Benchmarking the energy performance of the UK non-domestic stock: a schools case study

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Student Declaration

As the author of this thesis, Sung Min Hong, I 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.

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Abstract

Lack of awareness of building performance is often highlighted as a key barrier to improving the operational energy efficiency of non-domestic buildings. In 2008, the Display Energy Certificate (DEC) scheme was implemented in the UK to raise awareness and encourage higher levels of energy efficiency in public sector buildings. The thesis reports a review of the energy benchmarks that underpin the DEC scheme, which reveals that they are no longer appropriate for providing useful or relevant feedback. The research therefore aims to improve understanding of the energy performance of non-domestic buildings, and to explore ways in which their operational energy efficiency can be benchmarked with greater robustness.

The research comprises four phases of analysis within which data of varying granularity are analysed to acquire a holistic understanding of the patterns of energy use in English schools and the factors that influence their energy demand. First, the latest DEC records are analysed to assess the robustness of the scheme. Second, the patterns of energy use in primary and secondary schools are analysed in greater detail. Third, multiple regression analyses of energy use in relation to intrinsic building and occupant characteristics are carried out. Last, detailed information about the end-use energy consumption of a small number of modern secondary schools is analysed.

The main findings reveal shortcomings of the DEC scheme. The results highlight two key issues associated with the classification system: inappropriate levels of aggregation and misclassification of buildings. Energy benchmarks are found to be inappropriate and out-of-date for the majority of benchmark categories. Correlations between intrinsic features and empirical data on the energy performance of schools were found. The research concludes that the DEC scheme lacks robustness, and that its robustness could be improved by refining the classification system based on empirical data, introducing a framework for keeping up-to-date with the latest trends in energy performance, and producing benchmarks that are relevant to the circumstances of individual buildings.

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Glossary of Terms

Adjusted energy benchmarks are benchmarks that have been adjusted to take into account the influence of regional and seasonal weather on heating energy use, and the influence of extended hours of occupancy on the total energy consumption

Assessment end date is the date at which the one-year long monitoring period for energy consumption ended

Asset rating indicates how energy-efficient buildings are, based on the carbon emissions of buildings in question estimated through simulation models under ‘standard’ operational conditions

Benchmark category is the main classification system of the DEC scheme. Each category has a representative energy benchmark for calculating the operational rating of all buildings that belong to the category

Building type refers to a supplementary classification system of the DEC scheme, which helps the assessors to identify the correct benchmark category for a building

End-use energy consumption is the energy used by major sub-systems of a building such as lighting or heating

Operational rating (or DEC rating) indicates how efficiently an existing building is being used in energy terms once it is occupied based on the actual measured energy consumption

Operational energy efficiency refers to the level of efficiency of the management and operation practices of an existing building which is in use

Robustness refers to ways in which a benchmarking system provides sufficient means to provide feedback to building operators about their operational energy efficiency that is relevant and accurate

Separable energy uses are end uses that are uncommon in a particular activity type and are therefore allowed to be discounted from calculating the operational rating

Total useful floor area is a floor area metric which is used for calculating the operational rating. The term is synonymous with Gross Internal Floor Area (GIFA) which includes all enclosed spaces measured to the internal face of the external wall

Unique Property Reference Number (UPRN) is a 12-digit numbering system used within the Display Energy Certificate scheme for identifying a building or a site and the relevant certificates

Abbreviations and Acronyms

AIC	Akaike's Information Criterion
CCC	Committee on Climate Change
CDD	Cooling Degree Days
CIBSE	Chartered Institution of Building Services Engineers
CIP	Central Information Point
DCLG	Department for Communities and Local Government
DEC	Display Energy Certificate
DECC	Department of Energy and Climate Change
DfE	Department for Education
EFA	Education Funding Agency
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
EUI	Energy Use Intensity
HDD	Heating Degree Days
HVAC	Heating, Ventilation, and Air Conditioning system
L2A	Approved Document L2A - Conservation of fuel and power in new buildings other than dwellings
L2B	Approved Document L2B - Conservation of fuel and power in existing buildings other than dwellings
MAD	Median Absolute Deviation
NDBS	Non-Domestic Building Stock database
ND-NEED	Non-Domestic National Energy Efficiency Data framework
NEED	National Energy Efficiency Data framework
SAS	Statistical Analysis Software
SIC	Standard Industrial Classification
TM22	CIBSE Technical Memorandum 22 - Energy assessment and reporting method
TM46	CIBSE Technical Memorandum 46 - Energy Benchmarks
UPRN	Unique Property Reference Number
VIF	Variation Inflation Factor
VOA	Valuation Office Agency

Publications Arising from this Thesis

Peer reviewed journals

- **Hong, S.M.**, Paterson, G., Burman, E., Mumovic, D., Steadman, P. (2014) A comparative study of benchmarking approaches for non-domestic buildings: Part I: Top-down approach. International Journal of Sustainable Built Environment, DOI: 10.1016/j.ijsbe.2014.04.001
- Burman, E., **Hong, S.**, Patterson, G., Kimpian, J., and Mumovic, D. (2014) A comparative study of methods used to derive energy benchmarks for non-domestic buildings: Part II: Bottom-up methods, submitted to International Journal of Sustainable Built Environment
- Chatzidiakou, L., Mumovic, D., Summerfield, A., **Hong, S.M.**, Altamirano-Medina, H. (2014) A Victorian school and a low carbon designed school: comparison of indoor air quality, energy performance, and student health, Indoor and Built Environment, DOI: 10.1177/1420326X14532388
- Williams, J., **Hong, SM**, Mumovic, D., Taylor, I. (2013) Using a Unified School Database to Understand the Effect of New School Buildings on Performance, submitted to Intelligent Buildings International
- **Hong, S.M.**, Paterson, G., Mumovic, D., Steadman, P. (2013) Improved benchmarking comparability for energy consumption in schools, Building Research and Information, DOI: 10.1080/09613218.2013.814746
- Hawkins D., **Hong, S.M.**, Raslan, R., Mumovic, D., Hanna, S. (2012) Determinants of energy use in UK Higher Education Buildings Using Statistical and Artificial Neural Network Methods, International Journal of Sustainable Built Environment, 1, 50-63

Conferences

- Bordass, B., Cohen, R., Spevack, R., **Hong, S.M.**, Burman, E. (2014) Tailored benchmarking and its application to design and actual energy use, CIBSE-ASHRAE Technical Symposium, Dublin, Ireland, April 2014
- Chatzidiakou, L., Mumovic, D., Summerfield, A., **Hong, S.** (2013) Low Carbon vs. Victorian School Design: Indoor Air Quality, Energy and Health Responses, ASHRAE IAQ Environmental Health in Low Energy Buildings, 15-18 October 2013, Vancouver, Canada
- Paterson, G., **Hong, S.**, Mumovic, D., Kimpian, J. (2013) Real-time Environmental Feedback at the Early Design Stages, Education and Research in Computer Aided Architectural Design in Europe (eCAADe) Conference, September 2013, Delft, Netherlands

- **Hong, S.M.**, Pang, S., Paterson, G., Mumovic, D., Steadman, P. (2013) Identifying determinants of energy use of schools in England for benchmarking purposes, CIBSE Technical Symposium, Liverpool, April 2013
- 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, CIBSE Technical Symposium, 12-13 April 2013, Liverpool, UK.
- Williams, J., **Hong, S.M.**, Mumovic, D., Taylor, I. (2013) Assessing the social aspects of energy use in school using a unified database, CIBSE Technical Symposium, Liverpool, April 2013

Technical reports

- **Hong, S.M.**, Steadman, P., (2013) An Analysis of Display Energy Certificates for Public Buildings 2008 to 2012, Retrieved from https://www.bartlett.ucl.ac.uk/energy/news/display-energy-certificates

Chapter 1 Introduction

This chapter provides an overview of this research. The chapter begins by explaining the context and rationale for carrying out the research. This is followed by descriptions of the research questions, aims, and objectives. Lastly, the structure of the research and the outline of each chapter are described.

1.1 Context and Rationale for the Research

Finite resources, energy security and climate change are some of the most prominent drivers for improving energy efficiency and reducing anthropogenic carbon emissions. In response to these critical issues, the UK government has set a legally binding target to reduce net CO_2 emissions in 2050 by more than 80% from the 1990 baseline (HM Government, 2008). Among various sectors, CO_2 emissions from non-domestic buildings account for approximately 18% of national total emissions. Hence there is an imperative to reduce the emissions from these buildings to achieve the 2050 target (Carbon Trust 2009).

In the built environment, benchmarking is a technique that is often used by building operators to evaluate their energy performance. In its simplest form, an indicator of the energy performance of a building would be compared to a reference performance, whether it be historical data or a publicly available standard, to acquire a sense of how efficiently the energy is being used (CIBSE 2012). The technique generally aims to raise awareness of energy consumption but also provides motivation to improving the efficiency of operation. It is therefore an essential way to tackle one of the key barriers for improving the energy efficiency of existing non-domestic buildings, which is the lack of awareness of building performance (Carbon Trust 2009).

In 2008, the Display Energy Certificate (DEC) scheme was implemented in the UK under the European Energy Performance of Buildings Directive (EPBD) (CIBSE 2009; Department for Communities and Local Government (DCLG) 2008). Under the mandatory energy certification scheme, public buildings are required to display energy certificates that illustrate how efficiently they were being operated, hence raising awareness of the public and building operators. Consequently, it was anticipated that DECs would encourage investments in energy efficiency measures.

In the UK where benchmarks are historically used only on a voluntary basis, implementation of the DEC scheme has greatly improved the potential to promote energy efficient operation of existing buildings. The review of relevant literature revealed however, the following gaps in knowledge that could improve the robustness of benchmarking the operational energy efficiency of UK non-domestic buildings:

- There is a lack of understanding of the robustness of the current approach to benchmarking of buildings across the UK non-domestic stock, especially the methods used to derive energy benchmarks and the underpinning classification system.
- The extent to which incorporating intrinsic building and operational features, such as the built form or efficiency of building services, into a benchmarking process could improve the precision of evaluating the operational energy efficiency of UK non-domestic buildings remains unknown.

1.2 Research Aims, Questions and Objectives

This research aims to discover ways for robustly benchmarking the operational energy efficiency of existing buildings across the UK non-domestic sector.

The following research questions were formulated to guide the research:

- What are the benefits and limitations of using a top-down approach for deriving energy benchmarks for evaluating the operational energy efficiency of non-domestic buildings, and what are the factors that determine their robustness?
- How appropriate are classifications of buildings for benchmarking the operational energy efficiency of buildings across the stock?

- Are types of activity sufficient to categorise buildings for evaluating the operational energy efficiency, or should there be other factors, such as built form or number of computers, which could be incorporated into the benchmarking process to acquire a more precise evaluation of how efficiently energy is used in these buildings?

To address these research questions, the following objectives were established:

- Assess the data to improve the understanding of patterns of energy use in UK non-domestic buildings and provide insights into the appropriateness of the classification of benchmark categories and building types
- Explore and compare the benefits and limitations of top-down and bottom-up approaches for assessing and evaluating the operational energy efficiency of non-domestic buildings
- Examine whether there are cases for introducing additional features into the benchmarking process by assessing correlations between intrinsic building and operational characteristics, and the energy performance
- Collect and develop datasets on the latest and historical energy performance of non-domestic buildings and their characteristics to underpin the analyses

1.3 Research Outline

For clarity, the following terms have been used for naming the analysis chapters to portray the gradually increasing level of granularity of the underlying data and methods:

- Top-down: Analyses of stock-level whole building energy data
- Hybrid: Whole building energy data with complementary information on building and operational characteristics analysed using a multivariable method
- Bottom-up: End-use energy use data disaggregated using a bottom-up approach

- ***Chapter 2 - The Context: Drivers of Change***

  This chapter aims to cover the context within which the research is situated. Issues of global and local significance, and international and domestic policies that raise the importance of improving the energy efficiency of buildings are described.

- ***Chapter 3 - Benchmarking the Energy Performance of Non-Domestic Buildings***

  This chapter aims to establish the basic concept of benchmarking and its role in improving the operational energy efficiency of non-domestic buildings. Through a review of relevant literature, the latest developments in research and literature that aim to improve the robustness of benchmarking the energy performance of non-domestic buildings are discussed in detail.

- ***Chapter 4 - Methodology***

  This chapter aims to provide an overview of the research methodology prior to describing details of the methods in individual chapters. Details of the rationale behind the research design are described, with a particular focus on the arrangement of methods that were designed in a sequential order to triangulate the factors that influence the pattern of energy use of non-domestic buildings.

- ***Chapter 5 - Top-down Analysis of Public Sector Buildings***

  This chapter aims to improve understanding of the energy performance of public buildings using the latest DEC records through cross-sectional and longitudinal analyses. The methods that were used to process and analyse the DEC data are described in detail. The latest patterns of energy use of public buildings and how these have changed over the years are described. The data is also used to examine the robustness of the energy benchmarks that underpin the DEC scheme.

- ***Chapter 6 - Top-down Analysis of English Schools***

  This chapter aims to examine the adequacy of the DEC scheme, with regards to the benchmarks and methods, in benchmarking the energy performance of primary and secondary schools in England. The methods that were used to develop a dataset of the energy performance of schools and combine it with other datasets, and to analyse the data, are described in detail. The results from the analyses are presented.

- ***Chapter 7 - Hybrid Approach to Analysing English Schools***

  This chapter aims to improve the understanding of the influence of the intrinsic building features and the occupant characteristics on the pattern of energy use in schools. The methods that were developed to collect the information on the built form and its services are described, and how they were combined with the dataset from the previous chapter. The details and the results from the multiple linear regression analyses are described in detail.

- ***Chapter 8 - Bottom-up Analysis of English Schools***

  This chapter aims to further improve the understanding of the pattern of energy use of secondary schools and their relationship with the characteristics that were analysed in the previous chapter. The sources of data and the methods that were used to derive and analyse the end-use energy consumption are described in detail. The results from the analyses are presented.

- ***Chapter 9 - Discussion***

  In this chapter, results from chapters 5 to 8 are discussed collectively with the aim of addressing the key research questions. Potential implications of findings from the research for developing a robust and sustainable benchmarking system are discussed. Based on the outcome of the discussion, recommendations are made to CIBSE.

- ***Chapter 10 - Conclusions***

  This chapter summarises the research and highlights key findings. Contributions to knowledge, proposals for future work, and research limitations are described.

Chapter 2 The Context: Drivers of Change

This chapter describes the context that acts as a driver to improve the energy efficiency of non-domestic buildings. First, global and national issues such as climate change and energy security are described. Policy frameworks that were developed to reduce the anthropogenic carbon emissions from non-domestic buildings are described in detail.

2.1 Finite reserves of natural resources and energy security

Ever since the industrialisation of modern society the demand for energy by mankind has never been greater. The most recent International Energy Outlook published by the EIA[1] illustrates how the World's energy consumption has increased steadily over the past decades since the 1990's (EIA 2011). Moreover, projections of World consumption shows that this will rise steadily despite the impact of the economic recession, due to developing economies in non-OECD nations such as China and India, as well as expanding populations throughout the World (BP 2012; EIA 2011). However, by contrast with the ever-growing demand for energy, the reserves of natural resources such as oil, gas and coal that are essential to sustain economic activities and quality of life have been observed to decline over the past decades (Longwell 2002).

In recent years, a decrease in production of oil and gas from the North Sea has led the UK to become increasingly reliant on imported energy. What is worse is that this dependence is expected to increase further in the coming decades, therefore the UK is likely to be exposed to the risk of volatile and higher fuel prices. Hence, improving energy security to ensure reliable supplies of energy at stable prices has become one of the most important challenges to the UK (DECC 2009). Amongst a diverse range of measures to achieve greater energy security, improving energy efficiency is considered to be the most important as it not only reduces the demand for imported fuel such as gas and oil, creating less dependence on imported energy, but also contributes to tackling climate change.

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[1] US Energy Information Administration: http://www.eia.gov/

2.2 Climate change

The phenomenon commonly referred to as 'climate change' or 'global warming' refers to the warming trend of the Earth's climate which has become increasingly evident in past decades. The observed changes in climate shows that the linear trend in observed global surface temperature over the 50 year period from 1956 to 2005 (0.13 [0.10 to 0.16]°C per decade) is nearly twice that for the 100 years from 1906 to 2005 and that eleven of the twelve years between 1995 and 2006 are among the warmest years in the instrumental record of global surface temperature (IPCC 2007).

The natural concentration of gases in the atmosphere such as water vapour, carbon dioxide (CO_2), methane and the greenhouse effect from these gases, collectively termed greenhouse gases (GHG), has long been identified to be what maintains atmospheric temperatures at a level suitable to support life. The rapid increase in observed global temperature in the past century, however, has suggested that there are other factors that are driving climate change and it is increasingly becoming evident that most of the observed increase in global average temperatures since the mid-20th century is due to the increase in anthropogenic GHG emissions (IPCC 2007). Among the anthropogenic GHGs, CO_2 has been identified to be the most important contributor to change where annual emissions from various sectors of the economy such as buildings, energy supply, transport and industry have increased between the years 1970 and 2004 by approximately 80%. In addition, global atmospheric CO_2 concentration has increased from its pre-industrial value of about 280ppm, to 379ppm in 2005 which exceeds the natural range of variability over the last 650,000 years; and the rate at which the concentration is increasing has accelerated towards the present.

The projection of the warming trend into the future highlights that a continued increase in concentration level of GHGs in the atmosphere will further increase temperatures and that the impacts from the change we are experiencing currently such as prolonged droughts, more intense heat waves, flooding, and stronger hurricanes and typhoons will become more severe with possibilities of the effects extending to extinction of species, shortage in food production and health issues (Climate Action 2011). It is therefore of the utmost importance to control and improve the way we use energy, specifically the use of fossil fuels that emit CO_2, and thus reduce the subsequent anthropogenic GHG emissions into the atmosphere in order to prolong the way we live today.

2.3 International and domestic frameworks to curb anthropogenic CO_2 emissions

In recognition of the impacts of global warming, the United Nations Framework Convention on Climate Change (UNFCCC) was adopted at the United Nations Conference on Environment and Development (UNCED) in 1992. The convention provided an initiative to act on the issue by setting an objective for the ratifying countries to stabilise greenhouse gas concentrations in the atmosphere at a level that will prevent dangerous human interference with the climate system (UNFCCC 2011a).

Following the convention, the Kyoto Protocol, an international agreement that complements the UNFCCC, was adopted in Kyoto, Japan in 1997 and came into force in 2005. The significance of the protocol is that sets legally binding targets, unlike the convention, for the 37 industrialized countries and the European community to reduce GHG emissions by an average of 5% against emission levels in 1990 over the five-year period from 2008 to 2012 (UNFCCC 2011b). Moreover, the protocol also provides market-based mechanisms (Emissions Trading, the Clean Development Mechanism and Joint Implementation) for extra flexibility, in addition to requiring the ratifying countries to achieve the targets mainly through national measures. In addition, the requirement has led to the monitoring of GHG emissions, which is a vital step to identify the current status and to reduce levels further.

As a signatory to the Kyoto Protocol, the EU as a group of member states has an obligation to achieve an overall reduction of 8% against the 1990 level, where targets vary between the member countries according to their economic conditions. As a response to the protocol, the European Climate Change Programme (ECCP) was introduced by the European Commission (EC) in 2000 (European Commision 2006). Through a consultation process, the programme has led to the identification and development of various policies that are aimed at reducing GHG emissions across a broad range of areas to implement the Kyoto Protocol. In 2008, a

‘20-20-20’ plan was set into motion with the aim of reducing EU greenhouse gas emissions by at least 20% below 1990 levels; to make 20% of EU energy consumption come from renewable resources; and to make a 20% reduction in primary energy use compared with projected levels, to be achieved by improving efficiency (European Commision 2010).

2.4 Carbon emissions from non-domestic buildings

In many countries, buildings account for approximately 40% of the national carbon emission and energy use and are deemed to be the most cost-effective sector to reduce energy consumption (International Energy Agency (IEA) 2010). Similarly, carbon emissions from buildings in the UK account for nearly half the total national emissions and approximately 18% of the total is attributable to non-domestic buildings. As a result, reducing energy demand in non-domestic buildings has been identified as one of the key strategies to achieve the national reduction target by 2050 (HM Government 2010a).

A report by Carbon Trust (2009) has shown that absolute carbon emissions from non-domestic buildings have barely declined since the 1990s. Over the past two decades, carbon emissions from the stock have remained relatively stable with a historic reduction rate of 0.5% per annum as shown in Figure 2.1.

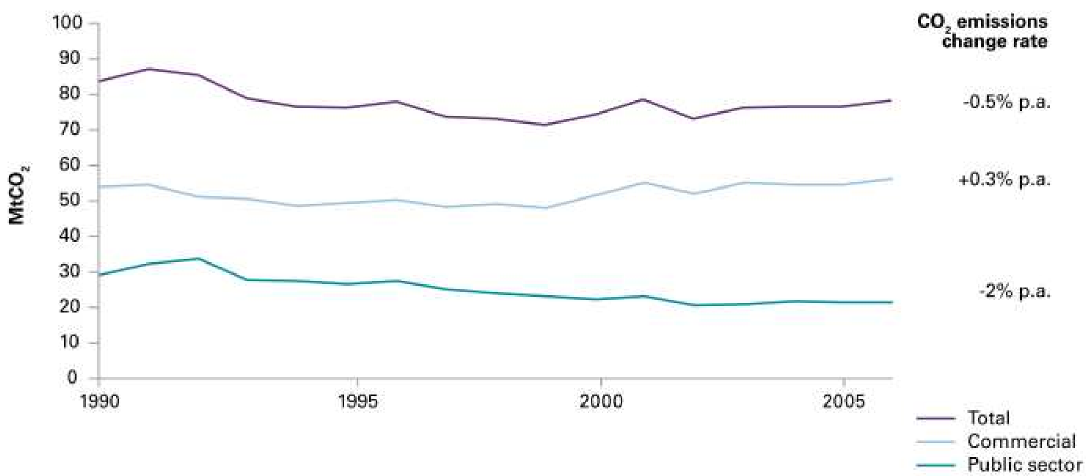

Figure 2.1 Historical annual emissions from 1990-2006 from commercial and public sector non-domestic buildings in the UK (Source: Carbon Trust 2009)

The projection based on this trend suggested that the cumulative reduction by 2050 would be less than 25% compared with the required reduction of 80% (Carbon Trust 2009). Various analyses however suggested that there is significant scope for reducing emissions from the non-domestic stock by improving energy efficiency measures. A report by CCC (2008) highlights that there is a significant scope for reducing carbon emissions in the stock with a technical potential to reduce emissions by 11 $MtCO_2$ in 2020 with energy efficiency improvements that have no, or even negative costs. Moreover, a report from the Carbon Trust (2009), based on an analysis of cumulative net cost and net carbon savings for non-domestic buildings, highlights that, based on a ‘Success Scenario’ reducing carbon emissions by 35%, from 106$MtCO_2$ in 2005 to 69$MtCO_2$ in 2020, will lead to a net financial benefit of £4.5 billion.

The report highlights that there is a need to deliver more energy efficient buildings that are operated more efficiently if the national target is to be achieved by 2050. Consequently, it illustrates that almost all available carbon reduction technologies will need to be implemented to both new and existing buildings, starting from cost-effective energy efficiency measures such as adopting more efficient management, and gradually moving towards more expensive options such as on-site low-carbon energy generation and non-cost-effective measures. The report also gives a list of issues which were identified as barriers to improving energy efficiency of the stock. Among these barriers, lack of awareness by owners, operators and occupants raises the importance of assessing and evaluating energy performance of buildings so that various stakeholders are motivated to take action to improve energy efficiency.

2.5 Energy certification of non-domestic buildings

There are numerous policy instruments that aim to reduce carbon emissions from buildings by tackling the problem from various angles. In the UK, for example, the requirement for energy efficiency in buildings set by the Buildings Regulations has become increasingly stringent year-on-year, forcing new and existing non-domestic buildings to become more energy-efficient (HM Government 2010b; HM Government 2010c). There is also Green Deal, which is a new initiative implemented with an aim to improve the energy efficiency of both domestic and non-domestic buildings by allowing an upfront payment for installation of energy efficiency measures (DECC 2011). There are also policies that target large organisations to reduce their carbon emissions such as the Climate Change Levy (CCL) or Carbon Reduction Commitment (CRC) scheme (DECC n.d.; Carbon Trust 2006).

Energy certification is a policy instrument that aims to improve the energy efficiency of the building stock by tackling one of the key barriers, the lack of awareness of how energy is used in buildings (Carbon Trust 2009). In general, these certificates provide indications of how energy efficient a new or existing building is, which in turn raises the awareness of various stakeholders in the building sector (International Energy Agency (IEA) 2010). The Energy Smart Labelling Scheme and the BCA Green Mark scheme of Singapore, the Energy Star scheme of the US, and Australia's National Australian Built Environment Rating System (NABERS) are some of the examples of how energy certification is adopted in different countries (National Environment Agency (NEA) 2008; Building Construction Authority (BCA) 2014; Environmental Protection Agency 2011; Office of Environment and Heritage (OoEH) n.d.).

In Europe, energy certification was rolled out across the member countries of the EU as part of the requirements of the Energy Performance of Buildings Directive (EPBD). The directive came into force with an aim to improve the energy efficiency in the building sector through various measures, including energy performance certificates (CIBSE 2003; European Parliament 2003). In 2010, a recast of the directive was adopted by the European Parliament with the aims of strengthening the provisions and extending the scope of the 2002 directive (European Parliament 2010).

2.6 Operational energy efficiency

Over the past decade it has been frequently observed that many buildings that are built to higher standards are performing poorly in comparison to their predicted performance (Bordass 2001; Bordass, Cohen, et al. 2001; Bordass et al. 2004). A similar trend has also been found in other parts of the world such as Canada and Australia where high levels of energy consumption in supposedly energy-efficient buildings were attributed to a similar set of issues

(Bannister 2009; Birt & Newshame 2009). A list of commonly found issues which were identified in these studies as the reason for the discrepancy showed that an improvement is required across the whole process of delivery of a building from its design and construction through to operation. What these findings suggest is that designing and constructing an energy-efficient building does not necessarily lead to delivering the required reduction in carbon emissions unless the building is managed and operated by the operators and occupants in an energy-efficient manner.

There are various factors that affect the operational performance of buildings which can lead to a building consuming more energy than was estimated during the design stage. These range from control settings of various building services to the types of equipment used to support the activity that takes place in a building and how these are used by the occupants. In order to improve the operational energy efficiency of existing buildings, an energy management practice such as an energy audit or post-occupancy survey is carried out to assess and evaluate the performance of the building and to highlight areas that require improvement. While there are various methods used to assess and evaluate the performance of existing buildings, benchmarking is considered to be an effective method to improve the operational energy efficiency due to the motivating nature of comparing the performance of the building in question to that of similar buildings (CIBSE 2012).

2.7 Display Energy Certificate Scheme

In 2008, the Energy Performance Certificate (EPC) and Display Energy Certificate (DEC) schemes were implemented in the UK through the Energy Performance of Buildings Regulations as a means to fulfil the requirements of EPBD (HM Government 2007). Although both schemes aim to improve the energy efficiency of non-domestic buildings by raising awareness of energy efficiency of buildings, they are clearly distinguished from one another by differences in underlying methods.

EPCs indicate how energy-efficient buildings are, based on their asset ratings. These ratings are based on the carbon emissions of buildings in question estimated through building simulation models under ‘standard’ uses, which means that EPCs are focussed on evaluating the levels of energy efficiency of a building with regards to its fabric and fixed building services (DCLG 2012b).

DECs on the other hand are certificates that indicate how efficiently an existing building is being used in energy terms once it is occupied. The main difference is that operational ratings which underpin the scheme are based on the actual energy consumption of buildings. This means that DECs reflect how energy is actually used by occupants in buildings, including the inefficient uses (DCLG 2008). These certificates therefore provide opportunities to encourage existing buildings to be used in a more energy-efficient manner.

The operational ratings are an evaluation of the operational energy efficiency of buildings, and are produced by comparing the actual annual carbon emissions of a building to a benchmark that is representative of the typical performance of similar buildings (equation 1).

$$\text{Operational Rating (OR)} = \frac{\text{Annual carbon emission of a building } (\text{kgCO}_2/\text{m}^2\cdot\text{yr})}{\text{Adjusted energy benchmarks } (\text{kgCO}_2/\text{m}^2\cdot\text{yr})} \times 100 \quad (1)$$

The operational energy efficiency of buildings are presented in the form of seven letter grades, from A (the best, i.e. lowest) to G (the worst, i.e. highest) where each band is set apart by 25 operational ratings. As shown by the equation, a building that has energy consumption comparable to the typical performance of similar buildings in that category would receive an operational rating of 100 which lies between the grades D and E. The benefit of using these ratings rather than the raw actual energy consumption (kWh/m^2) is that they are derived in relation to benchmarks which are adjusted to account for the circumstances of individual buildings, such as regional and seasonal variations in weather, as well as extended occupancy hours. The adjustment process also allows buildings in certain categories to deduct *separable* energy uses, which further reduce the discrepancy in characteristics between a building and the benchmark.

The scheme originally required non-domestic buildings that are occupied by public authorities or frequently visited by public and greater than $1000m^2$ in floor area to produce and display a DEC in a prominent location in the building (DCLG 2007). The recast of the directive and the amendment to the energy performance of buildings regulations saw a lowering of the threshold for DECs to 500 m^2 in 2013 and this is expected to be reduced further to $250m^2$ by 2015 (DCLG 2012; HM Government 2012b; CIBSE 2011). The DECs for buildings above and below $1,000m^2$ are currently valid for 12 months and 10 years respectively. Over the years, there have been various calls from the building industry to extend the DECs to commercial buildings. The possibility of extending DECs to the commercial sector was first proposed by the Department for Business, Innovation and Skills (BIS), and has since gathered momentum with a commitment by HM Government in The Carbon Plan to ‘extend Display Energy Certificates to commercial buildings.’ This commitment was however later reversed and the coverage of the scheme remains limited to public sector buildings (BIS, 2010; Gardiner & Lane, 2013; HM Government, 2011).

Chapter 3 Benchmarking the Energy Performance of Non-Domestic Buildings

This chapter gives an overview of benchmarking energy performance in the built environment. The basic concept of benchmarking and its role in the built environment is discussed. The literature focussing on various aspects of energy benchmarking is also reviewed in the following sections.

3.1 The role of benchmarking

The definitions of the words ‘benchmark’ and ‘benchmarking’ are given in the Oxford Dictionaries (n.d.) as “a standard or point of reference against which things may be compared” and an action taken to “evaluate (something) by comparison with a standard”, respectively. Benchmarking is a technique frequently used in businesses, that is employed to improve the operational performance of an organisation by assessing its internal performance against a benchmark (Camp 1989).

In the built environment, benchmarking is often employed as part of an energy management practice in existing buildings to assess and improve their energy efficiency (CIBSE 2012). This involves evaluation of the operational energy efficiency of buildings through comparison with standards such as historical energy use or established energy benchmarks. As a result, establishing and understanding the operational energy efficiency of a building assists and encourages building operators to make improvements. Benchmarking, therefore, is a technique that provides vast potential to influence and reduce the anthropogenic carbon emissions from non-domestic buildings.

In the UK, building energy-use benchmarks have existed from the late 1980’s. Historically, benchmarks have been used to give a feel for how buildings are performing against their peers, thus encouraging their owners and users to make them perform better (Bordass & Field 2007). However, without a supporting legal framework, the use of benchmarking was limited to those interested in improving energy efficiency on a voluntary basis, thus the potential for reducing consumption through benchmarking was limited.

In recent years, benchmarking has gained prominence due to the implementation of the Energy Performance of Buildings Directive in the UK (CIBSE 2003). The mandatory nature of the Display Energy Certificate (DEC) scheme means that opportunities to raise awareness and encourage more energy-efficient operation of existing non-domestic buildings have improved dramatically. Moreover, the requirement to display the certificate in a public place means that the operational energy efficiency has the potential to influence the reputation of an organisation, which could be a considerable motive. Hence, it has become crucial for the benchmarking process to be robust so that non-domestic buildings acquire an accurate evaluation of their operational performance.

3.2 Indicators of energy performance

In the built environment, an energy performance indicator (EPI) or Energy Use Index (EUI) is widely used to express the overall energy performance of a building, enabling its performance to be compared against another, as in benchmarking processes. In general, the indicators are commonly expressed in kWh/m^2/year or MJ/m^2/year (kWh/sqft/year or Btu/sqft/year, respectively, in countries which use imperial units (Sharp 1996)) or kgCO_2/m^2/year which expresses an overall CO_2 emission per unit floor area. The index is created generally by normalising the delivered energy consumption of a building relative to a determinant of energy use, which is usually the floor area of a building for the majority of building types in the UK and other countries. By normalising various determinants of energy use, the index can be used to compare energy performance between buildings to highlight the inefficiency of a building or its services.

Floor area is the most widely used denominator; however a study by Bordass (2006) shows that there is a large variation in conventions for measuring floor areas such as the Treated Floor Area (TFA) used by building services engineers; Net Internal Area (NIA) or Net lettable Area (NLA) widely used in commercial properties; and Gross Internal Area (GIA) commonly used by design and building teams. He emphasises that the most inaccurate aspect of the indicator is the denominator as people are often sloppy about both the units and the numerical values. In addition, there are other types of denominator used in certain types of buildings in which other characteristics of buildings or businesses are considered to represent energy use better than the floor area. For example, these might be the number of prisoners in prisons (kWh/prisoner), number of meals served in catering buildings of the Ministry of Defence (kWh/meal), the number of covers (place settings) in a restaurant (kWh/cover), the number of pupils in a school, or the numbers of bedrooms in a hotel.

