview

As part of the ANN training process, the accuracy of the energy predictions were tested with a proportion of the schools that made up the building characteristics dataset. The ANN input data is made up of a range of parameters, including construction age. A proportion of the differences in, for example, fabric quality and building systems between newer schools and older schools are likely to be picked up in the construction year neuron, as discussed in Section 6.3.1 ('Constriction Year') and Section 6.3.2 ('Construction Year'). Therefore, this neuron will exist within the trained network in the final design tool but fixed to the most recent date as a historical construction year is not a design or briefing parameter. However, in order to evaluate the accuracy of the tool at predicting energy use in new school designs, an additional level of validation was deemed necessary.

Validation of simulation tools is a non-trivial task (Morbitzer 2003). This complex issue has resulted in the development of validation procedures, such as the Building Energy Simulation Test (BESTEST) (Judkoff and Neymark 1995). The BESTEST procedure requires the specification of input parameters – such as construction details and internal heat gains – and the outputs for energy use that are assessed are end use, such as heating and cooling loads. As this level of detail in the SEED Tool's inputs cannot be specified and the outputs (based on DEC energy data) are not end use, the BESTEST procedure is not suitable for the SEED Tool. Professor Joe Clarke, the progenitor of the building energy simulation programme ESP-r, states that a programme's predictive accuracy can ultimately only be evaluated by comparing its outputs with actual buildings in use (Clarke 2001).

In view of this, multiple case studies of recently constructed buildings in use will be used to assess the accuracy of the SEED Tool at predicting energy use in new buildings. This is by no means a comprehensive validation process, however, it offers an assessment of the method's ability to predict operational energy use in new building designs. The case studies are four school buildings. As outlined in the sections that follow, the author was able to gain access to building characteristics and actual energy use data that correspond to the inputs and outputs of the ANN models. For comparison, the ANN predictions will be compared to the original design calculations, where available. The four schools were chosen due to their variation in size, construction material, location in England, ventilation strategy and phase of education.

It should be noted that the case studies will assess the ANN method. The SEED Tool interface will not be used to generate the inputs, instead, the inputs will be entered into the ANN algorithms in MATLAB. This is because the case studies are completed buildings and therefore have very specific geometry descriptions. It is therefore more efficient to input the geometry parameters directly into the ANN algorithm rather recreate them using the SEED Tool interface.

8.2.2 Loxford School of Science and Technology

Background

Loxford School of Science and Technology is a secondary school and sixth form with academy status. It has a primary school building on the same campus however it is only the secondary school and sixth form which forms the basis of this case study. Figures 8.2 and 8.3 show the case study building. The school is located in the Ilford area of the London Borough of Redbridge. It was built in 2010 and designed by AHR (2014)[1].

[1] AHR was formerly known as Aedas Architects

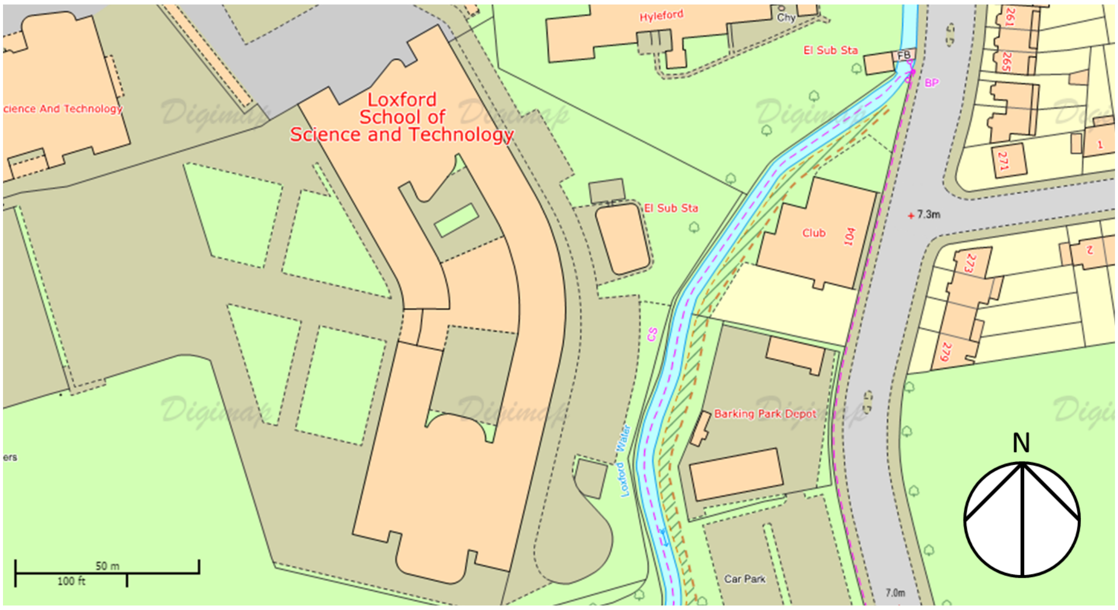


Figure 8.2: Loxford School: site plan

Figure 8.3: Loxford School: aerial satellite view

Loxford Building Characteristics

The school is a detached building with predominantly three storeys, however, there are two 'pods' which are four storeys. One pod contains the main assembly hall and refectory and the other contains a library/resource centre. The building has a curved facade and two court-yards. A major proportion of the building's facades face a predominantly west-east direction

– this is where the majority of teaching spaces are located. The building has a concrete frame with flat slab construction. The external skin is formed from pre-cast concrete panels finished with brick tiles. The heating fuel is natural gas, with space heating being provided via radiators. The building is predominantly naturally ventilated and designed to allow night cooling in the summer. Mechanical ventilation with heat recovery is provided to limited areas.

Table 8.1 shows a summary of the data that was collected in order to generate the ANN inputs. Data on Loxford school was gathered from a variety of sources. As the building was designed by the industrial sponsor[2] of this research, the author was granted access to the school's design team and architectural drawings. The DEC Energy Assessor[3] for this building was also affiliated with the industrial sponsor of this research and therefore access was granted to 'pre-visit questionnaires' (PVQ) and data used to create the building's Display Energy Certificate (DEC).

PVQs are questionnaires that were part of the Building Performance Evaluation (BPE) project, sponsored by Innovate UK (2015)[4]. The aim of PVQs is to collect data and information, describing various aspects of the buildings, including descriptions of the construction, building services and equipment. DECs are certificates that indicate how efficiently an existing building is being used, regarding energy consumption, when it is in operation. DECs are described in detail in Section 3.2. Table 8.2 shows the un-normalised data points that form the input parameters to the ANN algorithm.

Table 8.3 shows the actual energy use figures and building regulation compliance calculations for Loxford School. The actual energy use figures were sourced from the DEC cer-

[2] Details of the industrial sponsor partnership are given in Appendix A

[3] An Energy Assessor is a person who has been accredited by an approved accreditation scheme to produce DECs and the accompanying advisory reports

[4] Innovate UK was formerly known as The Technology Strategy Board (TSB)

Building parameter	**Value**	**Source**
Educational phase	Secondary	-
Construction year	2010	Design team
Ventilation strategy	Mixed mode	DEC
Number of pupils	2000	Design team
Occupancy hours	Standard	DEC
Floor area	$14610m^2$	DEC
Volume	$52596m^3$	Floor area x floor to floor height
Number of storeys	3-4	Drawings
Degrees N,S.E,W. facades are off true N,S,E,W.	-5^o (averaged)	Derived from drawings
North facade area	$1259m^2$	Derived from drawings and PVQ
South facade area	$1613m^2$	Derived from drawings and PVQ
East facade area	$1657m^2$	Derived from drawings and PVQ
West facade area	$1923m^2$	Derived from drawings and PVQ
Total glazing area	$1931m^2$	PVQ
Glazing percentage: north facades	13.3%	Derived from drawings and PVQ
Glazing percentage: south facades	15.3%	Derived from drawings and PVQ
Glazing percentage: east facades	33.9%	Derived from drawings and PVQ
Glazing percentage: west facades	37.5%	Derived from drawings and PVQ

Table 8.1: Loxford School: building parameters

ANN Input	**Un-normalised value**
Building depth ratio	6.63923
Surface exposure ratio	0.24087
Floor area	14610m^2
Orientation correction	-5^o
Construction year	2010
Ventilation strategy	[1] Mech. Vent.
Glazing ratio on northern facades	0.01757
Glazing ratio on southern facades	0.02024
Glazing ratio on eastern facades	0.04477
Glazing ratio on western facades	0.04960
Occupancy hours	[-1] Standard
Phase of education	[1] Secondary
Number of pupils	2000

Table 8.2: Loxford School: ANN inputs

Annual energy consumption	**Value**	**Source**
Actual		
Thermal	105kWh/m^2/yr	DEC
Electricity	75kWh/m^2/yr	DEC
Original Design Calculations		
Thermal	43.3kWh/m^2/yr	Part L2A
Electricity	15.8kWh/m^2/yr	Part L2A

Table 8.3: Loxford School: annual energy consumption

tificate which was issued on 28th November 2011. These energy use figures are what the ANN algorithms are aiming to predict. The compliance calculations were submitted as part of UK Building Regulations Part L2A (HM Govenment 2010). The Part L2A calculations are a rudimentary prediction of energy use at the design stage and therefore offer a baseline to compare the ANN predictions with.

Loxford ANN Predictions and Errors

Table 8.4 shows the ANN predictions against the actual annual energy consumption figures for the school. ANN percentage errors of 9.5% and 2.7% for thermal and electricity energy consumption respectively were recorded. Figure 8.4 shows a set of bar charts visualising the comparison between the ANN predictions, the original design calculations and the actual energy consumption figures. For thermal energy consumption, the ANN predictions are a 49.3% improvement on the original design calculations. For electricity energy consumption, the ANN predictions are a 76.2% improvement on the original design calculations.

Annual Energy Consumption	**Actual (kWh/m^2/yr)**	**ANN Prediction (kWh/m^2/yr)**	**RMSE (kWh/m^2/yr)**	**Percentage Error (%)**
Thermal	105	115	10	9.5
Electricity	75	73	2	2.7

Table 8.4: Loxford School: ANN results

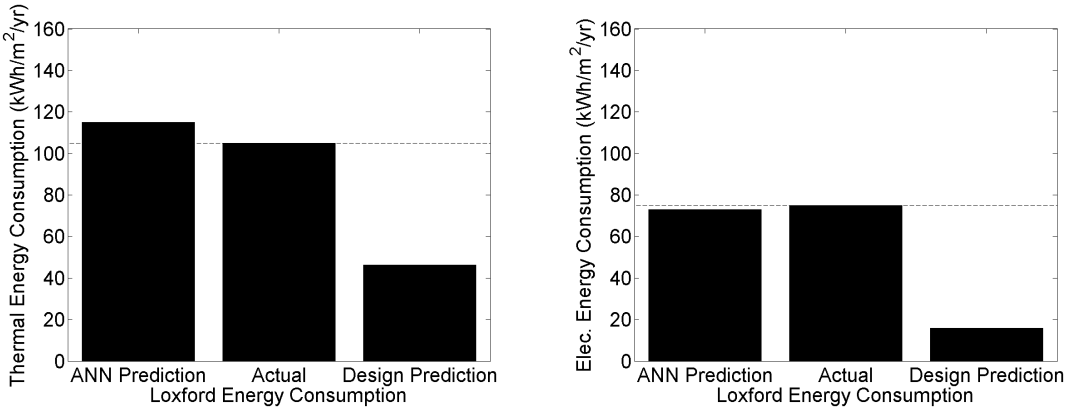


Figure 8.4: Loxford energy consumption comparisons between ANN predictions, actual energy use and original design calculations

8.2.3 Petchey Academy

Background

Petchey Academy is a secondary school located in the borough of Hackney in London. Figures 8.5 and 8.6 show the case study building. It was built in 2007 and designed by AHR (2014).

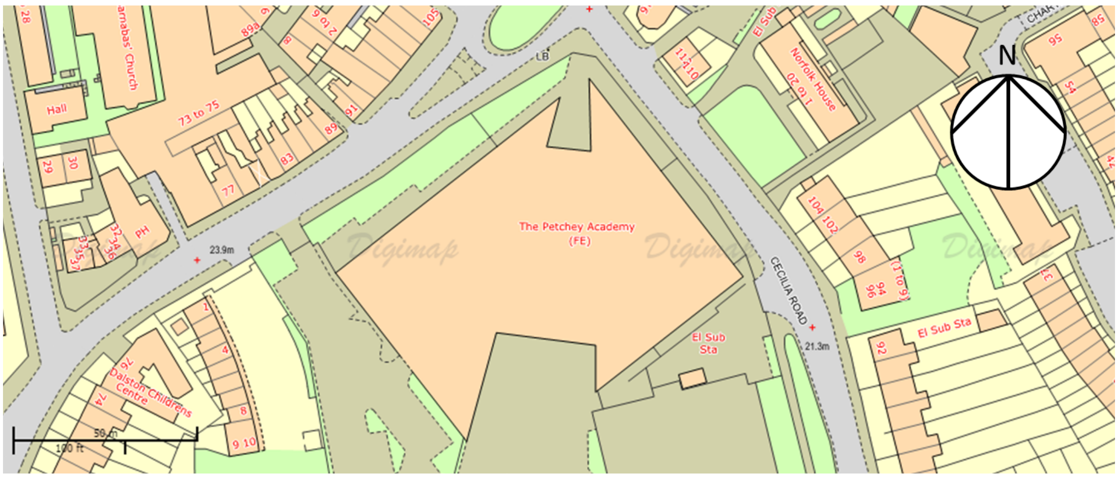


Figure 8.5: Petchey Academy: site plan

Figure 8.6: Petchey Academy: aerial satellite view

Petchey Academy Building Characteristics

The school is a detached building with predominantly three storeys. The majority of the facades face a north-west, north-east, south-west and south-east direction. The majority of the facade is a curtain wall, with glazed and opaque panels. The building also has blockwork external walls on the central strip of the building with areas of full render to external faces. The heating fuel is natural gas and the building is fully air conditioned.

Table 8.5 shows a summary of the data that was collected in order to generate the ANN inputs. As with the previous case study (Section 8.2.2), the building was designed by the industrial sponsor of this research, therefore the author was granted access to the school's design team, architectural drawings, PVQ and data used to create the DEC certificate. Table 8.6 shows the un-normalised data points that form the input parameters to the ANN algorithm.

Building parameter	**Value**	**Source**
Educational phase	Secondary	-
Construction year	2007	Design team
Ventilation strategy	Air conditioning	DEC
Number of pupils	1200	Design team
Occupancy hours	Standard	DEC
Floor area	10490m^2	DEC
Volume	37764m^3	Floor area x floor to floor height
Number of storeys	2-3	Drawings
Degrees N,S.E,W. facades are off true N,S,E,W.	-38^o	Derived from drawings
North facade area	900m^2	Derived from drawings and PVQ
South facade area	1076m^2	Derived from drawings and PVQ
East facade area	2241m^2	Derived from drawings and PVQ
West facade area	2043m^2	Derived from drawings and PVQ
Total glazing area	1194m^2	PVQ
Glazing percentage: north facades	32.0%	Derived from drawings
Glazing percentage: south facades	28.1%	Derived from drawings
Glazing percentage: east facades	30.2%	Derived from drawings
Glazing percentage: west facades	9.7%	Derived from drawings

Table 8.5: Petchey Academy: building parameters

ANN Input	Un-normalised value
Building depth ratio	9.58161
Surface exposure ratio	0.19641
Floor area	10490m^2
Orientation correction	-38^o
Construction year	2007
Ventilation strategy	[1] Mech. Vent.
Glazing ratio on north facades	0.03641
Glazing ratio on south facades	0.03200
Glazing ratio on east facades	0.03434
Glazing ratio on west facades	0.01108
Occupancy hours	[-1] Standard
Phase of education	[1] Secondary
Number of pupils	1200

Table 8.6: Petchey Academy: ANN inputs

Annual energy consumption	Value	Source
Actual		
Thermal	157kWh/m^2/yr	DEC
Electricity	146kWh/m^2/yr	DEC
Original Design Calculations		
Thermal	20.48kWh/m^2/yr	Engineering report
Electricity	30.26kWh/m^2/yr	Engineering report

Table 8.7: Petchey Academy: annual energy consumption

Table 8.7 shows the actual energy figures and original design calculations for the school. The actual energy use figures were sourced from the DEC certificate which was issued on 27th June 2013. These energy use figures are what the ANN algorithm is aiming to predict. The original design calculations were carried out by the project engineers at the early design stages. These figures give a baseline to compare the ANN predictions with.

Petchey ANN Predictions and Errors

Table 8.8 shows the ANN predictions against the actual energy consumption figures for the school. ANN percentage errors of 27.4% and 53.4% for thermal and electricity energy consumption respectively were recorded. Figure 8.7 shows the comparison between the ANN predictions, the original design calculations and the actual energy consumption figures. For thermal energy consumption, the ANN predictions are a 59.6% improvement on the original design calculations. For electricity energy consumption, the ANN predictions are a 25.9% improvement on the original design calculations. The ANN predictions are an improvement on the design calculation, however, the ANN prediction errors are the highest of the four case studies, particularly for electricity energy use. The reason the electricity energy use was not predicted with any great accuracy is likely because the building is fully air conditioned. As outlined in Table 4.11 (Section 4.2.3, 'Services'), there were no air conditioned buildings in the building characteristics dataset that was used to train the ANNs. This meant that the ANNs used in this research were not able to learn the pattern of electrical energy that air conditioned buildings consume. This is a limitation that is discussed in Section 9.3.2.

Annual Energy Consumption	Actual (kWh/m^2/yr)	ANN Prediction (kWh/m^2/yr)	RMSE (kWh/m^2/yr)	Percentage Error (%)
Thermal	157	114	43.0	27.4
Electricity	146	68	78.0	53.4

Table 8.8: Petchey Academy: ANN results

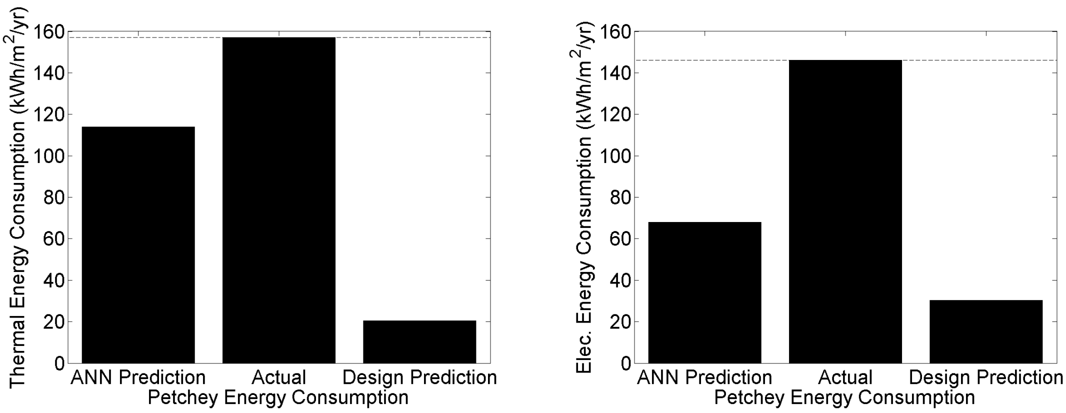


Figure 8.7: Petchey energy consumption comparisons between ANN predictions, actual energy use and original design calculations

8.2.4 Kingsmead Primary School

Background

Kingsmead Primary school is located in Northwich, Cheshire. Figures 8.8 and 8.9 show the case study building. It was designed by White Design (2015) and constructed in 2004.