Recently a study by Dooley (2011) suggested that floor area-based indicators are extremely useful during the design stage, when the building is being compared to an alternative version of itself to evaluate the influences of design elements such as solar shading or insulation levels. These indicators were however deemed insufficient as performance indicators for motivating energy efficiency of buildings through comparison of energy performance, due to a lack of understanding of how effectively a building will be used once it is occupied. The author therefore proposes a new form of metric Wh/m^{2}h which takes the annual energy consumption metric, kWh/m^2, divided by total person hours which are the total number of hours that all building users spend in the building during the year.

An analysis by Bruhns et al. (2011) however revealed that the correlation between occupancy levels and energy consumption in commercial offices in the UK was poor and that there is a lack of robust and low-cost methods for collecting accurate occupant density information, without which there would be considerable potential for abuse of benchmarks on this basis. Moreover, this analysis concludes by illustrating that benchmarking per square metre is more reliable, and that occupancy-related benchmarks should be regarded as complementary indicators and reported voluntarily, at least until robust methods of measuring and recording occupation density have been developed. The limitation of the analysis by Bruhns et al. (2011), however, is that it was only based on the Full Time Equivalent hours of occupancy which suggests that it does not fully reflect the transient population in the building, and that the scope was limited to data from large offices covered by the Better Buildings Partnership[2], which is an organisation of high-end commercial property owners. The inadequacy of using occupancy to evaluate energy consumption is also highlighted in a report from the Probe studies[3] where the reasons for not using occupancy were indicated as: floor areas are generally measured more often than occupancy; many aspects of building energy consumption are related more to area than occupancy; and hours of use by nominal occupants can vary widely (Bordass et al. 2001).

Regardless of the type of an EPI, CIBSE *Guide F* says that the performance indicators give only a broad indication of building efficiency and, therefore, must be treated with caution. Moreover, the *Guide* illustrates that overall performance indicators can mask underlying problems with individual end uses of energy, and that it should not be assumed that a building with a 'good' performance indicator is in fact being operated as efficiently as is possible, or offers no scope for cost-effective savings (CIBSE 2012).

The review has shown that there are varying approaches and perspectives to improving the comparability of benchmarking by examining the energy performance indicator. It was also shown that much of the work to assess the impact of occupancy levels and their relationship to energy use was implicitly focussed on offices. The extent to which a similar approach would apply to other building types therefore remains to be explored.

3.3 Approaches to deriving energy benchmarks

There are two fundamentally different approaches that are used to analyse or design systems in engineering disciplines: top-down and bottom-up. A top-down approach refers to the way in which a system is designed by first formulating an overview without details of the sub-systems. The system would then be refined further, subject to the availability of more detailed information. A bottom-up approach on the other hand would involve specification of lower-level system information that would then be used to build up a more precise overview. In much the

[2] For Better Buildings Partnership, see http://www.betterbuildingspartnership.co.uk/
[3] For Usable Buildings Trust, see http://www.usablebuildings.co.uk/

same way, the methods that are used to derive energy benchmarks for buildings can be grouped into these approaches based on the granularity of the information involved.

In the field of benchmarking, the top-down approach can be referred to ways in which energy benchmarks are derived based on building-level energy performance figures. These benchmarks are usually expressed as energy use intensities (EUI) and indicate how other buildings with similar demand use energy. A review has shown that there is a range of methods with varying levels of complexity that are top-down in their nature.

A top-down method which is widely used in the UK is to derive energy benchmarks based on descriptive statistics such as 50th and 25th percentiles from a distribution of the energy performance of sample buildings (Action Energy 2003; CIBSE 2012; Hernandez et al. 2008; Jones et al. 2000). Similar methods were also used to assess the energy performance of schools in Argentina and Greece (Filippin 2000; Santamouris et al. 2007). In recent years, the method was improved through the introduction of procedures to normalise the benchmarks, to tailor them to the individual circumstances of buildings in different regions with varying occupancy levels (CIBSE 2008).

There are top-down methods that are more complex in order to evaluate operational energy efficiency more precisely. The earliest attempts were made using multiple linear regression models to identify significant determinants of the energy use of buildings in the US (Sharp 1996; Sharp 1998; Monts & Blissett 1982). The approach now forms the basis of the US Environment Protection Agency's (EPA) Energy Star scheme (Environmental Protection Agency 2011). In addition, the same approach was used to benchmark the energy efficiency of commercial buildings in Hong Kong (Chung et al. 2006).

In recent years, the possibility of using an Artificial Neural Networks (ANN) method to benchmark the energy performance of buildings was explored in the US (Yalcintas 2006; Yalcintas & Ozturk 2007). An ANN is an information-processing system that is used to recognise a pattern in given data by mimicking the mechanisms of a human brain (Fausett 1994). Although it may be innovative, the robustness of the new method remains to be verified.

There were also studies that used Data Envelopment Analysis (DEA) techniques to identify frontiers, or buildings that are the most efficient users of given resources, and use them as a reference point to identify inefficient buildings (Zhou et al. 2008; Lee & Lee 2009; Lee & Kung 2011; Lee 2008). Rather than using descriptive statistics or regression models to establish the typical energy performance from a given data, the DEA method identifies the least energy-intensive building for a given characteristic. These efficient buildings then becomes the benchmarks for assessing levels of energy efficiency of other buildings.

While top-down approaches are the most commonly used, Federspiel et al. (2002) argue that there are two fundamental limitations. First, it is argued that benchmarks cannot be derived unless there is sufficient data for similar buildings. This is certainly a critical aspect of the top-down approach, which depends on the availability of sufficient data to represent the stock. Considering the diversity of buildings and activities that exist across the non-domestic building sector, it is currently unlikely that there will be sufficient data to derive top-down benchmarks for these building types. Second, the evaluation is based on an assumption that benchmarks are representative of the wide spectrum of energy efficiency levels in the stock. Taking into consideration that most top-down benchmarks are representative of the energy performance of buildings found at 50th or 25th percentiles without any basis in detail of the quality of fabric or efficiency of building services, it is correct that the benchmarks do not necessarily represent absolute levels of energy efficiency.

The bottom-up approach on the other hand refers to ways in which whole-building energy benchmarks are built up by aggregating system-level information. For example, benchmarks for schools would be derived by first estimating the energy performance of individual systems, such as the ventilation or lighting systems. These system-level consumption figures would then be aggregated together into a single EUI representing the hypothetical performance of a whole building.

There are a few examples of bottom-up approaches being used for benchmarking the energy performance of existing buildings. Federspiel et al. (2002) proposed using a simulation model to derive the whole building benchmarks for laboratories in the US. The author argues that the bottom-up approach allows benchmarks that depict the theoretical minimum performance of buildings, hence representing energy consumption achieved at the maximum level of operational energy efficiency. A series of assumptions were made however in the study in order to simplify the calculation process of the model. It was for example assumed that there are no conductive heat transfers or transmissions of solar energy through the building fabric, which are crucial parts of building physics that determine the demand for space heating and lighting. Similarly, default values were specified for a range of variables including those that describe the occupant density and schedule. The study by Federspiel et al. (2002) proposes a fresh perspective on producing benchmarks and what they portray, and ways in which the comparability of benchmarking could be improved considerably compared to the top-down approaches. The plethora of uncertainties associated with the assumptions that are made for estimating the optimum performance however is unlikely to reflect how buildings are actually used (Bordass et al. 2004).

The simulation-based approach to benchmarking was also explored by Mathew et al. (2004, 2010). These studies emphasise the limitations of empirical benchmarking methods in benchmarking the operational energy efficiency of complex buildings such as laboratories. Nevertheless, both studies do not provide details of and limitations of the assumptions that were made during the simulations. The studies therefore do not allow assessment of whether uncertainties associated with approximating occupant behaviour or building physics were resolved or addressed adequately.

Bottom-up approaches such as Simplified Building Energy Modelling (SBEM) or dynamic thermal modelling software are also used in the UK to estimate the energy performance of new buildings for producing EPCs or for demonstrating compliance with the Building Regulations (DCLG 2012a; HM Government 2010c). As described previously however, these estimations do not currently reflect the actual patterns of energy use and take into account the plug loads such as computers, printers or kettles. These methods therefore, have yet to be explored for benchmarking the operational energy efficiency of existing buildings.

Other bottom-up methods include the CIBSE *TM22* method which can be used to benchmark the energy consumption of major building systems or end uses (CIBSE 2012). Unlike the simulation-based approach, benchmarks for individual end uses are derived by using a tree diagram approach.

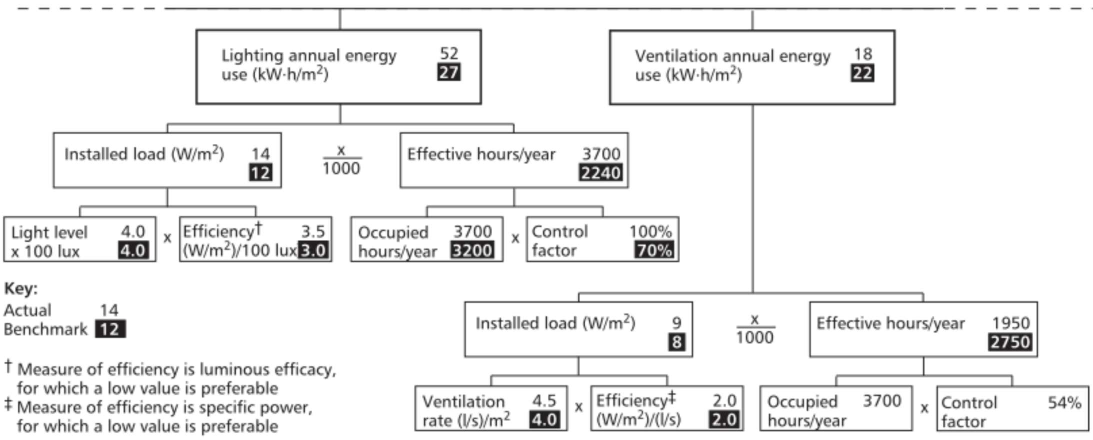

Figure 3.1 Tree diagram method in CIBSE TM22 (source: CIBSE 2012)

As shown in Figure 3.1, the energy consumption of each end use is derived based on parameters that describe specifications of equipment and the usage. Taking the end use lighting for example, the end-use energy consumption is derived based on the designed lighting level, efficiency of lighting, and parameters that describe the occupancy and maintenance. Similar to the simulation-based approaches, these benchmarks have the potential to portray absolute levels of efficiency in finer detail. The limitation of the method is however, that the implications of variations in building design on the energy uses are not taken into consideration. The variations in glazing area or shading design, and climate conditions such as cloud coverage for example, would all have different implications on the demand for artificial lighting in different buildings. Similarly, the method currently does not provide any means to estimate energy consumption for space heating or cooling, as these end uses are dependent on the thermal performance of buildings as well as features of building fabric such as thermal mass that are not accounted for by this method.

3.4 The robustness of top-down energy benchmarks

Deriving energy benchmarks that are representative of the stock is essential to developing and maintaining a robust benchmarking system. Benchmarks that are representative of the stock can provide an opportunity to gauge one building's performance in relation to peers. Inaccurate benchmarks on the other hand may mislead building operators into taking ineffective actions or at worst no actions at all to improve operational energy efficiency.

As described earlier, top-down benchmarks in the UK have been predominantly derived from statistical distributions. Due to difficulties in acquiring data for the entire population however, top-down benchmarks are generally derived by making inferences about the wider population from a smaller sample. This means that the robustness of the benchmarks is heavily dependent on various characteristics of the underlying sample.

Firstly, there is the sample size. Making inferences about a parameter of a population from a sample, which in this case would be the typical energy performance, means that the estimate is bound to have an associated degree of uncertainty. As Liddiard (2008) points out, it is often difficult to determine the reliability of energy benchmarks due to the general lack of transparency of the underlying data. A number of historical works however, provide references to standards which have been used to ensure that the benchmarks reliably represent the patterns of energy use in the stock. The sample size that is most frequently quoted as a threshold for determining the reliability of benchmarks is 50, although 100 samples has also been quoted occasionally (CIBSE 2012; Jones et al. 2000; Jones 2014; Bruhns et al. 2011). Despite the uses of such samples, no empirical evidence has been put forward to support the idea that the uncertainties associated with the resulting benchmarks are small enough for them to be deemed reliable.

The composition of buildings in the sample and their characteristics can also influence the robustness of the benchmarks. As Federspiel et al. (2002) highlight, the typical levels of performance portrayed by energy benchmarks are dependent on the energy efficiency levels of buildings in the underlying sample, which may not be representative of the stock. A sample that is biased towards inefficient buildings for example would lead to benchmarks that portray poor energy performance as being typical of the stock.

The sample should also be up-to-date with the latest patterns of energy use of the stock. Recently, a review of the CIBSE *TM46* benchmarks that underpin the DEC scheme was carried out by Bruhns et al. (2011). The study was based on actual energy consumption data of unprecedented scale, hence producing findings with a high level of statistical quality. The review showed positive results where 94% of buildings in the database were within one grade of their benchmark. Based on the overall statistic, the authors suggested that the benchmarks are indeed representative of the stock and are appropriate to support the DEC system. Hidden away from the main conclusions were however results that showed that benchmarks for electricity and fossil-thermal EUI were not at all relevant to the actual consumption of buildings (Figure 3.2).

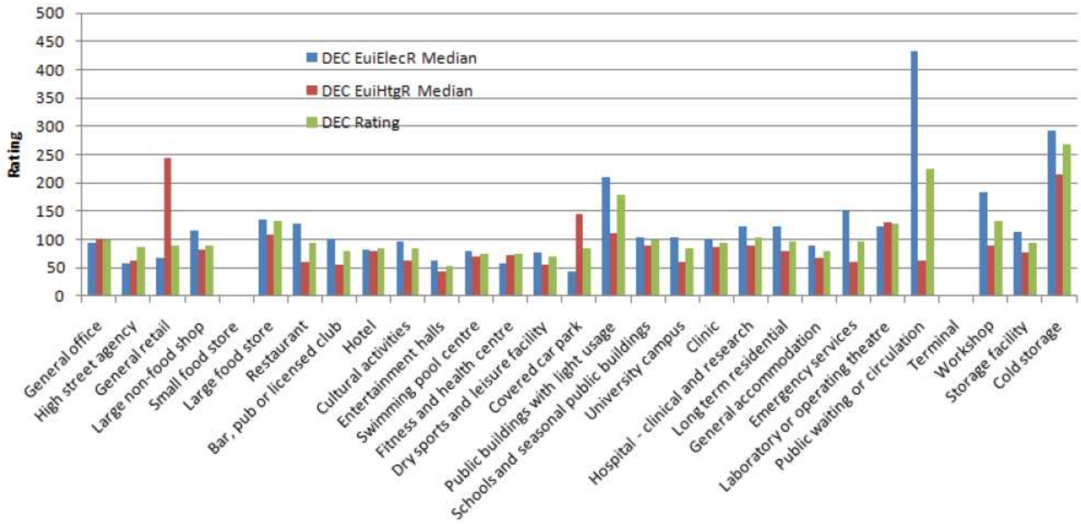

Figure 3.2 EUIs and operational ratings by building category (Bruhns et al. 2011)

As shown above, there is a general trend towards higher electrical EUI and lower fossil-thermal EUI compared to the benchmarks (Rating = 100) across numerous categories. It can also be seen that the resulting DEC ratings are similar to the benchmarks due to the cancelling effect of the opposing trends. Technically, this means that the benchmarks are not likely to be representative of the latest patterns of energy use in the stock.

3.5 Classification of buildings

The way non-domestic buildings are grouped into different categories plays an important role in benchmarking their energy performance. Buildings should be grouped in such a way that only those that have similar patterns of use and demands for energy are benchmarked together. A poor grouping of buildings can lead to feedback that does not provide true evidence of either a good or poor performance but rather a categorical error (Bordass & Field 2007). An example of such an error would be to compare performance of a large supermarket, which generally uses more energy-intensive equipment such as freezers and fridges, against a benchmark that represents general stores which are likely to be considerably less intensive in energy as much of that energy is used for lighting and providing a comfortable indoor environment.

The difficulty in classifying buildings correctly with their peers with similar patterns of energy use comes from the complexity and heterogeneous nature of buildings in the non-domestic stock. Unlike the domestic stock, there is a large variation in the way buildings are used, hence in the varying patterns of energy use, as shown in Figure 3.3. The types of activities engaged in by occupants, including their use of machinery, vary widely between buildings where, for example, in the retail sector there are general stores, lighting and electrical goods shops and food stores, each with distinctive sets of requirement for use, environment and equipment. In addition to the diversity of activities there is a diverse range of characteristics and qualities of buildings within the building stock such as built form, size, services and age, which can have varying influences on energy consumption. For example, there are at one extreme small buildings such as information kiosks with less than 30m^2 in floor area with a minimum level of building services, and at the other extreme heavily-serviced high-rise buildings which are tall and slender with floor areas greater than 5,000m^2 such as hospitals or commercial offices, or low-rise buildings with deep plans such as supermarkets or warehouses. The complexity of the stock due to variation in activities and physical properties of buildings is further exacerbated by a very loose relationship of built form to function (Bruhns 2000b). Taking the function ‘office’ as an example, office businesses can operate in various types of building from converted Victorian houses or purpose-built low-rise buildings with courtyards in office parks to temporary huts on construction sites. Consequently, the aspects of classification that have influence on or relevance to the benchmarking process depend largely on how buildings are grouped as well as the level of detail that the classification provides.

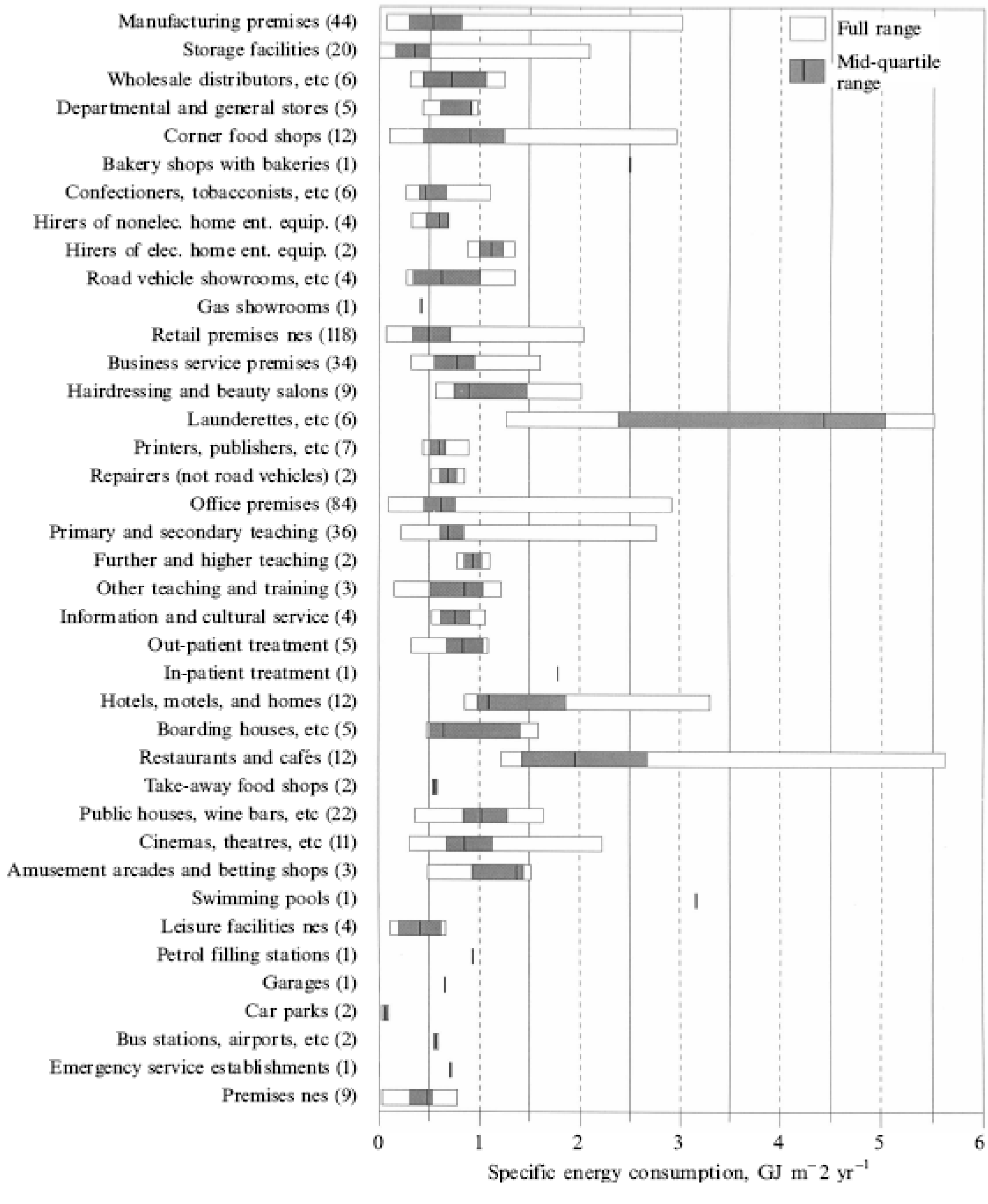

Figure 3.3 Frequency distribution of energy consumption of various non-domestic building types (Mortimer et al. 2000)

3.5.1 Basis of grouping

In the UK there are various classifications used to categorise non-domestic buildings into different groups for various purposes.

A common basis for this grouping is to categorise buildings by the economic activity, in the sense of the economic sector served. A classification which is widely used for classifying various activities in the non-domestic sector for purposes other than analysing energy consumption is the Standard Industrial Classification (SIC) (CSO 1980). The SIC is a well-established and widely used system that comprises a detailed and comprehensive system of categories that distinguish the manufacture of different types of commodity and the supply of different commercial, public and charitable services. Adaptation of the classification to analysing energy consumption in non-domestic buildings can be observed in the Energy Efficiency Office study that took place in the late 1980's (Herring et al. 1988). The study shows that there was an effort to relate the study to the SIC of 1980 as much as possible. It transpired however that the SIC does not allow an easy division of sectors. Some data on categories was therefore assembled according to the 1968 version of the SIC.

The adequacy of the SIC for use in a database for analysing energy consumption and for benchmarking purposes was evaluated in later years by Bruhns et al. (2000) and Bordass (2007), respectively, due to questions about the appropriateness of the classification. In both studies, the SIC was deemed inadequate on the grounds that it classifies the economic sector served by a business or institution that is occupying the building, but does not necessarily relate to the physical characteristics of the building and its energy consumption. A large food retail company such as Sainsbury's, for example, would be classified under the 'Food Retailing' category in the SIC. The problem that arises due to such classification is however the fact that the company comprises a diverse range of activities including offices, shops or warehouses that have considerable differences in the pattern of energy use. Benchmarking based on the economic activity classification to evaluate the energy performance of the company would therefore not yield any useful information.

By contrast, there are classifications that group buildings based on the type of activity that takes place in a building. The set of classifications used by the Valuation Office Agency (VOA) is a system that has been extensively used for analysing the energy consumption of non-domestic buildings as part of the National Energy Efficiency Data (NEED) framework of the

Department for Energy and Climate Change (DECC 2013). The classification system has also played a significant role in developing one of the key classifications in the Non-Domestic Building Stock (NDBS) database project. The strengths of the composite activity classification called the ‘primary’ classification comes from the detailed coding system (Bruhns et al. 2000). The coding system comprises letters and numbers which represent a category at each hierarchical level. At the top are the four principal divisions which form the first letter of the coding followed by a next letter through which 13 bulk classes are created from the combination. Further disaggregation into more detailed categories is made at the next level where a numeric code is added to the first two characters to form 57 ‘primary types’. Through the combination of codes at different levels, the primary classification allows buildings to be classified accurately according to what they are used for instead of relating to the economic sector which they serve.

There are however difficulties in using such classification for benchmarking purposes due to the differences between a hereditament and a building. The key difference between hereditaments and buildings is the boundary by which one entity is identified from another. A hereditament refers to an area of floor space with one owner or occupant who pays the rates but the boundary of a hereditament does not necessarily equate to the physical boundary of a building (Bruhns 2000). A hereditament can vary from being part of a building, a whole building, or a group of buildings on a site as long as the space is occupied by one entity. A positive aspect of such classification in the context of benchmarking is that the pattern of activity in each category can be expected to be reasonably homogeneous, hence the pattern of energy use (Bruhns 2000b). The challenge is however the fact that energy is often used, metered and benchmarked at a building level. Some of the intrinsic features that determine the demand for energy are also associated with buildings. Bruhns et al. (2000) suggest that there are possibilities for using the VOA classification in conjunction with the SIC coding for the analysis of the energy performance of non-domestic buildings. However, this remains unexplored.

A similar approach in categorising the non-domestic stock by the type of occupant activity can be seen in the benchmarks in CIBSE *TM46*, which aim to evaluate the operational performance of non-domestic buildings (CIBSE 2008). The classification system comprises two levels: benchmark categories and building type classifications. At the top level, the benchmark category is used for benchmarking the energy performance of buildings that accommodate similar activities. The building type classification on the other hand, is a further refined list of activities that provide guidance in selecting a correct benchmark category. In a report, Bruhns et al. (2011) explains that the classification was developed under the philosophy that activities in the same category are expected to have similar requirements for use, environmental conditioning and installed appliance loads, hence the pattern of energy use. Moreover, it was highlighted that there were issues associated with the activity classification of buildings and that a full review was necessary. The issues were mainly related to uncertainties associated with building type classifications that were temporarily allocated to benchmark categories due to a lack of evidence. The study concluded that there was a need to assess the building type classifications for issues such as misallocation or introduction of new benchmark categories.

There are also classifications which base the grouping on the physical properties of buildings. Adopting physical parameters of buildings as a basis for grouping to improve the relevance of benchmarking can be seen in a number of categories in CIBSE *Guide F*, which is a compilation of existing benchmarks into a harmonised format (CIBSE 2012). An example of this can be seen in the categories ‘Education (higher and further)’, ‘Industrial buildings’ and ‘Offices’ in which buildings are further grouped into sub-categories based on different physical and technical parameters. In the ‘Education’ category for example, a distinction is made between buildings which are naturally ventilated and those that are air-conditioned. Using the ventilation system as a basis for grouping can also be seen in the ‘Offices’ category where a distinction is made between offices of different sizes with different ventilation systems (Action Energy 2003). Due to the similarities between intrinsic features of the buildings, such a grouping would allow the comparison to show more accurate evidence of the efficiency of the building. With the potential of air-conditioned buildings to perform similarly to naturally ventilated buildings however, setting higher benchmarks for air-conditioned buildings by grouping them separately from naturally ventilated offices was considered inappropriate (Bruhns et al. 2011). This was due to concerns that this could encourage the addition of air-conditioning systems even when they are not necessary.

In addition to some of the classifications in CIBSE *Guide F*, a set of classifications that is comprehensive and detailed in categorising various physical parameters of buildings was developed in the NDBS database project. The parameters that were used as a basis for grouping are the built form and building services (Rickaby & Gorgolewski, 2000; Steadman, Bruhns, Holtier, et al., 2000) as well as wall and roof materials, glazing types and systems, and types of structural system (Gakovic, 2000; Steadman, Bruhns, & Gakovic, 2000).

3.5.2 Levels of classification

The level of detail that the classification in a benchmarking scheme provides also has influence over the relevance of the comparison. In general, the level of detail can be observed from the variation in the number of categories. A review of various existing classifications showed that there is a wide range of systems with varying levels of complexity.

The classification with the smallest number of categories was the classification in the EPBD which provides seven categories covering the entire non-domestic stock. While its simplicity may be useful for national level analysis, the loss of detail due to aggregation was deemed to be insufficient for use in benchmarking (Bordass & Field 2007).

There are also more refined classifications that were developed for the Simplified Building Energy Model (SBEM) tool and the CIBSE *TM46* (Building Research Establishment (BRE) 2014; CIBSE 2008). Both classifications provide a similar range of categories where SBEM provides 27 and *TM46* provides 29 categories. Despite the refinement however, the level of detail remains excessively coarse to address the diverse characteristics that exist in the non-domestic stock. In SBEM classification for example there is only one category to group all the buildings that accommodate retail activities. What is important to note here is that retail activities can vary greatly with regard to patterns of energy use. A hardware store for example may only use a small amount of electricity for lighting and perhaps gas for heating the space.

A large supermarket on the other hand would also belong to the retail category but use energy much more intensively due to equipment such as refrigerators or bakery ovens. A similar limitation can be observed in the *TM46* classification where there is one category for offices and one for schools. This means that the energy performance of a diverse range of buildings is compared to a shared benchmark value. While such aggregation considerably reduces the comparability, the authors of the review of DEC records argue that benchmarks do not necessarily need to be 'fair' for every building, but only as fair as can reasonably be managed (Bruhns et al. 2011).

At the other end of the spectrum, there are more detailed classifications such as the primary classification of the Non-Domestic Building Stock (NDBS) project and the classification found in CIBSE *Guide F*. These classifications provide in excess of 100 categories, acknowledging differences in activities and their implications on the pattern of energy use in much more detail. In general, these refined classifications would be beneficial in benchmarking the energy performance of buildings with greater relevance. The challenge may however lie in the fact that there will be fewer buildings under each category as the classification becomes increasingly more detailed.

The revision of various classifications and their complexity has shown that the number of categories vary immensely between different systems and that it is beneficial to disaggregate the categories in finer detail to improve the comparability of benchmarking. In addition, the review also suggested that the level of aggregation of the categories of the *TM46* classification system may require revision.

3.6 Comparability of benchmarking

There are various factors that determine the energy demand of non-domestic buildings. There are factors that are intrinsic to buildings such as the type of activity, the shape of buildings or occupancy hours that influence the basic demand for energy in providing a healthy and comfortable indoor environment to occupants (CIBSE 2012). There are on the other hand factors such as how equipment is used by occupants and how building services are operated that can lead to inefficient use of energy (Bordass, Cohen, et al. 2001). The extent to which the intrinsic features of a building that determine the demand for energy is comparable to other buildings that form the basis of energy benchmarks is therefore important in acquiring an accurate indication of how well a building is being operated.

A review of various benchmarking schemes has shown that adjustments are frequently made to account for the variation in the intrinsic features that are either specific to a geographical location or a building type. In the adjustment procedures, also known as normalisation, either the benchmarks or actual energy used in a building are adjusted to take into account the variation in individual circumstances that are appropriate to the category of activity, which in turn allows fairer comparison.

Adjustments for the seasonal and regional variation in weather conditions were found to be the most widely-used procedure in various countries to improve the accuracy of comparison. This procedure takes into account the weather-dependent characteristics of the space heating of a building in relation to external temperatures so that the performance of buildings in regions with different weather conditions can be compared to the relevant benchmarks.

In the UK (excluding Scotland), the benchmarks in CIBSE *TM46* are based on buildings located in the average UK climate with 2,021 heating degree days (HDD) with 15.5C° as the base temperature (CIBSE 2009). For more accurate comparison, the benchmark value for heating consumption of an individual building is corrected for heating degree days over the assessment period in the region where the building is located, to take into account the weather-dependent aspect of the performance. The adjustment is made using equation (2) below.

$$N_{dd} = [N\ (1 - P/100)] + [(N\ P\ /\ 100)\ (L\ /\ S)] \tag{2}$$

Where

N_{dd} is the fossil-thermal energy use of a school adjusted for degree-days (kWh/m^2/year)
N is the unadjusted fossil-thermal energy use (kWh/m^2/year)
P is the percentage of the fossil-thermal energy use pro-rated to degree-days (%)
L is the number of degree-days in the assessment period for the specific location
S is the standard heating degree-days for the category

A study of the benchmarking system in Germany by Cohen, Therburg, Bordass, & Field (2008) illustrates a similar procedure for adjusting energy consumption figures to account for variation in climate by period and regions. In addition to the current weather adjustment system, the study also highlights that a new model for weather adjustment is under development which will allow corrections to be made to account for variation in number of degree-days according to the differences in altitude in the same region.

A more general difference of the German system from the UK system is that the weather adjustment is made to the actual energy consumption of a building, which has the benefit of having a fixed benchmark for each category. However, this approach suffers the vagaries of using a model to correct the metered energy for the effects of weather, whereas the UK approach which has the benefit of reporting actual results is more rigorous because the proportion of the benchmark which is weather-dependent can be specified (Cohen et al. 2008).

In Australia which has a much warmer climate than the UK, the adjustment for climate in the National Australian Built Environment Rating System (NABERS) involves additions or subtractions not only for the heating degree days (HDD) but also cooling degree days (CDD) which take account of the weather-dependence of air-conditioning systems (Bordass & Field 2007). A weather adjustment procedure can also be seen in the US Energy Star rating system where HDD and CDD are used to account for the relationship between weather and the energy intensity of buildings in different regions (Environmental Protection Agency 2011).

There were also adjustments for occupancy hours or intensity of use which were intended to acknowledge the differences in energy demand of buildings due to variations in how long buildings are occupied. Taking supermarkets, for example, one store may be occupied throughout the day and close in the evening while another store could be open for 24 hours. The differences in hours of occupancy means that the 24-hour store would intrinsically require more energy to operate the equipment and building services. It would therefore be sensible to take into account the impact of different occupied hours on energy use when comparing the energy performance of these stores.

In the UK, benchmarks represent the energy performance of buildings that are occupied for standard number of hours (e.g. 2,040 hours per year for general offices) (Bruhns et al., 2011). For buildings with varying hours of occupancy, adjustments are made to the relevant energy benchmarks to account for effects of the extended hours of occupancy, to improve the comparability. However, adjustment for buildings with shorter operating hours than the stated reference occupancy hours is currently not allowed.

The allowance for separable energy uses is a unique method that is used in the UK's *TM46*. Separable energy uses are end uses in a building such as server rooms and catering facilities that generally consume considerable amounts of energy but which are uncommon amongst the majority of buildings in the category (CIBSE 2009). In the UK, there is an optional adjustment which allows separable energy uses to be excluded from the comparison so that, for example, an office with a large regional server room that consumes a large amount of energy is not penalised in the comparison with benchmark value for offices based on buildings with no separable energy uses. A review of the *TM46* benchmarks has argued that additional separable energy uses should be introduced for hospitals and universities since these may improve the relevance of benchmarking (Bruhns et al. 2011).

Beyond these parameters the review of relevant literature also showed studies that have integrated additional factors that determine the energy use of non-domestic buildings.

In the United States, Sharp (1996, 1998) assessed the impacts of various building and operational characteristics on the energy use of offices and schools as part of a benchmarking process. Through analyses of schools for example, Sharp (1998) found that year of construction and presence of walk-in-coolers were the most common characteristics in schools that were correlated with the electricity consumption. These factors were then used as a basis for normalising the energy performance of buildings to improve the comparability. The approach now forms the basis of the US Environment Protection Agency's (EPA) Energy Star scheme (EPA 2011). Similar approaches were used by Chung, Hui, & Lam (2006), Lee (2008), and Lee & Lee (2009) for benchmarking the energy performance of supermarkets and government office buildings respectively.

In Australia, the National Australian Built Environment Rating System (NABERS) takes a similar approach in normalising for a particular set of factors that affect the energy demand of each activity type (OoEH n.d.). Taking offices for example, the scheme allows for divisions in energy use between the landlords and tenants (OoEH 2011a). Moreover, the methodology allows adjustments for variation in the number of computers and occupancy hours. The rating of hotels on the other hand considers a completely different set of parameters that are specific to the activity type, such as number of guest rooms, hotel AAA rating, and climate (OoEH 2011b).

These studies have shown ways to improve the comparability of benchmarking by assessing and introducing additional factors into the methods. The variables examined in these studies were however limited to descriptions of buildings in the form of floor area, its occupants and equipment. The implications of the intrinsic building design such as the shape or the glazed proportions of the building fabric on the pattern of energy use, and the possibility of incorporating these factors into benchmarking therefore remains to be explored.

Chapter 4 Methodology

This chapter describes the research problem that was defined through the review of background and relevant literature. The rationale behind the chosen research design and methods is explained in detail, and the scope and limitations of the research are described.

Note that this chapter is intended to provide an overview of the research only to the extent of how it was designed and structured. The details of data and methods that are specific to each analysis will be described in each chapter to provide continuity throughout the study.

4.1 Research problem

The review of the background to the study in Chapter 2 showed that there is an imperative and opportunities to reduce the anthropogenic CO_2 emissions from UK non-domestic buildings in order to mitigate their effects and adapt to foreseeable changes in the environment and society. In Chapter 3, it was found that benchmarking the energy performance of non-domestic buildings plays an important role in raising awareness of how efficiently buildings are being operated and provides motives for building operators to aspire to achieve higher levels of energy efficiency. The review of relevant literature focussed on various aspects of benchmarking also showed however that there were gaps in knowledge about the benefits and limitations of current benchmarking practice as well as the prospect of adopting more advanced methods in order to provide feedback that accurately portrays the levels of operational energy efficiency of buildings across the UK non-domestic sector.

Below are summaries of the key gaps in knowledge:

- Uncertainties were raised as to how appropriate the current Display Energy Certificate (DEC) scheme is for benchmarking the operational energy efficiency not only of public sector non-domestic buildings but all buildings across the stock. The issues identified were:

    - Energy benchmarks for public buildings were found to be inaccurate representations of the latest patterns of energy use.
    - The activity classification that forms the basis of the scheme is made at an aggregated level of complexity compared to established classification systems for the entire non-domestic stock.

- A wide range of methods have been explored and used for benchmarking in other parts of the world. In the UK however, benefits and limitations, and the feasibility of adopting other methods remains to be explored. The issues identified were:
    - There was some use of multiple regression analyses to assess, identify, and normalise for various building and operational characteristics.
    - The implications of features intrinsic to buildings, such as the built form and architectural design for energy demand remain unexplored.
    - Simulation-based benchmarking methods have been used, although these involve numerous uncertainties.

These gaps were used as a basis for developing the research questions and the objectives described in Section 1.2.

4.2 Research design

4.2.1 Selection of approaches

There are three types of research design that are commonly employed to address research problems: qualitative, quantitative and mixed-methods approaches. As suggested by Creswell (2008), each approach is appropriate for addressing different types of inquiry.

As illustrated by the list of objectives (Section 1.2), understanding the latest trends of energy use in UK non-domestic buildings and the influences of intrinsic building and operational features on their energy performance were at the heart of the research. As may be expected, the insights that are required to address the research questions are difficult to acquire without employing empirical data. There are examples of using theoretical methods such as simulation models in parallel with sensitivity analysis techniques to acquire insights into the influences of various building and operational characteristics (Demanuele et al. 2010). As discussed previously however, these methods heavily rely on assumptions on how a building may be used by occupants which is often inaccurate, hence different from how buildings are used in reality (Bordass et al. 2004). Consequently, it was deemed essential to employ empirical data throughout the research in order to effectively address the proposed questions.

The decision to make extensive use of empirical data meant that quantitative methods of analyses would be vital for interpreting the energy consumption data in the context of benchmarking. Uses of descriptive and inferential statistics would allow the latest and historical patterns of energy use in various non-domestic buildings to be analysed in order to assess the factors that determine the robustness of the top-down benchmarks as well as the classification system. Correlation analyses would also provide useful insights in assessing and identifying the key intrinsic characteristics that influence the energy demand of non-domestic buildings, which would be essential for assessing the feasibility of adopting more advanced methods. Accordingly, a quantitative approach was deemed the most appropriate to address the key research problems.

4.2.2 Scope

Prior to the consideration of research methods, a set of boundaries was established to ensure that the research questions could be addressed with sufficient breadth and depth within the timeframe of the research programme. The selection of the type of research and the building type that would be investigated in depth were taken into consideration.

The primary consideration lies with the time and resources that would be required to develop a deeper understanding of the energy performance of all UK non-domestic buildings. This is largely due to the sheer volume and diversity of buildings in the non-domestic building stock as described in Section 3.5. A case-study approach was therefore deemed appropriate for the research, in the sense that a study of a specific building type could be used to illustrate how the robustness of benchmarking could be improved across various building types that are required to lodge DECs.

Among various building types, primary and secondary schools were selected as being the most appropriate candidates for addressing the research problems due to their characteristics and the feasibility of obtaining sufficient data.

Schools are generally more homogeneous than other building types with regards to the factors that determine energy performance such as the range of equipment, and the level and type of occupancy. Taking university buildings for example, it would not be difficult to find a broad range of activities such as laboratories and administration offices within these buildings. While belonging to the higher education sector, the elements that determine the demand for energy can vary significantly. In addition, it is also likely that these considerably different types of activities will exist together, occupying different parts of one building. Again, there are differences in the tenancy status of offices, ranging from a sole occupier of a building to tenant within a building occupied by multiple tenants. Schools on the other hand are generally similar in their activities and it is highly likely that they are the sole occupiers of their buildings, although there may be some cases where a school co-exists with a nursery or a community centre. The homogenous nature of schools would therefore allow energy performance to be analysed in relation to the intrinsic features of buildings with greater precision.

There is also considerably more data available on schools than any other non-domestic building type. There are various sources of data on the energy performance of non-domestic buildings: the DEC scheme and the online platform Carbon Buzz. In 2010, a large dataset from the DEC scheme of approximately 45,000 records was obtained for an analysis by a research team at University College London (UCL) via the Chartered Institution of Building Services Engineers (CIBSE). As shown by the review of DECs by Bruhns et al. (2011), the largest group of records in the DEC dataset was under the ‘Schools and seasonal public buildings’ category. An agreement to analyse the latest DEC data between UCL and CIBSE meant that the most recent dataset of approximately 120,000 records accumulated in the central database until June 2012 would become available for the research. This latest data will be the biggest set of consistently formatted data on energy use of public buildings in the UK. Taking into account the large proportion of school records that were in the previous dataset, a large fraction of the new dataset was also likely to relate to schools and would provide an unprecedented opportunity to analyse the pattern of energy use of schools with high levels of statistical significance. There is also the data from Carbon Buzz database, an online platform that collects data through from the design to operational stages of various non-domestic building types. The strength of the database comes from the fact that detailed energy consumption of end uses are collected via the CIBSE *TM22* methodology. This would therefore provide deeper insights into how energy is used and explain the underlying factors. The weakness on the other hand is that the dataset is small and that these are mainly buildings that were completed in recent years.

Overall it was decided that the research would be carried out using primary and secondary schools as a case study to illustrate how the robustness of benchmarking could be improved and what this could mean for other types of non-domestic building.

4.2.3 Research methods

The study of possible methodologies has clearly shown that the research should be designed in such a way that both general and specific questions could be addressed, in order to acquire a holistic view of how energy is used in schools and the factors that affect it.

Figure 4.1 shows a schematic diagram which illustrates the research design. The diagram describes the changes in characteristics of data, and the flow of information and data throughout the research.

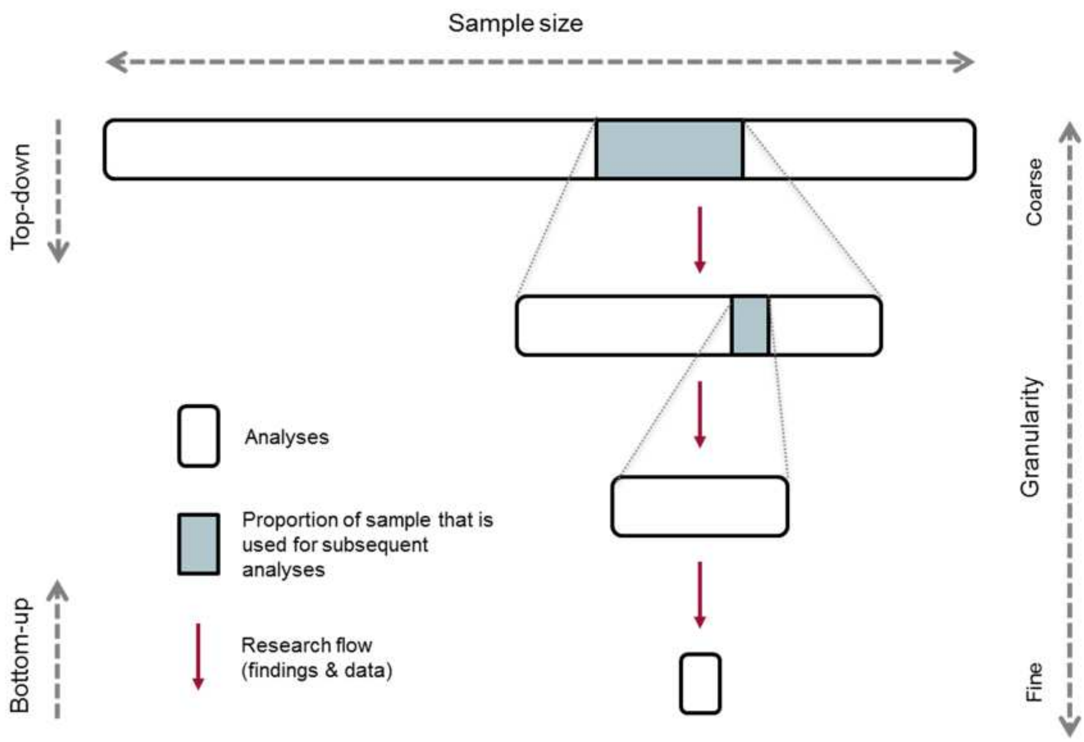

Figure 4.1 Schematic of the proposed research

The proposed design comprise four phases of analysis to take full advantage of the insights that could be acquired from data of varying characteristics. The underlying idea was that analyses of data ranging from those that are many in number but lacking in detail to those that are few in number but rich in detail would lead to different but complementary insights.

The strengths of the data with large sample size but coarse in granularity is that it is valuable for acquiring an insight into the general trends across a population not just limited to schools. Insufficient information on details such as built form or the specification of equipment however means that such analysis is not suitable for identifying the factors that contribute to long term trends. The strength of analysing detailed information on end-use consumption and information on the building services on the other hand, is that this gives a much deeper understanding of what makes up overall consumption in schools and why some schools are more intensive in energy consumption than others. The limitation in these instances however is that it is difficult to generalise the findings to a larger population due to the specific nature of the sample.

A detailed description of the overall structure of the research is shown in Figure 4.2. The diagram describes details of each analysis, the methods employed and the data types.

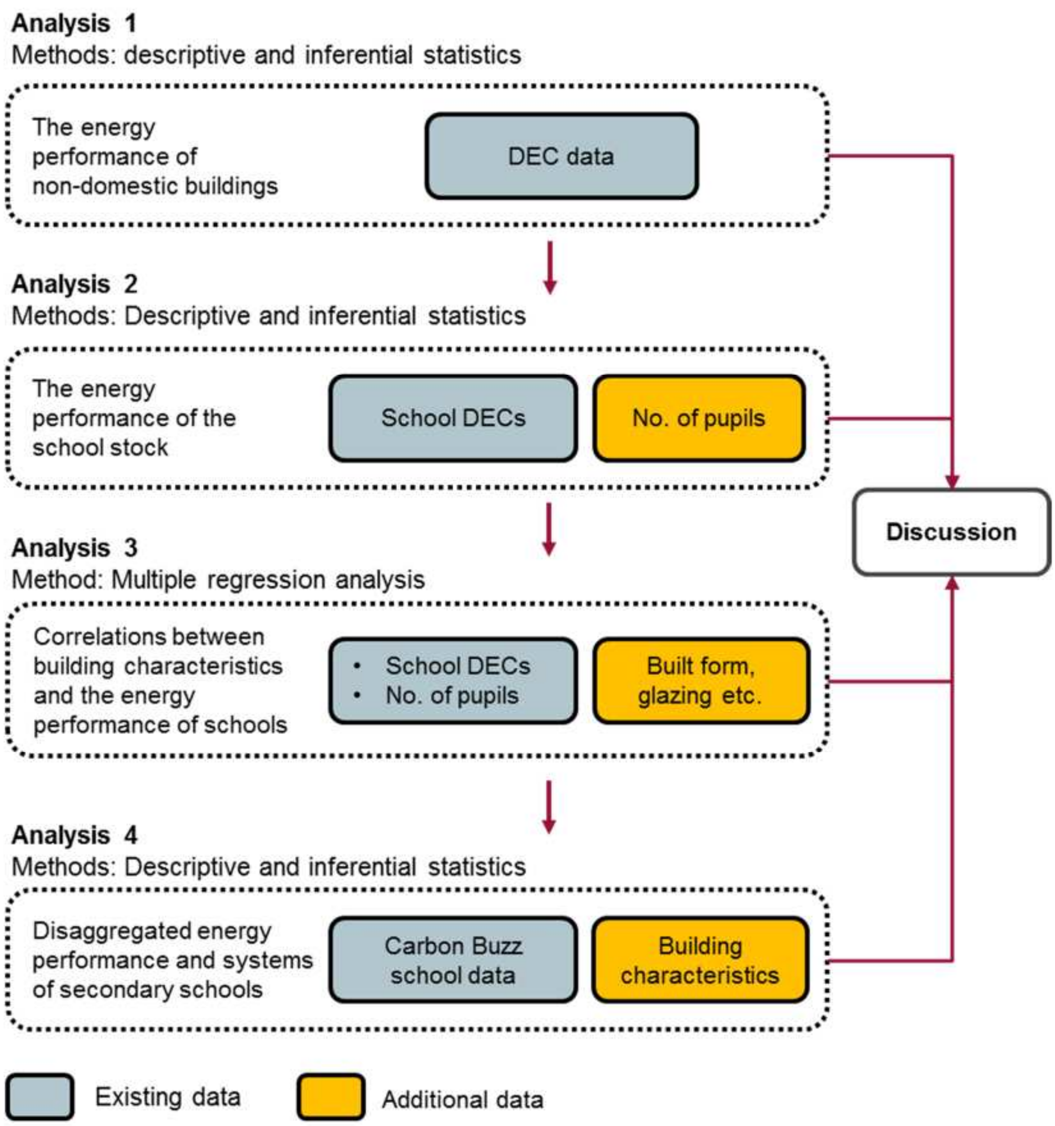

Figure 4.2 Description of the methods and the structure of the research

The hierarchical structure of the research means that each of the analyses will become progressively focussed on more specific elements. Below are descriptions of the aims of each analysis:

- The first analysis focusses on improving the understanding of the latest trends in the energy performance of public buildings that have lodged DECs. It also involves assessments of the energy benchmarks that underpin the mandatory DEC scheme based on empirical data. At this phase, the scope covers all non-domestic buildings for which data is available.

- The next phase marks the beginning of the case study where the focus of the research is narrowed down to the primary and secondary school stock. Having a narrower focus means that the analysis can delve deeper into the data. This phase involves not only descriptive statistics but also testing of various hypothesis to examine the implications of classifications and building characteristics. It also allows additional data to be joined to the existing data such as the number of pupils to enrich the picture.
- In the third analysis, the focus shifts towards assessing the correlations between the intrinsic features of buildings that determine the demand for energy and the energy performance of schools. There are however currently no existing data that describe the built forms of schools. This phase therefore involves a large data collection exercise to gather descriptions of buildings including the built form and glazing areas to further enhance the granularity of the dataset that was developed in the previous analysis.
- The last analysis focusses on detailed information obtained from site visits and sub-metering of modern secondary schools. At this phase, the data from Carbon Buzz with much finer detail such as specifications of building services and equipment is introduced into the research. This extremely detailed information is anticipated to provide insights on the breakdown of overall energy use into end uses in schools and why some schools are more intensive users than others. The addition of missing information on the built form, which is comparable to that developed in the previous analysis, also allows correlations between building characteristics and various end uses to be examined.

Once all analyses are complete, the findings from each chapter are gathered to form a basis for discussing the implications in improving the robustness of benchmarking the energy performance not only of schools but other non-domestic building types.

It should be noted that each chapter is structured in a self-contained way. Each chapter therefore comprises sections that describe how the data was collected and prepared, the methods that were used to analyse the data, and the results. This structure was deemed more appropriate in elaborating the process and the results than having a single methodology chapter, due to the scope and complexity of work, and the varying types of methods and data used in each phase.

4.2.4 Limitations

The decision to make extensive use of empirical data and the subsequent restriction of the scope of the research means that there are foreseeable limitations. Below are factors that are likely to influence the outcome of the research:

- The analysis of the latest energy performance will be limited to public sector non-domestic buildings due to the limited scope of the DEC scheme. Taking offices for example, the analysis only includes offices in the public sector including local and central government buildings. Without analysing the energy performance of private sector offices, the extent to which these public sector office figures would be comparable with the private sector will remain unknown.
- DEC records are collected from buildings that are greater than 1,000m^2 in floor area. This means that the energy performance of smaller buildings of various activity types is not accounted for in this research. There is therefore no immediate means to assess how representative the figures from the research will be of the entire population of a building type that comprises various sizes.
- Despite the cessation of site-DECs, there were limitations in identifying DECs that were lodged for a site rather than on a building basis due to uncertainties associated with flags that were used to identify these records. A limitation therefore exists in distinguishing DECs for buildings from those that represent the energy performance of groups of buildings on the same site.

4.3 Chapter summary

This chapter aimed to develop the research design based on the review of relevant literature and an exploration of various methodologies and methods.

Below is a summary of the chapter:

- Research problems were defined based on the review of literature and the context.
- A quantitative approach was selected as the framework for the research based on the importance of insights that can only be acquired by using empirical data.
- The research will involve a case study to address the research problems with sufficient breadth and depth within the timeframe of the research programme. Schools were deemed the most suitable due to their homogeneity and the availability of data.
- Four analysis chapters were designed in order to address research questions at varying levels of resolution. Each analysis involves data with varying sample sizes and granularity to gain different insights.
- A discussion chapter is used as a point at which the findings from the analysis chapters are triangulated to discuss the implications of the findings.

Chapter 5 Top-down Analysis of Public Sector Buildings

This chapter aims to understand the latest patterns of energy use of non-domestic buildings in the public sector and assess whether the benchmarks that underpin the Display Energy Certificate (DEC) scheme are robust. The following sections describe the methods and assumptions that were made to process and analyse the latest DEC records. The results from the analyses and the summary are presented at the end of the chapter.

5.1 Display Energy Certificate records

DEC records that were lodged since the implementation of the scheme in 2008 are collected and held by the Landmark Information Group in a central register[4] on behalf of the Department for Communities and Local Governments (DCLG). In September 2012, Landmark provided the Chartered Institution of Building Services Engineers (CIBSE) with a dataset of all DECs lodged until June 2012. The file contained 120,253 records that relate to 46,441 different buildings (or sites), many of which have multiple records. The file included numerous variables that describe the various aspects of public buildings which were used by the Energy Assessors[5] to produce a DEC (Hong & Steadman 2013). The raw dataset was later transferred to University College London (UCL) in the form of comma-separated values (CSV) and Microsoft Excel files.

5.2 Cleaning and processing the raw data

Prior to analysing the data, it was deemed essential to first examine the raw dataset for any signs of errors or invalid records. This decision was largely based on the previous analyses of DEC records by Bruhns, Jones, & Cohen (2011), which highlighted that extensive preparation work was required to identify and eliminate any invalid or uncertain records from the raw data. Each of the key variables in the raw dataset was therefore inspected and examined to assess whether the latest dataset would require cleaning and filtering to ensure the robustness of the results. This inspection revealed that issues associated with DEC records of uncertain nature

[4] Non-domestic energy performance register, see: https://www.ndepcregister.com/home.html
[5] An Energy Assessor is a person who has been accredited by an approved accreditation scheme to produce DECs and the accompanying advisory reports.

and erroneous classification inputs, which were observed in the previous study, persist in the new dataset (Bruhns, Jones & Cohen 2011). There was a need therefore to develop a set of rules and methods to clean and filter the data.

As the DEC records became publicly available only in 2010, there were only a few studies that had previously processed and analysed the records. The methods described in the study by Godoy-Shimizu et al. (2011) were considered but deemed inappropriate for this research, for the following reasons:

- The data that underpinned the study was an incomplete version of the DEC records. The authors of the study highlighted that there was no building type classification in the dataset, which is a key variable for identifying the specific activity type of buildings
- The study showed a lack of understanding of the DEC records whereby key characteristics such as electrically heated buildings, pro-rated DECs, or early renewals were not considered during the cleaning process
- Removal of the top and bottom 1% of the records based on floor areas and energy consumption discarded extreme records that may well be valid

The methods described in the study by Bruhns et al. (2011) on the other hand were deemed to be suitable as a basis for processing the latest DEC records, as they were developed and reviewed by experts who were involved in developing CIBSE *TM46*, which underpins the DEC scheme. The criteria were however developed and refined further in this research with assistance from members of the CIBSE Energy Benchmarks Steering Group[6]. Table 5.1 shows the summary of the procedures that were undertaken to prepare the data. The table also shows the numbers of records and buildings remaining after a series of omissions, which are explained in detail in the following section.

[6] CIBSE Energy Benchmarks Group was set up by CIBSE to oversee the development of the energy benchmarks in CIBSE *TM46* that underpin the DEC scheme.

Table 5.1 Summary of the data processing steps

#	Description	No. of Records after each step	No. of Buildings after each step
1	Import of raw data	120,253	46,441
2	Reclassification of benchmark categories and building types	"	"
3	Removal of uncertain records	86,549	36,652
4	Removal of DEC records that were renewed early	86,068	36,632
5	Removal of duplicate records	84,364	36,538
6	Removal of pro-rated DECs	73,160	31,802

The following sections describe the rationale behind each of the data processing steps as well as the criteria used to remove uncertain records.

5.2.1.1 Reclassification of benchmark categories and building types

Benchmark category and building type descriptions are variables that were included in the DEC dataset that describe the functions of buildings. Inspection of the inputs in the raw dataset showed numerous examples of typing errors as well as instances of benchmark categories being put into the wrong building type description and vice versa. The first step in preparing the raw data for analysis was therefore to amend the input errors associated with the benchmark categories and building types of individual records. The steps that were taken to correct the classification mistakes are described in detail in Table 5.2.

Table 5.2 Steps in the corrections of benchmark categories and building types

#	Description	No. Records
1	Unique combinations of all benchmark category and building type inputs using SAS[7]	142,397
2	Correct benchmark category and building types by manual assignment to the list of unique combinations in Microsoft Excel	753
3	Assign the reclassified benchmark categories to all records in SAS	120,253
4	Repeat step 3 to assign the corrected building types	120,253

[7] For Statistical Analysis Software (SAS), see http://support.sas.com/documentation/93/index.html

In step 2 (Table 5.2), the benchmark categories and buildings types were simply replaced when they were misplaced. For those records that had incorrect inputs either in benchmark categories or building types, or where there was than one building type description, corrections were made based on other variables that described the function of a building such as the address lines, which often contained names indicative of the activity type.

5.2.1.2 Removal of uncertain data

Each DEC record comprises variables that describe the characteristics of a building and its energy performance. In the previous analysis, Bruhns et al. (2011) identified and removed uncertain or erroneous records using a set of criteria relating to key variables. There were however various aspects of these criteria that were considered either out-of-date or inadequate for the present analysis. The criteria were therefore revised and a refined set of criteria was developed for the research, as follows:

- **Default Operational Rating (OR)**: Records where the Operational Rating was given as 200 or 9999 were excluded, since these are default[8] values given to DECs lodged with insufficient information on energy consumption.
- **Practically implausible OR:** Records where the OR was less than 5 and greater than 1000 were flagged and excluded. The lower boundary was defined based on the anecdotal experience of an expert from the CIBSE benchmarking steering group that an OR less than 5 is very unlikely to be achieved in an occupied building, and probably means that the building is vacant. It was also suggested that the highest OR values observed in valid DECs were of the order of 700 or 800, which therefore led to the conclusion that OR values greater than 1000 are likely to be errors.
- **Cancelled DECs**: On occasion DEC assessors may lodge a certificate and then realise that it contains mistakes. In these instances, the assessor may cancel the DEC and replace it with an amended certificate. The 'Report Status' variable in the dataset, which

[8] An operational rating of 200 is a default rating given to a building if valid meter readings for its energy consumption are not available. The default rating was later changed to 9999 in March 2010 and no longer allowed from 14 April 2011.

flags cancelled records suggested however that some cancelled DECs remained in the database from Landmark. These were therefore removed.

- **Very small buildings**: Records of buildings with total useful floor area recorded as less than 50 m^2 were removed, since such figures are likely to be errors. (Many DECs were however registered with floor areas between 50 m^2 and 1000 m^2 despite the fact that 1000 m^2 was the specified lower threshold of size throughout the period covered by the analysis: these are retained.)
- **Extreme CO_2 emissions**: Records showing total CO_2 emissions greater than 100,000 tonneCO_2/yr were removed as they were considered to be extreme outliers.
- **No electricity consumption**: Records where the Electrical Energy Use Index (EUI) was 0 were removed, since it is extremely improbable that an occupied building would use no electricity. These were deemed to be almost certainly errors.
- **Electrically heated buildings**: Buildings where electricity was the main heating fuel were flagged and treated separately in the analysis, since these are likely to have characteristically different patterns of energy use from buildings heated by fossil fuels.
- **No fossil-thermal energy consumption:** Once the electrically-heated building records were set aside, then any remaining records where the fossil thermal EUI was 0 were removed, since this would imply no heating at all, and such cases were thought likely to be errors. (Although there do exist some occupied non-domestic buildings that use no energy for heating as such, including certain types of shop.)
- **Composite DECs**: The DEC methodology allows buildings with mixed uses falling under different benchmark categories to assess their energy performance by means of a ‘composite benchmark’. This involves dividing the useable floor area of the building between the different uses, and applying the appropriate benchmarks in proportion to those areas. This meant that such buildings could not be assigned as a whole to a unique benchmarks for the purposes of analysis.

5.2.1.3 Corrections and early renewals

There are occasions when a new DEC is lodged a matter of months after another – they are only required annually - in order for example to report reduced energy consumption or to make other corrections. It is clearly desirable for the analysis to have no more than one DEC per building per year, if possible. Analysis of the number of days elapsing between the lodging of one DEC and its successor indicated that 0.6% of certificates in the data (754 out of 120,253) were lodged with assessment end dates less than six months from the previous lodgement. It was decided therefore to eliminate all records where the assessment period of the later record overlapped with the earlier record by up to 182 days.

5.2.1.4 Duplicate records

In principle, all duplicate records should have been removed from the database supplied by Landmark. A ‘report status’ variable should in theory have been used to indicate where records had been cancelled. Examination of this variable however showed that the relevant flag was not being rigorously applied and that approximately 0.6% of records showed the same consumption for the same building during the same assessment period. It was therefore necessary to devise a way of removing these unflagged duplicates. In order to avoid any uncertainties it was decided to discount all cases where more than one DEC had been lodged with the same energy consumption figures for the same period.

5.2.1.5 Pro-rated and site DECs

At the start of the DEC scheme a special arrangement was made for any institution with multiple buildings on one site, for example a hospital or a large school, to lodge a single DEC for the entire site (a ‘site DEC’). This was obviously unsatisfactory, since separate buildings might be of very different sizes, construction, using different fuels and so on. The arrangement was phased out in November 2009 and replaced with a provision that DECs could be lodged for buildings on shared sites, but without separate sub-metering, on a pro rata basis. It should, however, be noted that the ‘site DEC’ was still allowed on a voluntary basis after this date. To calculate the pro rata DECs the consumption for the entire site was divided between the separate buildings in proportion to floor area. However the problem remains, that pro-rated

DECs make no allowance for the different characteristics of the various buildings. For these reasons, pro-rated DECs were removed from the dataset. Pro-rated DECs were identified by the fact that they have the same site reference number, assessment end date and EUI values for electricity and fossil thermal energy.

5.3 Preparing data for cross-sectional and longitudinal analyses

The dataset that was prepared for the analysis comprised all DECs lodged up until June 2012. This meant that there were numerous cases where DECs were lodged for the same building over several years. Having access to such data therefore provided opportunities to examine the energy performance of buildings within specified time periods in *cross-sectional* analyses, as well as to follow trends over several years through *longitudinal* analyses.

The distinctively different nature of the two forms of analysis meant that it was necessary to adopt different methods for selecting the relevant DECs in each case. The following sections describe that process in detail.

5.3.1.1 Data selection for the cross-sectional analysis

The cross-sectional analysis was carried out to examine the pattern of energy use of non-domestic buildings based on their most recently deposited DECs. Due to the differences in the level of compliance however there was a variation in the dates when the latest DECs were lodged for each building. For example, some buildings were found to have lodged a certificate in 2012 whereas some buildings had lodged a DEC in 2009 but had not deposited another certificate since. A dataset for the cross-sectional study was therefore created, based on just the *latest* DEC from each building (Figure 5.1), to provide a sample representing current or recent performance, as was done previously by Bruhns et al. (2011).

Building	Assessment end dates					
	Oct 2008	2009	Before Feb 2010	After Mar 2010	2011	Jun 2012
A		●	●		●	●
B	●	●				
C	●					
D		●		●	●	
E					●	●
F	●	●		●		
G		●	●			
H		●				

Figure 5.1 Illustration of how the latest DECs were selected for the present cross-sectional analyses (blue cells indicate the latest DECs for each building)

It should however be noted that this dataset did not include any of the DECs analysed previously by Bruhns et al. (2011), who analysed DECs that were lodged up until February 2010. This meant that it was necessary to create a subset of DECs lodged between March 2010 and June 2012, to ensure that the present analysis was based solely on the new records. Since there were no variables in the dataset that indicated when each certificate was lodged, the assessment end dates were assumed as being the dates when the DECs were lodged.

Table 5.3 below shows the number of DECs under each benchmark category in the dataset for the cross-sectional analyses, and the percentages of total records that these represent. In all, there were 22,151 buildings used for the analyses. This represented approximately 70% of all buildings (31,802) that have lodged DECs since the scheme was implemented in October 2008.

Table 5.3 Number of buildings in the cross-sectional dataset by benchmark category

Benchmark category		N	% of all
1	General office	2,911	13%
2	High street agency	30	0%
3	General retail	33	0%
4	Large non-food shop	1	0%
5	Small food store	0	0%
6	Large food store	0	0%
7	Restaurant	21	0%
8	Bar, pub or licensed club	7	0%
9	Hotel	16	0%
10	Cultural activities	544	2%
11	Entertainment halls	203	1%
12	Swimming pool centre	261	1%
13	Fitness and health centre	42	0%
14	Dry sports and leisure facility	606	3%
15	Covered car park	0	0%
16	Public buildings with light usage	4	0%
17	Schools and seasonal public buildings	12,563	57%
18	University campus	1,442	7%
19	Clinic	728	3%
20	Hospital - clinical and research	573	3%
21	Long term residential	990	4%
22	General accommodation	196	1%
23	Emergency services	746	3%
24	Laboratory or operating theatre	74	0%
25	Public waiting or circulation	5	0%
26	Terminal	2	0%
27	Workshop	128	1%
28	Storage facility	25	0%
29	Cold storage	0	0%
All		**22,151**	**100%**

5.3.1.2 Data selection for the longitudinal analysis

The accumulation of DECs over the past four years means that it was possible to examine how the patterns of energy use in different building types have changed over the period. An important feature of the database created for the longitudinal analyses was that it tracked the energy performance of the same buildings over these years. This was to ensure that continuous trends could be followed for specified activities, year by year, and that any changes would be based on the same sample.