Kingsmead Building Characteristics

The school is a detached one storey building and is the smallest of the case studies, with an internal floor area of 1296m^2. The building has a curved facade with the majority of the teaching spaces facing a northery direction. Each classroom has an unheated glazed

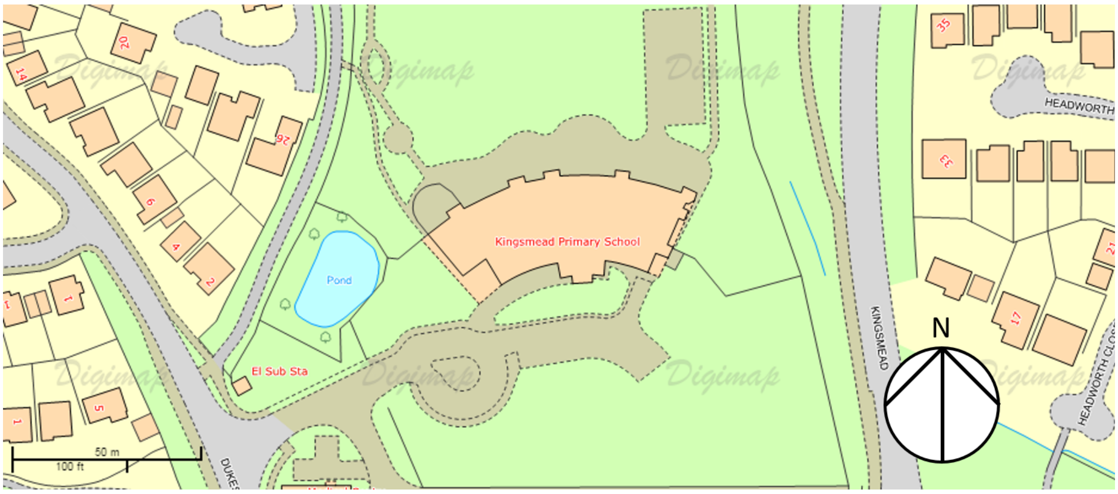


Figure 8.8: Kingsmead Primary School: site plan

Figure 8.9: Kingsmead Primary School

'wintergarden' that protrudes from the main building. The school hall and offices face a southerly direction. The building has a glulam timber frame and timber clad facades. The internal walls are a non-load-bearing concrete block construction.

The heating system is a biomass boiler and gas-fired condensing boiler. The biomass boiler was intended to provide the majority of the thermal requirement, being supported by the gas boiler when required, however, during the period of energy measurements for this case study (2005) the biomass boiler wasn't functioning and the gas boiler served the full heating load (DfES 2006). Solar water heaters were designed to provide 20% of the domestic hot water demand, however, as of the period of energy measurements for this analysis, the solar water heaters were not functioning and the gas boiler provided all of the hot water requirements (DfES 2006). Therefore, for the purposes of this analysis, all of the thermal energy consumption of the building can be viewed as being serviced from a gas boiler. The building is naturally ventilated, primarily by high and low openings on the facade and openable rooflights.

Table 8.9 shows a summary of the data that was collected in order to generate the ANN inputs. Data on Kingsmead was gathered primarily from a book published by The Department for Education and Skills (DfES 2006), entitled 'Schools For the Future: Design of Sustainable Schools, Case Studies'. Table 8.10 shows the un-normalised data points that form the input parameters to the ANN algorithm.

Table 8.11 shows the actual energy use figures for Kingsmead Primary School, measured in 2005. These energy use figures are what the ANN algorithm is aiming to predict. No original design calculations were publicly available for this school.

Building parameter	Value	Source
Educational phase	Primary	-
Construction year	2004	(DfES 2006)
Ventilation strategy	Natural ventilation	(DfES 2006)
Number of pupils	250	(DfES 2006)
Occupancy hours	0730-1800	(DfES 2006)
Floor area	1296m^2	(DfES 2006)
Volume	5163m^3	Derived from drawings
Number of storeys	1	Drawings
Degrees N,S.E,W. facades are off true N,S,E,W.	-10^o (average)	Derived from drawings
North facade area	375m^2	Derived from drawings
South facade area	230m^2	Derived from drawings
East facade area	137m^2	Derived from drawings
West facade area	141m^2	Derived from drawings
Total glazing area	883m^2	Derived from drawings
Glazing percentage: north facades	19%[5]	Derived from drawings
Glazing percentage: south facades	10%	Derived from drawings
Glazing percentage: east facades	23%	Derived from drawings
Glazing percentage: west facades	4%	Derived from drawings

Table 8.9: Kingsmead Primary School: building parameters

ANN Input	**Un-normalised value**
Building depth ratio	5.86039
Surface exposure ratio	0.42146
Floor area	1296m^2
Orientation correction	-10^o
Construction year	2004
Ventilation strategy	[-1] Nat. Vent.
Glazing ratio on north facades	0.05478
Glazing ratio on south facades	0.01698
Glazing ratio on east facades	0.02469
Glazing ratio on west facades	0.00463
Occupancy hours	[1] Extended
Phase of education	[-1] Primary
Number of pupils	250

Table 8.10: Kingsmead Primary School: ANN inputs

Annual energy consumption	**Value**	**Source**
Actual		
Thermal	103kWh/m^2/yr	DfES
Electricity	72kWh/m^2/yr	DfES

Table 8.11: Kingsmead Primary School: annual energy consumption

Kingsmead ANN predictions and errors

Table 8.12 and Figure 8.10 show the ANN predictions for annual energy use against the actual annual energy use figures for Kingsmead Primary. ANN percentage errors of 25.2% and 22.2% for thermal and electricity energy consumption respectively were recorded.

Annual Energy Consumption	Actual (kWh/m^2/yr)	ANN Prediction (kWh/m^2/yr)	RMSE (kWh/m^2/yr)	Percentage Error (%)
Thermal	103	129	26	25.2
Electricity	72	56	16	22.2

Table 8.12: Kingsmead Primary School: ANN results

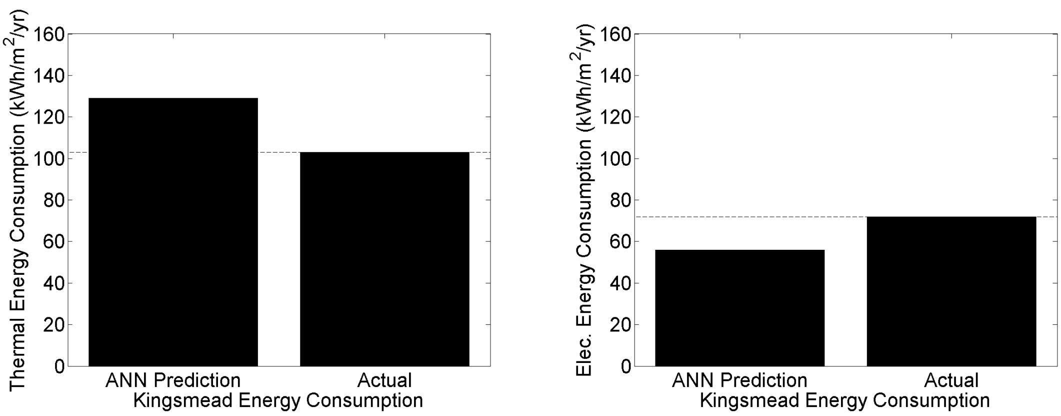


Figure 8.10: Kingsmead energy consumption comparisons between ANN predictions and actual energy use

8.2.5 The Academy of St Francis of Assisi

Background

The Academy of St Francis of Assisi is a secondary school in Liverpool. Figures 8.11 and 8.12 show the case study building. The building was designed by Capita Percy Thomas.

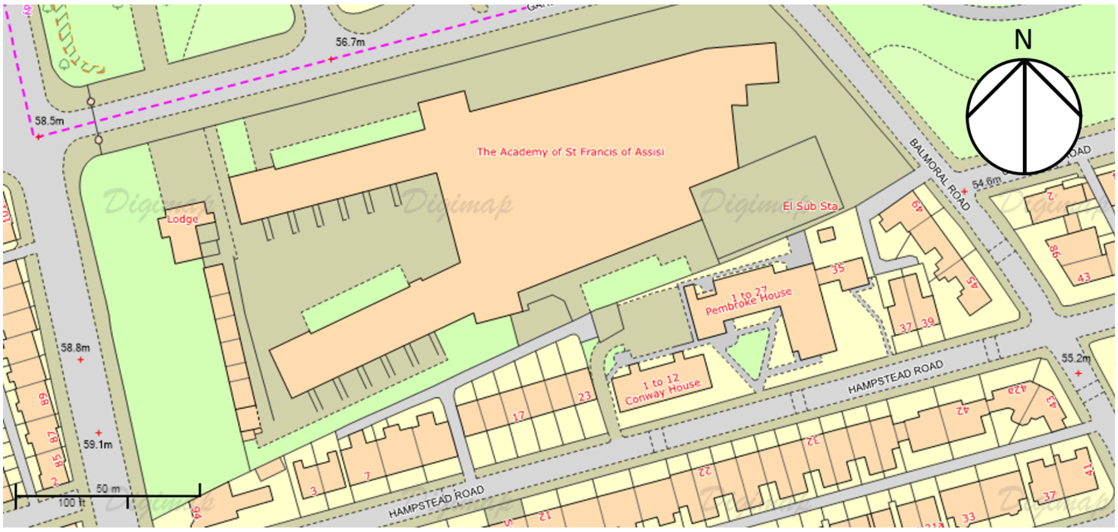


Figure 8.11: The Academy of St Francis of Assisi: site plan

Figure 8.12: The Academy of St Francis of Assisi: aerial satellite view

St Francis of Assisi Building Characteristics

The school is a detached building with a number of storeys, ranging from one to four storeys above ground and one storey underground, where the school's two halls are located. An atrium climbs the height of the four storeys above ground. The majority of the facades face a north-south direction. A variety of brick, copper cladding and timber form the external envelope of the building. Concrete forms the internal structure of the building. Parts of the lower storeys have a sedum roof. The south facing atrium has an ethylene tetrafluoroethylene (ETFE) skin – an inflated, transparent, plastic material. The thermal energy needs of the school are serviced by a gas boiler. The building is largely naturally ventilated, however, significant portions are mechanically serviced: the craft and science rooms have mechanical extracts; the underground spaces and dining room have mechanical supply and extract; and mechanical cooling is provided to two information and communications technology rooms.

Table 8.13 shows a summary of the data that was collected in order to generate the ANN inputs. As with the previous case study, data on St Francis was gathered primarily from a book published by The Department for Education and Skills (DfES 2006). Table 8.14 shows the un-normalised data points that form the input parameters to the ANN algorithm.

Table 8.15 shows the actual energy use figures and original design calculations for the school. The actual energy figures were sourced from DfES (2006). The energy use was measured in 2005 and into 2006. These energy use figures are what the ANN algorithm is aiming to predict. The original design calculations were carried out by the project engineers at the early design stages. These figures give a baseline to compare the ANN predictions with.

The Academy of St Francis of Assisi ANN Predictions and Errors

Table 8.16 shows the ANN predictions for annual energy consumption against the actual energy consumption figures for The Academy of St Francis of Assisi. ANN percentage errors of 11.6% and 5.5% for thermal and electricity energy consumption respectively were recorded.

Building parameter	Value	Source
Educational phase	Secondary	-
Construction year	2006	(DfES 2006)
Ventilation strategy	Part Natural, Part Mechanical	(DfES 2006)
Number of pupils	900	(DfES 2006)
Occupancy hours	0815-1800	(DfES 2006)
Floor area	7704m^2	(DfES 2006)
Volume	24268m^3	Derived from drawings
Number of storeys	1-5 (inc. basement)	Drawings
Degrees N,S.E,W. facades are off true N,S,E,W.	-16^o	Derived from drawings
North facade area	1581m^2	Derived from drawings
South facade area	1484m^2	Derived from drawings
East facade area	442m^2	Derived from drawings
West facade area	454m^2	Derived from drawings
Total glazing area	961m^2	Derived from drawings
Glazing percentage: north facades	18%[6]	Derived from drawings
Glazing percentage: south facades	39%	Derived from drawings
Glazing percentage: east facades	12%	Derived from drawings
Glazing percentage: west facades	10%	Derived from drawings

Table 8.13: The Academy of St Francis of Assisi: building parameters

ANN Input	**Un-normalised value**
Building depth ratio	6.12633
Surface exposure ratio	0.34439
Floor area	7704m^2
Orientation correction	-16^o
Construction year	2006
Ventilation strategy	[1] Mech. vent.
Glazing ratio on north facades	0.03731
Glazing ratio on south facades	0,07509
Glazing ratio on east facades	0.00669
Glazing ratio on west facades	0.00572
Occupancy hours	[1] Extended
Phase of education	[1] Secondary
Number of pupils	900

Table 8.14: The Academy of St Francis of Assisi: ANN inputs

Annual energy consumption	**Value**	**Source**
Actual		
Thermal	138kWh/m^2/yr	DfES (2006)
Electricity	73kWh/m^2/yr	DfES (2006)
Original Design Calculations		
Thermal	16kWh/m^2/yr	DfES (2006)
Electricity	22kWh/m^2/yr	DfES (2006)

Table 8.15: The Academy of St Francis of Assisi: annual energy consumption

Figure 8.13 shows the comparison between the ANN predictions, the original design calculations and the actual energy consumption figures. For thermal energy consumption, the ANN predictions are a 76% improvement on the original design calculations. For electricity energy consumption, the ANN predictions are a 64.5% improvement on the original design calculations.

Annual Energy Consumption	**Actual ($kWh/m^2/yr$)**	**ANN Prediction ($kWh/m^2/yr$)**	**RMSE ($kWh/m^2/yr$)**	**Percentage Error (%)**
Thermal	138	122	16	11.6
Electricity	73	69	4	5.5

Table 8.16: The Academy of St Francis of Assisi: ANN results

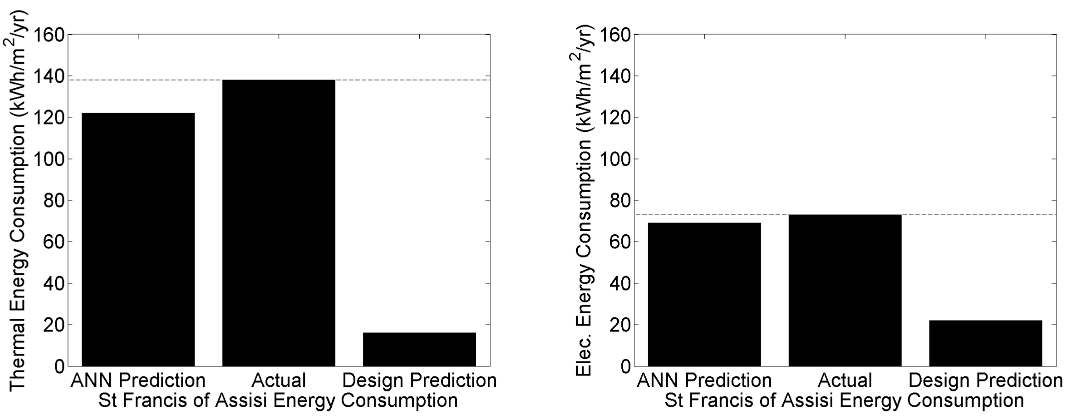


Figure 8.13: St Francis of Assisi energy consumption comparisons between ANN predictions, actual energy use and original design calculations

8.2.6 Summary

Table 8.17 shows a comparison of the mean absolute percentage errors (MAPE) between the original design calculations (where available) and the ANN predictions of the case studies. The results show that the ANNs are more accurate than the original design calculations, with an improvement of 59.6% for thermal energy predictions and 55.1% for electricity energy predictions. It was shown that the ANN method's greatest errors were in the prediction of the fully air conditioned building, Petchey Academy, as air conditioned buildings are outside the boundary conditions of the ANN training data. For comparison, Table 8.18 shows the updated comparison of MAPEs of original design calculations and ANN predictions for case studies that are not air conditioned, ie. within the boundary conditions of the ANN's training data. The updated ANN prediction MAPEs are reduced to 15.5% for thermal energy use and 10.1% for electricity energy use. These figures are an improvement of 58.1% for thermal energy predictions and 64.3% for electricity energy predictions when compared to the original design calculations. A holistic discussion of the case studies is provided in Section 9.3.2.

	Mean Absolute Percentage Error (MAPE) (%)	
	Thermal Energy Use	**Electricity Energy Use**
Original design calculations	78	76
ANN Predictions	18.4	20.9
Improvement	*59.6*	*55.1*

Table 8.17: Comparison of MAPEs of original design calculations and ANN predictions for all case studies

	Mean Absolute Percentage Error (MAPE) (%)	
	Thermal Energy Use	**Electricity Energy Use**
Original design calculations	73.6	74.4
ANN Predictions	15.5	10.1
Improvement	*58.1*	*64.3*

Table 8.18: Comparison of MAPEs of original design calculations and ANN predictions for case studies that are not fully air conditioned

8.3 Usability Workshops

8.3.1 Overview

This section describes a set of workshops held with design professionals in which they tested the usability of the SEED Tool interface. The workshops took place between the 30th September 2015 and the 22nd December 2015. The workshops involved a design task with set instructions together with time for general exploration where the designers were able to freely test the tool. In order to receive feedback on their user experience, a survey took place. The aim of this exercise was to discover the level of user satisfaction the participants had when using the SEED Tool. The workshops took place in the offices of the participants to minimise the time required by each professional to undertake the process. The following sections will describe the survey type used; design task implemented; and background of the participants, before outlining the feedback from the participants in detail.

8.3.2 Survey Types

Dyer (1993) distinguishes four different survey types:

- *The one-shot design*: data is collected from a single group drawn from the population of interest.

- *The before-after design*: data is collected from members of a single group on two distinct occasions.
- *The two-group controlled comparison design*: data is collected from two separate groups, where each group received a different form of treatment.
- *The two-group before-after design*: combination of the two-group controlled comparison design and the before-after design methods.

In this research, the workshops were based on the one-shot design method. Utilising the two-group controlled comparison design method would also have been interesting, with one group testing the SEED Tool and the other group testing a commercial early design stage simulation tool. However, due to the implications of this process, including sample size and the time needed to train users in the commercial tool, this was not deemed suitable within the setting of busy professional design practices, where the workshops took place.

8.3.3 Data Collection

There are various ways to collect data for surveys, including questionnaires, interviews and observations. The survey for this research was carried out in the form of a questionnaire. This approach was chosen as most workshops contained multiple participants, in a busy professional environment. A questionnaire format was deemed efficient and effective as it enabled multiple participants to give feedback simultaneously while negating the threat of group pressure affecting the responses. Questions within a questionnaire can be closed, where the range of possible answers are pre-determined, and open, where the participant can answer freely in their own words. This research contained both closed and open questions.

Participants were allowed to discuss the tool as they explored the SEED Tool interface, however, they were asked not to discuss their responses to the questionnaire, to avoid influencing each other's feedback. Furthermore, at the beginning of the process, each participant was assured their answers would be kept confidential to help ensure their responses were based on their own experience and not assumptions of what they may believe design professionals 'should know'. The workshops were structured in phases: questions about the professional background of the participants; a structured design task with a set goal plus a free reign trial of the tool; a system usability scale (SUS) test; closed questions on confidence inputting data into the tool; and open questions where the participants gave feedback to set questions in their own words. The questionnaires were filled out online and once submitted, stored in a password protected online database. The questionnaire given to the participants is presented in Appendix C.

8.3.4 Background of Designers

The workshops were carried out with 20 design professionals, of which 17 were architects, and 3 were engineers with an environmental science background. In the following sections, the term 'designer' will be used if a statement relates to both architects and engineers. All designers have industrial experience and range from recently graduated professionals to managing directors. 3 designers have experience in domestic buildings only; 4 designers have experience in non-domestic buildings only; and 13 designers have experience in both domestic and non-domestic sectors. 12 designers have experience designing education buildings. 14 designers stated that they have experience using simulation tools. 6 architects stated that they have no experience using building energy simulation tools.

8.3.5 User Interface Task

Users were asked to complete the task outlined in Figure 8.14. The aim of the task was to assess how users reacted to using the tool when given a simple design brief. As the tool is designed to explore the design space, the users were encouraged to freely test the tool with their own designs for as long as they desired, after completing the set task.

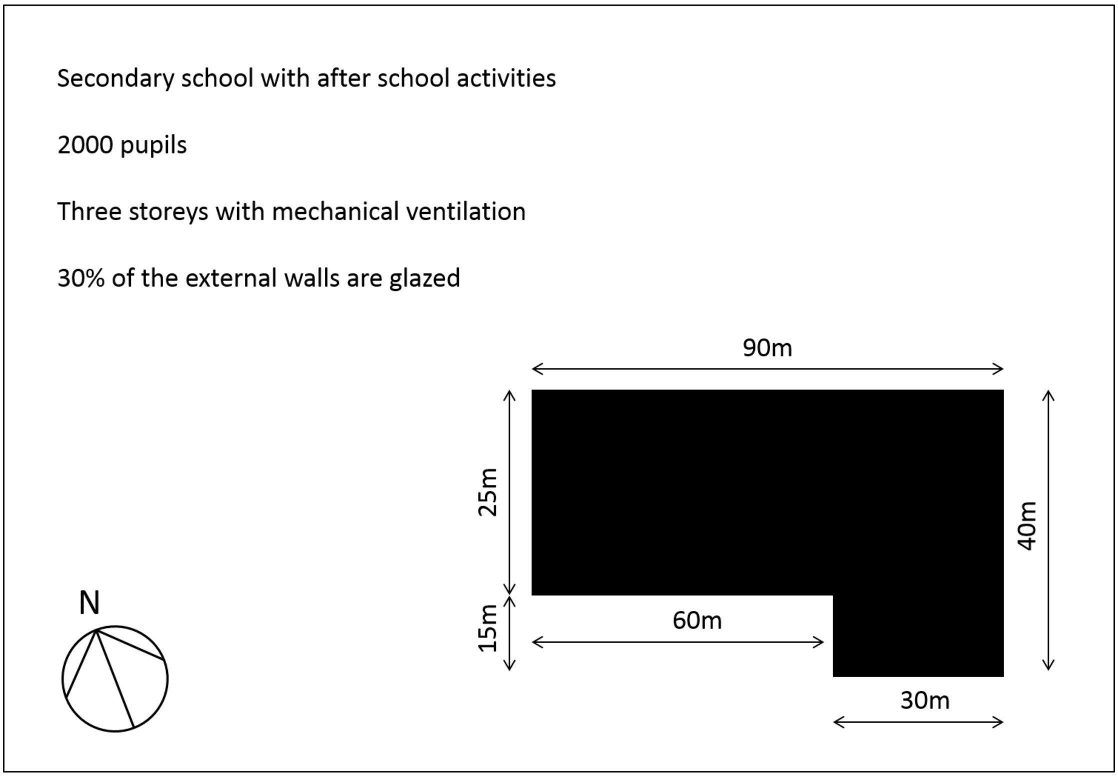


Figure 8.14: Workshop task: to be completed using the SEED Tool

8.3.6 System Usability Scale

Immediately after testing the tool, the users were asked to complete a standardised set of questions designed to test user interface satisfaction: The System Usability Scale (SUS) (Brooke 1996). The SUS is a set of 10 pre-defined questions. Using the Likert scale, users expressed their agreement with each question on a 5 point scale:

– Strongly agree

– Agree

– Neither agree nor disagree

– Disagree

– Strongly disagree

Half of the questions were 'positive' questions and the other half were 'negative' questions. The scoring system for each answer ranges from a minimum of 0 to a maximum of 4. The higher the score the more usable the tool is perceived to be. Positive questions were when 'strongly agree' gives the maximum score of 4 and 'strongly disagree' gives the minimum score of 0. Negative questions were when 'strongly disagree' gives the maximum score and 'strongly agree' gives the minimum score. The sum of the 10 scores was calculated and this number was multiplied by 2.5. The mean score for all of the participants was taken, giving a final overall score in the range of 0 to 100. Figure 8.15 shows the interpretation of the mean SUS scores.

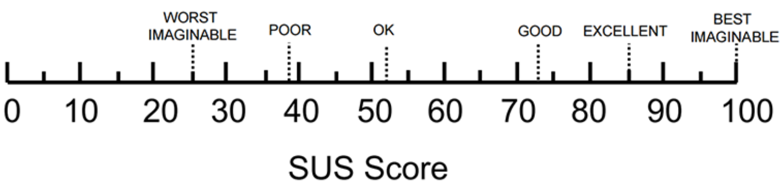


Figure 8.15: Interpretation of Mean SUS Scores (Bangor et al. 2009)

Figure 8.16 shows the results of the positive questions in the SUS test, whereby agreeing with the question indicates user satisfaction. Figure 8.17 shows the results of the negative questions in the SUS test, whereby disagreeing with the question indicates user satisfaction.

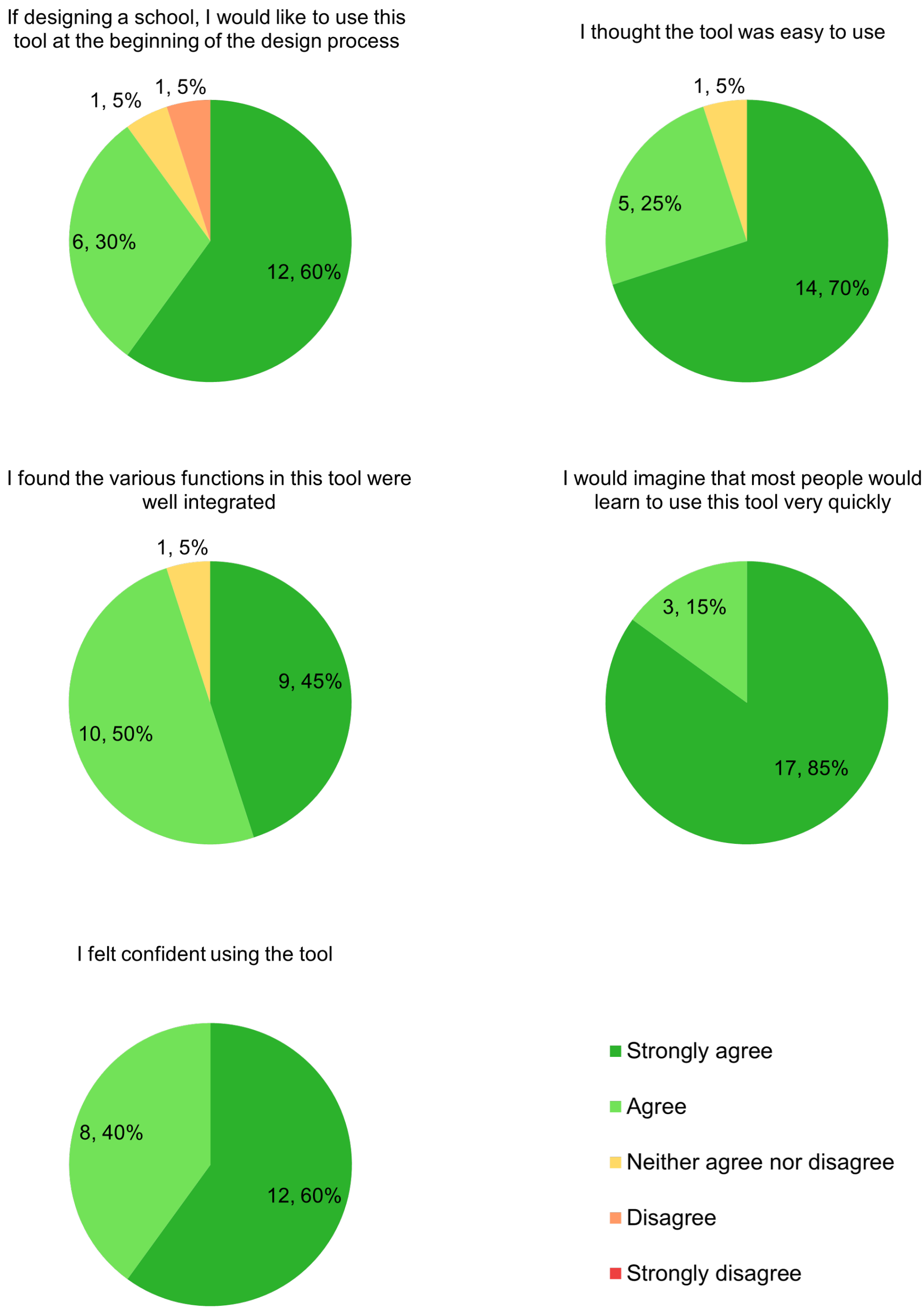


Figure 8.16: System Usability Scale (SUS) 'positive' question responses

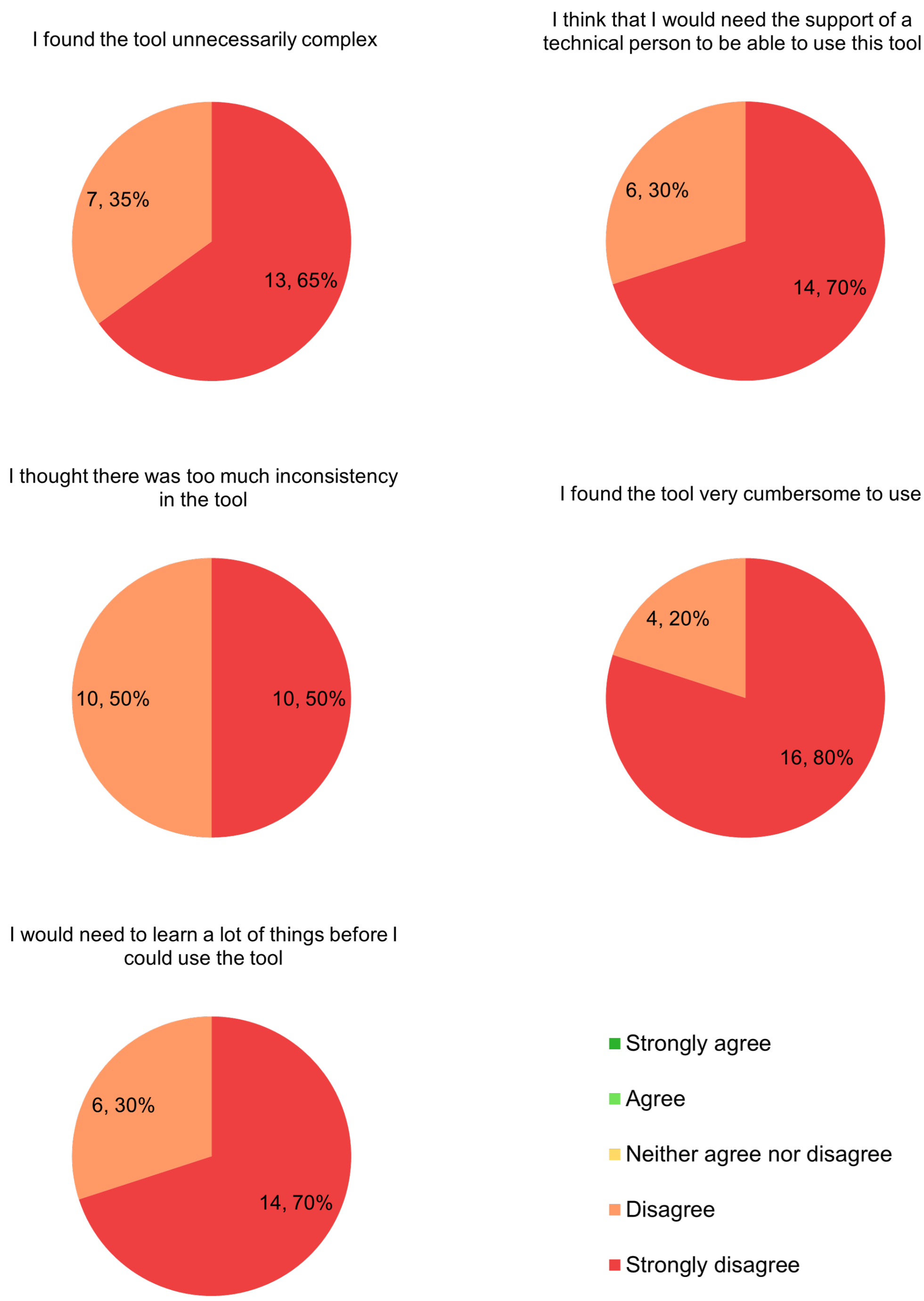


Figure 8.17: System Usability Scale (SUS) 'negative' question responses

The positive and negative question responses are grouped for clarity in interpreting the results, however, they were intertwined when the participants were answering the questions. The figures show that the tool scored favourably in relation to usability. Figure 8.16 shows that of the twenty designers, 18 said they would use the tool on a real project. One user was indifferent about the ease of use of the tool and one user neither agreed or disagreed that the functions in the tool were well integrated. All other users either agreed or strongly agreed with the 'positive' questions. Figure 8.17 shows that all of the designers either disagreed or strongly disagreed with all of the 'negative' questions, indicating user satisfaction. The mean SUS score for the tool was 90.8 out of a possible 100. As shown in Figure 8.18, this categorises the usability of the SEED Tool as 'excellent'.

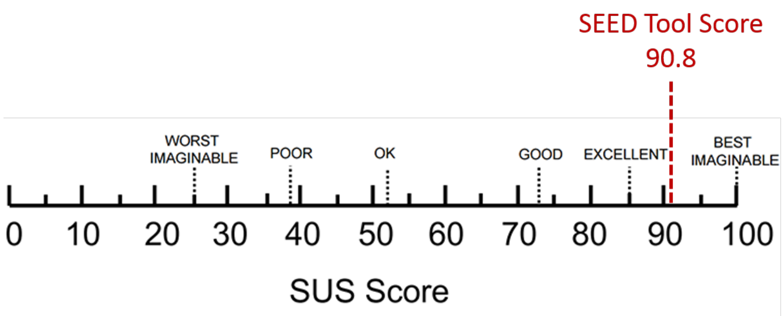


Figure 8.18: SEED Tool SUS score

8.3.7 User Confidence Altering Input Parameters

The users were asked how familiar they were with each of the tool's inputs. These questions were asked because a barrier to architects adopting energy prediction tools, as identified in Sections 1.4 and 2.3, is the complexity of model inputs in current tools. As such, these questions aimed to ascertain how confident each user would be when inputting design data into the tool. Figure 8.19 and Figure 8.20 show the responses.