A preliminary examination of the changes in energy performance suggested that 2008 - the first year of the scheme’s operation - was anomalous, and that the data revealed some uncertainties. The anomaly was considered to be associated with initial teething problems and therefore all records for this year were removed. In addition, DECs with assessment end dates in 2012 up to June were also discounted because of the year being incomplete. In the end it was decided to leave buildings that had DECs with assessment end dates in each of the three consecutive years 2009, 2010 and 2011 as the basis for the analysis.

Building	**Assessment end dates**				
	Oct 2008	2009	2010	2011	Jun 2012
A		●	●	●	
B	●	●	●	●	●
C	●				
D		●			
E				●	●
F		●	●	●	
G	●	●		●	
H				●	●

Figure 5.2 Illustration of how the DECs were selected for the longitudinal analyses (blue cells indicate the selected records)

Table 5.4 below shows the number of buildings in each category that have lodged DECs for each of the three years between 2009 and 2011. Notice that there were several benchmark categories in which there were no such continuous runs of records. In total, 8,535 buildings have lodged DECs over the three consecutive years. This indicates that approximately 27% of all buildings in the complete DEC dataset (31,802) have lodged DECs consistently year on year.

Table 5.4 Number of buildings in the longitudinal dataset in each year by benchmark category

Benchmark category		Number of buildings in each year
1	General office	1,071
2	High street agency	0
3	General retail	15
4	Large non-food shop	1
5	Small food store	0
6	Large food store	0
7	Restaurant	6
8	Bar, pub or licensed club	4
9	Hotel	4
10	Cultural activities	230
11	Entertainment halls	96
12	Swimming pool centre	98
13	Fitness and health centre	8
14	Dry sports and leisure facility	218
15	Covered car park	0
16	Public buildings with light usage	1
17	Schools and seasonal public buildings	5,137
18	University campus	415
19	Clinic	236
20	Hospital - clinical and research	182
21	Long term residential	383
22	General accommodation	55
23	Emergency services	326
24	Laboratory or operating theatre	14
25	Public waiting or circulation	4
26	Terminal	0
27	Workshop	21
28	Storage facility	10
29	Cold storage	0
All		**8,535**

5.4 Methods of analysis

This section describes in detail the quantitative methods that were used to analyse the cleaned DEC data. Descriptions of methods and the underlying assumptions are given separately for cross-sectional and longitudinal analyses.

5.4.1 Cross-sectional analysis

The dataset that was described in section 5.3.1.1 was analysed first to gain an up-to-date view of trends in the energy performance of non-domestic buildings in the public sector. The large volume of numeric data and the nature of the objectives led to extensive use of statistical techniques.

As discussed previously, the patterns of energy use in public sector buildings were analysed based on the 29 activity classifications of TM46 that the DEC assessors had selected. This was based on the underlying philosophy of the activity-based classification, which assumed that buildings with similar activities would have similar requirements for occupancy, environmental conditioning and installed appliance loads (Bruhns, Jones & Cohen 2011). This however meant that the patterns of energy use identified in the study were independent of the type of business sector that each building belongs to, but rather related to the energy benchmarks that correspond to each of the activity types. Taking the energy performance of the buildings under the 'Schools and seasonal public buildings' for example, the trends would include schools, but also other non-education building types such as club houses and village halls, which are nevertheless included in the same grouping.

The patterns of energy use of buildings of different activity types were initially assessed based on their Energy Use Intensities (EUI). The distribution of the annual electrical and fossil-thermal EUI of buildings under each activity category was assessed using descriptive statistics and box-and-whisker plots. Due to the variation in sizes of the sample in each category however only those categories with more than 100 buildings were analysed to acquire reasonably robust results. In addition, the energy performance statistics were derived based only on buildings that were occupied for the standard number of hours to reduce the variation in EUI. The fossil-thermal EUI statistics presented were however not normalised to standard weather conditions.

Throughout the analyses, the energy performance of buildings was examined in relation to the benchmarks set out in CIBSE *TM46* based on operational ratings. In addition to the use of operational ratings that are derived based on the total annual carbon emissions, fuel specific performance ratings were calculated for electricity and fossil-thermal energy using the same method (equation 3).

$$\text{Performance rating} = \frac{\text{Actual electrical or fossil-thermal EUI (kWh/m}^2\text{)}}{\text{Adjusted electrical or fossil-thermal benchmarks (kWh/m}^2\text{)}} \times 100 \qquad (3)$$

This means that buildings with electrical or fossil-thermal ratings of 100 would have energy consumption comparable to the typical performance of buildings in that category.

Descriptive statistics were extensively used throughout the analysis to describe the central tendency and the variations in the pattern of energy use. The distribution of the operational ratings of buildings in each category was assessed using quartiles rather than the means. This was due to the presence of small numbers of energy-intensive buildings that frequently skew the distribution of the energy performance of non-domestic buildings. The median and other quartiles were therefore considered to be more appropriate to describe these skewed distributions.

Box-and-whiskers diagrams were used to visually assess and compare the distribution of the energy performance of buildings in different benchmark categories. The description and definition of various properties of the diagram is explained in detail in Figure 5.3.

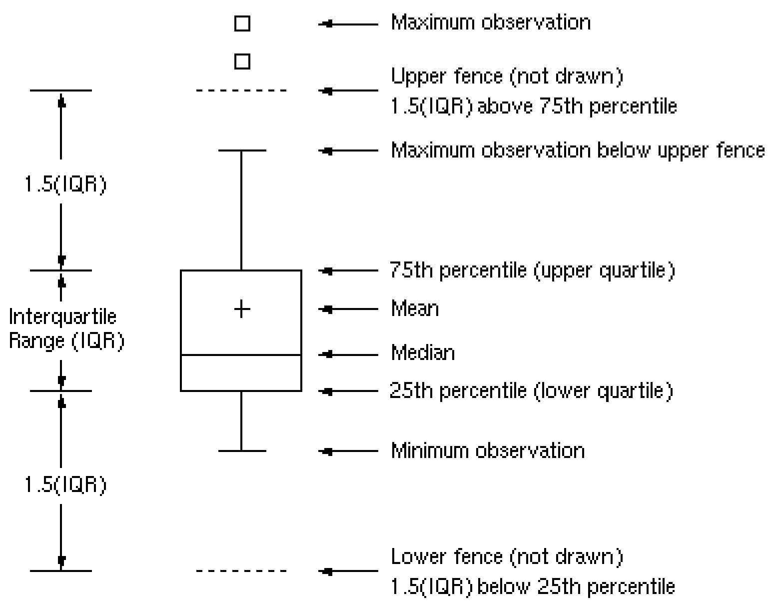

Figure 5.3 Diagram of box-and-whiskers plot (SAS Institute Inc., 2014)

A 'traffic-light' analysis was carried out to illustrate the severity of the deviation of the most recent performance of buildings from the benchmarks in each benchmark category. The median performance ratings for electrical and fossil-thermal energy use in each category were taken as a basis to determine the deviation.

Varying shades of red were used to show the different degrees to which ratings deviate from the benchmarks (Figure 5.4). The shades were designed so that they become gradually darker every 10% away from actual performance, with deviations greater than 30% marked by the darkest colour. The ratings that are within 10% deviation from the benchmarks were assumed to be an indication that the benchmarks are reasonably representative of the stock performance.

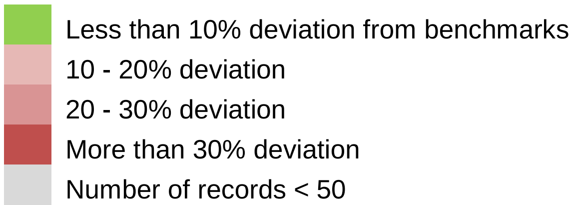

Figure 5.4 Description of the colour scheme used in the 'traffic-light' analysis

Buildings that use electricity as the main source of heating were separated from the main dataset and analysed separately (Section 5.2.1.2). The ‘Main Heating Fuel’ variable in the DEC database was used as a basis for identifying and filtering out those electrically-heated buildings. In all, 1,543 (3.3%) of buildings were separated from the main dataset. Prior to the analyses, the methods that were described in Section 5.2.1.2 were used to remove records of uncertain nature. 390 records (~25%) were found to be dubious and therefore removed from the analysis.

5.4.2 Longitudinal analysis

The dataset described in 5.3.1.2 was analysed to observe changes in the patterns of energy use of buildings in the public sector in the UK over the period from 2009 to 2011. The analysis was carried based on those cases where there are more than 100 buildings in any given benchmark category. This was to ensure that the results that were derived from the analyses are representative of the stock.

The year-on-year changes in the energy performance of buildings in different categories were assessed using a line graph. The median operational ratings were taken as the typical pattern of energy use of the sample buildings in each year. The different factors that contribute to the uses of electricity and fossil-thermal energy meant that two graphs, one for each fuel type, were plotted.

In addition to the analysis based on the typical performance, the changes in the distribution of the operational ratings were also analysed. The distribution was assessed by observing changes in the number of buildings that fall under each DEC grade band occurring over the three-year period. As discussed in Section 2.6, there are currently 7 letter grades, from letters ‘A’ to ‘G’. Each band is currently set apart by 25 operational ratings and starts from zero, which therefore means that all DEC records that have received ORs greater than 150 are given the grade ‘G’. To observe the changes in the number of buildings that are intensive users of energy but small in numbers, six additional grade bands were added for the purposes of analysis beyond grade ‘G’, starting from an OR of 175 (Table 5.5).

Table 5.5 The existing and additional grades and the OR ranges

Grade	Operational rating range	Note
A	0 < 25	Existing
B	25 < 50	“
C	51 to 75	“
D	76 to 100	“
E	101 to 125	“
F	126 to 150	“
G	< 150 - 175	“
OR > 175	< 175 – 200	Additional band
OR > 200	< 200 – 225	“
OR > 225	< 225 – 250	“
OR > 250	< 250 – 275	“
OR > 275	< 275 –	“

5.5 Results

This section presents results from the cross-sectional analysis of the DEC records. The initial part of the section presents the characterisation of buildings in the dataset. This is followed by results that show the patterns of energy use of non-domestic buildings in different categories. Lastly, results are presented from the assessment of the adequacy of the energy benchmarks for evaluating the energy performance of the public sector.

Figure 5.5 shows the total floor area of all buildings in each benchmark category.

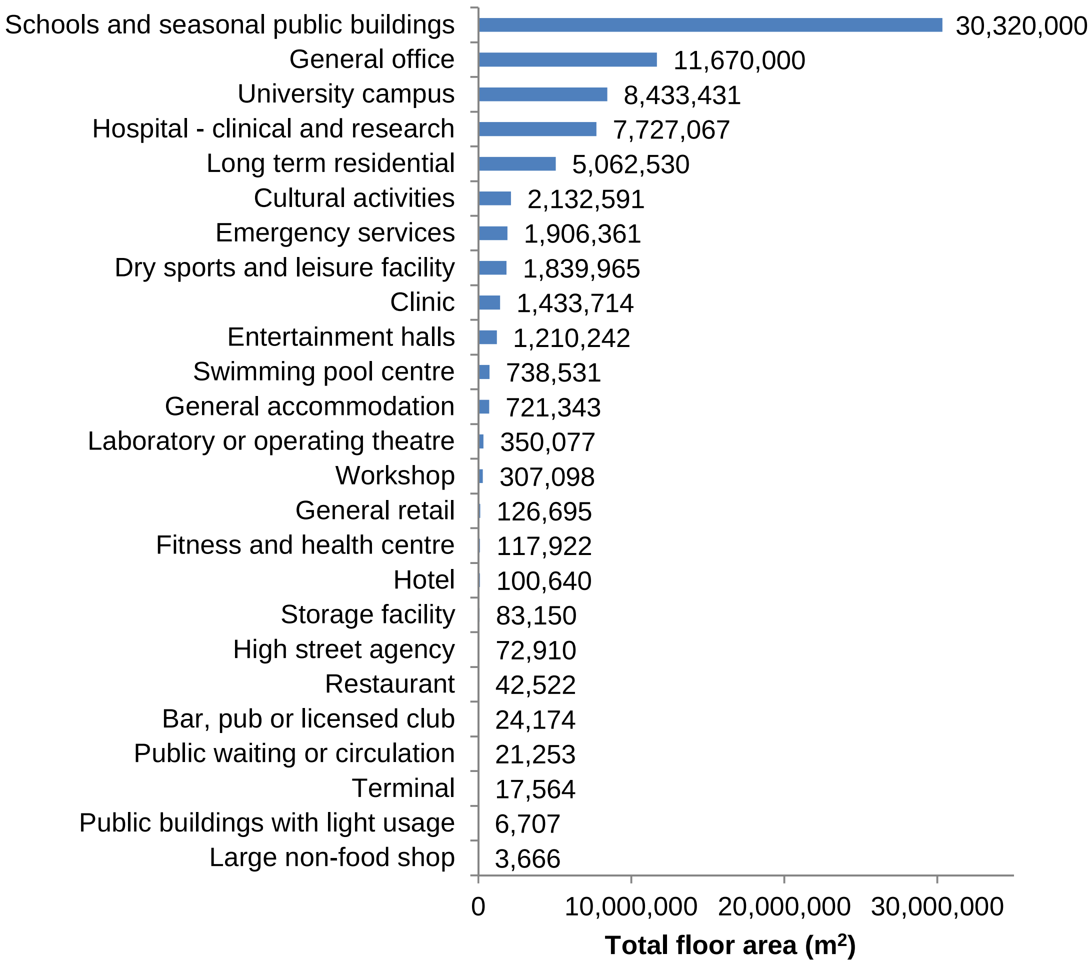

Figure 5.5 Total floor area of buildings in each category

It can be seen that buildings under the 'Schools and seasonal public buildings' account for the largest proportion of floor area, which reflects the number of records in this category that vastly outnumber all other categories. Buildings under the 'General office', 'University campus' and

‘Hospitals’ account for significant proportions of the total floor area in the dataset, despite much smaller sample sizes, which indicates greater floor area per building than schools.

There are a number of sources that provide the total floor area of various building types in the public sector that provide opportunities to determine the extent to which the DEC records represent the stock. These are for example studies such as those by Bruhns, Steadman, Herring, et al. (2000) or the data on public sector buildings from e-PIMS (HM Government 2012a). Difficulties in accurately comparing the statistics from different databases arise however, due to differences in the way buildings are classified. The ‘General office’ category for example comprises not only central and local government offices but also other office types such as law courts and warehouse offices. There is also a difference in the definition of entities whereby DEC records describe a building while the statistics provided from the Valuation Office Agency data are for premises, which can be part of a building, a whole building or several buildings. The issues associated with the classification system highlight difficulties in utilising the DEC data in conjunction with other data sources.

Figure 5.6 shows the distribution of sizes of buildings in each category ranging from buildings with floor areas between 30 and 100m^2 to buildings with floor areas greater than 30,000m^2. The numbers in brackets next to each category name show the sample sizes.

Overall, more than 60% of the buildings (15,236 of 22,151) were found to have floor areas between 1,000 and 3,000m^2. This is most likely due to the fact that DECs were required from buildings that are more than 1,000m^2 in total floor area, at least for the time period the analysis covered. The changes in the floor area of different buildings should become clearer in the future as the threshold for DECs reduces down to 500m^2 and then 250m^2.

Higher proportions of buildings with floor areas greater than 10,000m^2 were found under the categories that include large public and private buildings such as hotels, auditoriums, university buildings, hospitals and public transport stations. The very largest buildings, which exceed 30,000m^2 in floor area, were mainly hospitals and prisons as well as a few large public museums. At the other end of the spectrum, 1,012 buildings were smaller than 1,000m² in floor area. Inspection of a sample indicated that these are mostly nurseries or individual buildings within primary schools.

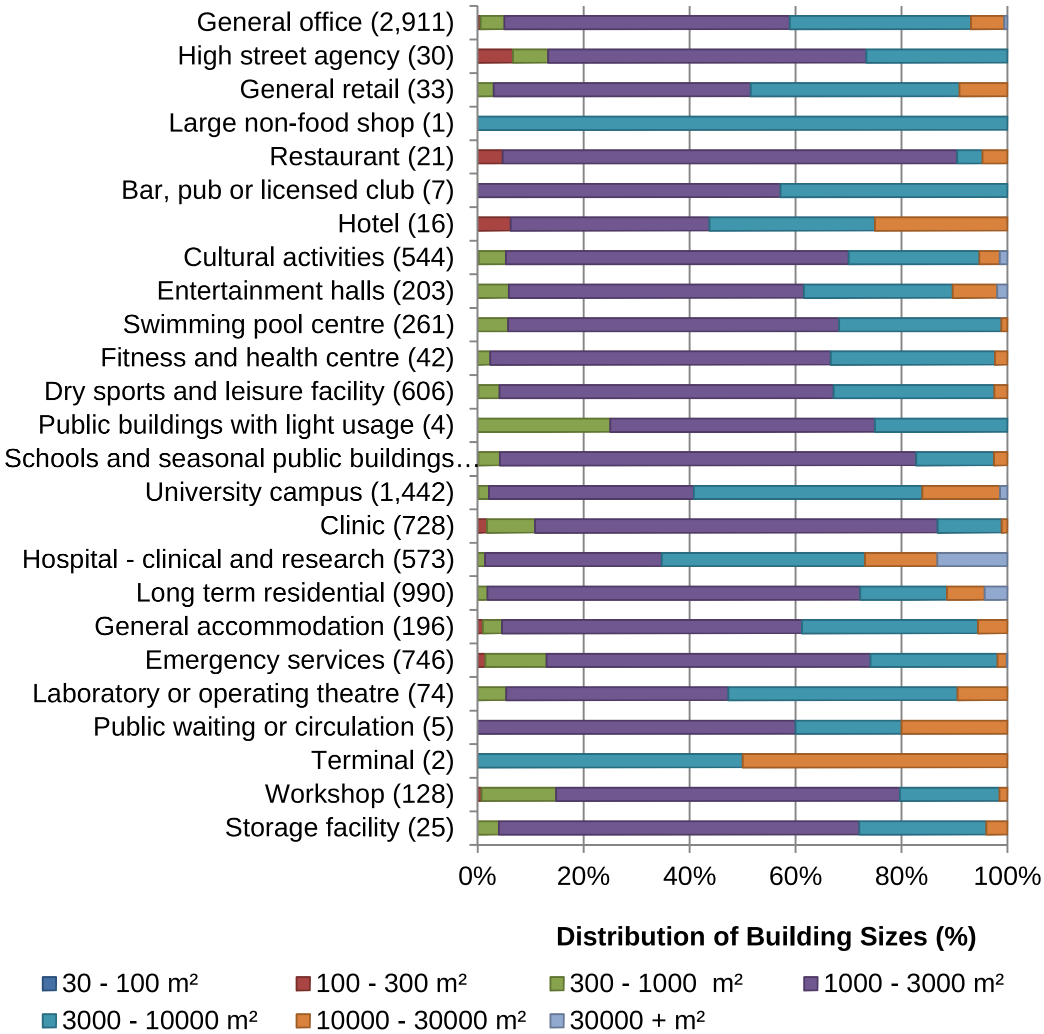

Figure 5.6 Distribution of buildings in size categories (m², percentages of all buildings)

Table 5.6 below shows statistics for floor area of the buildings that were presented in Figure 5.6. It can be seen that the median floor areas in all categories range between 1,294m² and 8,782m². Comparing the statistics with the mean floor area of various premises produced by Bruhns et al. (2000) showed that DEC records depict larger buildings within the non-domestic building stock, which would be expected. Taking buildings under the 'Swimming pool centre' category for example, the median of 2,187m² was considerably larger than the mean floor area of swimming pool premises according to Bruhns et al. (2000) of 1,000m^2. For most building types however, such comparison is likely to contain an element of uncertainty owing to the differences between buildings and premises.

Table 5.6 Descriptive statistics of the floor area of public sector non-domestic buildings

Benchmark category	N	Floor area (m^2)				
		Min	25th %	Median	75th %	Max
General office	2,911	88	1,470	2,486	4,510	58,392
High street agency	30	238	1,475	2,305	3,414	6,200
General retail	33	975	1,819	2,607	4,663	11,711
Large non-food shop	1	3,666	3,666	3,666	3,666	3,666
Restaurant	21	207	1,177	1,320	2,267	10,283
Bar, pub or licensed club	7	1,600	1,706	2,506	5,112	6,205
Hotel	16	238	1,558	4,928	10,158	17,017
Cultural activities	544	149	1,278	1,979	3,471	87,898
Entertainment halls	203	334	1,384	2,279	4,728	280,080
Swimming pool centre	261	346	1,450	2,187	3,535	17,816
Fitness and health centre	42	823	1,543	2,434	3,110	19,020
Dry sports and leisure facility	606	231	1,414	2,084	3,668	20,795
Public buildings with light usage	4	675	850	1,294	2,504	3,445
Schools and seasonal public buildings	12,563	57	1,264	1,644	2,472	21,900
University campus	1,442	123	2,002	3,603	7,267	71,843
Clinic	728	104	1,131	1,455	2,205	24,946
Hospital - clinical and research	573	670	2,199	4,672	10,718	280,912
Long term residential	990	347	1,360	1,750	3,345	68,528
General accommodation	196	123	1,438	2,364	4,749	22,398
Emergency services	746	178	1,187	1,783	3,075	33,178
Laboratory or operating theatre	74	615	1,444	3,050	5,900	23,834
Public waiting or circulation	5	1,580	1,880	2,276	5,383	10,135
Terminal	2	4,452	4,452	8,782	13,112	13,112
Workshop	128	300	1,193	1,778	2,585	27,422
Storage facility	25	991	1,671	2,091	3,054	14,617

Figure 5.7 below shows a box-and-whisker diagram of the electrical EUI of public sector non-domestic buildings.

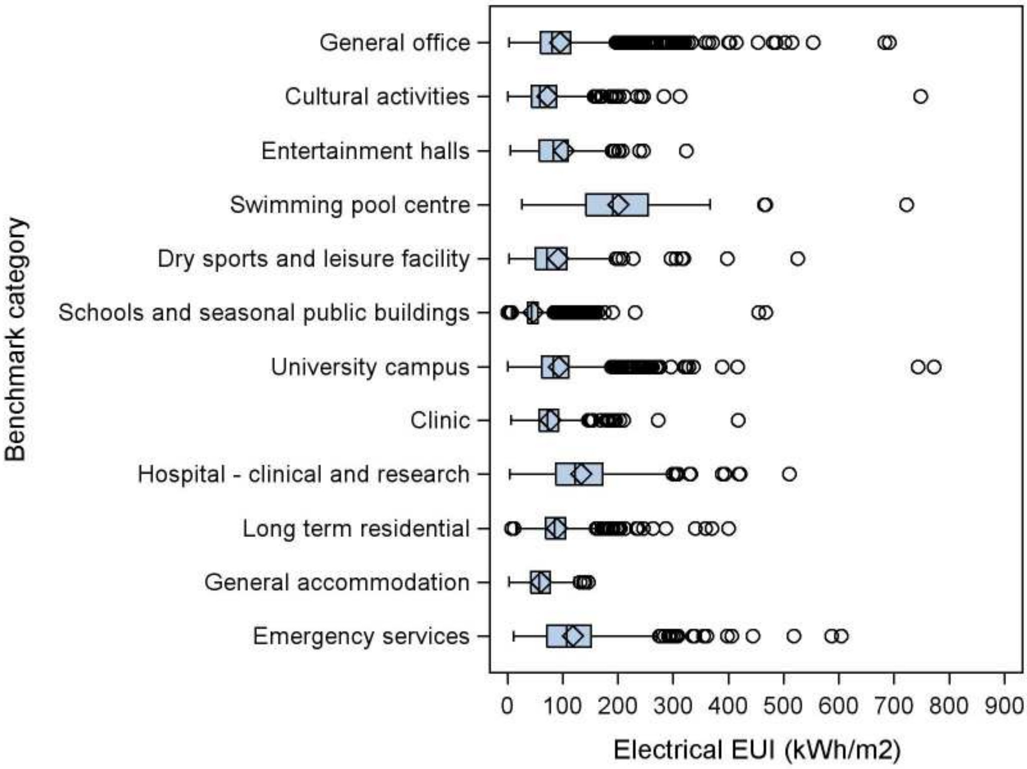

Figure 5.7 Box-and-whisker plot of electrical EUI of public sector non-domestic buildings (n > 100, standard occupancy hours)

The long tail of outliers found in many categories (Figure 5.7), which are presented as circles on the right hand side of the upper fences, suggest that electricity consumption is heavily skewed by a few highly energy-intensive buildings, some three times more intensive than a typical building (Table 5.7).

Among all categories, buildings under 'Swimming pool centre' were found to be most intensive in the use of electricity. This is likely due to the requirement to control the levels of relative humidity of the air owing to the constant evaporation of water in the pool (BRECSU, 1994). The treatment of air requires the use of a heating, ventilation and air-conditioning (HVAC) system, which is generally intensive in electricity, especially when the air needs to be dehumidified. The variability of the EUI was also the greatest in these buildings, with an inter-quartile range (IQR) of 112 kWh/m^2 (Table 5.7), which suggests that there is a large variation in the way centres were designed and are operated.

Table 5.7 Descriptive statistics for the electrical EUI of non-domestic buildings in the public sector (n > 100, standard occupancy hours)

Benchmark Category	N	Electrical EUI (kWh/m^2)					
		Min	25th %	Median	75th %	Max	IQR*
General office	1,862	3	60	81	114	691	54
Cultural activities	315	1	44	59	89	748	45
Entertainment halls	155	5	57	83	109	324	52
Swimming pool centre	115	26	142	191	254	723	112
Dry sports and leisure facility	304	3	50	71	107	526	57
Schools and seasonal public buildings	9,588	1	36	44	55	468	19
University campus	1,000	1	62	83	111	772	49
Clinic	422	6	57	72	92	418	35
Hospital - clinical and research	573	4	87	122	172	511	85
Long term residential	990	7	69	85	105	400	36
General accommodation	104	3	43	57	77	147	34
Emergency services	746	11	71	108	151	604	80
All	16,174						

* Interquartile range (IQR)

Buildings under the 'Hospitals - clinical and research' and 'Emergency services' categories were also found to be highly energy-intensive, with median electrical EUIs of 122 and 108 kWh/m^2. The intensive uses of electricity in hospital buildings is likely due to the requirement for high ventilation rates to control infections and also uses of specialist laboratory equipment and X-ray machines that are intensive in energy (Carbon Trust 2010). Many hospital buildings also operate 24 hours, hence the higher intensity. Emergency service buildings such as police stations, fire stations and ambulance stations also operate 24 hours.

Figure 5.8 shows a box-and-whisker diagram of fossil-thermal EUIs of public sector non-domestic buildings. Note that the distribution is based on the raw fossil-thermal energy uses, which have not been corrected for variation in weather conditions likely to influence demand.

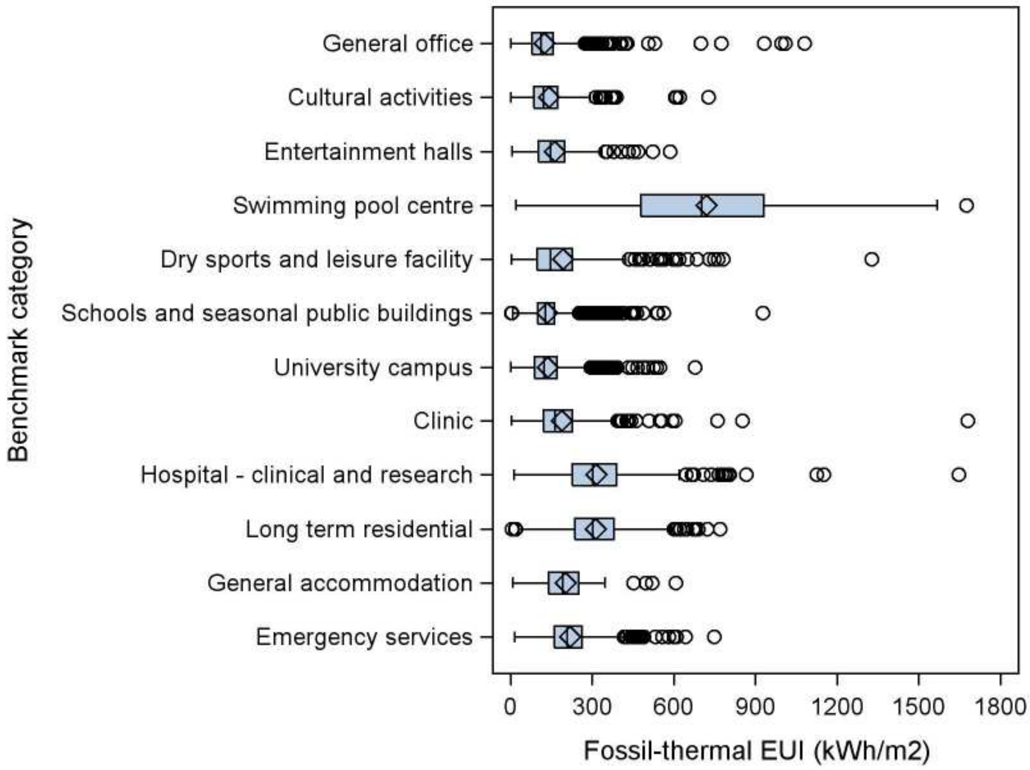

Figure 5.8 Box-and-whisker plot of the fossil-thermal EUI of public sector non-domestic buildings (n > 100, standard occupancy hours)

The distribution of fossil-thermal EUIs shows that there is a large variation in the pattern of energy use between various benchmark categories. Similar to the pattern of electricity use, the energy used for heating was also found to be skewed positively in many categories.

Buildings that house swimming pools are found to be the most intensive users of fossil fuels with an extremely high median value of 702 kWh/m^2 (Table 5.8). A guide published by the Building Research Energy Conservation Support Unit (BRECSU, 1994) suggested that in these buildings most of the fossil-thermal energy is used for keeping the water and the air of the pool warm. The guide also shows that demand for energy in providing hot water is considerably lower, with cost implications of approximately 2% of the total energy cost. The BRESCU guide is old however, and the way energy is used in swimming pool centres may have changed in recent years.

Table 5.8 Descriptive statistics for the fossil-thermal EUI of non-domestic buildings in the public sector (n > 100, standard occupancy hours)

Benchmark Category	N	Fossil-thermal EUI (kWh/m^2)					
		Min	25th %	Median	75th %	Max	IQR*
General office	1,862	1	79	112	157	1,081	78
Cultural activities	315	1	86	122	173	727	87
Entertainment halls	156	5	102	147	199	587	97
Swimming pool centre	115	21	478	702	931	1,676	453
Dry sports and leisure facility	305	4	97	146	227	1,327	130
Schools and seasonal public buildings	9,588	3	100	128	161	927	61
University campus	1,000	1	88	124	171	678	83
Clinic	422	4	120	164	228	1,680	108
Hospital - clinical and research	573	14	226	301	388	1,648	162
Long term residential	990	7	237	301	380	770	143
General accommodation	104	9	139	192	251	608	112
Emergency services	746	15	160	209	263	748	103
All	16,176						

* Interquartile range (IQR)

Buildings that were categorised under 'Hospital - clinical and research' and 'Long term residential' were also found to be noticeably more intensive in fossil-thermal energy use than other buildings. The breakdown of the overall energy use of a typical hospital showed that the space heating is the most intensive end use and that the energy used for supplying hot water was also noticeably intensive (Carbon Trust 2010). This is mostly due to the requirements for hospitals to maintain adequate levels of space heating throughout 24 hours for the whole year. Hot water usage would also be greater than the other buildings due to the long hours of occupancy of both the patients and the staff. The 'Long term residential' category comprises buildings that in theory accommodate similar levels of occupancy such as mental health hospitals, nursing homes and prisons that are occupied for 24 hours. The high levels of fossil-thermal energy use in these buildings is therefore likely to be due to the increased demand for space heating and hot water supply.

As discussed earlier, there are various factors that may contribute to such a large variation in fossil-thermal EUIs. A closer observation of the buildings under the benchmark category 'Dry sports and leisure facility' showed that one such factor is the misclassification of buildings. Despite the use of the word 'dry', it was found that building type 'Sports centre with pool' was allocated under the category, hence the high maximum value for fossil-thermal EUI. When compared to sports facilities that do not have highly energy-intensive pools, these buildings are highly likely to receive a poor rating despite having considerably different demands for energy. This therefore highlights that the energy performance of some buildings is being unfairly evaluated due to a classification error.

Electrically heated buildings

The following sections show results from analyses of the energy performance of buildings that are not 'typical' due to their being electrically heated or because they operate for longer hours than normal.

In the UK, most non-domestic buildings are heated using gas or other forms of fossil fuel. There are however buildings that use electricity for space heating and domestic hot water supplies. While the requirement for heating in these buildings may be similar to the other buildings, the use of electricity to deliver the heat means that the pattern of energy use would be considerably different from a typical building using gas. This section describes the characteristics and energy performance of buildings that use electricity as the main heating fuel (MHF).

Figure 5.9 below shows that in most categories the majority of buildings use fossil fuels as the main source of heat. There are however a number of benchmark categories under which the proportion of electrically heated buildings is noticeably higher than others. More than 75% of the buildings under the 'Large non-food shop' were found to be electrically heated, which is likely due to the large variation in types of business and the way the buildings are conditioned. All 'Covered car park' buildings are identified as being heated using electricity. This is however likely due to the fact that these buildings are not heated at all and the most likely purposes of electrical energy use is the lighting.

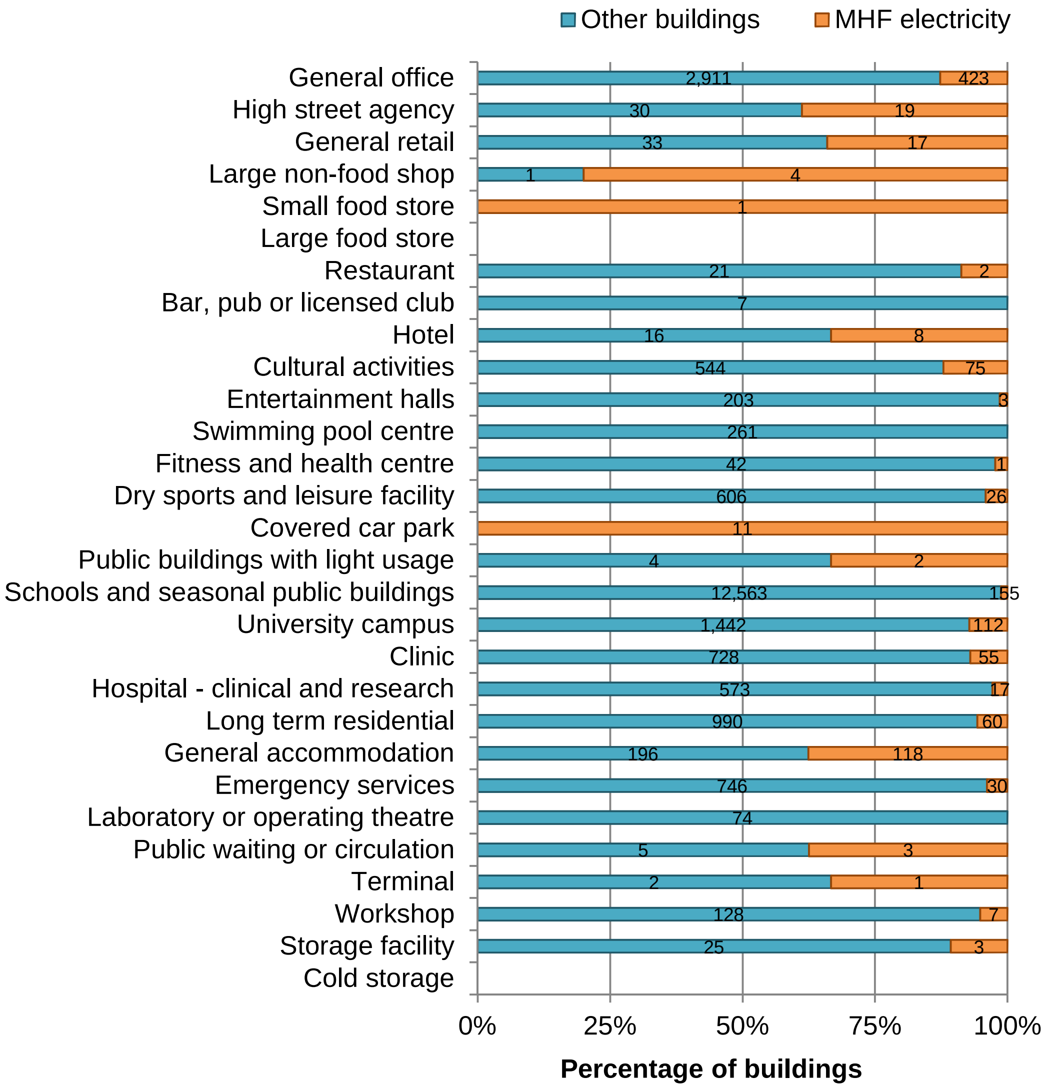

Figure 5.9 Numbers of electrically heated (MHF) buildings and non-electrically heated buildings in the dataset

Buildings under 'High street agencies' and 'General retail' categories were found to comprise a mix of fossil fuel-heated and electrically heated buildings. These categories are similar to 'Covered car park' in that there is no benchmark for fossil-thermal energy use. It therefore means that the benchmarks were developed based on the assumption that many of the buildings that belong to these categories would not be heated using fossil fuels. The high proportion of non-electrically heated buildings under these categories however suggest that a better understanding is needed of the pattern of heating energy use of buildings in these categories.

Among the categories with relatively large sample sizes, ‘General accommodation’ (38%) had the highest proportion of electrically heated buildings. A closer inspection of the buildings under the category revealed that these were mostly student housing.

Table 5.9 Comparisons of the median EUI of electrically and non-electrically heated buildings

Benchmark category	MHF = Other			MHF = electricity		
	N	Electricity EUI (kWh/m²) Median	Fossil-thermal EUI (kWh/m²) Median	N	Electricity EUI (kWh/m²) Median	Fossil-thermal EUI (kWh/m²) Median
General office	2911	86	116	423	146	0
High street agency	30	82	100	19	138	0
General retail	33	90	97	17	105	0
Large non-food shop	1	66	16	4	93	9
Small food store	0	-	-	1	567	0
Large food store	0	-	-	0	-	-
Restaurant	21	127	246	2	244	52
Bar, pub or licensed club	7	157	107	0	-	-
Hotel	16	85	170	8	147	77
Cultural activities	544	70	124	75	104	0
Entertainment halls	203	87	149	3	197	12
Swimming pool centre	261	192	696	0	-	-
Fitness and health centre	42	102	178	1	186	0
Dry sports and leisure facility	606	79	167	26	82	2
Covered car park	0	-	-	11	34	0
Public buildings with light usage	4	69	146	2	33	0
Schools and seasonal public buildings	12563	45	130	155	91	3
University campus	1442	86	128	112	108	14
Clinic	728	75	158	55	122	0
Hospital - clinical and research	573	122	301	17	202	41
Long term residential	990	85	301	60	109	43
General accommodation	196	58	202	118	119	14
Emergency services	746	108	209	30	217	0
Laboratory or operating theatre	74	242	238	0	-	-
Public waiting or circulation	5	118	43	3	54	0
Terminal	2	193	227	1	392	0
Workshop	128	62	120	7	80	45
Storage facility	25	37	77	3	29	0
Cold storage	0	-	-	0	-	-

As would be expected, many categories show that electrically heated buildings tend to be more intensive in electricity use than buildings that are heated using fossil fuels. In many categories, the difference in the pattern of energy use between electrically and non-electrically heated buildings is very noticeable. The distinct differences in categories with considerable sample sizes suggest that there is a potential for providing separate benchmarks for those buildings that use electricity as the main heating fuel, to make a more accurate evaluation of their performance. It could on the other hand be argued that separate benchmarks are not necessary, as the operational ratings are produced based on total carbon emissions.

Table 5.10 Comparison of typical total carbon emissions between MHF electricity and other buildings

Benchmark category	Annual total CO_2 emissions ($tonneCO_2/yr$)			
	MHF Other		MHF Electricity	
	N	Median	N	Median
General office	2911	185	423	160
High street agency	30	126	19	102
General retail	33	219	17	125
Large non-food shop	1	145	4	136
Small food store	0	0	1	19
Restaurant	21	210	2	137
Bar, pub or licensed club	7	275	0	0
Hotel	16	419	8	334
Cultural activities	544	128	75	90
Entertainment halls	203	209	3	237
Swimming pool centre	261	532	0	0
Fitness and health centre	42	209	1	49
Dry sports and leisure facility	606	178	26	80
Covered car park	0	0	11	136
Public buildings with light usage	4	122	2	12
Schools and seasonal public buildings	12563	86	155	86
University campus	1442	283	112	156
Clinic	728	109	55	88
Hospital - clinical and research	573	574	17	236
Long term residential	990	204	60	194
General accommodation	196	170	118	167
Emergency services	746	181	30	196
Laboratory or operating theatre	74	531	0	0
Public waiting or circulation	5	301	3	91
Terminal	2	1131	1	428
Workshop	128	106	7	104
Storage facility	25	82	3	44

The small differences in the median of total CO_2 emissions (Table 5.10) indicate that this could be true for some categories. There are however categories such as 'Cultural activities' or 'General office' where differences in the median CO_2 emissions between electrically heated and fossil fuel heated are greater than 10%. The result therefore suggests that it would be reasonable to separately benchmark the energy performance of electrically heated buildings that show clear evidence of different pattern of energy use as was explored by Jones (2014).

Extended occupancy hours

The following section analyses distributions of the energy performance of buildings that have claimed extended hours of occupancy. In theory, buildings that are occupied for longer hours than what is considered to be the standard for a specific activity type should be more energy-intensive. The analyses therefore focussed on understanding the distribution of buildings that were claimed to be operating for extended hours, and examining whether there are correlations between the occupancy hours and the empirical energy performance data.

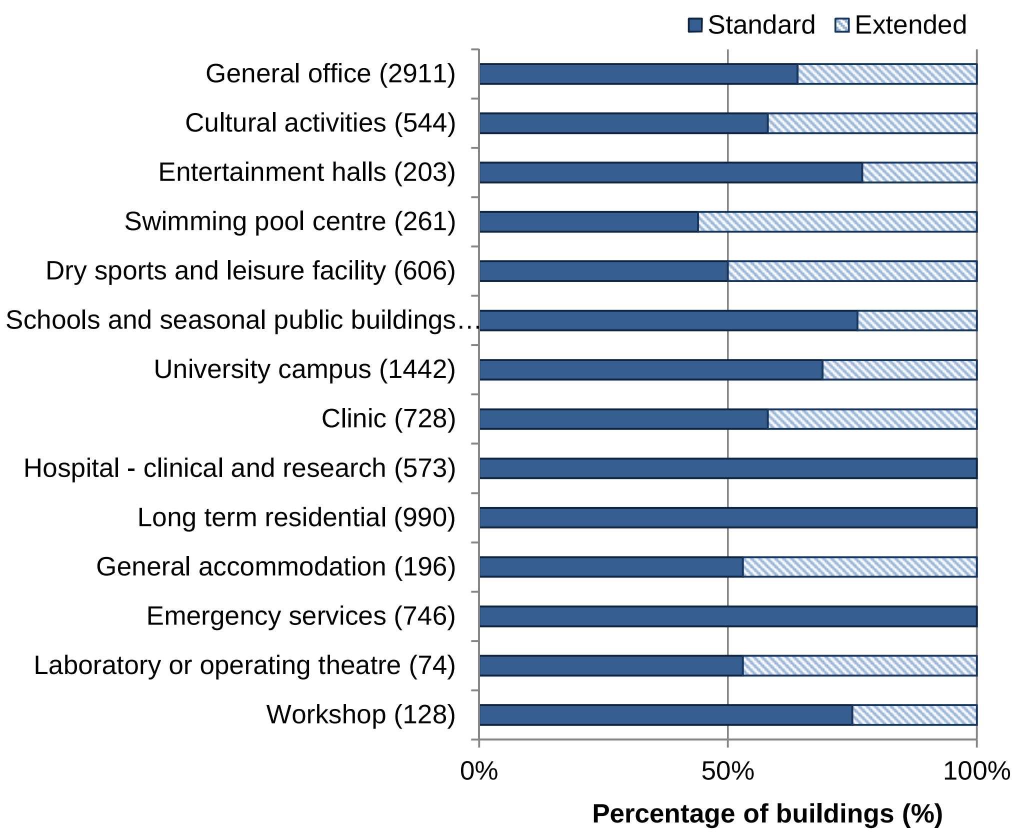

Figure 5.10 Percentages of buildings in each benchmark category which have reported standard or extended occupancy hours

Figure 5.10 shows the percentages of buildings in each benchmark category that have claimed standard hours or extended occupancy hours respectively[9]. Note that these are categories that include more than 50 buildings from the dataset described in Section 5.4.1. The total number of buildings in each category is shown in brackets.

It can be seen that between 23 and 56% of buildings in 11 out of 14 categories have indicated that they are occupied for extended numbers of hours (Figure 5.10). Among the categories, buildings under the ‘Swimming pool centres’ and ‘Dry sports and leisure facilities’ categories were found to operate the longest with 56% and 50% of the buildings claiming the extended hours adjustment. Such a high proportion of buildings claiming extended hours suggests that what is considered to be the ‘typical’ hours of occupancy in these buildings may have changed over the years. Similar proportions of buildings occupied for extended hours can be found in other categories. These include 47% of the buildings under ‘General accommodation’, many of them halls of residences at universities and boarding houses, and buildings under ‘Laboratory or operating theatre’ which include laboratories run by the NHS or universities.

The three categories - ‘Hospital – clinical and research’, ‘Long term residential’ and ‘Emergency services’ - do not claim any extended hours of occupancy due to that fact that the norm here is a 24 hour service, hence the standard hours of occupancy are equal to the total number of hours per year.

The relationship between extended operating hours and energy use was examined in more detail in public sector office buildings. Figure 5.11 and Figure 5.12 are scatter plots of extended occupancy hours against electrical and fossil-thermal EUIs for offices, with the respective regression lines. These results are just for the building types ‘Central government office’ and ‘Local government office’ under the ‘General office’ benchmark category. Note that only those

[9] Each benchmark category has a designated reference hours of occupancy, which is considered to be the ‘standard’ hours of occupancy. For buildings with ‘extended’ hours of occupancy, energy benchmarks are adjusted to account for the increased use of the building.

buildings that were identified as being occupied for extended hours were used for the analysis. In total, this included 272 Central government offices and 225 Local government offices.

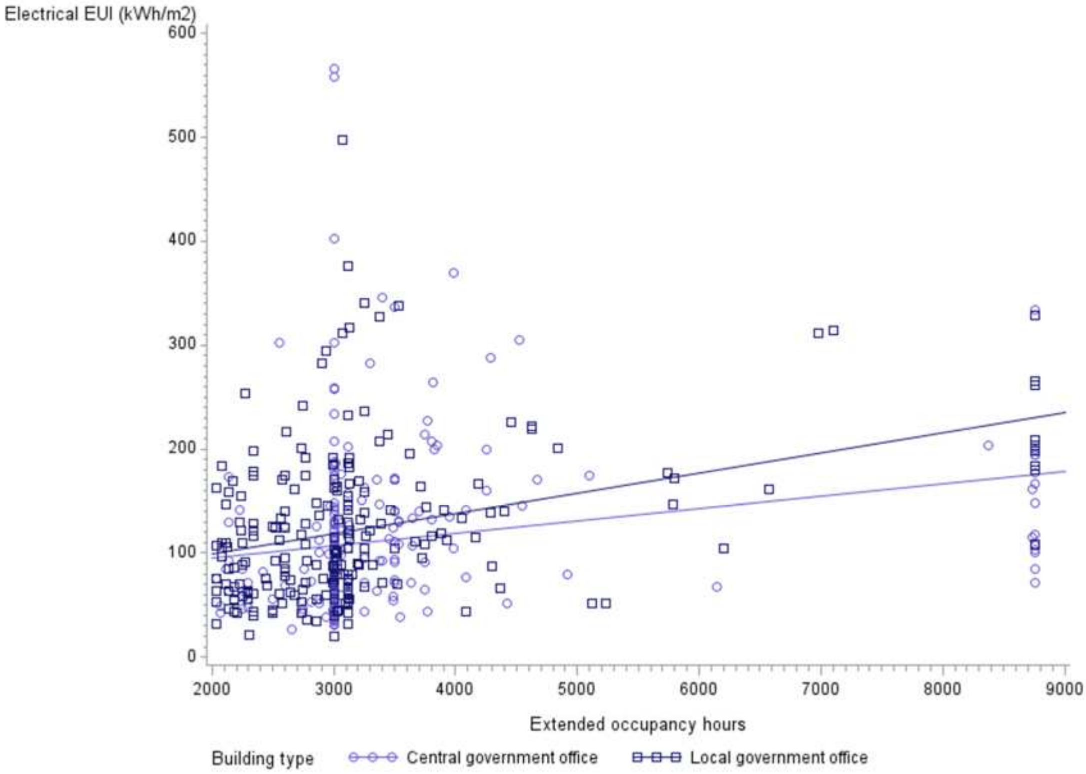

Figure 5.11 Scatter plot of occupancy hours and electrical EUI for Central and Local government office buildings (kWh/m²)

The plot of Figure 5.11 shows considerable variation in electrical EUIs in relation to extended occupancy hours. The line of best fit shows that there is generally a positive relationship between extended hours and electricity consumption in both Central and Local government offices. This indicates that public sector offices are indeed likely to use more electricity, as their hours of use are extended. Pearson correlation coefficients of 0.23 and 0.37 for Central and Local government buildings respectively however, suggested that the relationships are relatively weak. The broadly scattered patterns of energy use also suggests that there are considerable variations in EUIs even when occupancy hours are similar. There are numerous factors such as controls and operation that could contribute to such a phenomenon. The intensive uses of electricity despite small number of occupied hours may be for example due to parasitic loads from equipment or fixed building services being left on during unoccupied hours (e.g. lighting).

The figure also shows a clustering of records around 3,000 hours occupancy where 50% of the records were found to lie between 2,860 and 3,350. A closer examination showed that 116 of 143 (81%) records that claimed precisely 3,000 hours of occupancy belonged to the same organisation. There were, on the other hand, 26 central and local government offices (5% of the total) claiming the maximum allowed hours of occupancy. These suspicious cases of extended occupancy hours raise questions about the reliability of claims of extended hours.

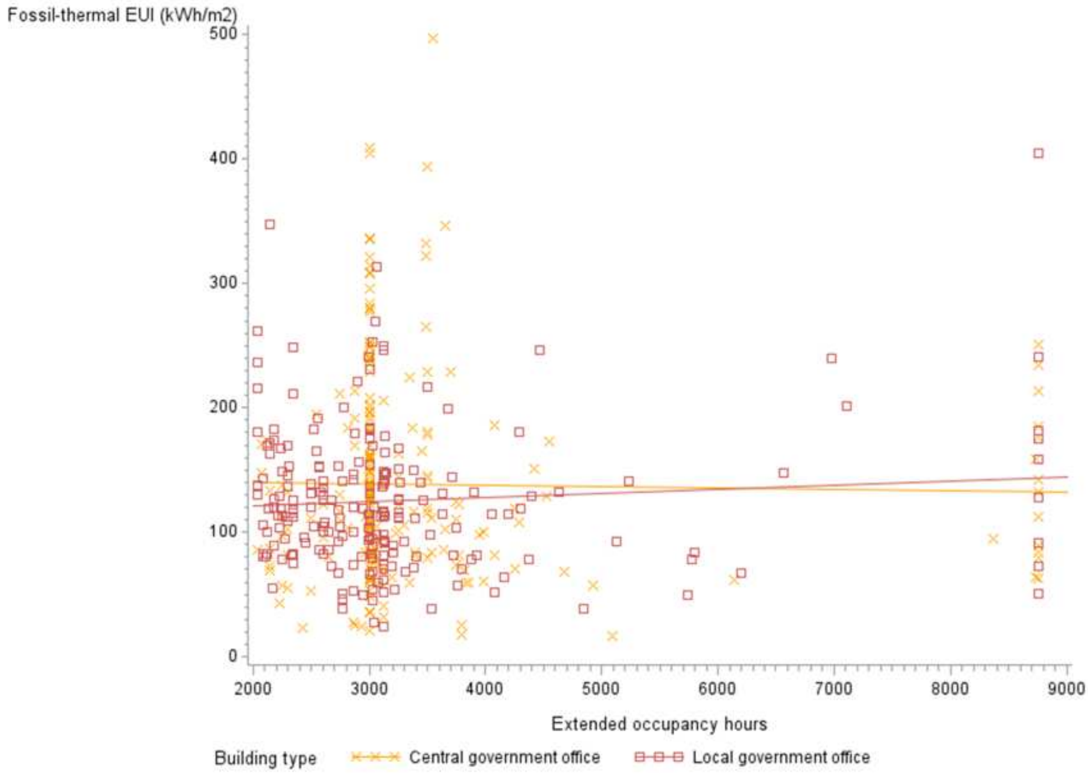

Figure 5.12 Scatter plot of occupancy hours and fossil-thermal EUI for Central and Local government buildings (kWh/m^2)

As with electrical consumption, Figure 5.12 shows a considerable variation in heating energy consumption in relation to occupancy hours. The line of best fit indicates however that there is hardly any systematic relationship between the two variables. (Pearson correlation coefficients are -0.02 and 0.08 for Central and Local government buildings respectively.) This suggests that the operation of the building services providing space heating and domestic hot water is independent of the hours of occupation. There may be different reasons for such a weak correlation. One cause could be that extended occupancy hours are being claimed inappropriately. Another reason could be that the control systems in these buildings have not been commissioned correctly, and are heating the space and hot water regardless of the pattern of occupancy of the building.

The week correlations between electrical and fossil-thermal EUIs and extended hours claimed by office buildings shows just how much the patterns of energy use varies even when buildings are occupied for a similar period. This therefore suggests that there are other factors that determine the pattern of energy use and that consideration of occupancy hours, at least for public sector offices, does not contribute towards the relevance of benchmarking.

Longitudinal analysis

The following sections show changes over time in the patterns of energy use of buildings in the six benchmark categories that have the largest sample sizes. Note that the results are based on the analyses of the longitudinal dataset described in Section 5.4.2.

Figure 5.13 shows the changes in median ratings for electricity uses from 2009 to 2011 from a sample made up of the same buildings in each year.

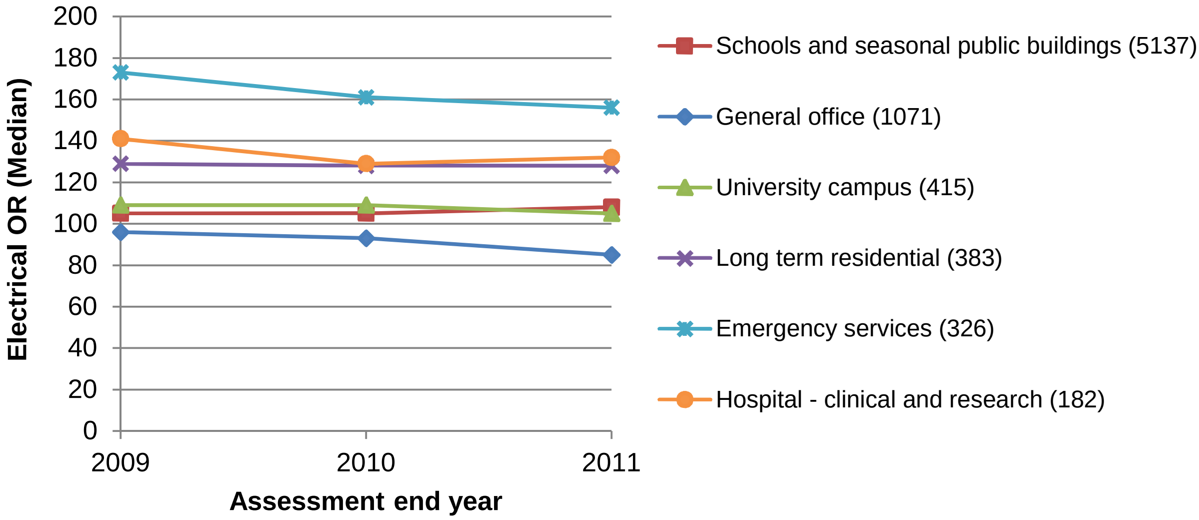

Figure 5.13 Changes in median electricity ratings between 2009 and 2011 (numbers of buildings in all three years are shown in brackets)

The line graphs show that there is no clear trend that could be observed by buildings in the six categories taken together. A reduction in the median operational rating was however observed in five out of six categories. Over the three years, the median operational rating for the electricity consumption of buildings under the ‘General office’ and ‘Emergency services’ categories reduced the most, by 10 and 11% respectively. Similarly, the electrical OR of the buildings under the ‘University campus’, ‘Hospital – clinical and research’ and ‘Long term residential’ categories reduced by between 1% and 6%. There are numerous factors that may have led to such reductions in the pattern of electricity use during the period. One common property of all these buildings is that they have continued to lodge DECs over the three-year period that was analysed and possibly for more years. In a context where there is considerable variation in the extent of compliance of non-domestic buildings with the DEC scheme, these particular buildings are perhaps likely to be operated by personnel or organisations that are more interested in improving their energy efficiency (Hong & Steadman 2013).

Figure 5.14 shows the changes in median ratings for fossil-thermal energy use from 2009 to 2011 from a sample made up of the same buildings in each year.

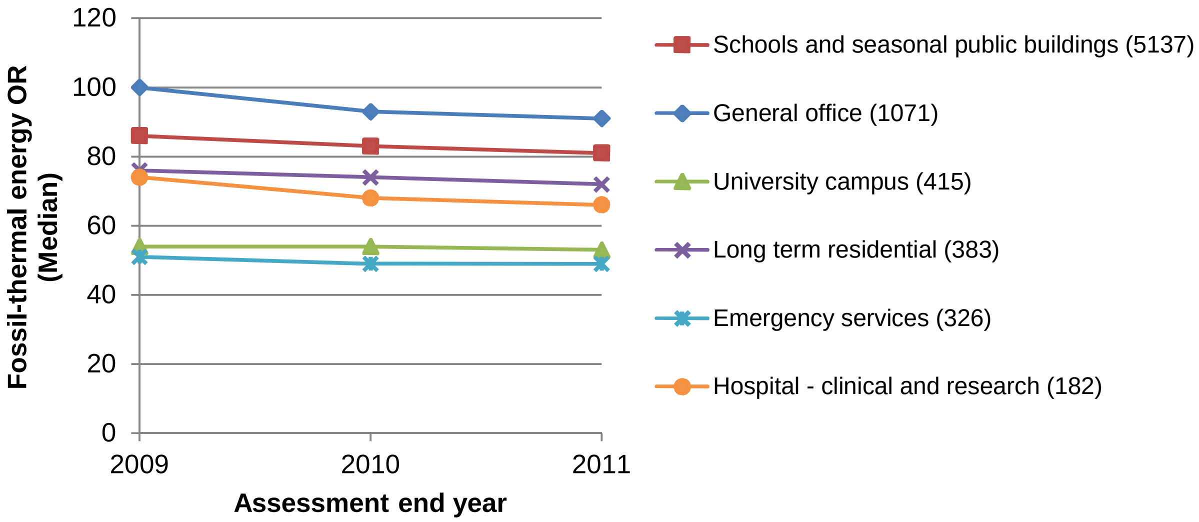

Figure 5.14 Changes in median fossil-thermal ratings over three years (numbers of buildings in all three years are shown in brackets)

The fossil-thermal energy use of buildings in all six categories was found to have decreased over the three-year period. The largest reduction in fossil-thermal ratings was found in buildings under the ‘Hospital – clinical and research’ and ‘General office’ categories with reductions of 11 and 9% respectively. The fossil-thermal performance changed the least in buildings under ‘University campus’ with a 2% reduction in the median. As with the electrical EUI, there are numerous factors such as the warming climate, improved efficiency and better management, and rising fuel prices that may have led to such trends.

The changes in the pattern of electricity and fossil-thermal energy use are distinctively different, although both show trends towards lower median values for ratings in most of the benchmark groups. Although limited to specific public sector buildings, these changes highlight the fact that the pattern of energy use continues to change and at different rates for different building types, which is likely due to differences in factors that influence the operation of different buildings.

Adequacy of TM46 energy benchmarks

The following sections show results from an assessment of the energy benchmarks in *TM46* that underpin the Display Energy Certificate scheme. The latest DEC records were used as a basis to examine whether the energy benchmarks are robust for the purposes of providing an accurate picture of how efficiently buildings were being operated. Note that the results in this section are based on the dataset that was prepared for cross-sectional analysis, which was described in detail in Section 5.3.1.2.

Figure 5.15 shows the distributions of the operational ratings of the building under the benchmark categories that have more than 50 records. Note that an OR of 100 would mean that the operational performance of a building (or buildings) would be equal to the benchmarks.

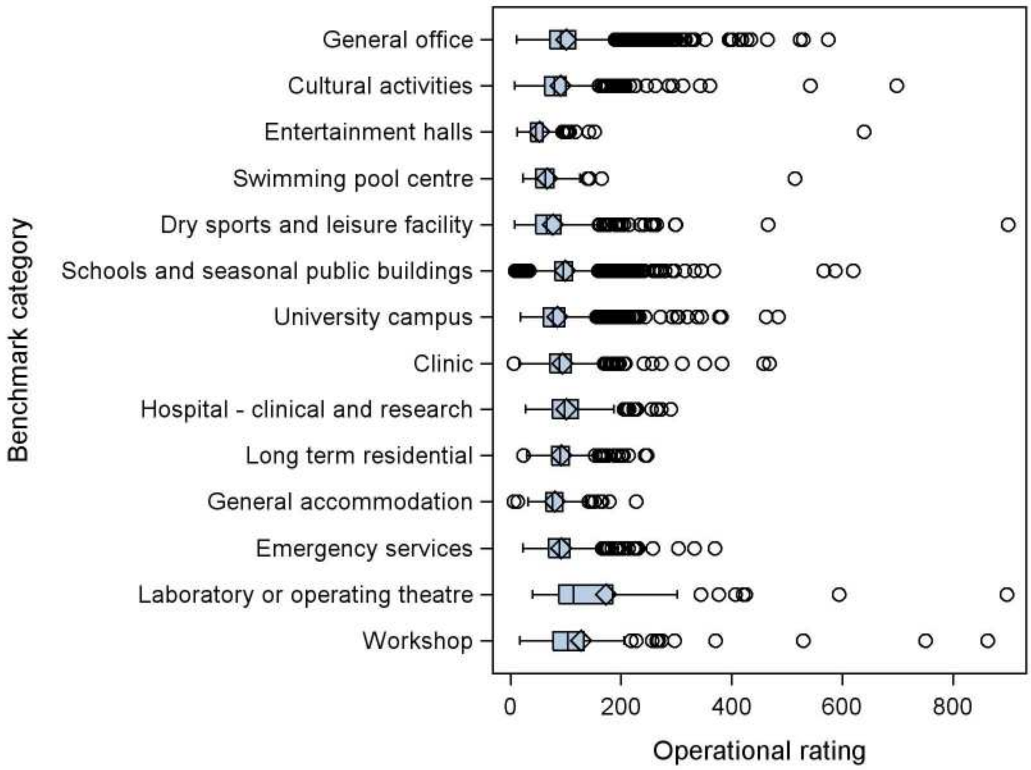

Figure 5.15 Box-and-whisker plot of operational ratings by benchmark category

Out of 14 categories analysed, the median operational rating of buildings under 12 categories were found to be less than 100. In categories 'Entertainment halls' and 'Swimming pool centre', more than 90% of the buildings were receiving operational ratings below 100. Moreover, more than 65% and up to 80% of the buildings in seven other categories were also found to be below 100. The large proportion of buildings that have received lower ratings indicate that the assessed buildings are generally performing better, or are less intensive in overall energy use, than what is considered to be typical performance for each activity group. This suggests that the energy benchmarks that were established in 2008 are too generous and therefore do not provide adequate feedback, which is likely due to the changes observed earlier in the longitudinal analysis.

Table 5.11 Statistics on operational ratings of buildings by benchmark category

Benchmark category	N	Operational Rating					
		Min	25^{th} %	Median	75^{th} %	Max	IQR*
General office	2911	11	71	91	118	575	47
Cultural activities	544	8	62	79	100	699	38
Entertainment halls	203	12	37	46	59	640	22
Swimming pool centre	261	22	46	63	78	515	32
Dry sports and leisure facility	606	8	46	65	91	900	45
Schools and seasonal public buildings	12563	9	81	95	112	620	31
University campus	1442	18	60	77	98	484	38
Clinic	728	6	71	89	109	468	38
Hospital - clinical and research	573	27	76	98	122	290	46
Long term residential	990	24	75	90	106	247	31
General accommodation	196	6	64	76	95	227	31
Emergency services	746	22	69	88	107	370	38
Laboratory or operating theatre	74	40	87	115	185	898	98
Workshop	128	17	77	104	133	863	56

*Interquartile range (IQR)

It can be seen that many of the operational ratings in every category are heavily positively skewed by extreme outliers that, in some categories, are more than ten times more intensive in energy use than the median. The highest ratings were found in the ‘Dry sports and leisure facility’, ‘Laboratory or operating theatre’ and the ‘Workshop’ categories with operational ratings close to or equal to 900 (Table 5.11). A closer examination of the buildings under ‘Dry sports and leisure facility’ showed one sports centre in a university that was consuming more than 20 times the electricity of the benchmark, whilst the fossil-thermal energy use was less than half of the benchmark. The record indicated that the building was operating for standard hours of occupancy and that it was mainly heated by gas, which therefore suggested that there were other factors such as equipment or facilities that are very intensive in electricity use in the building. Further investigations showed that two buildings under the ‘Laboratory or operating theatre’ were a physics research facility and a chemistry building and that they were located within the same university as the sports centre. Although the presence of these potentially energy-intensive activities may help explain part of the unusually high levels of electricity use, more detailed investigation with site visits would be needed to fully understand the factors that are behind the high operational ratings.

The reason behind the operational rating of 863 of one building under the ‘Workshop’ category was on the other hand less difficult to understand. The building was a crematorium, which was found to use 2404 kWh/m^2 of fossil-thermal energy per year. Considering the constant and extensive demand for heat in such buildings and the fact that the benchmarks for the category were intended for general workshops or facilities such as vehicle repair shops this will have led the building to receive such a high rating.