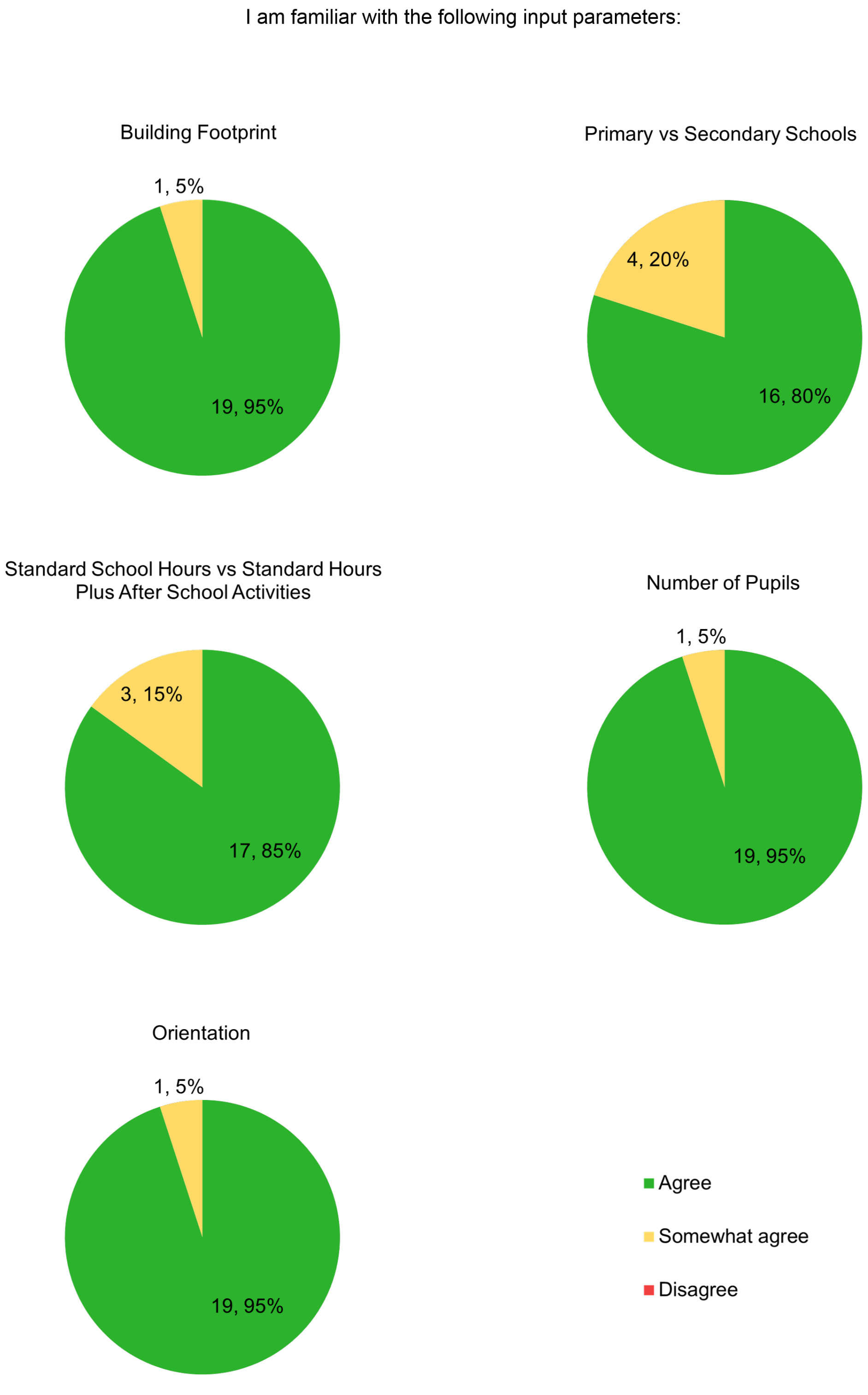


Figure 8.19: Knowledge of SEED Tool Inputs: Participants Responses (1 of 2)

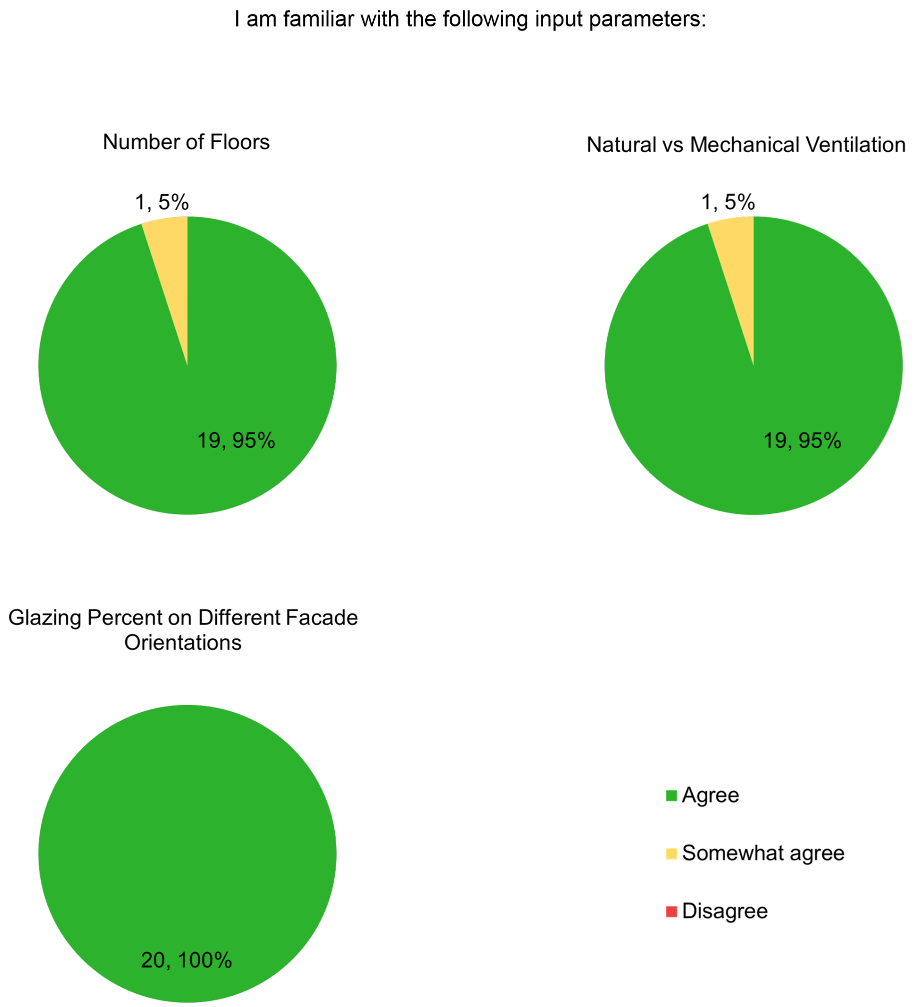


Figure 8.20: Knowledge of SEED Tool Inputs: Participants Responses (2 of 2)

The results show that the majority of designers agreed that they were familiar with all of the inputs. The input of selecting whether the school is a Primary School or Secondary School had four users somewhat agree to being familiar with the input and the input of selecting *standard school hours* versus *standard hours plus after school activities* had three users somewhat agreeing that they were familiar with this input. Users were asked what extra information would be desired if they disagreed that they were familiar a particular input. The majority of the users stated that no further information would be needed describing the inputs. Three users stated that as they did not attend schooling in the UK, they were unaware of the exact meaning and age range of the students in English primary and secondary schools. One user made a general suggestion that a one sentence description should be given with each input. .

8.3.8 Open Questions

The following sections outline the responses to the set of open questions given to the participants. As the questions were open, the participants answered in their own words. As some answers overlapped with others and common themes ran throughout, the responses are grouped and presented in the following sections. The original questions are given in Appendix C.

Interpreting the Results

Visual Presentation

It was stated that giving the energy results per metre squared helped the user compare results with different design options. The simple graphics were said to be 'without clutter and unnecessary detail', and therefore helped the participants focus and spend time on what the results mean, rather than spending time simply trying to produce a coherent result as they do with other tools. Two architects stated that the bar chart design visualised the results better than figures alone, helping them to better visualise and interpret the results – another stating that the bar graph updating in real-time gave 'meaning' to the results, something they said gets lost when they receive static numbers as results in other tools. The combination of bar graphs and figures were said to be intuitive to read and that the results stood out in a very clear and simple manner. On the negative side, one architect felt that the fact that there was no breakdown in end uses made interpreting the results difficult.

Benchmarks

The presence of energy benchmarks was said by a number of architects to be helpful as they put the results in 'context'. A number of architects stated that they do not know what high, low or typical energy consumption figures are for school buildings and therefore without benchmarks, the tool would be less meaningful.

Prediction Range

A number of architects and all three engineers pointed out that the prediction ranges in the bar graphs were useful. It was expressed that users with a familiarity in statistics would be able to understand the meaning of the error bars, however, users without this knowledge may not fully understand them. The previous observation seems to have been correct for five architects in the study, who stated that they did not know what the prediction ranges were; of these five users, one stated they understood their meaning after pressing 'i'[7] on the keyboard which helped explained it. It was also expressed by an engineer that the prediction ranges give the user confidence in the integrity of the tool as they are aware from professional experience that simulations do not produce results which exactly match with reality. Prevailing feedback stated that the predictions, along with the ranges of uncertainty, was the correct amount of information needed at the very early stages of design.

[7]'i' brings up extra information on the interface, as outlined in Section 7.2.3

Feedback

Real-time

All designers stated that the real-time feedback was useful with many claiming it to be the most helpful aspect of the tool. Along with the efficiency aspects of real-time feedback, for example, reducing the need to run multiple simulations, as discussed below ('Speed of Results'), it was brought up by a number of designers that having the results updating in real-time helped them appreciate the impact of individual alterations to a design; by visualising the results in real-time as inputs were altered, the designers said they were able to learn the relationships between different inputs and energy use outputs. Due to the ability of assessing the impact different inputs had on the energy outputs, it was claimed that the tool acts as an 'interactive sensitivity study'. The interactivity of the tool was said to allow the user to quickly identify what inputs had the greatest impact on the energy outputs and therefore enabled the user to prioritise those inputs when making design changes. An engineer said this was beneficial as there are many inputs they do not have the time to isolated for individual analysis. On top of this, a number of architects stated that the tool was educational as they were able to 'learn' what impact different building characteristic inputs had on the energy outputs. One architect stated that because the bar graphs moved as they altered inputs, they felt as if they were manipulating the results like a 'puzzle', stating that the objective of the puzzle was to get the energy bars as low as possible.

Speed of Results

Along with real-time feedback, it was said the speed in which an initial set of results were able to be produced was amongst the most beneficial aspect of the tool. Every designer said that the tool was simple to use on the first time of trying, contributing to obtaining a quick set of results from the first attempt. Of the sixteen designers that have experience with building energy simulation tools, they all stated that this tool is superior in relation to speed of output compared with other tools. Interactivity was mentioned in the previous section ('Real-time'); on the point of interactivity in relation to speed, it was said that this aspect allowed the user to quickly explore conceptual ideas and proposals, without spending time setting up and running multiple simulations, which involves managing and re-entering 'masses' of data. Moreover, it was expressed that time and resources are often limited during concept design and for competition bids, and therefore the efficiency (speed) of using this tool make it suitable for these early design stages. In line with this, it was claimed that in other tools commonly used by the participants, designs cannot be as easily explored as with this tool – one engineer stated that they use energy simulations only after the majority of architectural decisions have been made and that they could envisage using a tool like this to explore design ideas with their architectural project partners.

Overall Experience

Intuitiveness

It was stated that the simplicity of the tool and real-time aspect were the main factors that made the tool intuitive to use. The simplicity of the tool was said to be such that architects could use the tool without the need for technical training. The fact that the inputs were limited by typical school building conditions, in the form of sliders and tick boxes, was said to make the tool intuitive as the user knows that the input data is always within reasonable limits, one engineer stating that the 'GIGO' (garbage in, garbage out) scenario is therefore less likely than with other tools. Nonetheless, some designers acknowledged that they were aware the results may be 'rough' and that a separate tool would be needed at the detailed design stages. The warnings that appeared at the bottom of the interface were also said to be helpful. Many shared the view that this constraint allowed them to freely explore design ideas because the tool does not let them stray from realistic boundaries of English school buildings. Moreover, it was said that this was useful for inexperienced designers or designers designing an English school building for the first time.

What users liked the most

When asked what aspects of the tool the users like the most, the most common responses were: the speed in which the user gets a result; the real-time feedback and interactivity of the tool; the simple interface and lack of clutter; and the fact that the inputs are constrained by sliders and tick boxes, with no requirement for numerical input. The interface was generally considered to be simple, 'approachable' and 'pleasant' to use with inputs that are easy for architects (non-simulation experts) to understand. One architect stated that the tool enabled a quick assessment of energy without 'needing an engineer on the phone'.

Recommended Improvements

Two engineers stated that they would have liked more details, such as U-values and floor-to-ceiling heights. An architect suggested enlarging the building footprint canvas, as they are used to drawing packages that dedicate more screen space for geometry input; another requesting a 3D visualisation of the building geometry. Another architect requested using the same shortcut commands that other popular CAD tools use. A common request was for the ability to save results and compare with future results. The ability to view energy costs was recommended; it was said that this would be useful when presenting to clients. Other recommendations were in making some of the tool's features more prominent, such as the 'tips', and the tabs for 'Activity', 'Geometry', 'Services' and 'Glazing'.

Difference Between Architects and Engineers

One observation was how architects typically desired information to be broken down into 'real-world' scenarios, whereas engineers tended to be satisfied with 'technical' descriptions. For example, within the tool, it is mentioned in the help screen (as supplementary information) that the tick boxes marked 'standard school hours' and 'standard hours plus after school activities' represent 1400 annual hours and >1400 annual hours respectively as per the CIBSE TM46 (CIBSE 2008) for schools[8]. An architect made the point that this information should be broken down into plain language, such as opening and closing times in a school day. The engineers did not find the present description of hours to be a problem. Conversely, the engineers tended to want more information, for example, U-values, as previously mentioned ('Recommended Improvements').

8.4 Summary

This chapter was a validation, in a broad sense, of the accuracy of the ANN method and usability of the SEED Tool. The chapter was broken into two main parts: case studies and user workshops. The first main part, case studies, assessed the accuracy of the ANN algorithm at predicting new building designs by inputting data from four recently constructed school buildings (2004-2010) and comparing the ANN predictions with actual metered energy figures. The second main part described a set of workshops that were set up to test the usability of the tool. The workshops involved a number of design professionals testing the software and completing a questionnaire.

The main findings from the case studies were:

- The mean absolute percentage errors (MAPEs) for these four case studies was 18.4% for thermal energy use and 20.9% for electricity energy consumption.
- The aforementioned ANN case study MAPEs are 4.5% and 1.6% lower than the MAPEs recorded during the ANN training process for thermal and electricity energy use respectively.

[8] 'Standard hours' and 'extended hours' are described in detail in Section 3.4

– The aforementioned ANN case study MAPEs are 59.6% and 55.1% lower than the original design calculations, for thermal and electricity energy use respectively.

– The ANNs predicted the energy consumption for a secondary school building with mechanical ventilation with the greatest accuracy, recording percentage errors of 9.5% and 2.7% for thermal and electricity use respectively.

– The ANNs predicted the energy use of a secondary school building with full air conditioning with the least accuracy, as air conditioned buildings are outside the boundary conditions of the ANN training data.

The main findings from the workshops were:

– For the System Usability Scale (SUS) the SEED Tool recorded a score of 90.8 out of 100, categorising the tool's usability as *excellent* for the targeted user (architect) and within the boundary conditions of the tool: early design stage school design in England.

– The designers stated that receiving results in real-time helped them understand what inputs had the greatest impact on the energy consumption outputs.

– Furthermore, it was stated that tool could be used as an educational tool – acting as an 'interactive sensitivity study', where users learn the relationships between building characteristics and energy use.

– The designers liked the uncluttered and simple appearance of the tool, making it 'approachable', 'pleasant' and intuitive to use.

– It was found that the simplicity of the tool made the designers concentrate on what implications the results have rather than put the majority of their effort into simply creating a result.

– The presence of benchmarks was said to give meaning to the results as it placed them in context with typical buildings; this view seemed more prevalent amongst architects.

– The designers stated that they liked the speed in which they received results, an aspect which was said to be beneficial during the time constrained early stages of design.

– The designers liked the fact that user inputs were restricted to typical values for school buildings in England, removing *garbage-in-garbage-out* scenarios

– It was observed that architects tended to desire information to be presented in non-technical language, whereas engineers recommended including more technical inputs and descriptions.

The following chapter will discuss the findings of this research.

Chapter 9

Discussion

9.1 Overview

The previous chapter was a validation of the accuracy of the artificial neural network (ANN) method and usability of the SEED Tool interface. This chapter will discuss the findings of this research as a whole and reflect on the wider implications in industry and academia. The discussion is in three main parts: Section 9.2 reflects on the data collection process that was necessary to carry out this research; Section 9.3 reflects on the machine learning method that predicts operational energy use of school buildings in England; and Section 9.4 reflects on the creation of a user-friendly tool with the aim of enabling non-simulation experts, such as architects, the ability to use the machine learning method as a design tool at the early design stages.

9.2 Data Collection

The research presented in this thesis has shown that the availability of suitable data is necessary for adopting a machine learning approach. The challenge is obtaining such data in sufficient quantity. The Display Energy Certificate scheme was the primary source of data in this research. In the UK, the DEC scheme requires non-domestic public buildings that fall under specific criteria[1] to undertake its process. DECs are certificates that indicate how efficiently an existing building is being used, regarding energy consumption. Information collected from the scheme offers a source of data for statistical analysis, enabling an understanding of energy use – Bruhns, H., Jones, P., & Cohen (2011) carried out such a study. However, currently in the UK, there is not a corresponding dataset of building characteristics. The lack of such a dataset makes the analysis of energy use determinants limited. Furthermore, the ability to produce prediction models, based on a building's characteristics, is also limited. The DEC database provides some information on building characteristics, such as floor area and ventilation strategies, as described in Section 3.4.2. However, this database does not describe many other characteristics which may affect energy use. Moreover, data obtained from the DEC scheme is only available for public buildings in the UK. Therefore, data from private sector buildings, such as retail and commercial buildings, tend not to be collected through the scheme. A framework which supplies sufficient building characteristics data for future expansion and use of this method would require a more comprehensive database. CarbonBuzz, as outlined in Section 2.5.2, has the potential to crowdsource such data on a large scale (Robertson et al. 2015). However, significantly more data is required in this platform before techniques, such as machine learning, can be used (Robertson et al. 2015). Therefore, due to the lack of availability of building characteristics data, the first part of the methodology in this research, was to create a building characteristics dataset (Chapter 3).

As described in Section 3.4.1, several methods to collect building characteristics data were considered, however, a desktop approach was preferred over site visits, due to the time and resources available for a doctorate and the fact that artificial neural networks require

[1] see Section 3.2 for criteria that makes a building require a DEC

many samples to learn from (see Section 3.3.2). The data collection process benefited from the fact that ordnance survey maps are now digitalised, enabling the measurement of building parameters in a much faster way than analogue means of measuring from physical maps. The limitations of this desktop approach, however, was that limited data could be collected. For example, the collection of construction material properties, energy end uses and building services efficiencies was unable to be collected. Furthermore, despite the fact that the desktop data collection approach allowed data on more buildings to be collected, compared to site based surveys, the process was timely. The machine learning approach of learning the patterns in large amounts of data was, in part, to demonstrate the benefits of utilising big data analysis algorithms within the construction industry. As mentioned in Section 2.5.1, big data is a broad term for data that is high in volume, velocity and variety (Forbes 2013; Gartner 2016), with datasets that are at a size and complexity level that deem traditional statistics and data processing techniques inadequate. Therefore, innovative forms of information processing are required (Gartner 2016), such as neural networks. As such, the lengthy data collection process in this research, albeit streamlined in a desktop approach, is not the typical process undertaken when working with big data. As mentioned, this research is a demonstration of the benefits of big data within the construction industry. What is needed, are sources of data for building design researchers and practitioners to utilise. Section 2.5.2 introduced a number of schemes which collect building data, such as the 3D model of the non-domestic building stock of England and Wales by UCL Energy Institute (2014) and the aforementioned CarbonBuzz. However, these schemes tended to be pilot studies or did not contain sufficient data to be used for machine learning purposes. It is envisioned that as sources of data within the building industry increase and are openly available, big data methods, such as that demonstrated in this research, will be able to be developed. As such, existing and future database frameworks in the construction industry should be supported by the building design and research community.

9.3 Artificial Neural Network Method

9.3.1 Overview

The literature reviewed in Section 2.4.5 showed that ANNs can be trained to control HVAC systems with fewer inputs than traditional building simulation methods. A further benefit of using ANNs over traditional methods was their ability to make energy predictions in real-time. It was demonstrated that ANNs have advantages for forming the basis of a design tool as they can be designed to be simpler (requiring fewer inputs) and produce quicker results than traditional building simulation models. However, further development is needed in order to progress current models beyond simple building geometries. It was shown that energy predictions in existing buildings with ANNs have been tested with 'synthetic' (simulated) and 'real' data, however, there is no evidence of an ANN method as a design tool for new buildings being constructed and trained from real data. It was shown that, in theory, ANNs are able to form the basis of performance prediction tools. However, from this evidence, it has emerged that there is a gap in knowledge to develop an ANN method for energy use predictions of new buildings that is based on real-world data and create a user-friendly design tool that is able to surpass simple geometry constraints. The following sections discuss the levels of success reached by training an ANN with real-world data to predict the energy consumption of school buildings, with a focus on new school designs, so that it may form the basis of a design tool (as discussed in Section 9.4).

9.3.2 Performance

The performance of the ANNs were assessed in two parts. Firstly, as part of the ANN training process, the ANNs were tested based on their accuracy at predicting a portion of the collected building characteristics dataset (Section 5.3). Secondly, the ANNs ability to predict energy use in recently constructed school buildings was assessed with four case studies

(Section 8.2).

The ANN method showed success in terms of predicting energy use with higher accuracies than the design calculations in the CarbonBuzz (2014) database for educational buildings. As previously mentioned, CarbonBuzz is an online RIBA/CIBSE platform that hosts data on buildings, including energy use data. Energy use data at various stages of a building's development is uploaded, including original design calculations and measurements made once the building is constructed and in operation. The *performance gap*, within the context of building energy consumption, is the difference in energy use (and carbon emissions) between predictions made during design and measured performance once a building is built and in use. Table 9.1 shows the comparison between the current performance gap, as determined by an audit on the CarbonBuzz data (UCL Energy Institute 2013) (described in Section 1.5 'CarbonBuzz'), and the ANN mean absolute percentage errors (MAPEs), calculated from test data within the collected building characteristics dataset (Section 6.2.1 and 6.2.2).

	Difference Between Predicted and Actual Energy Use (%)	
	Thermal Energy Use	**Electricity Energy Use**
CarbonBuzz data (schools)	32	47
ANN: test data	22.9	22.5
Improvement	*9.1*	*24.5*
Case studies original design calculations	78	76
ANN: case studies	18.4	20.9
Improvement	*59.6*	*55.1*

Table 9.1: Comparison between predicted and actual energy use

The results in Table 9.1 show that that the ANN models are an improvement of 9.1% for the prediction of thermal energy use and 24.5% for the prediction of electricity energy use when compared to the performance gap evidenced in the CarbonBuzz database.

As part of the ANN training process, the accuracy of the energy predictions were tested with the schools that made up the building characteristics dataset. The ANN inputs were made up of a range of input parameters, including construction age. A proportion of the differences in, for example, fabric quality and building systems between newer schools and older schools are likely to be picked up in the construction year neuron, as discussed in Section 6.3.1 ('Constriction Year') and Section 6.3.2 ('Construction Year'). Therefore, this neuron exists within the trained network in the final design tool but fixed to the most recent date as a historical construction year is not a design or briefing parameter. However, in order to validate the accuracy of the ANN method at predicting energy use in new school designs, four case studies were carried out (Section 8.2). The case studies were all recently constructed school buildings (2004-2010) with actual energy data.

Table 9.1 shows the MAPEs of the ANN method when predicting the energy use of the four case studies. These errors are less than the MAPEs recorded when training and testing the ANN method with the building characteristics dataset, also shown on Table 9.1. This provides evidence that the ANN method predicts new school buildings with no less accuracy than older buildings. Furthermore, Table 9.1 shows a comparison of the MAPEs between ANN predictions and the original design predictions of the case studies. The ANNs were more accurate than the original design calculations, with an improvement of 59.6% for thermal energy predictions and 55.1% for electricity energy predictions. This significant improvement highlights the success of the ANN method in being able to more accurately predict energy consumption than current design calculations for new school buildings. Section 2.3 revealed that accuracy is sacrificed, to some degree, in analysis tools in order to increase the speed at which results are generated. The ANN method presented in this thesis forms the basis of a prediction tool that does not sacrifice accuracy when generating faster, real-time, results.

During the case study analysis, it was shown that the ANN method's greatest error was in the prediction of electricity energy use for Petchey Academy. Petchey Academy was the only fully air conditioned case study building. The ANN's error at predicting electrical energy use in this school was 53.4%. This figure, however, was an improvement of 25.9% on the prediction of the original design calculation which had an error of 79.3%. Nonetheless, the ANN error may still be viewed as excessive. Table 4.11 (Section 4.2.3, 'Services') shows that no buildings collected in this research had air conditioning – therefore the ANN training dataset did not include air conditioned buildings. Due to the extra electricity consumed by air conditioning systems, it is deemed that the energy use of fully air conditioned buildings cannot be accurately predicted by the ANN method in this research as it did not have this type of data to learn from. This applies to continuous data also. As outlined in Section 7.2.3, an inherent limitation in ANN models is their inability to extrapolate – that is, make predictions for inputs outside the range of input training data. Building physics based models (traditional building energy simulation tools) do have the ability to extrapolate, which is a benefit over an ANN based prediction method. This issue highlights the necessity of having a design within the range of parameters of the ANN training data to ensure an accurate prediction when using an ANN based method. As such, any ANN based prediction tool made available to the building design community must make it clear what these boundary conditions are.

As with any prediction model, the ANN prediction errors, summarised in Table 9.1, contain a number of component errors and uncertainties, as introduced in Section 2.3.8. In order to understand the ANN prediction errors in more detail and discuss how they could be reduced in future research, it is useful to examine the contributing components of the errors. The following is a breakdown of these components:

- Systematic errors of the ANN model
- Random errors within real-world conditions

As outlined in Section 2.3.8, the systematic errors are the errors inherent within a mathematical model and the random errors are the differences between input parameter values and their true value. The systematic errors are the errors associated with the architecture of the ANN. Section 5.3 and Section 5.3.1 outlined the methods applied in order to reduce the systematic errors. This process involved two main aspects. Firstly, cumulatively adding building characteristic input parameters (input neurons) to the ANN in an order based on evidence of their influence on energy consumption, as outlined in Section 5.3.1. Secondly, altering the number of hidden neurons in the ANN models, as each set of input patterns were introduced, as outlined in Section 5.3. The systematic errors may be reduced by exploring alternative ANN architectures, such as increasing the number of hidden layers, and including new inputs parameters, as discussed in Section 10.5.

As discussed in Section 2.3.8, random errors include natural variability, such as material properties and building dimensions; occupancy behaviour; and climate. Occupancy behaviour alone can affect the outcome of energy predictions by 10-40% (Clevenger and Haymaker 2006). Furthermore, as mentioned in Section 1.5, the aforementioned energy performance gap occurs for a number of reasons, including (CBxchange 2014):

- Inaccuracies during the design process
- Design changes

– Poor quality of construction

– Inadequate commissioning

– Systems not operating as intended

Traditional building simulation tools are based on mathematical building physics models. As these models are based on building physics alone, they tend not to incorporate the aforementioned uncertainties. As previously stated: *"A major hindrance in modelling real problems is the lack of understanding of their underlying mechanisms because of complex and nonlinear interactions among various aspects of the problem [...] in many cases, the best solution is to learn system behaviour through observations"* (Samarasinghe 2007, p.1-2). Samarasinghe lays the argument to predict the behaviour of real-life systems through the study of observed data of these systems in operation, rather than modelling each individual relationship in theory. The ANN method presented in this thesis follows this approach by modelling the relationship between observed building behaviour (DEC energy use data) and measured building characteristics. This method accounts for some of the complex and random interactions of, for example, occupancy behaviour. Nonetheless, the fact that occupancy alone can affect the outcome of energy predictions by up to 40% (Clevenger and Haymaker 2006) highlights the difficulty in producing prediction models, of any type, with very small errors. The observational errors may be reduced by utilising measured data which more closely match their true value, such as using site survey measurements over digital map measurements – a process which would be more timely, unless the data is crowdsourced, as discussed in Section 3.4.1.

This research provides evidence that a machine learning approach, trained with real-world data, can be used to predict the operational energy performance of buildings with greater accuracy than traditional simulation methods. Traditional building simulation offers greater flexibility in its inputs than any other form of design aid (Morbitzer 2003), as discussed in Section 1.4. Although they have often been shown to be poor predictors of operational energy use of buildings, their flexibility allows for scenario and comparative studies. Scenario studies can involve the user testing the robustness of the building design under 'worst case scenarios ', such as future climate studies (CIBSE 2014). Comparative studies are where different design options' energy use figures are compared within a controlled environment to assist in the design decision making process. Therefore, building simulation remains an important asset for energy analysis. Nonetheless, due to the uncontrolled environment of real life, alternative approaches should be adopted when making predictions on the operational energy use of building designs. These alternative approaches may involve data input methods within traditional building simulation tools, such as agent-based modelling (Lee and Malkawi 2013), or real-world data based systems, similar to the machine learning approach presented here.

9.3.3 Model Behaviour

In order to evaluate how the ANN behaves in comparison to the behaviour of the buildings in the collected building characteristics dataset, corresponding sets of scatter plots and box plots were compared. The first set of graphs plotted energy use intensity against collected building characteristics (Sections 4.3.1 and 4.3.2). The coefficient of determination (R^2) values tended to be small (<0.5) for the scatter plot results in this analysis. This is in part due to the noise in the real-world data and also because the R^2 value is an indicator of a linear correlation, not a general correlation. Furthermore, in fields that involve human behaviour, such as the operation of buildings, low R^2 values can be expected (Frost 2013). The second set of graphs plotted ANN energy use outputs against ANN inputs generated by a Monte Carlo method (Section 6.3.1 and 6.3.2). The results of the Monte Carlo method (coefficient of determination and Kruskal-Wallis analysis) showed that the relationships between the

ANN inputs and energy outputs tended to follow a similar pattern to that of the collected data, with the ANN results tending to be concentrated along the trend lines in the scatter plots. This indicates that the ANNs were able to learn the relationships between the building characteristics and energy use despite the weak correlations (R^2 values) displayed when the building characteristics dataset was statistically analysed. There were some instances, however, when the ANN results did not follow a similar pattern to the building characteristics dataset. For example, the four glazing ANN inputs – glazing ratios on north, south, east and west facade orientations – did not all follow the trends shown in the building characteristics dataset. For the causal analyses, discussed below, all four glazing ratios were altered in sync together to simplify the analyses of the effect glazing has on thermal and electricity energy consumption. The results of this analysis were in line with the results of the building characteristics dataset. These results suggest that for the trained ANNs in this research, glazing should be treated globally, and not divided into different orientations. Glazing on different orientations do have different effects on the environment inside buildings due to the location of the sun and site conditions on different orientations, therefore it would be desirable to increase the size of the dataset in order for a future ANN method to learn these relationships with greater accuracy. This highlights a limitation of the ANN model over traditional building simulation. Traditional simulation is conducted under a controlled environment and therefore individual parameters can be analysed in isolation of all other parameters. As the ANN method was conducted under real-world conditions, some parameters may be correlated with others, therefore deeming them inadequate as input parameters as their apparent influence on energy use outputs may be misleading to the design tool user.

In order to understand more complex relationships between building characteristics and energy use, causal strength analyses were carried out (Section 6.4.1 and 6.4.2). The causal strength analyses were useful, as they enabled the analysis of individual parameters as all other parameters remained at a baseline level. A noted example of this was with floor area and pupil numbers. As expected and as shown in Figure 4.4 (Section 4.2.3, 'Geometry'), floor area is correlated to pupil numbers: as floor area increases, pupil numbers tend to increase. Both the statistical analysis of the building characteristics dataset and global sensitivity analysis of the ANN Monte Carlo data showed that as floor area increased, electrical energy use per square meter tended to increase. It was suggested that this is likely due to larger buildings tending to be secondary schools, which make greater use of ICT and electrical laboratory equipment. However, as the causal analysis was able to test the effects when only the floor area was altered, the results showed that electricity use intensity decreased as floor area increased. The effect of increasing floor area while keeping phase of education and pupil numbers at baseline levels resulted in the pupil density figures altering. In this case, a building with a large floor area and baseline pupil numbers resulted in a lower pupil density. A building with fewer pupils per square meter is therefore likely to consume less electrical energy as there will be fewer laptops and other electrical equipment used, explaining the reduction in electrical energy use intensity. This highlights the benefits of the multivariate approach inherent in the ANN method.

9.4 User-friendly Design Tool

9.4.1 Context

Section 2.3.6 outlined the different psychological states experienced when undertaking a task (Figure 2.8). In order for architects to be in a state of 'flow' when using a design tool – that is, in a mental state of energised focus, full immersement and enjoyment of the process – the task in which they are participating in must contain these conditions (as described in Section 2.3.6):

– Goals are clear

– Feedback is immediate

– Balance between challenge of task and skill of participant

These three aspects formed the basis of the design of the SEED Tool and the assessment of usability in workshops where design professionals provided feedback of their user experience when using the interface. For the System Usability Scale (SUS) the SEED Tool recorded a score of 90.8 out of 100. This categorises the tool's usability as *excellent* and is therefore deemed successful. It should be noted that the SUS score reflects the experience of the targeted user (architect), within the boundary conditions of the tool: early stage school design in England. The following sections discuss the different components of the SEED Tool interface which contributed to this SUS score.

9.4.2 Inputs

The inputs for the SEED Tool were based on:

– Intuitive methods to create ANN inputs

– Being constrained to typical values for English school buildings

The user inputs, outlined in Section 7.2.2 ('Drawing the Building Geometry' and 'Inputs'), were designed to be the minimal amount of information needed to generate inputs required for the final ANN models. The majority of the users in the user testing workshops (Section 8.3) stated that they were familiar with the inputs and did not need to seek further assistance or references to use the tool. This, together with the uncluttered and simple appearance of the tool was said to make it 'approachable' and intuitive to use. It was found that the simplicity of the tool made the designers concentrate on the energy implications of their design inputs rather than put the majority of their effort into simply generating a prediction. This is significant, as Lawson (2004) found that much of the time taken when using traditional building simulation is in the inputting of data, such that the designer can only afford to do it after the major design decisions have been made. Lawson (2004) states that when this happens, environmental analysis tools act as evaluation tools, rather than design tools. Furthermore, as outlined in Section 8.3.4, the majority of the designers that took part in the user workshops were architects. The fact that these users were confident inputting information into the SEED Tool is significant as a major barrier to non-simulation experts, such as architects, is the complexity of the tools, as shown in Sections 1.4 and 2.3. Attia (2012) found that architects found simulation "cumbersome, tedious, and costly" (Attia 2012, p.7), which forced them to outsource simulation tasks to experts during the early design stages. The fact that users were familiar with the SEED Tool inputs indicates that it would not be rejected in practice on the basis of complexity. An argument from this research is not that architects should displace the role of the engineer or simulation expert. Rather, the argument is that architects should be involved in the analysis of energy use, particularly at the early stages of design, in order to make design decisions that are based on environmental considerations. In this way, it can be foreseen that the architect will be more engaged with the engineers and simulation experts throughout the design process.

There was no ability for designers to type values into the model. Instead, they were constricted by sliders and tick boxes. Furthermore, when the design inputs exceed the data ranges of the data collected in the building characteristics dataset, a warning would appear, letting the user know that the design inputs exceed the parameter ranges of typical school buildings in England. Attia and De Herde (2011) stated that default values within simulation tools are favourable for non-simulation experts. Rather than having fixed point defaults, the SEED Tool allowed for default ranges in the aforementioned manner. Feedback from the usability workshop showed that users reacted favourably for the guidance and boundaries built into the tool. The workshop participants stated that this allowed them to freely explore design ideas as they know the tool does not allow them to stray from realistic boundaries of English school building parameters and therefore produce more realistic results. This aligns with research carried out by Attia and De Herde (2011) who found that a lack of quality control (of inputs) often results in 'garbage in garbage out' (GIGO) scenarios when analysis tools are used by non-simulation experts. The fact that users were confident in their understanding of the inputs and guided by what reasonable values the inputs should have, demonstrate that the 'flow' condition to lower the challenge of using the tool to the skill set of non-simulation experts, such as architects, was achieved. It could be envisioned that model input guidance could be integrated into future developments of existing design tools. This would help non-technical designers, such as architects, or designers designing a particular type of building, eg. English schools, for the first time.

It should also be noted that different types of users have different needs. It was observed that architects typically desired information to be broken down into plain language, as outlined in Section 8.3.8, whereas engineers desire more technical information, for example, U-values. This resonates with research carried out by Prazeres (2006), who found that users with different backgrounds desire different levels of detail – architects preferring constrained, intuitive displays, while simulation 'experts ' will sacrifice intuitiveness for greater flexibility. This highlights the conflict that many design aids have in that satisfying the desires of one type of user may come at the expense of another. Building simulation tools, designed specifically for early stage design exploration, would benefit by allowing their users the ability to 'dig down' into the inputs to gain greater detail, if desired, while remaining 'uncluttered' with inputs on the surface.

9.4.3 Interpreting the Results

The outputs of the SEED Tool were based on:

- Comparisons with benchmarks
- The provision of prediction ranges
- The simultaneous presentation of all outputs

A number of architects in the workshops stated that they did not know what high, low or typical energy use figures were for school buildings. It can be assumed that engineers will be more familiar with energy benchmarks than architects. An indication of this, beyond comments made in the interviews, is the fact that the CIBSE TM46 energy benchmarks (CIBSE 2008) are published by an engineering professional body rather than an architectural professional body. As such, the presence of benchmarks was said to give 'meaning' to the results as it placed them in context with typical buildings; a view that seemed more prevalent amongst architects as previously mentioned. This is significant as it was found in the literature review (see Section 2.3.5) that most tools fail to offer result comparisons, such as regulation compliant baselines or citable resources (Attia and De Herde 2011). It was found that architects would often ask "what to do next based on the simulation results" (Attia and De Herde 2011, p.100). Simply being able to gain an output from an analysis tool is not enough. The goal should be to gain useful information to make informed design decisions. The inclusion of benchmarks ensures the goals are clear to the user, to better enable a 'flow' condition.