These cases with extremely high operational ratings highlight that there are numbers of factors that hinder the robustness of the benchmarking scheme. As found earlier, the main cause of concern lies with the classification system, which does not adequately group buildings with similar patterns of energy use. There are plethora of examples of misclassifications such as ‘Day centres’ under ‘Schools and seasonal public buildings’ or hospitals of different kinds allocated to different benchmark categories in relatively arbitrary ways that do not reflect differences in typical energy use (Hong & Steadman 2013). There is also the possibility that these poor ratings are produced due to, for example, greater occupancy levels or operating hours, or use of the separables that are not sub-metered or not allowed, or due to other factors that are not accounted for by the current method (Better Buildings Partnership (BBP) 2012; Bruhns, Jones & Cohen 2011).

The variation in operational rating in each category was investigated further by examining the differences between the operational rating for each fuel type and the respective benchmarks. Figure 5.16 shows deviations of median ratings for electricity and fossil-thermal fuel use from 100, the value that represents typical performance in *TM46* benchmarks. The figure also shows median operational ratings for each benchmark category, which are based on consumption of both fuel types together. The bars extending to the left of zero indicate that the median ratings are below the benchmarks. The bars extending to the right indicate that the ratings are greater than the benchmarks. Note that benchmark categories that do not have records are also displayed on the chart.

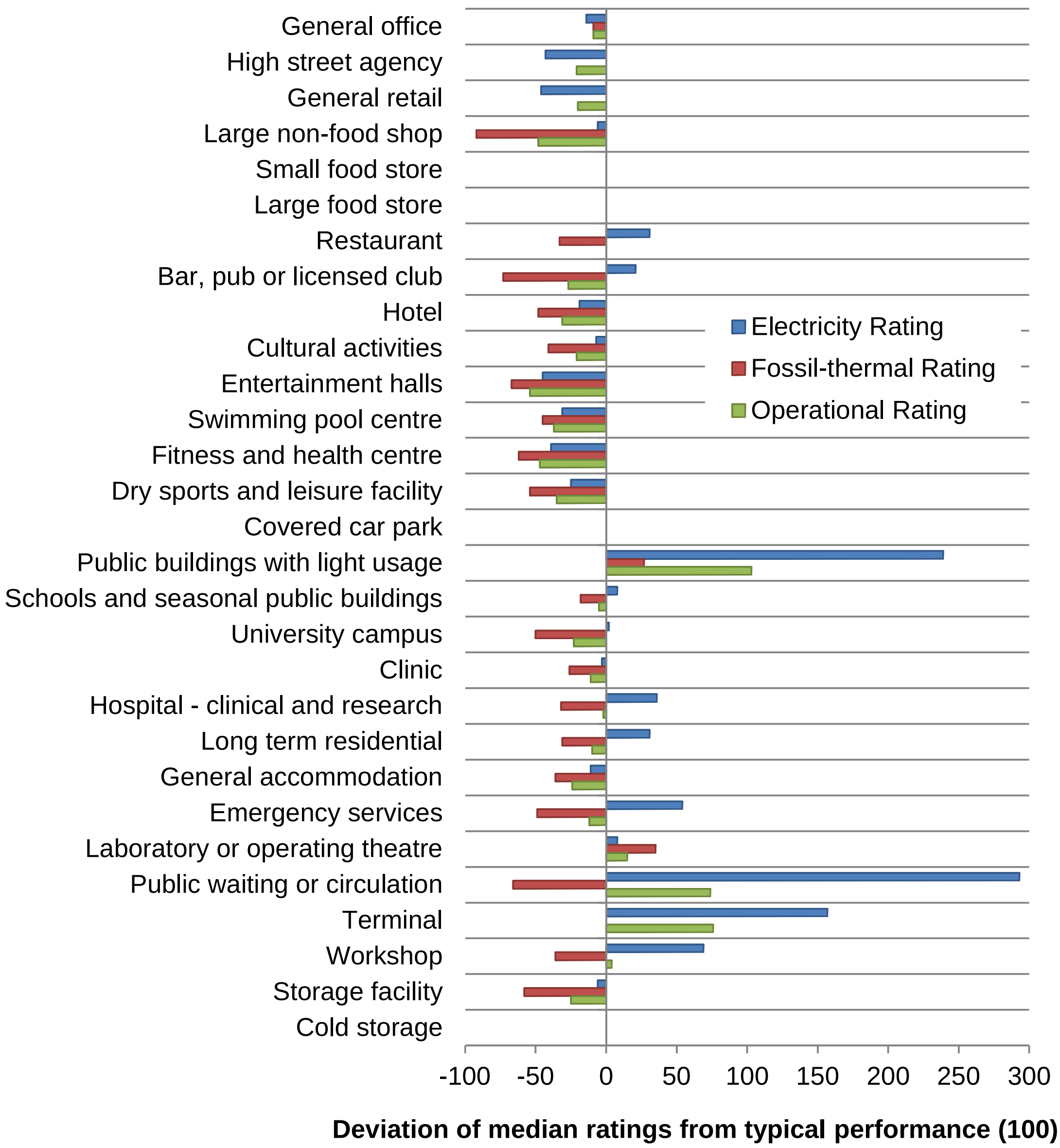

Figure 5.16 Energy ratings by fuel type by benchmark category

Many categories show a trend towards higher electricity consumption and lower fossil-thermal energy use compared with the benchmarks. This is consistent with the findings of the previous review by Bruhns et al. (2011) and the fact that the two analyses were based on records from different periods further emphasises the presence of such trends.

The figure also shows that the differences in ratings for the two fuel types, in the two directions, are cancelled out in some of the combined operational ratings. The 'Hospital – clinical and research' category, for example, shows that the resultant operational rating is very close to the benchmark (98) despite the highly deviating median ratings for electricity (136) and fossil-thermal energy uses (68). This therefore shows that the energy benchmarks for electricity and fossil-thermal energy are not an accurate representation of the respective patterns of fuel use of the public building in question.

Table 5.12 Traffic light analysis of operational ratings by benchmark category

Benchmark Category	**N**	**Electrical Rating** Median	**Fossil-thermal Rating** Median	**Operational Rating** Median
General office	2,911	86	91	91
High street agency	30	57	.	79
General retail	33	54	.	80
Large non-food shop	1	94	8	52
Restaurant	21	131	67	100
Bar, pub or licensed club	7	121	27	73
Hotel	16	81	52	69
Cultural activities	544	93	59	79
Entertainment halls	203	55	33	46
Swimming pool centre	261	69	55	63
Fitness and health centre	42	61	38	53
Dry sports and leisure facility	606	75	46	65
Public buildings with light usage	4	339	127	203
Schools and seasonal public buildings	12,563	108	82	95
University campus	1,442	102	50	77
Clinic	728	97	74	89
Hospital - clinical and research	573	136	68	98
Long term residential	990	131	69	90
General accommodation	196	89	64	76
Emergency services	746	154	51	88
Laboratory or operating theatre	74	108	135	115
Public waiting or circulation	5	393	34	174
Terminal	2	257	100	176
Workshop	128	169	64	104
Storage facility	25	94	42	75
All	22,151			

The severity of the deviation of the statistics of operational ratings of each fuel type and the combined figures was assessed further through a traffic light analysis (Table 5.12). The median ratings for electricity and fossil-thermal energy, and the operational ratings, were coded with different colours based on the sample size and the rating. Varying shades of red and green were used to indicate the different degrees to which ratings deviated from the benchmarks. The colour scheme and the underlying criteria are described in detail in Figure 5.4.

The median operational ratings of five out of 14 benchmark categories are within 10% of the corresponding benchmarks (Table 5.12). These include two categories ‘General office’ and ‘Schools and seasonal public buildings’ which have the largest sample sizes. The benchmarks for these categories however are not accurately representative of the pattern of energy use of the stock. When the deviation of electrical and fossil-thermal ratings from the benchmarks is observed more closely, it can be seen that the low level of deviation in these categories are results of the cancellation effect, which was found earlier in Figure 5.16.

If the benchmarks are assessed based on the median ratings by fuel type, the median electrical ratings of nine out of 14 categories were more than 10% away from the benchmarks. The median ratings in five of these categories were found to be below the benchmarks, and the medians for ‘Entertainment hall’ and ‘Swimming pool centre’ were both more than 30% away from the respective benchmarks. At the other end of the spectrum, four categories were found with median electrical ratings more than 30% greater than the benchmarks. The deviation was more severe in fossil-thermal ratings where 13 out of 14 categories were found to deviate more than 10% from the benchmarks. 12 of these categories were found to be below the benchmarks and nine were found to deviate more than 30% from the benchmarks.

5.6 Chapter summary

This chapter aimed to assess the latest Display Energy Certificate (DEC) records to improve the understanding of the pattern of energy uses of various building types. The analyses were also intended to examine whether the benchmarks that underpin the DEC scheme are robust.

The summary of findings are listed below:

- Prior to any analysis, extensive work was required to develop a set of criteria to identify uncertain records and inspect, clean and prepare the raw DEC dataset from Landmark. This showed that the process through which DECs are accumulated and managed in the central register is currently not suitable for sustaining a benchmarking scheme.
- There were difficulties in using DEC data to analyse the energy performance of non-domestic buildings by economic sectors or organisations as there are no other ways to categorise buildings other than by the type of activity. The differences between the definition of buildings and premises as the boundary of entities also add difficulties in utilising the data with other datasets.
- More than 60% of the buildings in the dataset were between 1,000 and 3,000m^2 in floor area. Comparison with mean floor areas of various premises in the non-domestic stock established in previous studies showed that the study is likely to depict the energy performance of relatively larger buildings.
- Patterns of energy use were found to vary considerably and to be highly positively skewed in all benchmark categories owing to small numbers of extremely energy-intensive buildings. Investigation of the extreme cases showed that these buildings were often placed in the wrong categories. The large variation in energy use intensities (EUI) also hinted that the current benchmarking method may not be robust enough to adequately address the variation in characteristics of buildings in the stock and their operation.
- Electrically-heated buildings were found to have very different patterns of energy use from their non-electrically heated counter parts. The differences were evident in

various benchmark categories even when the total CO_2 emissions were compared. These findings suggested that these buildings should be benchmarked separately to acquire a fair evaluation of their operational energy efficiency.

- A large proportion of buildings (between 23 and 56% of buildings in 11 out of 14 categories) were found to claim extended hours of occupancy in numerous benchmark categories. This suggested that occupancy hours have changed over the years from what CIBSE *TM46* considers to be typical values.
- Analyses of the relationships between extended occupancy hours and patterns of energy use of local and central government offices showed that there were considerable variations in EUI despite similar hours of occupancy. The weak correlation between electricity and fossil-thermal energy uses and extended occupancy hours in these buildings suggested that there must be other factors that determine the energy performance of the buildings.
- Longitudinal analysis of EUIs of buildings that had lodged DECs over three consecutive years between 2009 and 2011 showed that fossil-thermal EUIs gradually declined over the period. The electrical EUI was also found to decline over the same period with the exception of buildings under the 'Schools and seasonal public buildings' category, which increased by 6%.
- Median operational ratings in 12 out of 14 categories were below 100, which showed that the *TM46* benchmarks are too generous. Further examinations of the ratings by fuel type showed that electrical EUIs and fossil-thermal EUIs were generally higher and lower than the corresponding benchmarks respectively. The median ratings were also found to frequently deviate by more than 30% from the benchmarks. These results showed that many benchmarks no longer accurately represent recent patterns of energy use.

In summary, issues associated with various aspects of the DEC scheme raised by the study showed that it lacks robustness for benchmarking the operational energy efficiency of public sector buildings. As it currently stands, issues associated with classification and energy benchmarks are key areas of concern that have the potential to hinder the effectiveness of the scheme and its credibility. It was also clear that various aspects of the scheme (e.g. extended occupancy hours) would need to be reassessed in order to accommodate the changes that have taken place since its implementation six years ago.

The issues that were raised but for which there was insufficient data to acquire a holistic understanding on the other hand would require evidence from the more specific analyses carried out in the following chapters.

Chapter 6 Top-down Analysis of English Schools

This is the first of a series of analyses that are presented in the next three chapters, which provides a general overview of the pattern of energy use in the school stock. The present chapter aims to gain a deeper understanding of the energy performance of primary and secondary schools in England and examine whether the current framework provides adequate means for evaluating their operational energy efficiency. Moreover, ways to improve the comparability of benchmarking are explored by examining the influences that various building and operational characteristics have on the demand for energy use.

The study was carried out in three parts. The initial section describes the process through which the Display Energy Certificate (DEC) records for schools and information from other sources were collected, processed and combined together into a manageable format. This is followed by descriptions of the methods that were used to analyse the energy performance of school buildings and the underlying assumptions. Lastly, the results from the analyses are presented.

6.1 Development of a school information dataset

The first step of the study was to collect and prepare relevant data so that the pattern of energy use of schools could be analysed at a higher resolution than in the previous chapter. The initial framework for the dataset was based on the DEC records for schools, which were used in the previous chapter. This is largely due to the fact that such a large volume of actual energy consumption figures of schools was not previously available, but also the fact that there are variables in the dataset that describe other characteristics of the buildings such as floor area and types of ventilation strategy. Although these records had already been cleaned and filtered as described in Section 5.2, it was necessary to manipulate the data further to ensure that the energy performance of primary and secondary schools could be analysed separately. The main reason behind this was the way various building types are grouped into broader benchmark categories in *TM46*. As described in Section 3.5, there are two classification systems that underpin the DEC scheme. The main classification that affects the evaluation is the activity-based benchmark categories, of which there are 29. The secondary classification comprises 237 building types, but this classification is currently used only to provide guidance to the assessors for allocating their buildings to the correct benchmark categories. In its current state, DEC records for both primary and secondary schools are found under the ‘Schools and seasonal public buildings’ category, which also contains various other building types (Table 6.1).

Table 6.1 List of building types and the number of records under the schools and seasonal public buildings category

Category name	Building type	N
Schools and seasonal public buildings	Clubhouse	0
	Community centre	168
	Community facilities	74
	Community meeting place	5
	Creche	1
	Creche/childcare facility	20
	Day centre	170
	Dog racecourse	0
	Hunting and fishing	0
	Marina or sailing club	0
	Nursery or kindergarten	85
	Pre-school facility	25
	Primary and secondary teaching establishments	111
	Primary school	6,631
	Private school	22
	Reserves centre	5
	School	462
	Secondary school	1,300
	Social clubs	1
	Special school	419
	Speedway	3
	State primary school	2,496
	State school	160
	State secondary school	403
	Unlicensed club	0
	Village hall	2

As shown in Table 6.1, there are a number of building types that raise suspicions with regards to the robustness of the classification system. First, there are building types such as 'Day centres' which are not schools or seasonal public buildings. There is also the building type 'Speedway' that does not belong in the public sector. Second, there are different levels of specificity of building types that cause confusion and difficulties in identifying primary and secondary schools from other types of school. Building types 'Private school' and 'State school' group for example differentiate schools by their governance. The problem arises when these classifications exist in conjunction with building types 'Primary school' and 'Secondary school', which can either be private or state schools. There is also the portmanteau building type 'School', which is perhaps the most ambiguous classification under the benchmark category and does not provide much useful information about the type of activity that takes place in these buildings. These examples highlight issues that add to the list of classification errors that were raised in the previous chapter and which emphasises the need to refine the building type classifications if the DEC data are to be used more extensively for the development of future benchmarks.

For the reasons stated above, it was necessary to extract only the records that related unambiguously to either primary or secondary schools to make sure that the analyses is based purely on records for primary and secondary school buildings. For this study, records with building types 'Primary school', 'Secondary school', 'State primary school' and 'State secondary school' were therefore extracted from the dataset of refined DEC records described in section 5.2.

Once the dataset of DEC records for just primary and secondary schools was created, it was linked with additional information from EduBase[10], which is the public portal maintained by the Department for Education (DfE). That website provides a vast range of information on educational establishments including primary and secondary schools in England. The information that was considered to be relevant to the study was the details of addresses and numbers of pupils. There were also descriptions of other characteristics such as boarding

[10] For EduBase, see: http://www.education.gov.uk/edubase/home.xhtml

schools and the main specialisms of schools. Inspection of these variables however indicated that they were either often not rigorously entered or there were very few schools that had inputs (e.g. boarding schools). It was therefore decided that these incomplete variables would not be used for the study. The relevant information was extracted from the public portal in January 2013. The dataset comprised information on 39,604 primary and secondary schools across England. The full list of variables in the dataset can be found in Appendix A.

The data from DfE was joined to the DEC records by means of several processes to ensure that the records were matched correctly. An initial step in joining the two datasets was to identify the variables that were unique to each school and shared between the two datasets so that they could act as links when the datasets were joined. The common variables between the DEC records and the DfE dataset were the names of the schools and the postcodes. An inspection of the street addresses in the DEC dataset however revealed that these were often different from DfE records due to the ways in which the assessors put in the addresses when producing DECs. It was therefore decided that postcode would be a more reliable identifier of each school.

The next step was to identify the buildings that had lodged DECs at the same postcode and others that had not. An inspection showed that 81% of the records were unique to the given postcodes and that the majority of these were primary schools (Table 6.2).

Table 6.2 The number of unique DECs by postcode by phase of education

Phase of education	1 DEC per postcode		2 or more DECs per postcode		All
	N	%	N	%	N
Primary schools	7,705	70%	1,482	13%	9,187
Secondary schools	1,224	11%	662	6%	1,886
All	8,929	81%	2,144	19%	11,073

Subsets of postcodes and names of schools were then created from each of the datasets and the merging was carried out using a combination of Statistical Analysis Software (SAS) and manual inspection. Initially, the DfE dataset was joined using SAS to a subset of DEC records which had lodged only one record per postcode. Once the two datasets were joined together, each DEC record and the corresponding DfE record were manually inspected using Microsoft Excel to ensure that a correct match had been made, based on the names of schools and their postcodes.

As a final step, schools that indicated that they were occupied for extended hours were discounted from the analyses. This was to ensure that the patterns of energy use of schools analysed in the study were representative of typical operation. This exclusion is however limited to the cross-sectional analyses outlined below.

As shown in Table 6.3, the final dataset comprised 7,731 schools. In the academic year 2012/13, there were 16,784 and 3,281 state-funded primary and secondary schools in England respectively (DfE, 2013). The sample in the dataset therefore represented approximately 40% of the primary schools and 32% of the secondary schools.

Table 6.3 Summary of changes in the number of DEC records in the dataset

#	Data processing steps	No. DEC records after each step		
		Primary	Secondary	Total
1	Cleaned and filtered DEC dataset	-	-	73,160
2	Sub-set school records	30,625	5,610	36,235
3	Latest DEC record from each building	12,488	3,051	15,539
4	Joined with pupil information	8,625	1,519	10,144
5	Extended hours of occupancy removed	6,686	1,045	7,731

Prior to the analyses of the patterns of energy use of schools, the fossil-thermal energy use was partially adjusted so that the trend in energy consumption could be assessed more accurately. This is due to the strong correlation between the climate and the demand for space heating energy in buildings. Seasonal and regional variations in weather means that buildings in different geographical locations or where the energy use was measured during different periods will be influenced by varying external conditions. The adjustment was made using equation (4) below, which is an adapted version of the equation (2) that is used to assess the DEC operational ratings (CIBSE 2006b).

$$N_{dd} = [N\ (1 - P/100)] + [(N \times P\ /\ 100) \times (S\ /\ L)] \quad (4)$$

Where:

N_{dd} the fossil-thermal energy use of a school adjusted for degree-days (kWh/m^2 per year)
N the unadjusted fossil-thermal energy use (kWh/m^2 per year)
P Percentage of the fossil-thermal energy use pro-rated to degree-days (%)
L the number of degree-days in the assessment period for the specific location
S the standard heating degree-days for the category

The original equation was reorganised to normalise the fossil-thermal energy use of schools to a standard number of heating degree-days rather than adjusting standardised energy use to the heating degree-days of a specific location.

The three variables in the equation, P, L and S were determined based on previous work by Bruhns et al. (2011), other publications, and insights from building services engineers. The main source of figures that was readily available for variable P was Table 1 in CIBSE *TM46* (CIBSE 2008). To improve the relevance of benchmarking, the methodology currently adjusts between 30 and 70% of the fossil-thermal energy benchmarks, depending on the type of activity. For schools, the existing method allows 55% of the fossil-thermal energy consumption to be adjusted to account for regional and seasonal variations in weather. A review of relevant publications and discussions with building services engineers however suggested that this is likely to be a conservative figure. A publication by the Building Research Energy Conservation Support Unit (BRECSU, 1996) suggested that space heating could account for up to 80% of the total fossil-thermal energy use of a typical school. In this study, 80% rather than 55% of the fossil-thermal energy use of schools in the dataset was assumed to be used for space heating.

Heating degree days are frequently used in studies of the built environment as a measure of the variation in external temperatures over time. The degree-day values are acquired by calculating the differences between the external temperatures and a reference temperature, which is a temperature at which heating is no longer considered to be required in buildings (CIBSE 2006b). Degree days are used to adjust the energy benchmarks to account for variation in weather under the DEC scheme. The up-to-date monthly degree days for different weather regions in the UK are recorded and provided to assessors through the Central

Information Point (CIP), which is part of the national register website[11] (CIBSE 2009). In addition to the degree days for specific locations, the standard number of heating degree days was defined. In their study, Bruhns et al. (2011) explain that the ‘raw’ energy benchmarks in *TM46* are based on 2,021 heating degree-days, which is considered to represent the average UK climate. The relevant table in *TM46* indicates that the figure is based on the average of the heating degree days measured from 1998 to 2007 relative to the base temperature of 15.5°C (CIBSE 2008). It was therefore decided that 2,021 would be suitable for use as the variable ‘S’ in equation 4.

The adjustment of the space heating proportion of the total fossil-thermal EUI to the standard degree-day region of the UK and the removal of schools that were operating for extended hours meant that the statistics were directly comparable with the *TM46* benchmarks.

6.2 Methods of analysis

This section describes the methods that were used to analyse the pattern of energy use of schools, the process through which the data was analysed, and the underlying assumptions and uncertainties.

The analyses in this section were carried out in several steps. Initially, the latest patterns of energy use of primary and secondary schools were described using cumulative frequency distribution curves. The positively skewed distributions of the energy performance of buildings under the ‘Schools and seasonal public buildings’ category observed in the previous chapter led to a decision to describe these distributions using median, upper and lower quartiles. This was to avoid small numbers of extreme outliers from distorting the central tendency and the variations in distribution when the mean and the standard deviation are used.

Changes in the patterns of electricity and fossil-thermal energy use were also assessed in order to complement the cross-sectional view of the energy performance of the schools. The

[11] For national register website, see: http://www.ndepcregister.com

samples of schools in each year were extracted from the dataset of DEC records, which was cleaned and filtered as described in Section 5.2. Changes in the electrical and fossil-thermal EUI of the sample schools between 2008 and 2011 were assessed based on the ratio between the actual EUI and the adjusted benchmarks, to ensure that the effects on energy use of weather and variation in occupancy hours were excluded from the trends (see Section 5.4.1 for a detailed explanation). The median of the ratio was assumed to be representative of the typical performance of the buildings in each year.

An objective of whole-building energy benchmarks is to provide estimates that are representative of the typical performance of the stock. An aspect of the energy benchmarks that is seldom discussed is the uncertainty associated with the figures that are used for benchmarking. This is largely due to the general lack of transparency of the data that underpin the benchmarks (Liddiard 2008). Insufficient information on the data, such as the sample size or the date when they were collected, means that it is often difficult to assess how representative they are of the typical performance of the stock. Exploring the influences that varying sample sizes have on the statistical accuracy of the median, or the typical energy performance, was therefore deemed important for improving the robustness of the benchmarks.

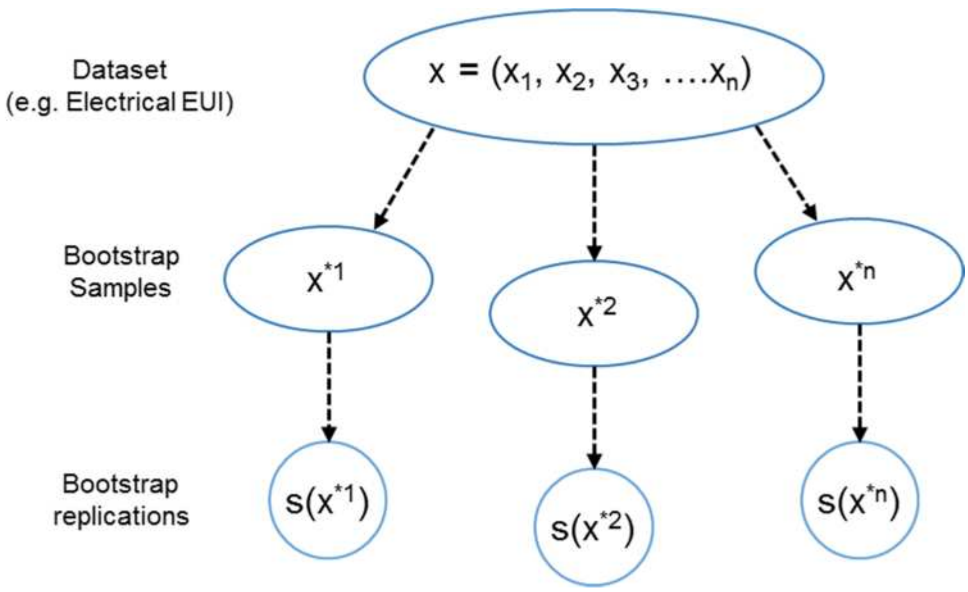

Figure 6.1 Schematic of a bootstrap analysis for assessing the statistical accuracy of a statistic s(x) of a dataset (adapted from: Efron, 1993)

Bootstrapping is a method that is used to assess the statistical accuracy of population estimates such as means or medians (Efron 1993). The method involves making statistical inferences of the sampling distribution and the confidence intervals of a population estimate by repeatedly resampling from a given sample and describing its properties (Figure 6.1).

As shown in Figure 6.1, B bootstrap samples (e.g. x^{*1}) of size *n* are created from the dataset by random sampling. Bootstrap replicates (e.g. $s(x^{*1})$) are then obtained by calculating a statistic of interest, such as mean or median, for each bootstrap sample. Lastly, statistical properties such as the standard deviation of the distribution of the bootstrap replicates are calculated and used as measures of the accuracy of the statistic s(x).

In the study, 1,000 bootstrap samples (B = 1,000) of varying sizes were created by randomly selecting energy consumption figures from the dataset. The samples were selected using the unrestricted random sampling method in SAS where records are randomly selected with an equal probability and with replacements which meant that a record that was selected once could be selected again for the same sample (SAS Institute Inc. 2014b). The sample sizes explored in the study started from five and were increased by doubling the previous sample (e.g. 5, 10, 20, 40, 80, 160, 320 and 640) until there were negligible changes in the confidence intervals of the sampling distribution of medians. To examine the accuracy of deriving an energy benchmark from 10 records, for example, medians from 1,000 samples of 10 randomly selected records were used. The statistic calculated for each bootstrap was the median as this is the commonly used statistic for producing energy benchmarks. The use of medians rather means means that percentile intervals are more suitable for assessing the statistical accuracy of the statistic rather than standard errors, which are typically used for normally distributed samples. From the bootstrap distribution of medians, the 2.5^{th} and 97.5^{th} percentiles were used as lower and upper limits on the 95% confidence intervals.

In addition to the analyses of the patterns of energy use and their accuracy, the study also involved exploration of the relationships between various characteristics and their impact on the pattern of energy use. These analyses were intended to identify factors that are either strongly correlated with or have statistically significant influence on the pattern of energy use, as a means to explore ways to improve the robustness of benchmarking. Several methods were employed to assess the correlations or the significance of the differences between the patterns of energy use of groups of schools with different characteristics. Prior to the assessments, however, the normality of the electrical and fossil-thermal EUIs distributions was tested to determine statistical techniques that would be appropriate for the data. This was due to the differences in the statistical assumptions that are made when using the parametric tests as opposed to non-parametric methods. A main statistical assumption that underpins the parametric tests among other assumptions is that the data is normally distributed (Field & Miles 2010). The normality of the distribution of the electrical and fossil-thermal EUIs was therefore tested using the Kolmogorov-Smirnov (K-S) test in SAS. This test involves comparison of the distribution of the sample with that of a normal distribution of comparable mean and standard deviation. If the test result is significant at 95% confidence level ($p < .05$) then the distribution is considered to be non-normally distributed. The tests on the electrical and fossil-thermal EUIs of primary and secondary schools were all found to be significant ($p < .01$), which meant that the distributions of the samples were non-normal. Non-parametric tests, which do not assume that the sampling distribution is normally distributed, were therefore considered to be more appropriate for the study.

Correlations between the building and occupant characteristics and the patterns of energy use were assessed based on correlation coefficients, scatter plots and the coefficient of determination, R^2, which is the value of the line of best fit.

For binary variables - those have only two categories - Wilcoxon rank-sum, or Mann-Whitney, tests, rather than Student’s t-tests, were used to assess the statistical significance of differences in trends of energy use. For nominal variables - those that have more than two categories - Kruskal–Wallis tests were used, rather than the analysis of variance (ANOVA), to assess the statistical significance of the differences in EUIs of buildings in different categories. These tests were followed by Wilcoxon rank-sum tests to identify the precise location of where the significant difference occurred. A Bonferroni correction was used to reduce the level of significance at which results are reported to prevent the Type 1 error rate from increasing due to multiple Wilcoxon two-sample tests (Field & Miles, 2010). In both cases, the 95% significance level was used as a basis for identifying statistical significance (p value less than 0.05).

6.3 Results

This section presents the patterns of energy use in primary and secondary schools in England. Figure 6.2 shows the distribution of electricity use of primary and secondary schools in England. Note that a number of extreme outliers were not plotted in the chart in order to improve the legibility of the distribution.

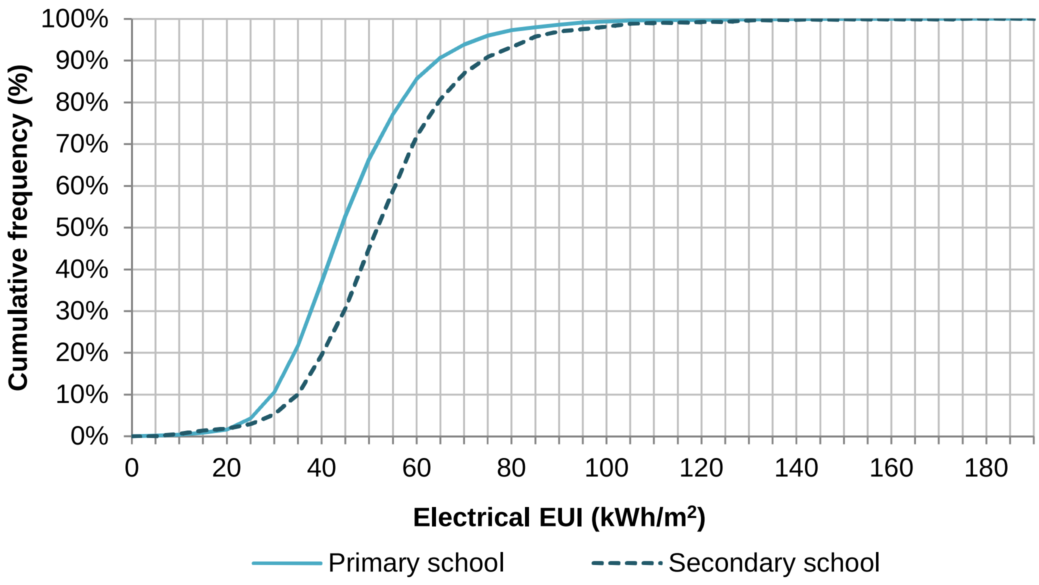

Figure 6.2 Cumulative frequency distribution curves of the electrical EUI of primary and secondary schools in England

As observed in the previous chapter, the long tail of the distribution to the right indicates that the electrical EUIs of both types of school are positively skewed. The differences in the intensity of electricity use is also evident from the distance between the curves shown in Figure 6.2. The median electrical EUI of primary schools was noticeably lower than that of the secondary schools with values of 44 kWh/m^2 and 51 kWh/m^2 respectively (Table 6.4). The difference in the EUI of primary and secondary schools was found to be statistically significant

(Wilcoxon-Mann-Whitney, $p < .0001$). This significant difference therefore suggested that the ways that electricity is used in primary and secondary schools are distinctively different, which may be due to various factors. One likely reason is the greater uses of electrically-intensive equipment in secondary schools such as computers, laptops, and also the presence of teaching facilities that require greater use of electrical equipment such as laboratories (Global Action Plan 2006; Carbon Trust 2012). As can be seen from the distribution curves, the variations in the data for the two types of school were reasonably similar with interquartile ranges of 17 and 19 kWh/m^2 respectively.

Table 6.4 Statistics of the electrical EUI of primary and secondary schools in England

Phase of education	**N**	**Electricity EUI (kWh/m^2)**					
		Min	25th %	Median	75th %	Max	IQR*
Primary	6,686	1	36	44	53	191	17
Secondary	1,045	1	42	51	61	174	19
All	7,731	1	36	45	55	191	19
Existing benchmarks							
CIBSE TM46			-	40			
CIBSE Guide F							
- Primary			22	32			
- Secondary			25	33			
ECG 73**							
- Primary			20	28			
- Secondary			24	30			

* Inter-quartile range (IQR)

** Energy consumption guide (ECG) (BRECSU, 1996)

In addition to the descriptive statistics, Table 6.4 shows electricity benchmarks for schools published over the past two decades. The comparison of the sample median to the existing benchmarks shows that what was perceived as typical performance of schools has gradually changed over the years. The benchmarks in the energy consumption guide (ECG) for example were derived from a survey conducted in the late 1990's. The differences in the sample median and the ECG figures show that schools were considerably less intensive then in electricity use. The fact that separate energy benchmarks for primary and secondary schools are not provided in CIBSE *TM46* was also a noticeable change in the way the energy performance of schools has been benchmarked. Unlike the previous benchmarks, both primary and secondary schools are currently benchmarked against the shared value of 40 kWh/m^2. The statistically significant differences between the electrical EUI of primary and secondary schools that was found above however suggest that this aggregated grouping of the two types of schools is not likely to provide an accurate evaluation of their respective energy performance. For primary schools the intrinsically less intensive use of electricity means that these buildings are more likely to receive better grades than the secondary schools.

Figure 6.3 shows recent changes in the operational ratings of electricity consumption of primary and secondary schools.

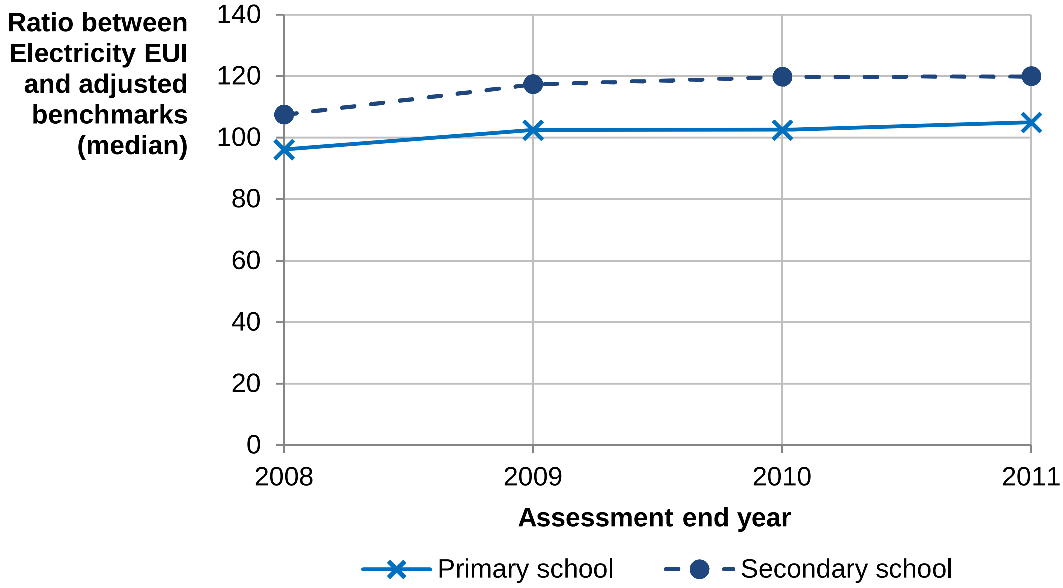

Figure 6.3 Changes in the electricity use of primary and secondary schools between 2008 and 2011

It can be seen that electricity consumption has gradually increased between 2008 and 2011, where the median ratios of primary and secondary schools have changed by approximately 9 and 12%, respectively. These trends reflect the increasing prevalence of the virtual learning environments that involve the use of electrical technologies such as ICT equipment. The increases in the intensity of electricity use suggest that schools are likely to have continued their uptake of ICT and electrical equipment and that the trend has continued up to the present (Global Action Plan 2006; Ofsted 2011). Moreover, it can be seen that secondary schools are notably more intensive in electricity use than primary schools which is likely due to the greater use of electrical equipment in ICT (Carbon Trust 2012).

Figure 6.4 shows the distributions of the weather-corrected fossil-thermal EUIs of primary and secondary schools in England. Note that a number of extreme outliers were not plotted in the chart in order to improve legibility.

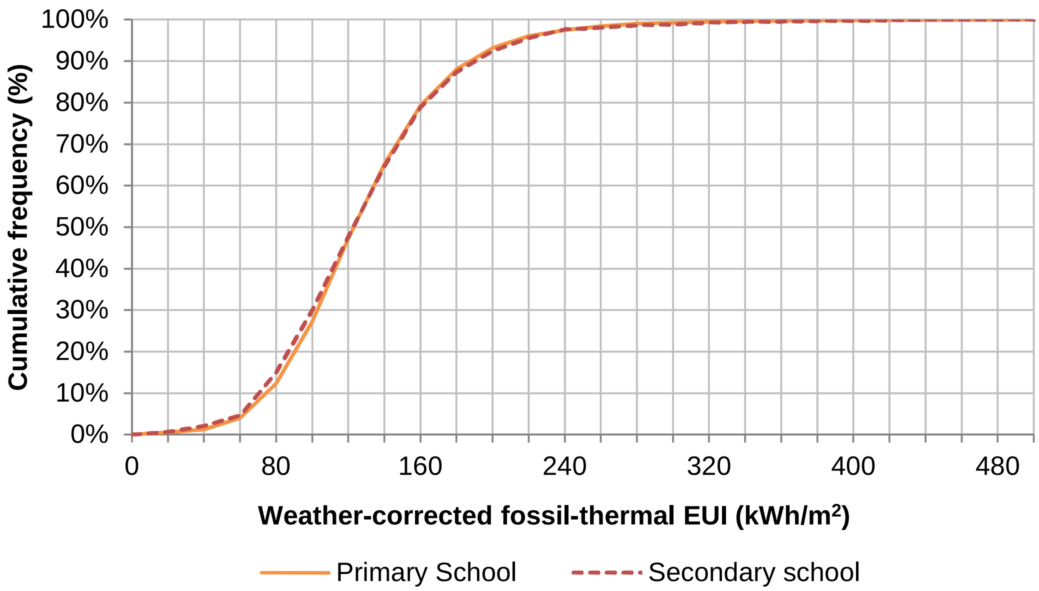

Figure 6.4 Cumulative frequency distribution curves of the weather-corrected fossil-thermal EUIs of primary and secondary schools in England

The distributions of the weather-corrected fossil-thermal EUIs shows that the pattern of energy use, mainly for providing space heating and domestic hot water, are very similar between primary and secondary schools. The medians of the heating consumption of primary and secondary schools are 122kWh/m^2 and 121kWh/m^2 respectively and the variations in the data were also found to be very similar (Table 6.5). A hypothesis test showed that the difference in fossil-thermal energy uses between primary and secondary schools was not statistically significant (Wilcoxon-Mann-Whitney, $p > 0.05$). This therefore suggested that the way schools are heated and hot water is supplied to pupils are alike regardless of the type of school. This is likely due to the fact that the demand for space heating is associated with prevailing weather conditions and the building characteristics such as the quality of the fabric, rather than how the occupants behave in the buildings, which was the likely explanation behind the variations in electricity use.

Figure 6.5 shows year-on-year changes in the fossil-thermal EUIs of primary and secondary schools from 2008 to 2011. Note that the figure displays the median of the ratio between the actual consumption and the adjusted benchmarks.

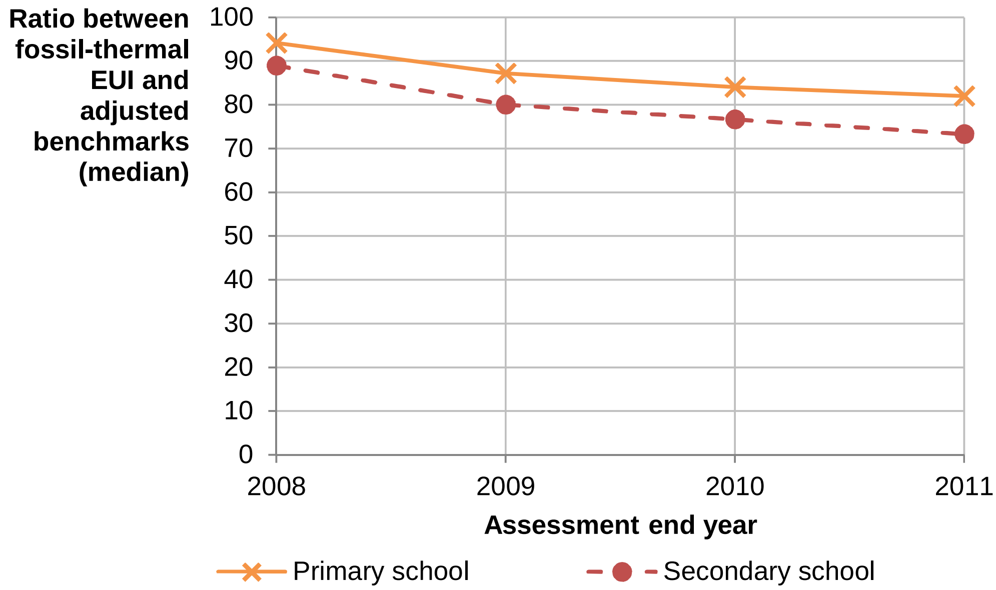

Figure 6.5 Changes in the fossil-thermal EUIs of primary and secondary schools between 2008 and 2011

It can be seen that heating consumption in both primary and secondary schools has gradually decreased over the past four years (Figure 6.3). Over the four-year period, the ratio was found to decrease from 94 and 89 to 82 and 73, which are approximately 13% and 18% decreases respectively. There are many factors that may have caused the reduction in heating energy use of schools such as climate change, rising fuel prices, implementation of energy efficiency measures or more efficient management. The lack of detailed information on the sample schools with regards to their operation means that further study would be needed to explain precisely why such a trend is occurring across a large proportion of the stock. These contrasting trends in electricity and fossil-thermal use in schools were also found in the study by Godoy-Shimizu et al. (2011) in which a similar phenomenon was traced back to 1999. This indicates that the way schools use energy continues to change over time and therefore it is necessity to identify the factors that cause such changes, particularly in fossil-thermal energy use, to fully understand the trends.

It should be noted that the performance figures from DECs lodged in 2012 were not included in Figure 6.3 and Figure 6.5 since records for the complete year were not available. The trends were derived from a sample of schools that have lodged DECs with data collection ending in a specific year, therefore, to include 2012 would not be a like-for-like comparison.

Table 6.5 below presents statistics for the weather-corrected fossil-thermal EUIs of primary and secondary schools. Current and past energy benchmarks for schools in the UK are also presented for comparison purposes.

Table 6.5 Statistics for the weather-corrected EUI of primary and secondary schools in England

Phase of education	**N**	**Adjusted fossil-thermal EUI (kWh/m^2)**					
		Min	25th %	Median	75th %	Max	IQR*
Primary	6,686	2	97	122	153	597	56
Secondary	1,045	5	94	121	154	802	60
All	7,731	2	97	122	153	802	56
Existing benchmarks							
CIBSE TM46			-	150			
CIBSE Guide F							
- Primary			113	164			
- Secondary			108	144			
ECG 73**							
- Primary			126	173			
- Secondary			136	174			

* Inter-quartile range (IQR)

** Energy consumption guide (ECG) (BRECSU, 1996)

As with the electricity consumption, the comparison of the latest fossil-thermal EUI figures for primary and secondary schools with the current and past energy benchmarks shows that what was regarded as a typical performance has changed considerably over the past decades. It can be seen that what was seen as the average (or median) fossil-thermal EUIs of primary and secondary schools has decreased considerably over the decade from 173 and 174 kWh/m^2 in the late 1990's to 150 kWh/m^2 in 2008. Moreover, the noticeable difference between the actual fossil-thermal EUI of the sample and the energy benchmark in *TM46* suggests that this latest benchmark is no longer representative of the typical performance of primary and secondary schools. The insignificant differences in the fossil-thermal EUI between primary and secondary schools does however suggests that providing a shared value is likely to be sufficient for benchmarking heating consumption.

Figure 6.6 to Figure 6.9 show changes in medians and the confidence intervals of the sampling distributions of electrical and fossil-thermal EUIs of primary and secondary schools from the bootstrap analyses. Note that the vertical bars at each point indicate the 95% confidence intervals of each statistic based on the 2.5th and 97.5th percentiles of the sampling distribution.

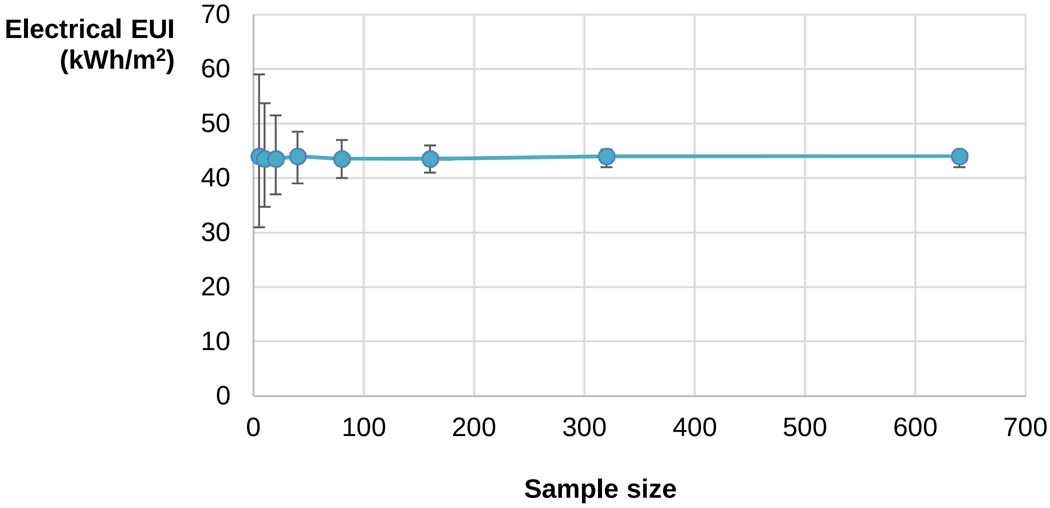

Figure 6.6 Changes in median electrical EUI of primary schools and the corresponding confidence intervals derived from varying sample sizes

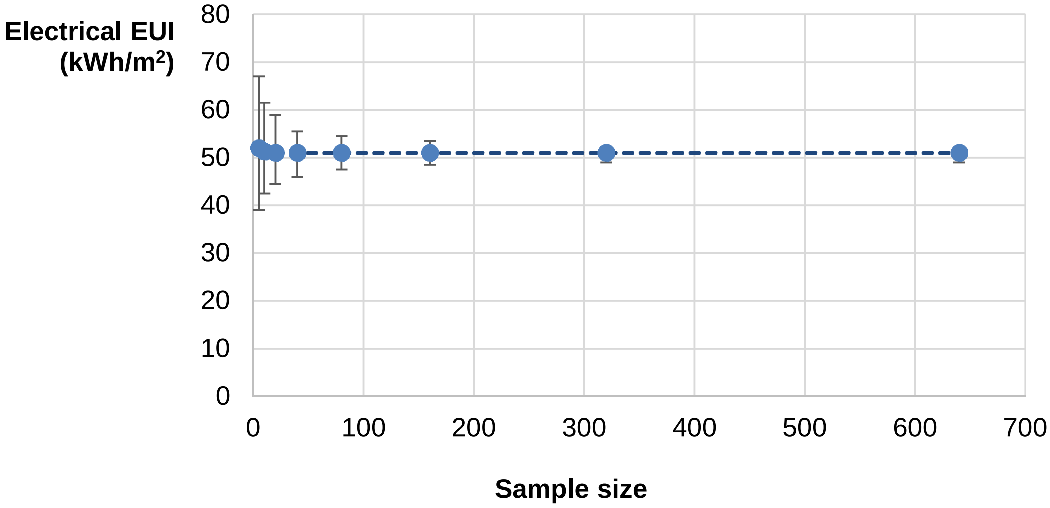

Figure 6.7 Changes in median electrical EUI of secondary schools and the corresponding confidence intervals derived from varying sample sizes

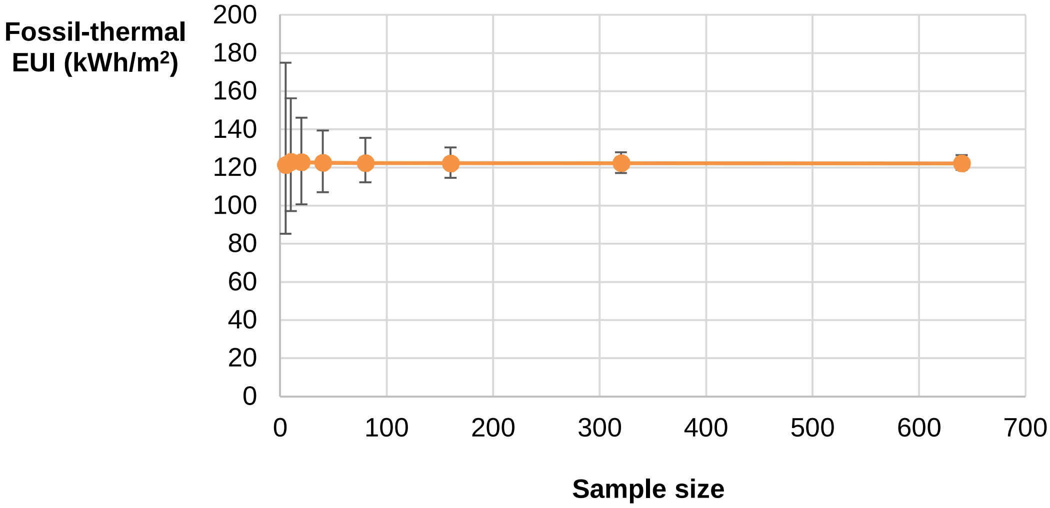

Figure 6.8 Changes in median fossil-thermal EUI of primary schools and the corresponding confidence intervals derived from varying sample sizes

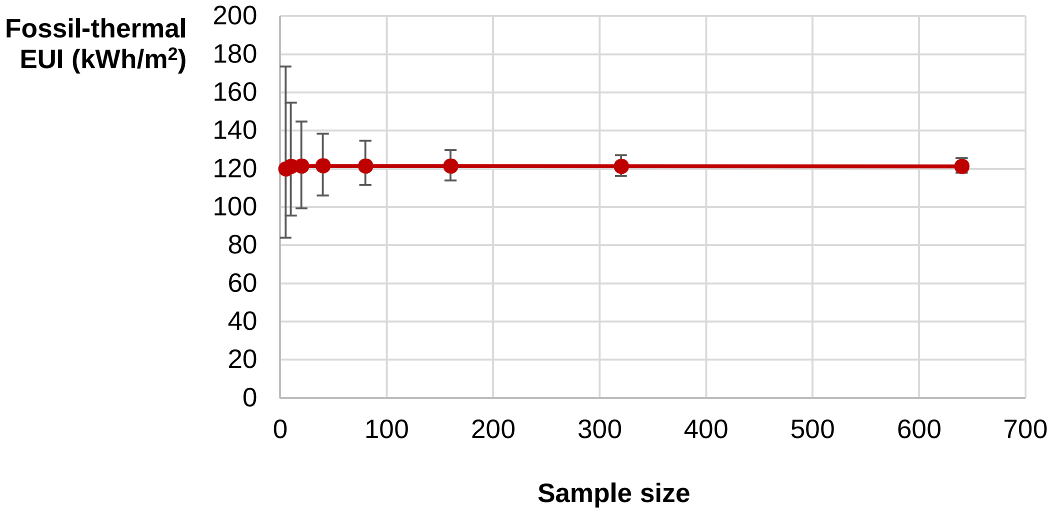

Figure 6.9 Changes in median fossil-thermal EUI of secondary schools and the corresponding confidence intervals derived from varying sample sizes

The four figures show a similar trend in the way the population estimate changes, which in this case is the median, and in the associated confidence intervals. In general, there is not much fluctuation in the median derived from samples of varying sizes. What is noticeable however is the dramatic decrease in the upper and lower confidence intervals as the sample size increases. Taking the median electrical EUI of primary schools for example, the upper confidence interval of the statistics was found to reduce the most from 59 kWh/m^2 to 53.8 kWh/m^2 when the sample size changed from 5 to 10 (Figure 6.10). When the sample sizes became greater however the rate at which the intervals changed reduced to less than two when medians were derived from sample sizes of 80 and 160. This suggested that the influence of the change in sample sizes on the accuracy of the typical energy performance of the school stock is considerable and that larger sample sizes are likely to yield more accurate measures.

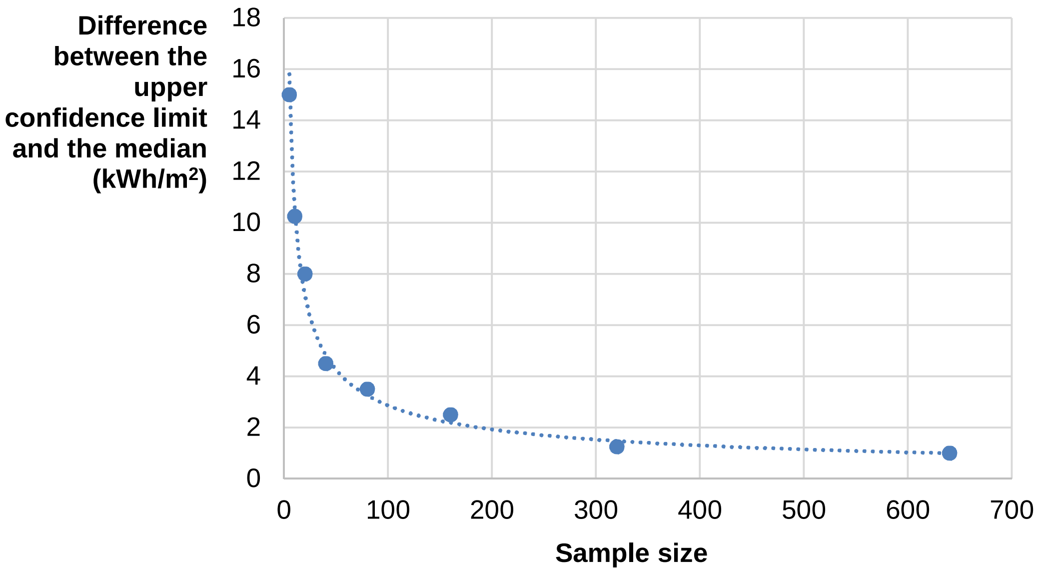

Figure 6.10 Differences between the upper confidence limit of the electrical EUI of primary schools from median with varying sample sizes

The significant reduction of the rate at which the confidence intervals decrease with increase in sample size however suggests that it is not necessary to have a very large sample size (e.g. n = 1,000) to estimate the typical energy performance of the school stock with reasonable accuracy. It can also be seen that the rate at which the confidence limit reduces to a reasonable range when the sample sizes were around 200. It does on the other hand show that energy benchmarks that are derived from small sample sizes should be treated with caution as they may not be accurate representations of the typical energy performance of the stock. The results thus indicate that, given the sufficiently large sample sizes, the statistics for the electrical and fossil-thermal EUIs in Table 6.4 and Table 6.5 are likely to be highly accurate estimations of the typical performance of the primary and secondary schools in England.

Figure 6.11 below shows the cumulative frequency distribution of annual electricity and fossil-thermal energy use normalised by number of pupils rather than by floor area.

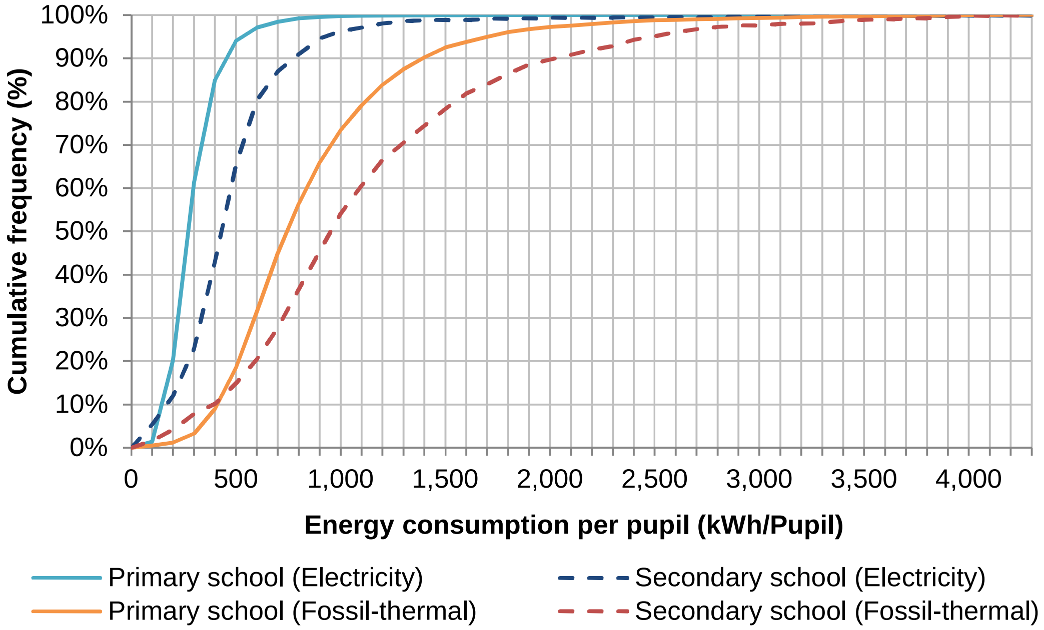

Figure 6.11 Cumulative frequency distribution of energy use per pupil by school type

The distribution curves in Figure 6.11 show distinctively different levels of energy use per pupil in primary and secondary schools. Primary schools were found to use significantly less electricity per pupil than secondary schools with medians at 270 kWh/pupil and 430 kWh/pupil, respectively (Wilcoxon-Mann-Whitney, $p < .0001$). Conversely, a comparison of the trends in fossil-thermal energy use per pupil showed that the energy used for heating per pupil is significantly lower in primary schools than in secondary schools with medians at 744 kWh/pupil and 965 kWh/pupil, respectively (Wilcoxon-Mann-Whitney, $p < .0001$). The difference is likely to have been produced however by differences in the density of pupils rather than other factors. A comparison of the levels of energy use per floor area (kWh/m^2) and energy consumption per pupil (kWh/pupil) showed that approximately 6m^2 and 8m^2 is allocated per pupil in primary and secondary schools respectively.

Figure 6.12 and Figure 6.13 are scatterplots of the annual electricity consumption (kWh/yr) of primary and secondary schools compared with floor area and number of pupils. The lines of best fits are displayed for determination of the relationships.

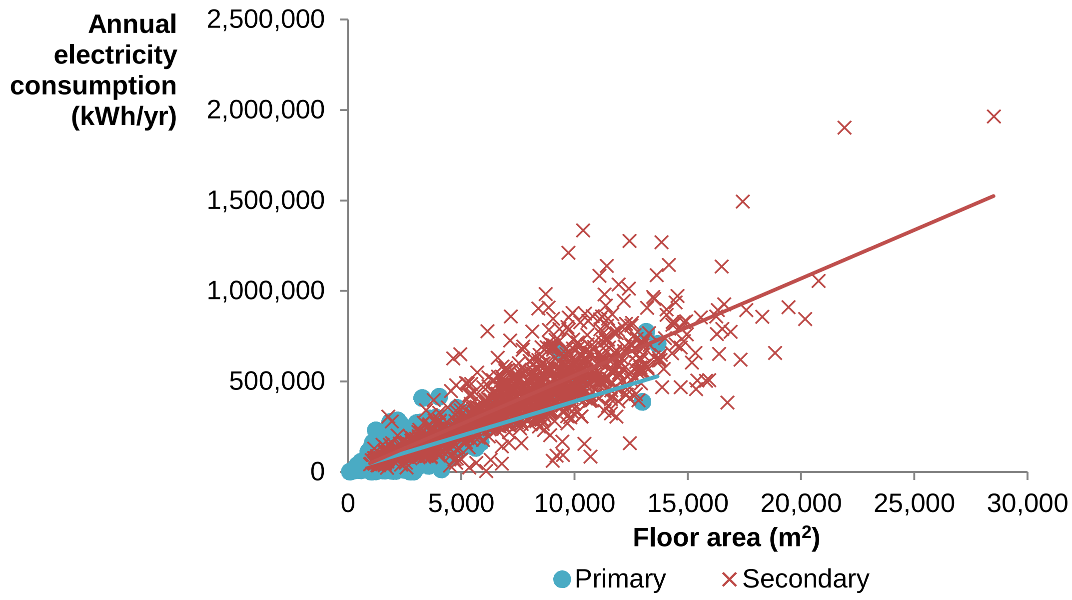

Figure 6.12 Scatter plot of annual electricity use and floor area by school type

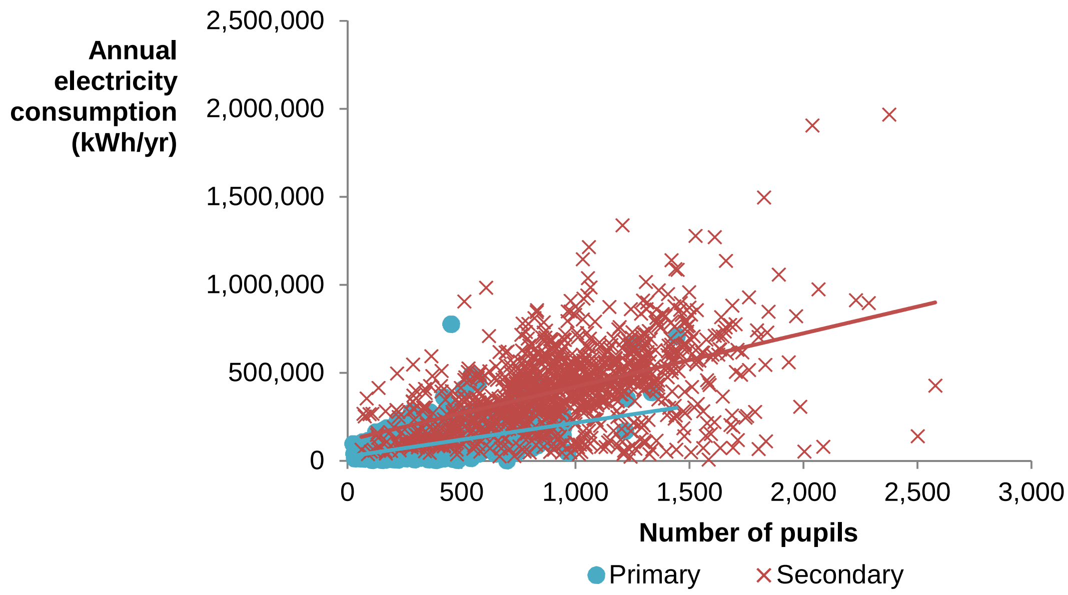

Figure 6.13 Scatter plot of annual electricity use and number of pupils by school type

The scatter plots in Figure 6.12 and Figure 6.13 show that there are positive relationships between annual electricity consumption and both floor area and number of pupils in primary and secondary schools. It can also be seen that there is a cluster of primary schools near the lower end of the spectrum, around 3,000m^2, where secondary schools are found across a much wider spectrum of sizes – ranging above 15,000m^2.

The plots also show that the data points are more clustered around the line of best fit between floor area and annual electricity consumption by comparison with the fit to number of pupils. The variation in scatter of the data points and in the correlation coefficients between electricity consumption of primary and secondary schools with floor area and number of pupils indicate that there is a stronger correlation between electricity consumption and floor area (Table 6.6).

Table 6.6 Comparison of Spearman's correlation coefficient between the annual electricity consumption of primary and secondary schools and the floor area and the number of pupils

Phase of education	**Spearman Correlation Coefficients, N = 6,686** Prob > |r| under H0: Rho=0	
Annual electricity consumption (kWh/yr)	Floor area (m^2)	Number of pupils
Primary school	0.69	0.58
	<.0001	<.0001
Secondary school	0.85	0.51
	<.0001	<.0001

Figure 6.14 and Figure 6.15 below are scatterplots of weather-corrected annual fossil-thermal energy consumption (kWh/yr) of primary and secondary schools with floor area and number of pupils. The line of best fit and the corresponding R^2 value are given for comparison purposes.