As outlined in Section 2.3.3, Hamza and DeWilde (2013) conducted research looking at how to present building simulation results in the 'boardroom', that is, to individuals that may not be experts in the field of building physics. Amongst their conclusions, they stated that uncertainty in the models needs to be made clear. As such, the energy use outputs of the SEED Tool were presented with prediction ranges, in the form of statistical error bars, rather than being deterministic point values in order to convey the message to SEED Tool users that there is a level of uncertainty in the results. A number of users in the workshops pointed out that the prediction ranges in the bar graphs were useful; one engineer claimed that this gave them confidence in the integrity of the tool as they are aware from professional experience that simulations do not produce results which exactly match with reality. As discussed in Section 9.3.2, the prediction of building energy performance has inherent uncertainties (Wit and Augenbroe 2002), with occupancy behaviour alone affecting the outcome of energy predictions by up to 40% (Clevenger and Haymaker 2006). Many factors are simply unknowable (Clevenger and Haymaker 2006), however, currently, there is no standard framework for modelling uncertainty in building energy models (Chong et al. 2015). As such, building prediction practices rarely convey these uncertainties (Wit and Augenbroe 2002). This results in predictions being offered to the design team as deterministic values (Wit and Augenbroe 2002). Wit and Augenbroe (2002) states that it is imperative to convey these uncertainties to the design team. Chong et al. (2015) claims that instead of providing deterministic, single point, estimates, the results should be provided as a range or probabilistic estimates. This quantifies the uncertainty and gives the design team greater confidence in the predictions (Chong et al. 2015) – as identified in the usability workshops. Analysis tools and the presentation of energy use predictions to the design team should highlight the fact that absolute precision in the final building performance is not achievable. Failure to do this, particularly with non-simulation experts, such as architects or clients, can lead to misleading results.

The outputs for thermal and electrical energy use are displayed simultaneously, side-by-side, in The SEED Tool. This was to enable the user to consider the impact that their decisions had on multiple factors. This is in line with the Integrated Performance View (IPV) (ESRU 2011), introduced in Section 2.3.3, which automates the results visualisation process – removing the time needed to set up the results visualisations and offering the user a more holistic view of building performance. Presenting multiple outputs also addresses the issue of wicked problems (Rittel, H., W., Webber, M. 1973) inherent in design, discussed in Section 1.2 ('Wicked Problems'). Wicked problems involve issues such as solving one problem, creates another problem. An example of this within the SEED Tool is the selection of ventilation strategy. When the user alternates from a naturally ventilated building to a mechanically ventilated building, they will often see a decrease in thermal energy use, as presented in Section 6.3.1 ('Services'), due to the fact that mechanically ventilated buildings tend to be more sealed and therefore lose less heat by ventilation heat loss, however, they will typically also see an increase in electrical energy use, as outlined in Section 6.3.2 ('Services'), due to the electricity load of mechanical ventilation equipment. It is therefore up to the designer to find an overall balance of energy, between thermal and electricity energy use, that they are satisfied with. In the user workshops, one of the participants stated that they used the SEED Tool like a *puzzle*: testing different design decisions to achieve a balance between thermal and electrical energy use in order to get the best overall performance. This is in line with the wicked nature of design. Furthermore, the fact that users see the tool in this way, in a way *playing* with the tool, also highlights the fact that they had a clear goal, enhancing the 'flow' condition. Energy use is only one aspect of environmental design and therefore a limitation of the SEED Tool is that it does not analyse other factors, such as daylight, glare and thermal comfort. In order for a more holistic approach to results visualisations, a tool would benefit by conveying a wider range of environmental outputs, while adhering to the other recommendations for user interface design, such as placing the results in context and keeping the interface intuitive and uncluttered.

9.4.4 Feedback

The feedback of the SEED Tool was based on:

– Real-time results

– Inputs and outputs being on one window

All participants in the usability workshops claimed that real-time feedback was useful. It was said that the real-time aspect enables the user to carry out an 'interactive sensitivity study' as users are able to learn the relationships between building characteristics and energy use. This was made possible, both by the real-time feedback and also because the inputs and results were in the same window. With each set of input conditions, the users were able to associate the input conditions with the energy outcomes by glancing back and forth between the input conditions and the energy outputs. As outlined in Section 1.4 ('Why Architects Reject Building Simulation') and Section 2.3, traditional building simulation methods can be a slow process. This is in part due to the calculation time required for the simulations to make their predictions. As such, the majority of tools reviewed in Section 2.3.10 did not have real-time capabilities, and the ones that did, tended to have trade-offs, such as limited geometry capabilities or reduced accuracy.

Parametric design is an ever growing field within architecture. Parametric design is an algorithmic process that enables parameters and rules to be defined in a design – the building form (and related outputs) thereby emerges from the relationships between the design elements (Jabi 2013). It is linked with generative and computational design, as showcased in many growing organisations and conferences such as SmartGeometry (2016). Part of its appeal within architecture is the fact that the designer can set up design relationships and view the resultant changes in geometry in real-time as the variables are altered. In this sense, the computational process is interactive, in the way that interactive art installations are, where users are fully engaged in the process rather than being passive observers. The real-time aspect of the SEED Tool and the fact that users treat it as a *puzzle*, as previously discussed, indicates that the users are engaged in the interactivity of the activity, rather than observing a set of static results. Furthermore, as mentioned in Section 2.3.3, Hamza and

DeWilde (2013) states that human perception is very sensitive to changes in pictorial positions and therefore results that are in motion is an effective communication tactic.

Moore's law is the observation that the number of transistors in an integrated circuit doubles approximately every two years (Moore 1975), vastly increasing the performance of computation year on year. As computational power increases, it is inevitable that simulation engines will produce faster results in the future. There will likely be a time when all typical building simulation predictions are made in real-time. It should be stressed, however, that gaining results in real-time is the goal, as opposed to 'fast' results (for example, seconds), to be in line with the interactive nature of parametric design and the aforementioned claim by Hamza and DeWilde (2013) that 'motion' is an important communication condition.

Chapter 10

Conclusion

10.1 Overview

This thesis presents research carried out to develop a method of communicating a building's predicted energy consumption in real-time as early design and briefing parameters are altered interactively. The research had three aims:

1. Develop and analyse a dataset of measured real-world building characteristics
2. Develop a machine learning method that uses real-world data to predict building energy use
3. Specification and development of a tool that enables non-simulation experts to predict energy use in real-time at the early architectural design stages

As a demonstrative case, the research focused on school design in England. The first part of the research involved the creation of a dataset of actual energy use and measured building characteristics of school buildings across England. This data was used to train a set of artificial neural networks (ANNs) to predict the energy consumption of school designs based on a number of building characteristics. A user-friendly design tool, aimed at non-simulation experts, such as architects, was then created. The tool was named the 'SEED Tool' (School Early Environmental Design Tool). The SEED Tool uses the ANNs as its prediction method – this enables thermal and electrical energy use to be predicted in real-time. The user inputs of the tool the were based on the building characteristic ANN inputs.

10.2 Key Findings

- The ANN method predicts energy use of building designs with greater accuracy than traditional building simulation methods.
- Focussing the design of user interfaces on positive psychology theory (*flow*) results in architects – non-simulation experts who tend to reject analysis tools – to fully engage with the software. For the System Usability Scale (SUS) the SEED Tool recorded a score of 90.8 out of 100. This categorises the tool's usability as *excellent*. This score applies to the targeted user (architect) and within the boundary conditions of the tool: early stage school design in England.
- Designers responded to real-time feedback of environmental performance as they stated they were able to learn the relationships of building characteristics and performance by the acceleration of change in outputs as they alter design and briefing inputs.
- Real-time feedback together with multiple results being presented simultaneously, enables designers to tackle *wicked* problems of design as they are able to make design decisions in a holistic manner.
- The application of machine learning techniques together with actual design and energy data provides evidence that big data techniques are beneficial in the building design industry.

- The behaviour of the ANN inputs largely corresponded with the statistical trends found in the building characteristics dataset – this indicates that the ANNs were able to learn the relationships between the building characteristics and energy use despite the weak correlations (R^2 values) displayed when the building characteristics dataset was statistically analysed.

10.3 Contribution to Knowledge

- The development and analysis of a building characteristics dataset for school buildings in England identified patterns of energy use of these buildings in relation to building geometry, services, occupant activity, glazing, site and weather parameters.
- The review of environmental analysis tools in Section 2.3 showed that no prediction method used real-world data in order to address the energy 'performance gap'. As such, an energy use prediction method for new building designs based on real-world (operational) data is a contribution to knowledge.
- Section 2.3 revealed that accuracy is sacrificed in analysis tools in order to increase the speed at which results are generated in environmental analysis tools. The method presented in this thesis demonstrated that accuracy does not need to be sacrificed when generating faster, real-time, results.
- The review of ANNs within the building energy sector in Section 2.4.5 showed that the use of an ANN method has not been developed for the design of new buildings beyond a rectangular plan. As such, an ANN environmental design tool for the design of new buildings with geometry capabilities of a polygon plan is a contribution to knowledge.

10.4 Research Limitations

This research was carried out under the time frame and resources of a doctorate, and as such had limitations, many of which were mentioned throughout this thesis. Below is a summary of these limitations:

- In order to gather sufficient data for the ANNs to learn from, buildings built over a number of past decades were included in the building characteristics dataset. The case studies (Section 8.2) were carried out to ensure the method predicted energy use in new school buildings with sufficient accuracy. Nonetheless, a limitation was that the building characteristics dataset did not contain wholly recently constructed buildings, which would innately contain characteristics that relate more closely to new buildings, such as fabric quality and modern building services.
- The ANN algorithm cannot accurately predict the energy use of buildings which contain characteristics outside of those within the building characteristics dataset, such as buildings with air conditioning.
- The desktop approach is limited to high-level data, as such, desired information of higher resolution, such as fabric performance, end use energy data, detailed occupancy information and boiler efficiencies was not able to be collected.
- Chapter 3 outlined the assumptions that were made when collecting the building characteristics of schools. As noted in the aforementioned chapter, these assumptions, such as floor-floor heights, introduced elements of uncertainty into the dataset.

10.5 Suggestions for Further Work

Further areas of work that could develop and progress this research were identified, as outlined below:

- **Explore alternative ANN architectures:** the ANN architecture was altered in this research, however, increased performance may be achieved through the use of alternative network architectures and training methods. Alternative methods of analysing what inputs produce the lowest generalisation errors should also be explored. A change to the network architecture may increase the complexity of networks. In event of this, a larger dataset (sample size) may be required, as outlined by Equation 3.1 (Section 3.3.2)

- **Expand the current data collection process:** to include more school buildings, other building sectors and international buildings. Increasing the size of the dataset may increase the accuracy of the method and also allow alternative ANN architectures to be explored as previously discussed. If the current methodology was to be adopted for different types of building or in other countries, the same or equivalent data sources would need to be in place, such as measured energy use data.

- **Target additional inputs:** in order to better predict energy use, recommended additional input parameters to the building characteristics dataset include building services efficiencies, U-values, floor-floor heights, basement floor area, and energy end uses. As more inputs become available, the design of an interface should be developed in accordance with the needs of different users, for example, architects and building services engineers. This may include an 'uncluttered' interface on the surface, with the ability to 'dig down' to greater levels of detail should the user desire.

- **Link the method to a data collection scheme:** such databases may include CarbonBuzz (when the database is sufficiently populated) or UCL Energy Institute's 3D model of the non-domestic building stock of England and Wales. If the method was linked to a dynamic database which is updated over time, the ANN models will have up-to-date building characteristics data to learn from, enabling more accurate predictions as building designs and use evolve, for example as building regulations are updated.

– **Develop a national database:** such a scheme, within the UK, may be similar to the CBECS system in the US (survey process) (Section 2.5.2). The scheme should aim to collect the building characteristics recommended by this research.

– **Develop the method into a refurbishment tool:** in this case, additional building characteristic parameters, typical of refurbishments, are likely to be needed, such as efficiencies of services and fabric performance data. In this way, users would be able to view the energy use implications of, for example, increasing insulation levels or replacing building services with more efficient systems in existing buildings.

– **Build the method into alternative platforms:** currently, the SEED Tool runs on Windows only. In order for the tool to be used across multiple operating systems and devices, a web-based version of the programme could be developed. One method, which would enable the SEED Tool to be embedded in a website efficiently would be to transfer the source code to JavaScript. Additionally, the code structure outlined in Section 7.3.2 (Figures 7.10 and 7.11) could be scripted into a commercial parametric tool, such as Grasshopper (McNeel 2012). This would allow for greater manipulation of the ANN geometry inputs, eg. surface-volume ratio, based on the 3D model's geometry.

– **Building Information Modelling (BIM):** currently, the data entered and produced by the SEED Tool cannot be exchanged with other tools. Future methods should allow for the transfer of data between tools in line with the conditions of BIM Level 3 (see Section 2.3.9).

10.6 Perspective

It is the hope that this research contributes primarily to to two areas. Firstly, it is hoped that it will inspire future environmental design tools to be user-friendly, intuitive, accurate and produce outputs in real-time. Such tools should be engaging to architects and perform closer to the natural, fluid and immediate ways in which designers think, acting as a desired design aid, rather than being a burden. In this way, architects will be able to sketch performance as well as form – both informing each other. Finally, it is hoped that this work contributes to the growing trend of utilising big data. By demonstrating the use of big data within the building industry, it is hoped that public and private institutions see the benefit of sharing data. In this way, methods such as machine learning will be able to be developed that will feed information on how buildings actually perform back to the design studios more seamlessly than occurs today: resulting in buildings performing more closely to design intentions.

References

Abu-Mostafa, Yaser (2012). *Lecture 7: The VC Dimension (Online Lecture by California Institute of Technology)*. URL: https://work.caltech.edu/telecourse.html (visited on March 3, 2013).

Aedas (2014). *Aedas*. URL: http://www.aedas.com/en (visited on November 30, 2014).

AHR (2014). *AHR*. URL: http://www.ahr-global.com/ (visited on November 30, 2014).

Alliance for Sustainable Energy (2015). *OpenStudio*. URL: https://www.openstudio.net/ (visited on July 8, 2015).

Andre, P and J Nicolas (1994). "Use of an Integrated Software System for Building Design and System Simulation". In: *Systems Simulation in Buildings*. Liege, Belgium.

Architecture Association (2014). *Algorithms & Actualisation*. URL: http://www.aaschool.ac.uk/VIDEO/lecture.php?ID=2668 (visited on February 11, 2015).

Arup (2015). *Passive Design Assistant*. URL: http://www.arup.com/Publications/Passive_Design_Assistant (visited on February 22, 2015).

Attia, S. (2012). "A tool for design decision making: Zero energy residential buildings in hot humid climates". PhD thesis. Université Catholique de Louvain.

Attia, Shady et al. (2012). "Simulation-based decision support tool for early stages of zero-energy building design". In: *Energy and Buildings* 49, pp. 2–15.

Attia, Shady G. and A. De Herde (2011). “Early Design Simulation Tools For Net Zero Energy Buildings : A Comparison of Ten Tools”. In: *Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association*. Sydney, Australia, pp. 14–16.

Autodesk (2011). *Autodesk Ecotect Analysis*. URL: `www.autodesk.com/ecotect` (visited on March 3, 2011).

— (2014). *Autodesk Ecotect Analysis*. URL: `http://usa.autodesk.com/ecotect-analysis/` (visited on November 30, 2014).

— (2015). *Autodesk Vasari*. URL: `http://autodeskvasari.com/` (visited on July 8, 2015).

Baker, Lindsay (2012). *A History of School Design and its Indoor Environmental Standards, 1900 to Today*. Tech. rep. Berkeley: UC Berkeley.

Bangor, Aaron, Philip Kortum, and James Miller (2009). “Determining What Individual SUS Scores Mean: Adding an Adjective Rating Scale”. In: *Journal of Usability Studies* 4.3, pp. 114–123.

Banham, R (1960). *Theory and Design in the First Machine Age*. London: Architectural Press.

Baxt, William G (1992). “Analysis of the Clinical Variables Driving Decision in an Artificial Neural Network Trained to Identify the Presence of Myocardial Infarction”. In: *Annals of Emergency Medicine* 21.12, pp. 1439–1444.

BBC (2011). *Q&A: Building Schools for the Future*. URL: `http://www.bbc.co.uk/news/education-10682980` (visited on March 9, 2015).

Beale, M, M Hagan, and H Demuth (2013). *Neural Network Toolbox: User's Guide*. Natick, MA: Mathworks.

Ben-Nakhi, Abdullatif E. and Mohamed a. Mahmoud (2004). “Cooling load prediction for buildings using general regression neural networks”. In: *Energy Conversion and Management* 45.13-14, pp. 2127–2141.

Bentley Systems (2011). *GenerativeComponents*. URL: http://www.bentley.com/en-US/Promo/GenerativeComponents (visited on July 20, 2011).

Braden, Bart (1986). “The Surveyor’s Area Formula”. In: *The College Mathematics Journal* 17.4, pp. 326–337.

BRE (1998). *Energy Consumption Guide 73: Saving Energy in Schools*. Watford: Building Research Establishment.

— (2015). *BREEAM*. URL: http://www.breeam.org/ (visited on February 16, 2015).

Brooke, John (1996). “SUS: A Quick and Dirty Usability Scale”. In: *Usability Evaluation in Industry*. Ed. by Patrick W Jordan et al. London: Taylor and Francis, pp. 189–194.

Brooks, R A (1991). “Intelligence Without Representation”. In: *Artificial Intelligence* 47, pp. 139–159.

Brownlee, J (2013). *How to Identify Outliers in your Data*. URL: http://machinelearningmastery.com/how-to-identify-outliers-in-your-data/ (visited on November 4, 2015).

Bruhns, H., Jones, P., & Cohen, R. (2011). “CIBSE Review of Energy Benchmarks for Display Energy Certificates – Analysis of DEC Results to Date”. In: *CIBSE Technical Symposium*. Leicester, UK.

Buys, J and E Mathews (2005). “Investigation into capital costs of HVAC systems”. In: *Building and Environment* 40.9, pp. 1153–1163.

Carbon Trust (2009). *Building the Future, Today*. URL: http://www.carbontrust.co.uk/publications/pages/publicationdetail.aspx?id=CTC766 (visited on May 14, 2012).

CarbonBuzz (2014). *CarbonBuzz: an RIBA CIBSE Platform*. URL: http://www.carbonbuzz.org/ (visited on December 14, 2014).

CBxchange (2014). *CBx*. URL: http://cbxchange.org/ (visited on December 14, 2014).

Chella, A, P Ciarlini, and U Maniscalco (2006). "Neural Networks as Soft Sensors: a Comparison in a Real World Application". In: *International Joint Conference on Neural Networks (IJCNN)*. Vancouver, BC, pp. 2662 –2668.

Chong, Adrian, Weili Xu, and Khee Poh Lam (2015). "Uncertainty Analysis in Building Energy Simulation: A Practical Approach". In: *14th Conference of International Building Performance Simulation Association*. Hyderabad, India, pp. 2796–2803.

CIBSE (1998). *AM11 Building Energy and Environmental Modelling*. London, UK: Chartered Institute of Building Services Engineers.

— (2004). *CIBSE Guide F: Energy Efficiency in Buildings*. London: Chartered Institute of Building Services Engineers.

— (2006). *CIBSE Guide A: Environmental Design*. London: Chartered Institute of Building Services Engineers.

— (2008). *CIBSE TM46: Energy benchmarks*. London: CIBSE Publications.

— (2009). *CIBSE TM47 Operational Ratings and Display Energy Certificates*. London: CIBSE Publications.

— (2014). *Design for Future Climate : Case Studies (TM55)*. London: Chartered Institute of Building Services Engineers.

— (2015). *AM11 Building Performance Modelling*. London, UK: Chartered Institute of Building Services Engineers.

Clarke, J (2001). *Energy Simulation in Building Design*. Oxford: Butterworth-Heinemann.

Clevenger, Caroline and John Haymaker (2006). "The Impact of the Building Occupant on Energy Modeling Simulations". In: *Joint International Conference on Computing and Decision Making in Civil and Building Engineering*. Montreal, Canada, pp. 1–10.

Cohen, Robert et al. (2001). "Assessing building performance in use 1: the Probe process". In: *Building Research & Information* 29.2, pp. 85–102.

Csikszentmihalyi, M (1990). *Flow: The Psychology of Optimal Experience*. New York, NY: Harper & Row.

— (1997). *Finding Flow: The Psychology of Engagement with Everyday Life*. New York, NY: Basic Books.

Dassault Systems (2014). *Gehry Technologies (GT) Digital Project*. URL: `http://www.3ds.com/products-services/catia/portfolio/digital-project/` (visited on November 30, 2014).

DCLG (2008). *A Guide to Display Energy Certificates and Advisory Reports for Public Buildings*. URL: `http://webarchive.nationalarchives.gov.uk/20120919132719/http://www.communities.gov.uk/publications/planningandbuilding/displayenergycertificates` (visited on January 16, 2016).

— (2012). *A Guide to Display Energy Certificates and Advisory Reports for Public Buildings*. URL: `https://www.gov.uk/government/publications/display-energy-certificates-and-advisory-reports-for-public-buildings` (visited on October 10, 2013).

DCLG (2015). *A Guide to Display Energy Certificates and Advisory Reports for Public Buildings*. URL: https://www.gov.uk/government/publications/display-energy-certificates-and-advisory-reports-for-public-buildings (visited on May 5, 2016).

DECC (2008). *Climate Change Act 2008*. URL: http://www.decc.gov.uk/en/content/cms/legislation/cc_act_08/cc_act_08.aspx (visited on May 14, 2012).

— (2013). *Building Energy Efficiency Survey (BEES): Phase 1*. URL: https://www.gov.uk/government/publications/decc-non-domestic-building-energy-use-project-phase-1 (visited on April 4, 2016).

— (2014). *The Non-domestic National Energy Efficiency Data-Framework (ND-NEED)*. URL: https://www.gov.uk/government/statistics/the-non-domestic-national-energy-efficiency-data-framework-nd-need.

— (2015). *Domestic National Energy Efficiency Data-Framework (NEED) Methodology*. URL: https://www.gov.uk/government/publications/domestic-national-energy-efficiency-data-framework-need-methodology (visited on April 4, 2016).

Department for Communities and Local Government (2008). *The Government's methodology for the production of Operational Ratings, Display Energy Certificates and Advisory Reports*. Wetherby: Communities and Local Government Publications.

DesignBuilder (2015). *DesignBuilder - Simulation Made Easy*. URL: http://www.designbuilder.co.uk/ (visited on July 8, 2015).

DfE (2011). *Data, Research and Statistics âĂŞ School Characteristics*. URL: http://www.education.gov.uk/schools/performance/secondary_11/s12.html (visited on May 20, 2012).

— (2013). *Education and Training Statistics for the United Kingdom : 2013*. URL: `https://www.gov.uk/government/publications/education-and-training-statistics-for-the-uk-2013` (visited on April 5, 2014).

DfES (2003). *Building Schools for the Future*. URL: `http://webarchive.nationalarchives.gov.uk/20130401151715/http://www.education.gov.uk/publications/eOrderingDownload/DfES0134200MIG469.pdf` (visited on March 22, 2015).

— (2006). *Schools for the Future: Design of Sustainable Schools, Case Studies*. Norwich, UK: TSO (The Stationary Office).

Dobbs, Justin and Brandon Hencey (2012). "Automatic Model Reduction in Architecture: A Window into Building Thermal Structure". In: *SimBuild 2012, Fifth National Conference of IBPSA-USA*. Madison, WI, pp. 562–568.

Dodge, Yadolah (2003). *The Oxford Dictionary of Statistical Terms*. Oxford, UK: Oxford University Press.

Duda, R O, P E Hart, and Stork D G (2001). *Pattern Classification*. New York, NY: John Wiley & Sons.

Dudek, Mark (2000). *Architecture of Schools*. Oxon: Routledge.

Dyer, C (1993). *Beginning Research in Psychology: A Practical Guide to Research Methods and Statistics*. Oxford, UK: Blackwell Publishers.

Eastman, Chuck (2009). "Automated Assessment of Early Concept Designs". In: *Architectural Design* 79.2, pp. 52–57.

EDINA (2012a). *Digimap - Historic / Ancient Roam element (log-in required)*. URL: `http://digimap.edina.ac.uk` (visited on June 12, 2012).

EDINA (2012b). *Digimap - Ordnance Survey / Roam element (log-in required)*. URL: http://digimap.edina.ac.uk (visited on May 12, 2012).

Ekici, Betul Bektas and U. Teoman Aksoy (2009). “Prediction of building energy consumption by using artificial neural networks”. In: *Advances in Engineering Software* 40.5, pp. 356–362.

Ellis, PG et al. (2006). “Automated multivariate optimization tool for energy analysis”. In: *Proceedings of SimBuild*. Cambridge MA: IBPSA.

Esri (2012). *ArcGIS: Apply Geography to Every Decision*. URL: http://www.esri.com/software/arcgis/ (visited on May 20, 2012).

ESRU (2011). *Energy Systems Research Unit*. URL: http://www.strath.ac.uk/esru/ (visited on July 14, 2011).

Evans, Stephen, Rob Liddiard, and Philip Steadman (2014). “A 3D Geometrical Model of the Non-domestic Building Stock of England and Wales”. In: *Building Simulation and Optimization 2014 Conference*. London, UK.

Farley, B and W Clark (1954). “Simulation of Self-organizing Systems by Digital Computer”. In: *Transactions of the IRE Professional Group on Information Theory* 4.4, pp. 76–84.

Fausett, L (1994). *Fundamentals of Neural Networks: Architectures, Algorithms and Applications*. New Jersey, NJ: Prentice-Hall Inc.

Forbes (2013). *Gartner's Big Data Definition Consists of Three Parts, Not to Be Confused with Three "V"s*. URL: http://www.forbes.com/sites/gartnergroup/2013/03/27/gartners-big-data-definition-consists-of-three-parts-not-to-be-confused-with-three-vs/\#601c0ddb3bf6 (visited on December 1, 2015).

Fortran (2011). *The Fortran Company*. URL: `http://www.fortran.com/` (visited on July 3, 2011).

Frost, Jim (2013). *Regression Analysis: How Do I Interpret R-squared and Assess the Goodness-of-Fit?* URL: `http://blog.minitab.com/blog/adventures-in-statistics/regression-analysis-how-do-i-interpret-r-squared-and-assess-the-goodness-of-fit` (visited on November 10, 2014).

Gartner (2016). *Big Data*. URL: `http://www.gartner.com/it-glossary/big-data/` (visited on December 1, 2015).

Geebelen, Benjamin and Herman Neuckermans (2003). "Optimizing Daylight Simulation for Speed and Accuracy". In: *Building Simulation 2003, Eighth International IBPSA Conference*. Eindhoven, Netherlands, pp. 379–386.

Giannakis, G.I. et al. (2013). "Simulation Speedup Techniques for Computationally Demanding Tasks". In: *Proceedings of BS2013, 13th Conference of International Building Performance Simulation Association*. Chambery, France, pp. 3761–3768.

Gibbons, J and S Chakraborti (2003). *Nonparametric Statistical Inference*. New York: Marcel Dekker, Inc.

Gillard, Derek (2011). *Education in England: A Brief History*. URL: `http://www.educationengland.org.uk/history/` (visited on September 24, 2015).

Global Action Plan (2006). *UK Schools Carbon Footprint Scoping Study for Sustainable Development Commission*. London: Sustainable Development Commission.

Godoy-Shimizu, Daniel et al. (2011). "Using Display Energy Certificates to Quantify Schools' Energy Consumption". In: *Building Research & Information* 39.6, pp. 535–552.

Google (2011). *Google Sketchup*. URL: `http://sketchup.google.com/` (visited on August 9, 2011).

— (2012a). *Google Earth*. URL: `http://www.google.com/earth/index.html` (visited on March 20, 2012).

— (2012b). *Google Maps*. URL: `http://maps.google.co.uk/` (visited on March 20, 2012).

— (2016). *Google Deepmind*. URL: `https://deepmind.com/` (visited on May 5, 2016).

Gratia, Elisabeth and André De Herde (2002). "A simple design tool for the thermal study of an office building". In: *Energy and Buildings* 34.3, pp. 279–289.

Hamza, Neveen and Pieter DeWilde (2013). "Building Simulation Visualization for the Boardroom: An Exploratory Study". In: *Journal of Building Performance Simulation* 7.1, pp. 52–67.

Harvard Magazine (2014). *Why "Big Data" Is a Big Deal*. URL: `http://harvardmagazine.com/2014/03/why-big-data-is-a-big-deal` (visited on April 4, 2016).

Hawkins, D. et al. (2012). "Determinants of energy use in UK higher education buildings using statistical and artificial neural network methods". In: *International Journal of Sustainable Built Environment* 1.1, pp. 50–63.

Haykin, S. (1999). *Neural Networks: A Comprehensive Foundation*. New Jersey: Prentice, Inc.

Hebb, Donald (1949). *The Organization of Behavior*. Hoboken, NJ: John Wiley & Sons Inc.

Hensen, J. (2004). "Towards More Effective Use of Building Performance Simulation in Design". In: *Developments in Design & Decision Support Systems In Architecture And Urban Planning*. Eindhoven, pp. 291–306.

Hensen, J. L. M., Roberto Lamberts and C. O. R. Negrao (2002). "Building performance simulation at the start of the 3rd millennium". In: *Building and Environment* 37.8-9, pp. 765–767.

Hilbert, Martin and Priscila López (2011). "The World's Technological Capacity to Store, Communicate, and Compute Information." In: *Science (New York, N.Y.)* 332.6025, pp. 60–5.

Hirsch, Jeff (2009). *eQUEST: The Quick Energy Simulation Tool*. URL: http://www.doe2.com/equest/ (visited on July 8, 2015).

Historic England (2011). *Education Buildings*. URL: https://content.historicengland.org.uk/images-books/publications/dlsg-education-buildings/education_final.pdf/ (visited on November 11, 2015).

HM Govenment (2010). *The Building Regulations 2000: Approved Document L2A, Conservation of Fuel and Power in New Buildings other than Dwellings*. October. London, UK: NBS, part of RIBA Enterprises Ltd.

HM Government (2014). *Technology Strategy Board*. URL: https://www.gov.uk/government/organisations/technology-strategy-board (visited on June 22, 2014).

— (2015). *Innovate UK*. URL: https://www.gov.uk/government/organisations/innovate-uk (visited on May 15, 2015).

— (2016). *Check a Public Building's Display Energy Certificate*. URL: https://www.gov.uk/check-energy-performance-public-building (visited on January 16, 2016).

HM Treasury (2016). *Budget 2016*. London: HM Government.

Hong, Sung-min (2014). "Benchmarking the Energy Performance of the UK Non-domestic Stock: A Schools Case Study". PhD thesis. University College London.

Hong, Sung-Min et al. (2014). "A comparative study of benchmarking approaches for non-domestic buildings: Part 1 – Top-down approach". In: *International Journal of Sustainable Built Environment* 2, pp. 119–130.

IES (2015). *Integrated Environmental Solutions*. URL: `https://www.iesve.com/software/interoperability/sketchup` (visited on July 8, 2015).

Innovate UK (2015). *Building Performance Evaluation*. URL: `https://connect.innovateuk.org/web/building-performance-evaluation` (visited on November 11, 2015).

— (2016). *Building Performance Evaluation Programme: Findings from Non-domestic Projects*. Swindon: Innovate UK.

Jabi, W (2013). *Parametric Design for Architecture*. London, UK: Lawrence King Publishing Ltd.

Judkoff, R and J Neymark (1995). *International Energy Agency Building Energy Simulation Test (BESTEST) and Diagnostic Method: Report TP-472-6231*. Tech. rep. Golden, CO: National Renewable Energy Laboratory.

Julie's Bicycle (2016). *Julie's Bicycle*. URL: `http://www.juliesbicycle.com/` (visited on April 4, 2016).

Kalogirou, S (2000). "Artificial neural networks for the prediction of the energy consumption of a passive solar building". In: *Energy* 25.5, pp. 479–491.

Keil, M, P M Beranek, and B R Konsynski (1995). "Usefulness and Ease of Use: Field Study Evidence regarding Task Considerations". In: *Decision Support Systems* 13.1, pp. 75–91.

Kusuda, Tamani (1999). "Early history and future prospects of building system simulation". In: *Proceedings of Building Simulation*. Kyoto: IBPSA, pp. 3–15.

Lam, Khee Poh, Nyuk Hien Wong, and Feriadi Henry (1999). “A study of the use of performance-based simulation tools for building design and evaluation in Singapore”. In: *Proceedings of Building Simulation*. Kyoto: IBPSA.

Landmap (2012). *Download - Building Heights*. URL: http://www.landmap.ac.uk/index.php/Datasets/Building_Heights/Building-Heights-Download (visited on May 20, 2012).

Landmark (2013). *Non-domestic Energy Performance Register*. URL: https://www.ndepcregister.com (visited on February 1, 2013).

Lawson, B. (2004). *What Designers Know*. Oxford: Architectural Press.

— (2006). *How Designers Think: The Design Process Demystified*. 4th. Oxford: Architectural Press.

Lechner, N. (2001). *Heating, Cooling, Lighting: Design Methods for Architects*. Hoboken, NJ: John Wiley and Sons.

Lee, Yoon Soo and Ali Malkawi (2013). “Simulating Human Behavior: an Agent-based Modelling Approach”. In: *13th Conference of International Building Performance Simulation Association*. Chambery, France: IBPSA, pp. 3184–3191.

Li, Qi et al. (2015). “Building Energy Modelling at Urban Scale: Integration of Reduced Order Energy Model with Geographical Information”. In: *Proceedings of BS2015, 14th Conference of International Building Performance Simulation Association*. Hyderabad, India, pp. 190–199.

Mahmoud, Mohamed a. and Abdullatif E. Ben-Nakhi (2003). “Architecture and performance of neural networks for efficient A/C control in buildings”. In: *Energy Conversion and Management* 44.20, pp. 3207–3226.

Marr, Bernard (2015). *Big Data: 20 Mind-Boggling Facts Everyone Must Read*. URL: http://www.forbes.com/sites/bernardmarr/2015/09/30/big-data-20-mind-boggling-facts-everyone-must-read/\#304fac796c1d (visited on December 12, 2015).

Mathworks (2013). *MATLAB: The Language of Technical Computing*. URL: http://www.mathworks.co.uk/products/matlab/ (visited on March 20, 2013).

Max Fordham (2014). *Bill Gething*. URL: http://www.maxfordham.com/people/bill-gething (visited on December 4, 2014).

McCulloch, Warren and Walter Pitts (1943). "A Logical Calculus of the Ideas Immanent in Nervous Activity". In: *Bulletin of Mathematical Biophysics* 5.

McNeel (2012). *RhinoScript Wiki*. URL: http://wiki.mcneel.com/developer/rhinoscript (visited on June 6, 2012).

Metropolis, N and S Ulam (1949). "The Monte Carlo method." In: *Journal of the American Statistical Association* 44.247, pp. 335–41.

Microsoft (2012). *Bing Maps*. URL: http://www.bing.com/maps/ (visited on March 15, 2012).

— (2016). *Excel Online*. URL: https://office.live.com/start/Excel.aspx (visited on February 1, 2016).

Minsky, M and S Papert (1969). *An Introduction to Computational Geometry*. Cambridge, MA: MIT Press.

Mitchell, T., M. (1997). *Machine Learning*. Cambridge MA: MIT Press and The McGraw-Hill Companies, Inc.

Moore, Gordon (1975). “Progress in Digital Integrated Electronics”. In: *Electron Devices Meeting, 1975 International*. Institute of Electrical and Electronics Engineers (IEEE), pp. 11–13.

Morbitzer, C (2003). “Towards the Integration of Simulation into the Building Design Process (PhD Thesis)”. PhD thesis. University of Strathclyde.

National Building Specification (2014). *BIM Levels Explained*. URL: `https://www.thenbs.com/knowledge/bim-levels-explained` (visited on March 3, 2016).

NREL (2011). *Energy-10*. URL: `http://www.nrel.gov/buildings/energy10.html` (visited on January 15, 2011).

— (2015). *BEopt*. URL: `https://beopt.nrel.gov/` (visited on July 8, 2015).

Nuttgens, P (1997). *The Story of Architecture*. London: Phaidon Press Limited.

Pakdaman Naeini, M, H Taromian, and H B Hashemi (2010). “Stock Market Vaule Prediction using Neural Networks”. In: *International Conference on Computer Information Systems and Industrial Management Applications (CISIM)*. Krakow, Poland, pp. 132–136.

Pradhan, M, S K Pradhan, and S K Sahu (2012). “Anomaly Detection Using Artificial Neural Networks”. In: *International Journal of Engineering Sciences & Emerging Technologies (IJESET)* 2.1, pp. 29–36.

Prasad, B (2008). *Speech, Audio, Image and Biomedical Signal Processing using Neural Networks*. Berlin: Springer-Verlag.

Pratt, Kevin B and David E Bosworth (2011). “A Method for The Design And Analysis of Parametric Building Energy Models”. In: pp. 2499–2506.

Prazeres, L (2006). “An Exploratory Study about the Benefits of Targeted Data Perceptualisation Techniques and Rules in Building Simulation”. PhD thesis. University of Strathclyde.

Prazeres, L et al. (2007). “Delivering Building Simulation Information via New Communication Media”. In: *International Building Performance Simulation Association (IBPSA) Sixth International Conference.* Beijing, China, pp. 1499–1504.

Processing (2014). *Processing 2*. URL: `https://www.processing.org/` (visited on November 30, 2014).

Punjabi, Sonia and Valerian Miranda (2005). “Development of an Integrated Building Design Information Interface”. In: *Proceedings of Building Simulation*. Montréal, pp. 969–976.

Pyle, Dorian (2003). *Business Modelling and Data Mining*. San Francisco, CA: Morgan Kaufmann Publishers.

Ratti, Carlo, Nick Baker, and Koen Steemers (2005). “Energy Consumption and Urban Texture”. In: *Energy and Buildings* 37.7, pp. 762–776.

RIBA (2013). *RIBA Plan of Work 2013*. URL: `http://www.ribaplanofwork.com/` (visited on December 20, 2014).

Riether, G and T Butler (2008). “Simulation Space: A New Design Environment for Architects”. In: *Education and research in Computer Aided Architectural Design in Europe (eCAADe)*. Antwerp, Belgium, 133–142 (Section 03).

Rittel, H., W., Webber, M., M. (1973). “Dilemmas in a General Theory of Planning”. In: *Policy Sciences* 4.2, pp. 155–69.

Robert McNeel and Associates (2014). *Rhino 3D*. URL: `http://www.rhino3d.co.uk/` (visited on June 1, 2014).

Robertson, Craig, Dejan Mumovic, and Sung Min Hong (2015). “Crowd-sourced building intelligence: the potential to go beyond existing benchmarks for effective insight, feedback and targeting”. In: *Intelligent Buildings International* 7.2-3, pp. 147–160.

Robinson, S (1994). *Successful Simulation: A Practical Approach to Simulation Projects*. New York, NY: McGraw-Hill Book Company.

Rochester, N et al. (1956). “Tests on a Cell Assembly Theory of the Action of the Brain, Using a Large Digital Computer”. In: *IRE Transactions on Information Theory* 2.3, pp. 80–93.

Rosenblatt, F (1958). “The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain”. In: *Psychological Review* 65.6, pp. 368–408.

Rutten, D., McNeel (2011). *Grasshopper*. URL: `http://www.grasshopper3d.com` (visited on March 3, 2011).

Saltelli, A., Chan, K., Scott, M. (2000). *Sensitivity Analysis*. New York: Wiley-Blackwell Publishing.

Samarasinghe, S. (2007). *Neural Networks for Applied Sciences and Engineering: From Fundamentals to Complex Pattern Recognition*. New York: Auerbach Publications.

Sanguinetti, Paola et al. (2010). “Real-Time Design Feedback : Coupling Performance-Knowledge with Design Iteration for Decision-making”. In: pp. 1–8.

Sarle, Warren S (2000). *How to measure importance of inputs ?* URL: `ftp://ftp.sas.com/pub/neural/importance.html` (visited on May 20, 2012).

— (2002). *Neural Network FAQ, part 2 of 7: Learning*. URL: `ftp://ftp.sas.com/pub/neural/FAQ2.html` (visited on October 11, 2014).

Schlegel, Andreas (2015). *ControlP5: A GUI (Graphical User Interface) Library For Processing*. URL: `http://www.sojamo.de/libraries/controlP5/` (visited on January 12, 2015).

Sefaira (2011). *Sefaira: Building a Green Future*. URL: `http://www.sefaira.com/` (visited on July 3, 2011).

Shiffman, Daniel (2012). *The Nature of Code*. New York City: Self-published via Kickstarter.

Shneiderman, B. (1996). "The eyes have it: a task by data type taxonomy for information visualizations". In: *Proceedings 1996 IEEE Symposium on Visual Languages*. IEEE Comput. Soc. Press, pp. 336–343.

SmartGeometry (2016). *SmartGeometry*. URL: `http://smartgeometry.org/` (visited on February 3, 2016).

Steadman, Philip (2014). *Building Types and Built Forms*. Kibworth: Matador.

Steadman, Philip, Stephen Evans, and Michael Batty (2009). "Wall Area, Volume and Plan Depth in the Building Stock". In: *Building Research & Information* 36.5-6, pp. 455–467.

Steadman P., Bruhns H.R., Rickaby P.A. (2000). "An Introduction to the National Non-domestic Building Stock Database". In: *Environment and Planning B: Planning and Design* 27.1, pp. 3–10.

Stergiou, Christos and Dimitrios Siganos (1996). "Neural Networks". In: *Surprise* 4.

Stigler, Stephen (2008). "Fisher and the 5% level". In: *Chance* 21.4, p. 12.

Struck, C R et al. (2011). "Towards More Effective Communication for Integrated System Performance Data". In: *CISBAT*. Lausanne, Switzerland, pp. 961–966.

Sutherland, I E (1963). "Sketchpad, A Man-machine Graphical Communication System". PhD thesis. Massachusetts Institute of Technology (MIT).

Thomas, Randall (2006). *Environmental Design: An Introduction for Architects and Engineers*. 3rd ed. Oxon: Taylor and Francis.

Thomas, Randall and Trevor Garnham (2007). *The Environments of Architecture*. Oxon: Taylor and Francis.

Troy, P (2010). *Simulation Before Design? A New Software Program for Introductory Design Studios*. URL: `http://www.arch.calpoly.edu/research/documents/research-0910/peters-1-2010.pdf` (visited on March 15, 2011).

Turing, Alan (1950). "Computing Machinery and Intelligence". In: *Mind* LIX.236, pp. 433–460.

Turk, M and A Pentland (1991). "Eigenfaces for Recognition". In: *Journal of Cognitive Neuroscience* 3.1, pp. 71–86.

UCL Energy Institute (2013). *Summary of Audits Performed on CarbonBuzz by the UCL Energy Institute*. URL: `http://www.carbonbuzz.org/downloads/PerformanceGap.pdf` (visited on March 12, 2015).

— (2014). *A New Database and 3D Model of Energy Use in the National Non-domestic Building Stock*. URL: `https://www.bartlett.ucl.ac.uk/energy/news/database-model`.

UCLA (2015). *HEED: Home Energy Efficient Design*. URL: `http://www.energy-design-tools.aud.ucla.edu/heed/` (visited on July 8, 2015).

US Department of Energy (2011). *Building Energy Software Tools Directory*. URL: `http://apps1.eere.energy.gov/buildings/tools\_directory/` (visited on March 1, 2011).

US Department of Energy (2015). *EnergyPlus Energy Simulation Software*. URL: http://apps1.eere.energy.gov/buildings/energyplus/ (visited on June 6, 2015).

US Green Building Council (2015). *LEED*. URL: http://www.usgbc.org/leed (visited on February 16, 2015).

Uto (2014). *@ [uto]*. URL: http://utos.blogspot.com/ (visited on November 30, 2014).

Van Dijk, Edwin and Peter Luscuere (2002). "An architect friendly interface for a dynamic building simulation program". In: *Sustainable Building 2002*. Oslo.

Vastag, Brian (2011). *Exabytes: Documenting the 'Digital Age' and Huge Growth in Computing Capacity*. URL: http://www.washingtonpost.com/wp-dyn/content/article/2011/02/10/AR2011021004916.html?sid=ST2011021100514 (visited on December 12, 2015).

Vilnis Vesma (2016). *Standard Heating and Cooling Degree Days for the UK*. URL: http://www.vesma.com/ddd/std-year.htm (visited on March 12, 2016).

Wagg Society (2013). *Interactive Map of All Buildings in The Netherlands*. URL: http://waag.org/en/project/interactive-map-all-buildings-netherlands.

Weytjens, Lieve et al. (2011). "The Architect-friendliness Of Six Building Performance Simulation Tools: A Comparative Study". In: *International Journal of Sustainable Building Technology and Urban Development* 2.3, pp. 237–244.

White, A., Holmes, M., Hacker, J. (2012). "Passive Design Assistant: A tool to elucidate the principles of passive design". In: *CIBSE ASHRAE Technical Symposium*. April. London.

White Design (2015). *White Design: Beautiful Affordable Sustainable*. URL: http://www.white-design.com/ (visited on November 12, 2015).

Wired (2015). *Finally, Neural Networks that Actually Work*. URL: `http://www.wired.com/2015/04/jeff-dean/` (visited on December 16, 2015).

Wit, Sten de and Godfried Augenbroe (2002). “Analysis of Uncertainty in Building Design Evaluations and its Implications”. In: *Energy and Buildings* 34.9, pp. 951–958.

Yalcintas, Melek (2006). “An energy benchmarking model based on artificial neural network method with a case example for tropical climates”. In: *International Journal of Energy Research* 30, pp. 412–421.

Yalcintas, Melek and Sedat Akkurt (2005). “Artificial neural networks applications in building energy predictions and a case study for tropical climates”. In: *International Journal of Energy Research* 29, pp. 891–901.

Yalcintas, Melek and U Aytun Ozturk (2007). “An energy benchmarking model based on artificial neural network method utilizing US Commercial Buildings Energy Consumption Survey (CBECS) database”. In: *International Journal of Energy Research* 31, pp. 412–421.

Yang, Jin, Hugues Rivard, and Radu Zmeureanu (2005). “On-line building energy prediction using adaptive artificial neural networks”. In: *Energy and Buildings* 37.12, pp. 1250–1259.

Yang, Liu, Joseph C. Lam, and C.L. Tsang (2008). “Energy Performance of Building Envelopes in Different Climate Zones in China”. In: *Applied Energy* 85.9, pp. 800–817.

Appendix A

Industrial Sponsor: AHR/Aedas Architects

AHR (2014) is an award winning architecture practice. It is one of Europe's largest and longest standing practices, with experience dating back to 1835. From the commencement of this research until 2014, AHR was part of Aedas (2014), one of the world's largest architecture practices. Both AHR and Aedas have experience in a range of sectors including education, offices, health and masterplanning.

The practice has a strong interest in research and innovation, particularly in the areas of sustainability and computational design. As such, the practice has a dedicated research and development (R&D) group who led the design of the award-winning Al Bahar Towers, UAE, and played an important role in the design of Holland Park School, UK, and Keynsham Civic Centre, UK.

As the topic of this research relates to both sustainability and computation, the delivery of this thesis is central to the practice's research agenda. The research outcomes will be used to advise architects of the influential factors for energy use in school buildings.

Throughout the duration of this doctoral research, the author assisted the industrial sponsor in a number of projects and activities as outlined below:

- Carried out research and energy simulations, exploring adaptation options to future-proof a live school design project from the effects of climate change[1]; as part of this process, the author wrote a case study for CIBSE Technical Memorandum 55 (CIBSE 2014)
- Created a set of environmental design rules for a masterplan project in Malaysia
- Carried out lighting analyses to assess whether the design of the London Cable Car stations provide adequate daylight
- Carried out lighting simulations to determine whether direct sunlight, reflected from a proposed glazed tower adjacent to a railway line had the potential to produce glare that may adversely affect train driver visibility
- Advised the practice, nationally, on which building energy simulation tools to adopt
- Provided ad hoc environmental design input to a number of live design projects

[1]This research was for the 'Design for Future Climate' project, funded by the Technology Board (TSB), now called Innovate UK(HM Government 2015)

Appendix B

Publications

The following publications have been produced as a result of this research.

Journal Papers

Paterson, G., Mumovic, D., Das, P., Kimpian, J. 2017. 'Energy Use Predictions with Machine Learning During Architectural Concept Design'. In: *Science and Technology for the Built Environment* 23.6, pp. 1036–1048.

Hong, S., Paterson, G., Burman, B., Steadman, P., Mumovic, D. 2014. 'A Comparative Study of Benchmarking Approaches for Non-Domestic Buildings: Part 1 – Top-Down Approach'. In: *International Journal of Sustainable Built Environment* 2.2, pp. 119–130.

Hong, S., Paterson, G., Burman, B., Mumovic, D., Steadman, P. 2013. 'Improved Benchmarking Comparability for Energy Consumption in Schools'. In: *Building Research & Information* 42.1, pp. 47–61.

Conference Papers

Paterson, G., Mumovic, D., Kimpian, J. 2014. 'Using a Monte Carlo Method on Trained Artificial Neural Networks for Identifying Energy Use Determinants of Schools in England'. In: *Proceedings of the 2014 Building Simulation and Optimization Conference*. 23-24 June 2014, UCL, London, UK. London: The Bartlett, UCL Faculty of the Built Environment Institute for Environmental Design and Engineering (IEDE), paper 075.

Paterson, G., Hong, S., Mumovic, D., Kimpian, J. 2013. 'Real-time Environmental Feedback at the Early Design Stages'. In: *Computation and Performance – Proceedings of the 31st International Conference on Education and Research in Computer Aided Architectural Design in Europe*. 18-20 September 2013, Delft University of Technology, Delft, The Netherlands. Delft: eCAADe (Education and Research in Computer Aided Architectural Design in Europe) and Delft University of Technology, Volume 2, pp. 79–86.

Paterson, G., Hong, S., Mumovic, D., Kimpian, J. 2013. 'Utilising Measured Building Data To Gain Environmental Feedback In Real-Time As Early Design And Briefing Decisions Are Made'. In: *CIBSE Technical Symposium*. 11-12 April 2013, John Moores University, Liverpool, UK. London: Chartered Institute of Building Services Engineers, Session 15, Paper 2.

Kimpian, J., Cripps, A., Paterson, G., Bull, J. 2016. 'The Role of Crowd-sourced Data in Improving the Accuracy of Energy Use Forecasts'. In: *CIBSE Technical Symposium*. 14-15 April 2016, Heriot-Watt University, Edinburgh, UK. London: Chartered Institute of Building Services Engineers, Session 2, Paper 1.

Professional Guides

Paterson, G., Rigamonti, D., Kimpian, J. 2014. 'Case Study 4: Harris Academy Purley'. In: K. Butcher, ed., *CIBSE TM55 Design for Future Climate: Case Studies*. London: CIBSE Publications.

Professional Reports

Rigamonti, D., Paterson, G. 2012. *Design for Future Climate: Harley Academy, Purley*. London: Innovate UK.

Contribution to Books

Deutsch, R. 2015. *Data-Driven Design and Construction: 25 Strategies for Capturing, Analyzing and Applying Building Data*. NJ, USA: John Wiley & Sons.

Appendix C

User Testing Workshop Questionnaire Questions

Background

What profession best describes you?

□ Architect

□ Building Services Engineer

□ Environmental Designer/Specialist

□ Other (please state below)

How many years have you been working in the building design industry?

□ 0-2 years

□ 2-5 years

□ Over 5 years

Does your area of expertise lie within the design of domestic or non-domestic building sector?

□ Domestic

□ Non-domestic

□ Both domestic and non-domestic

How many schools have you been involved in the design of in your career?

□ 0

□ 1-4

□ 5 or more

Typically, when do you you first use building energy simulation in the design process?

□ Conceptual design stage

□ Scheme design stage

□ Detail design stage

□ I personally don't use simulation software

Task

Please generate a building with the below parameters using the SEED Tool

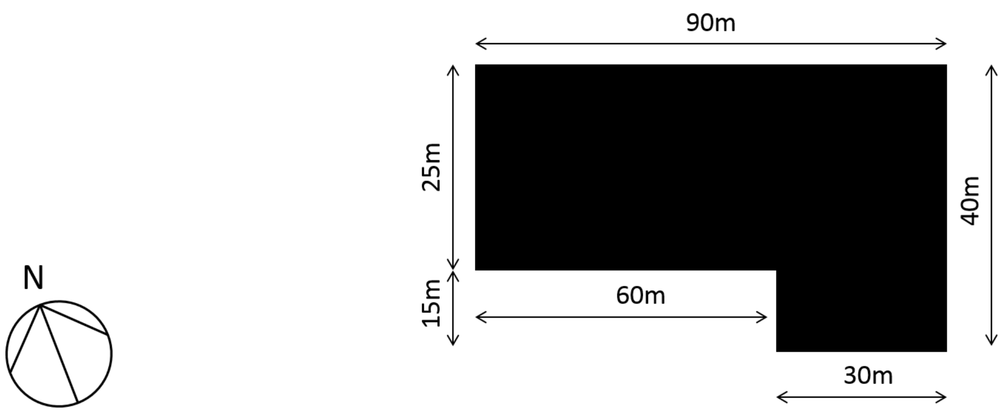
Feel free to play around with the tool as well

Secondary school with after school activities

2000 pupils

Three storeys with mechanical ventilation

30% of the external walls are glazed



Usability Assessment

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
If designing a school, I would like to use the SEED Tool at the beginning of the design process	☐	☐	☐	☐	☐
I found the tool unnecessarily complex	☐	☐	☐	☐	☐
I thought the tool was easy to use	☐	☐	☐	☐	☐
I think that I would need the support of a technical person to be able to use this tool	☐	☐	☐	☐	☐
I found the various functions in this tool were well integrated	☐	☐	☐	☐	☐
I thought there was too much inconsistency in the tool	☐	☐	☐	☐	☐
I would imagine that most people would learn to use this tool very quickly	☐	☐	☐	☐	☐
I found the tool very cumbersome to use	☐	☐	☐	☐	☐
I felt confident using the tool	☐	☐	☐	☐	☐
I would need to learn a lot of things before I could use the tool	☐	☐	☐	☐	☐

Inputs

I am familiar with the following input parameters:

	Disagree	Somewhat	Agree
Building footprint	☐	☐	☐
Primary vs secondary schools	☐	☐	☐
Standard school hours vs standard hours plus after school activities	☐	☐	☐
Number of pupils	☐	☐	☐
Orientation	☐	☐	☐
Number of floors	☐	☐	☐
Natural vs mechanical ventilation	☐	☐	☐
Glazing percent on different facade orientations	☐	☐	☐

Please describe what extra information would be desired if you did not agree with any of the above.

Results

Please comment on why you did/did not find the results easy to interpret.

Please comment on why you did/did not find the results updating in real-time helpful.

Are there any other comments regarding the results you wish to share? If so, please discuss.

Overall Experience

What did you like about the tool?

What improvements would you recommend?

What aspects, if any, made the tool intuitive to use?

Were you happy with the speed in which you received results from this tool compared with other building energy simulation tools? Please discuss.

Are there any other general comments about the tool you wish to share? If so, please discuss.