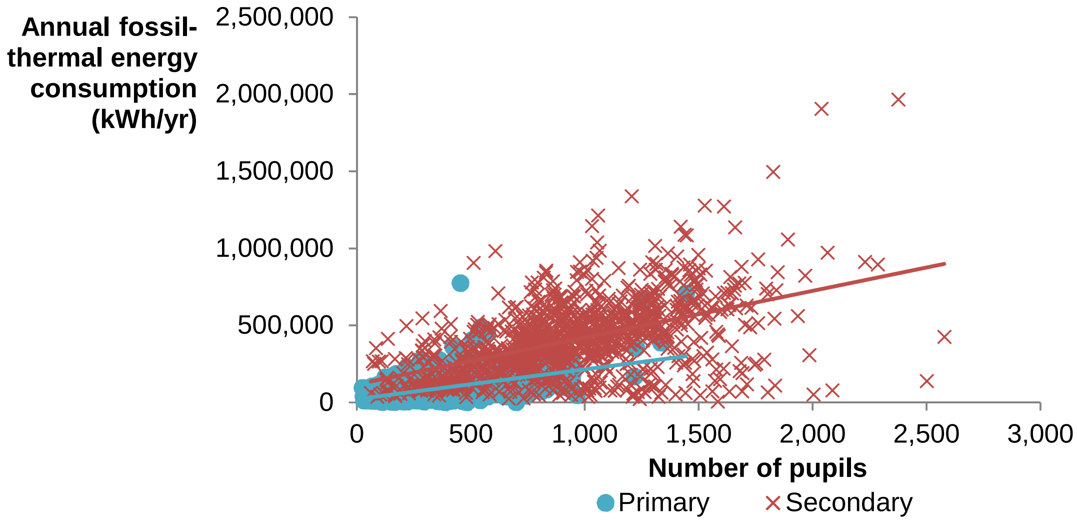

Figure 6.14 Scatter plot of weather-corrected annual fossil-thermal energy use and floor area by school type

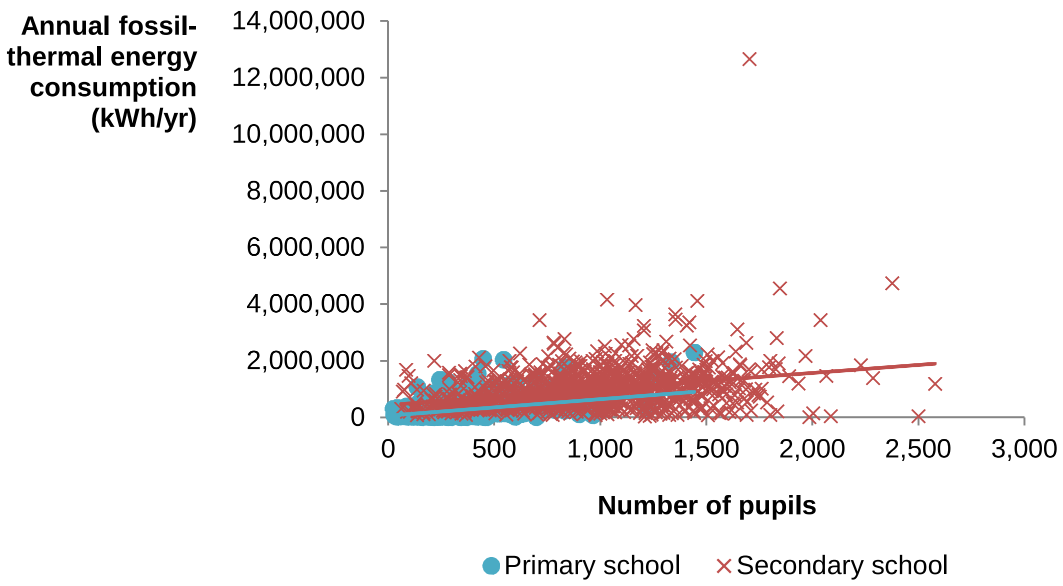

Figure 6.15 Scatter plot of weather-corrected annual fossil-thermal energy use and number of pupils by school type

The scatter plots show that there is a positive relationship between heating energy use and both floor area and number of pupils. The data points for secondary schools are however much more widely spread in Figure 6.14 than Figure 6.12, which suggests that the relationship is less clear for floor area. Figure 6.15 also shows that there is one secondary school whose pattern of fossil-thermal energy use is substantially different from the rest of the sample. A closer examination of the data showed that the school was using 802 kWh/m^2 for heating (weather corrected), which was the most intensive school in the dataset (Table 6.5).

The assessment of the strength of the correlations between fossil-thermal energy use and both floor area and number of pupils showed that, like electricity consumption, there was a stronger correlation between annual fossil-thermal energy use and floor area in both primary and secondary schools (Table 6.7).

Table 6.7 Comparison of Spearman's correlation coefficients between the weather-corrected annual fossil-thermal energy consumption of primary and secondary schools, floor area, and number of pupils

Phase of education	**Spearman Correlation Coefficients, N = 1045**	
	Prob > |r| under H0: Rho=0	
Annual fossil-thermal energy use (kWh/yr)	Floor area (m^2)	Number of pupils
Primary school	0.70	0.50
	<.0001	<.0001
Secondary school	0.79	0.33
	<.0001	<.0001

The differences in the correlation coefficients shown in the analyses of electricity and fossil-thermal energy use of primary and secondary schools clearly indicate that floor area accounts for a greater proportion of the variation in annual electricity and fossil-thermal energy use than does the number of pupils. These findings agree with the conclusions of a study of energy use by schools in New Zealand by Isaacs, Baird, & Donn (1990) showing that energy use is better related to floor area than to number of pupils. This therefore suggests that using floor area as a denominator of the EUI metric expressed as kWh/m^2 is more appropriate for benchmarking the energy performance of primary and secondary schools than numbers of pupils.

The 'internal environment' variable in the DEC data provides a useful insight into how schools are ventilated to provide fresh air and to maintain a thermally comfortable environment. The categorical variable groups different operational strategies into seven categories, of which schools were found under six categories (Table 6.8).

Table 6.8 Number of schools by the type of ventilation strategy

Internal environment	Phase of education	
	Primary school	Secondary school
Air Conditioning	11	7
Heating and Mechanical Ventilation	140	48
Mixed-mode with Mechanical Ventilation	21	9
Mixed-mode with Natural Ventilation	114	67
Heating and Natural Ventilation	6,396	914
Natural Ventilation Only	4	.
All	6,686	1,045

The buildings that use mechanical ventilation systems or air-conditioning systems are in theory likely to consume more electricity, due to components such as fans, and heating and cooling coils, than the naturally ventilated buildings which are the dominant form of ventilation in the UK. The following analyses therefore focus on assessing whether actual differences in demand for energy use that might be expected between schools with different ventilation strategies can be observed in the sample.

Table 6.9 shows statistics for electricity and fossil-thermal EUIs of primary and secondary schools by type of ventilation strategy.

Table 6.9 EUI statistics and the distribution of schools by the internal environment

Internal environment	Primary			Secondary		
	N	Electricity EUI	Fossil-thermal EUI	N	Electricity EUI	Fossil-thermal EUI
		Median (kWh/m^2)			Median (kWh/m^2)	
Natural Ventilation Only	4	49	147	.	.	.
Heating and Natural Ventilation	6,396	43	122	914	51	122
Mixed-mode with Natural Ventilation	114	48	119	67	53	122
Mixed-mode with Mechanical Ventilation	21	50	106	9	66	95
Heating and Mechanical Ventilation	140	50	118	48	57	112
Air Conditioning	11	47	99	7	49	97

The statistics show that electricity consumption is noticeably higher in mechanically ventilated schools and heating consumption is lower. This is likely due to the increased electrical load from components of the HVAC system such as fans and pumps in mechanically ventilated buildings, which generally use more electricity than their naturally ventilated counterparts (Bordass, Cohen, et al. 2001). By contrast, the differences in fossil-thermal energy use of schools with different systems are negligible.

Initial hypothesis tests indicated that there are statistically significant differences between the different school types with different ventilation strategies for electricity use (Kruskal-Wallis, $p < .0001$). The difference was not found to be significant however for fossil-thermal energy use (Kruskal-Wallis, $p > .05$).

Table 6.10 shows the results from a series of Wilcoxon-Mann-Whitney tests, which were carried out to identify any significant differences.

Table 6.10 Summary of the results from Wilcoxon-Mann-Whitney tests on the electrical EUIs of schools with different internal environment types

Internal environment type	Phase of education	
	Primary	Secondary
	p-value	
Heating and Natural Ventilation *versus* Heating and Mechanical Ventilation	**< .0001**	**< .0125**
Heating and Mechanical Ventilation *versus* Mixed-mode with Mechanical Ventilation	> .0125	> .0125
Mixed-mode with Natural Ventilation *versus* Mixed-mode with Mechanical Ventilation	> .0125	> .0125
Mixed-mode with Mechanical Ventilation *versus* Air Conditioning	> .0125	> .0125

A significant difference in electricity use of schools with natural ventilation and mechanical ventilation was found in both primary and secondary schools (Wilcoxon-Mann-Whitney tests, $p < .0001$). There were however no significant differences between schools with ventilation strategies that involve mechanical systems (Wilcoxon-Mann-Whitney test, $p > 0.0125$). This suggests that the subtle differences in the classification of ventilation strategies, illustrated in CIBSE *TM46*, do not reflect actual differences in energy use – at least in the case of schools. This therefore raises the possibility of revising the classification system so that categories with no significant differences in energy use can be grouped together, particularly 'Mixed-mode with Natural Ventilation' and 'Mixed-mode with Mechanical Ventilation'. It should be noted however that the majority of the schools in the dataset were naturally ventilated and therefore the sample sizes of schools with air conditioning and mechanical ventilation were small. Further studies with a well-distributed sample and a greater number of schools with air-conditioning and mechanical ventilation would be necessary to confirm the results.

6.4 Chapter summary

In this chapter, the patterns of energy use in primary and secondary schools in England were analysed to understand these patterns but also to explore opportunities for improving the robustness of benchmarking.

The findings from the analyses are listed below:

- Various building types that were deemed to have different patterns of use and energy consumption were found under the 'Schools and seasonal public building' category. There were also different levels of specificity of building types (e.g. School) that cause confusion and difficulties in identifying records and utilising the valuable data for benchmarking purposes. These findings highlighted the challenges raised by the drawbacks of the current classification system in assessing the energy performance of schools as well as developing future benchmarks.
- The analyses have shown that there are significant differences in electricity use between different school types, where secondary schools were significantly more intensive than primary schools. The difference in fossil- thermal energy use was however insignificant. Nevertheless, the difference in the patterns of energy use highlighted that the current classification of schools is not appropriate for accurately assessing their operational energy efficiency.

- Analysis of the changes in patterns of energy use of schools from DEC records with assessment end dates between 2008 and June 2012 has shown a gradual increase in intensity of electricity consumption and a decrease in fossil-thermal energy use. The contrasting trends observed over the past decade have indicated that the pattern of use of energy by schools continues to change in response to developments in technology and other factors.
- The accuracy of the median energy performance values that are derived from varying sample sizes were found to improve dramatically with increases in size. The rate at which the accuracy improved however was found to reduce considerably once the sample reached a certain size (typically > 200).
- Floor area was found to be more strongly related to annual electricity and fossil-thermal energy use for both primary and secondary schools than number of pupils. This confirmed that the current use of floor area as a denominator for the performance indices of EUI (kWh/m^2) for normalising and comparing the energy performance of schools is appropriate.
- Comparisons of electricity consumption between primary and secondary schools with different ventilation strategies showed statistically significance differences. Schools that are predominantly naturally ventilated were found to use significantly less electricity than schools using varying levels of mechanical ventilation to supply fresh air and maintain a comfortable indoor environment. The implications of the finding for benchmarking could not be addressed properly however due to the predominance of naturally ventilated buildings in the dataset.

In summary, the analysis of the stock-level data specific to primary and secondary schools have provided deeper insights on the various aspects of the current DEC framework as well as the general patterns of energy use and the factors influencing these patterns.

Adding to the issues of misclassification found in the previous chapter, building types with different levels of specificity that cause confusion further emphasised the lack of robustness of the current classification system. The distinctively different patterns of energy use between primary and secondary schools also indicated possibilities of finding comparable differences between other building types.

The historical changes in the patterns of energy use in schools suggested that these trends are likely to continue in the future. This means that the energy benchmarks are bound to become disassociated with the patterns of energy use of the school stock as time passes. Moreover, the findings from bootstrapping analyses suggested possibilities for establishing sample sizes that would improve the confidence of the representativeness of energy benchmarks.

The small number of variables that were analysed in this chapter, although providing useful insights, only broadly describe the intrinsic features of buildings. The following chapters therefore aim to improve the understanding of the relationships between a wider range of intrinsic features and empirical data on the energy performance of schools.

Chapter 7 Hybrid Approach to Analysing English Schools

This chapter aims to assess and identify factors that are correlated with patterns of energy use of schools that were not explored in the previous chapter. As the second part of the three-part case study, the dataset developed in this chapter is aimed at exploring more detail on the intrinsic features such as the local environment, the age and the built form that, in theory, would influence the demand for energy uses in non-domestic buildings. The main objectives of the study are therefore to develop a dataset with additional variables that describe the features that are intrinsic to school buildings in greater detail, and to explore the data in order to complement the findings from the previous chapter.

The study was carried out in two parts. The initial part of the study involved preparing a dataset that could be analysed to achieve the objectives. This not only involved developing and merging different datasets but also required a substantial data collection exercise, due to the lack of any existing database providing finer detail on the intrinsic features of buildings such as their shape and how the fabric was designed. The data from the collection exercise was then merged with the dataset that was used for analysing the pattern of energy use of schools in England in the previous chapter (Section 6.1). Lastly, the dataset prepared at finer granularity was analysed using a multivariable analysis method to assess the impact that the intrinsic features of school buildings had on their energy performance. The results and the summary of the findings are presented at the end of the chapter.

7.1 Building characteristics survey

Unlike the Commercial Buildings Energy Consumption Survey (CBECS)[12] database in the US, there were no pre-existing databases in the UK describing the intrinsic features of buildings such as their shape, exposure or glazing areas that in theory would influence the demand for energy. As described in more detail in previous chapters, the data from Display Energy Certificates (DEC) and the Department for Education (DfE) provide reasonable information on

[12] For CBECS, see: http://www.eia.gov/consumption/commercial/index.cfm

such characteristics of buildings as sizes, ventilation strategies and numbers of pupils. These datasets did not, however, describe the intrinsic features of the buildings themselves and therefore the initial step of the study was to collect the information which was otherwise not available.

The following sections describe in detail the sampling of schools for the analyses and how data on the intrinsic building features was collected using online resources.

7.1.1 Sampling of schools

Prior to the collection of additional data, a step was taken to consider and design the way the sample would be selected for the multivariable analyses. The main objective of the initial step was to estimate an adequate sample size so that the influences of different characteristics on the pattern of energy use found in the study can be used to make inferences about the population of the school stock.

There are numerous ways in which sample sizes can be estimated for multiple regression analyses. These range from rules of thumb to more complex methods that require considerations of key characteristics of the analysis at hand. Green (1991) for example proposes two methods for estimating the minimum sample size acceptable to test the overall fit and to test the individual independent variables in the model using the following equations:

$$N_{\text{overall fit}} = 50 + 8k \tag{5}$$

$$N_{\text{independent variables}} = 104 + k \tag{6}$$

where k is the number of independent variables in a model.

These methods however oversimplify the factors that affect the significance of a statistical procedure (Field & Miles 2010). The rule of thumb proposed by Green (1991) was therefore not used in this study.

Cohen (1992) on the other hand suggests using power analysis to determine the appropriate sample size, and that three variables need to be defined to do so. These variables are:

- Size of the effect that the research intends to detect
- The level of probability at which the results will be accepted as being statistically significant
- The statistical power that is desired to prevent the Type 2 error from occurring

Field & Miles (2010, p.198 Fig. 7.9) provides a diagram that can be used to estimate the required sample size for multiple regression analyses. The diagram provides sample sizes required for analyses which aim for different effect sizes and comprise different numbers of independent variables at the significance level of 0.05 and statistical power of 0.8, which are recommended by Cohen (1992). This was used as a basis for estimating the sample size. Moreover, the number of independent variables that are to be used in the final model was estimated based on previous studies by Sharp (1996; 1998) both of which concluded that six variables were the most significant. Due to the difficulties in estimating the number of variables, a more conservative number of ten was used for the estimation. For analyses that aim to find the medium-sized effect (r = 0.3) with 10 independent variables, the diagram suggested a sample size of 150. While this number was taken as the target for secondary schools, the target sample size for primary schools was adjusted upwards. This was in response to a pilot study that was carried out on primary schools in London in order to assess the feasibility of the proposed method (Hong, Pang, et al. 2013). The size of the sample that was collected for the pilot study was 110, which meant that a much larger sample size would be needed for analyses of primary schools to reduce the bias for schools in London. According to the data extracted from the Edubase (Section 6.1), schools in London were found to account for approximately 11% of the school stock in England. This meant that approximately 900 schools would needed to reduce the bias. Experience from the pilot study suggested however that such a collection exercise would require tremendous time and resources, which meant that it was not likely to be feasible within the timeframe of the study. The target sample size for primary schools was therefore increased to 500 (inclusive of the London sample) to reduce the bias as much as possible.

Once the sample size was estimated, an exploration was made of the process through which the sample was to be selected. The main constraint in selecting the sample was that information on the energy performance and the other characteristics previously described was limited to schools that had lodged DECs. Moreover, the number of schools for which information on the number of pupils was available was small still. In an ideal situation schools would be randomly selected from the entire school stock. The requirement for detailed information on schools and their pupils and the limited availability of such data however meant that there was little control over where the sample was to be selected from. The dataset that was developed in Chapter 6 (Section 6.1) was therefore assumed to be the effective population and the sample was selected from that dataset to ensure that the variables that describe the building and occupant characteristics of schools were retained.

The sample was selected with the aim of properly representing the geographical distribution of the school stock whilst being useful for identifying and comparing the influences that each characteristic has on energy performance. Initially, lists of all primary and secondary schools in the dataset were produced as a preparation for the sample selection. The schools on the lists were then shuffled into a randomised order with the aid of the random number generator function of Microsoft Excel 2013. This was to ensure that there was no particular order in which the sample was selected from the datasets so as to minimise bias.

There were several methods that were considered for the collection of additional information on the buildings. In the built environment, detailed information on buildings can often be collected via on-site surveys. Being able to visit the buildings means that a surveyor is able to collect detailed information on not just the building but also its occupants, which can be very useful for identifying causes of inefficiency (Cohen et al. 2001). The main limitation in adopting this approach was however the fact that site visits are highly intensive in time and resources, not to mention the time consumed in the bureaucratic process of acquiring access to schools. The fact that one of the objectives was to collect information on a sufficient number of schools so that the findings could be used to make inferences to other schools within the time frame of a PhD programme meant that adopting such an approach was not practically feasible. The other method that was available was the approach developed by Hawkins et al. (2012). In that study, a method was developed whereby information that describes the built form and other parameters of university buildings was collected via online tools and databases. The ability to capture much of the information that describe the intrinsic features of buildings without visiting the buildings meant that a large number of buildings could be surveyed at the expense of much less resource and time. It was therefore decided that the online method would be adopted as a basis and refined for collecting the data in the study.

Another aspect of the data collection process that was defined was the set of criteria on which a school would be selected from the dataset. This was largely to reduce the factors that create uncertainties in the analyses of influence of building characteristics on energy consumption, but also to ensure that the desk-top based survey method could be used to collect sufficient information. Factors that were deemed to have the potential for introducing uncertainties to the analyses were schools with multiple buildings, extensions or part refurbishments.

As discussed earlier, the influences of building characteristics were deemed difficult to assess in schools with multiple buildings since the way the buildings interact with the surrounding environment would be different from those that only have a single main building. Taking shading for example, schools with multiple buildings are likely to have limited access to the sun due to the overshadowing effect between those buildings whereas a single building school might not. Schools that were partly refurbished or where an extension was added would also introduce uncertainties. Typically a building will last for approximately 50 years, although there are numerous schools that are more than 100 years old. During its lifetime, many changes can be made to a building that can influence its energy use. There are for example possibilities for buildings to be refurbished, either partly or as a whole, or an extension could be added to an existing building to satisfy changing demands. The changes in the requirement to improve energy efficiency when an existing building undergoes refurbishments or an extension erected under the Building Regulations Part L2B means that some buildings will have parts with different levels of thermal performance (HM Government 2010c).

Below is a set of criteria that was produced to select buildings that would enable analysis of determinants of energy use on a building basis while facilitating the desk-based collection approach:

- Schools with one main building
- Uniform building characteristics (age, construction material, etc.)
- Can be seen using Google street view or the Bing Bird’s eye view function

At the end of the data collection exercise, detailed information was collected from 550 schools which comprised 497 primary schools and 53 secondary schools.

7.1.2 Selection of the intrinsic features

Prior to selecting and developing methods for collecting intrinsic features of buildings, an option to categorise schools based on archetypes was investigated. Archetypes of buildings are typically established based on key features such as architectural style or age, which represent the built form, composition of spaces, and construction. Such an approach can be beneficial in various ways, especially when there are limited resources to study the effects of changes on a wider building stock (Bull et al. 2014; Mavrogianni et al. 2012). With regards to assessing the impact of intrinsic features of buildings on the energy performance schools however, such an approach was deemed inappropriate for several reasons. First, existing archetypes of schools were developed by other researchers based on the built form and layout but not taking into account the features that influence the energy performance of schools. Second, there is a diverse range of ways in which archetypes are constructed, which are often associated with uncertainties on how representative they are of a sector or the stock due to insufficient information. Third, these archetypes only cover the periods up to 1970’s until which point schools were built with distinct period features that allowed buildings to be categorised into archetypes (Steadman 2014; Harwood 2010). This means that archetypes of schools that were built during the past 30 to 40 years do not exist. Unlike the past school buildings, these contemporary buildings vary widely in their form, materiality and efficiency. This is likely to be due to the developments in construction materials and techniques, and mechanical systems, which allowed school buildings to be designed with greater freedom. Such diversity of building characteristics within the past decade means that it is extremely difficult to develop a generic archetype to represent the characteristics of contemporary buildings. It was therefore deemed inappropriate to adopt an archetype approach for categorising and analysing the patterns of energy use of schools.

There is plethora of factors that are intrinsic to buildings that, according to principles of building physics, have the potential to influence the way energy is used in buildings, including schools (Mumovic & Santamouris 2009). CIBSE *Guide F* distinguishes various factors that influence the energy consumption of buildings into two main themes, the site considerations and the built form (CIBSE 2012). Site considerations include external factors such as the weather conditions, both at local and micro scale, the orientation of a building and influences from surrounding buildings. The built form on the other hand concerns the building-specific factors such as the form, levels of insulation and design of windows or glazing. The primary focus of the next phase was therefore to collect sufficient information on the site and building-related factors to complement the information that was carried through from DECs and EduBase datasets. The constraints on resources, however, meant that it was important to identify and collect a set of variables that express the key characteristics of buildings that, in theory, have significant impacts on energy consumption.

Initially, relevant literature was reviewed to identify variables that had previously been used for similar purposes. The list of variables used by other authors to describe the features that are intrinsic to the site and buildings is shown in Table 7.1.

Table 7.1 List of variables that describe the intrinsic site and building features

Study	Variables	Related building physics
Ratti, Baker, & Steemers (2005)	Surface-to-volume ratio	Heat loss
	Orientation of a façade	Passive solar gain
	Urban horizontal angle (UHA)	Overshadowing due to surrounding buildings
	Obstruction sky view (OSV)	Insolation on a façade
Yang, Lam, & Tsang (2008)	U-value	Heat loss
	Shading coefficient	Passive solar gain
	Window-to-wall ratio (%)	Heat transfer and daylight
	Skylight-to-roof ratio (%)	Heat transfer and daylight
Hawkins et al. (2012)	Age	Variation in the thermal performance and efficiency of building services
	Primary external wall material	Provision of thermal mass
	Fraction exposed	Heat loss, ventilation and daylight
	Aspect ratio	Depth of floor plan: daylight and ventilation
	Shading factor	Overshadowing due to surrounding buildings
	Sheltering factor	Obstruction from prevailing wind
	Glazing type	Heat transfer
	Glazing ratio	Heat transfer and daylight
	Weather data	External conditions

The adequacy of variables for use in the study was assessed based on the following criteria:

- That the variable adequately expresses the intrinsic features of the site or building
- That the information can be acquired with reasonable input of resources
- That the method that underpins the variable is robust

During the process, variables such as U-value or shading coefficient were deemed inaccessible to the study due to the difficulties of acquiring such detail from existing buildings. There were other instances where a variable was deemed useful but required modifications. Variables such as the aspect ratio that express how deep the floor plan of buildings are for example was deemed useful and feasible for collection. The underlying method was however deemed not robust owing to the complexity of the shape of buildings. Such variables were therefore modified or replaced with other variables that were deemed more appropriate for the study. Variables such as the urban horizontal angle (UHA) and obstruction sky view (OSV) were on the other hand deemed effective and robust. The underlying method used by Ratti, Baker, & Steemers (2005) however involved a tool that was developed specifically for the study, which was not readily available. The demanding requirement for additional resources meant that these variables were replaced with another form of variable, which is described in Section 7.1.3.2.

In addition to the variables that were identified from previous studies, additional variables were also developed and introduced to the study based on the principles of building physics (Table 7.2).

Table 7.2 List of key variables and their descriptions

Characteristic	Description	Information required
Building age	Year of construction	-
Site exposure	Exposed, semi-exposed, or sheltered from wind	-
Orientation	Angle at which a ‘vertically’ oriented external wall is set relative to North	-
Façade adjacency	Presence of obstructions in all directions	-
Depth ratio	Depth of the floor plan	Floor area, height and façade lengths
Compactness ratio	Compactness of the footprint of a building compared to a circle	Façade lengths
Surface-to-volume ratio	Degree of exposure to the external environment	Floor area, height and façade lengths and footprint
Glazing ratio	Amount of glazing on the external walls	% glazing on each façade, façade length and height
Glazing type	Single or double glazing	-
Roof shape	Pitched, sloped or flat	-
External shading	Evidence of purpose-designed shades on façades	-
Wind catchers		-
Glazing on roof	Evidence of purpose-designed roof lights	-

Once the desired variables were identified, a list was made of information that would be required to derive the geometrical variables such as the surface-to-volume ratio or the glazing ratio.

7.1.3 Gathering information

The following sections describe in detail how information on the variables was collected and basic measurements were made. The underlying assumptions are also discussed.

Note that there have been attempts to collect this information through various approaches ranging from contacting central government including the Department for Education (DfE) and the Education Funding Agency (EFA) to making direct contact with the head teachers of the schools. It was however found that access to such data would take much longer than expected and the data therefore could not be acquired in these ways for the study.

It should also be noted that data used here was collected in collaboration with Greig Paterson, an Engineering Doctorate student at the UCL Engineering Doctorate Centre in Virtual Environments, Imaging and Visualisation (VEIV)[13]. This was due to the close similarity of the requirements for information on building characteristics in the two PhD projects despite the differences in research aims. Paterson's research focuses on 'Advanced Modelling Techniques Utilising Performance Data and Environmental Simulation as Early Architectural Design Drivers'.

7.1.3.1 Building age

The year in which a building was built is a variable that was deemed useful for capturing the state of the building in terms of the quality of the fabric and the efficiency of building services. The difficulties in acquiring the date at which the building was constructed from local or central government meant that an alternative method had to be used to estimate a building's age.

[13] For VEIV, see: http://engdveiv.ucl.ac.uk/

The ages of buildings were acquired using several methods, all of which involved uses of online resources and research. An initial approach was to search the internet for information about the school through websites such as the school's homepage or a Wikipedia[14] page that provided details such as the history of school, key dates such as the establishment of the school, details of refurbishment or relocation. In cases where the information was not available via the internet, the method developed by Hawkins et al. (2012) was used. This method involved searching through a database of historical maps for different regions to deduce the year or period during which the school was likely to have been constructed. The online tool that was used during this process was Ancient Roam, which is part of the Digimap[15] service. The tool provides access to historical Ordnance Survey (OS)[16] maps dating from the 1840s to the 1990s for any place in the UK by decade.

For each school, the maps that are representative of each decade were searched from the earliest date until the school appeared on the map (Figure 7.1). The specific year in which the building was constructed was refined further by referring to the date at which the map was created.

Figure 7.1 Historical maps showing a map (a) without a school and a map (b) with a school

[14] For Wikipedia, see: http://www.wikipedia.org/
[15] For Digimap, see: http://digimap.edina.ac.uk/digimap/home
[16] For Ordnance Survey, See: http://www.ordnancesurvey.co.uk/

The period between the dates when the maps were created was then used to infer the date at which the school would have been constructed. Once the period was identified, the average of the two dates was calculated and assumed as the year the school was built. For modern schools that were built after the 1990's, for which the historical OS maps are not available via Digimap, the 'historical imagery' function of the Google Earth was used to search the past satellite images and estimate the construction date.

Once the year in which buildings were likely to have been constructed was identified, consideration was given to the type of variable that would be most appropriate for assessing the impact of building age in relation to the patterns of energy use of schools. This is due to the changes in the UK Building Regulations that have gradually imposed more stringent standards on the thermal performance and the energy efficiency of new buildings. The regulations with implications on energy use in buildings were introduced as early as in 1962, which was extended to energy-conservation measures in the following years (Davies 2013). In 1985, Building Regulations Part L 'Conservation of fuel and power' that aimed to improve the thermal performance of new buildings was introduced for the first time. Over the following years, the Regulation was reviewed and updated gradually in 1995, 2002, 2006, 2010, and 2013, requiring higher levels of efficiency from new and existing buildings. These step changes in the standards meant that schools in the sample could be organised into categories that represent the years when the Building Regulations were updated. Consequently, such an approach would reflect the incrementally improving standards of the building fabric. Whilst this approach would have been appropriate for studying only those schools that were built after the introduction of Part L however, it was deemed unsuitable for this analysis. This was due to the fact that a large number of schools in the stock were constructed prior to the introduction of the Building Regulation, some stretching back to the 19th century. To categorise the schools based on the changes in Building Regulations would mean that all schools that were built between the 19th century and 1984, which covers more than one hundred years, would be grouped in a single category whilst contemporary schools would be categorised into groups that represent as little as 4 years. Due to the disproportionate size of the bins, it was deemed more appropriate to consider building age as a continuous variable rather than a categorical variable. The age of a building was therefore calculated by subtracting the estimated construction year from the year when this study was conducted, which was 2013.

There were several limitations of the method that are likely to have introduced a degree of uncertainty to the age estimate. The use of averages meant that there was uncertainty in the accuracy of any building's age. This was however deemed sufficient for the study as this was the only way to acquire such information until more accurate data becomes available in the future. Another area of uncertainty came from the limitations in information with regards to the details of refurbishments that may have taken place during a building's life. Such changes are likely to have happened to schools that were built a long time ago. This therefore implies that the results should to be interpreted with caution.

7.1.3.2 Site conditions

Buildings in different locations are exposed to site-specific conditions that can have considerable effect on the patterns of energy use (CIBSE 2012). Some of the effects of the site are micro climate factors such as exposure to wind and overshadowing, and the orientation of buildings. The following sections describe in detail how these site features were captured.

Exposure to winds

The wind environment of a site can provide benefits to and constraints on the way energy is used in buildings. Sites that are exposed to winds can be beneficial for buildings that were designed to harness natural forces to passively provide and maintain adequate indoor air quality to the occupants. During the winter however exposure to cold winds is likely to lead to greater infiltration of cold air that can in turn increase the demand for space heating (Mumovic & Santamouris 2009). The degree to which a building is exposed to wind was therefore recorded using ordinal categories - 'exposed', 'semi-exposed' and 'sheltered' - rather than the numeric values used by Hawkins et al. (2012) and Ratti et al. (2005) for the reasons discussed earlier.

The environments around sites were observed and assessed using online tools such as the Bird's eye function of Bing Maps[17] and Google Maps[18] services, which provide up-to-date satellite images of the UK. To describe and categorise the surrounding buildings, a boundary was established that was approximately four times the height of a building (4H) away in each direction (Figure 7.2).

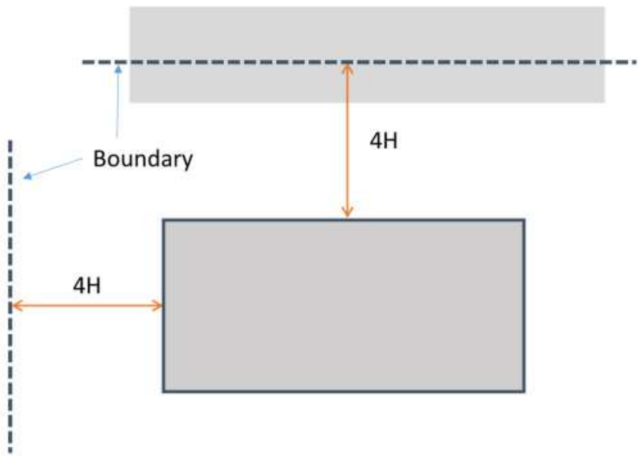

Figure 7.2 Boundary condition for exposure to wind and solar gains

The degree of exposure was then assessed based on the density and height of the objects such as buildings or vegetation that were on or close to the boundary:

- A building was deemed to be exposed to the wind for example if there were no objects near the boundary, which was frequently observed in schools with large playing fields or car parks.

- A building was deemed to be semi-exposed if there were objects surrounding the building but which are similar or lower in height than the building. In some cases where the surrounding buildings were taller but sparse in density as shown in Figure 7.3a, the site exposure was considered to be semi-exposed rather than sheltered.

- A building was deemed to be sheltered from the wind if the surrounding objects were taller than the building (Figure 7.3b).

[17] For Bing Maps, see: www.bing.com
[18] For Google Maps, see: https://www.google.co.uk/maps

Figure 7.3 Examples of a (a) semi-exposed building and a (b) sheltered building

Orientations of walls and buildings

In the built environment, the orientation of buildings is often used to describe the direction in which the main façade faces. A terraced house for example would have a clear set of facades that give it the sense of orientation. The orientation of buildings was deemed important as it can significantly affect how well a building utilises the heat and daylight from the sun, hence the energy efficiency (Mumovic & Santamouris 2009). Buildings in the northern hemisphere for example are often designed to face south to benefit from the solar gain whilst being able to control it to avoid overheating.

There were however challenges in recording the orientation of school buildings based on the existing approach used by Hawkins et al. (2012). This is due to the diversity of designs with large variations in built form and arrangement of classrooms. Unlike the domestic stock, which is more homogeneous and where it is therefore easier to identify the orientation of a building, the large variation in school designs means that it is extremely difficult to determine the main façade of a building. If we imagine a hypothetical building with a square footprint and with an equal amount of glazing on all façades for example, it would not be possible to decide which was the main façade, hence it would not be possible to determine the orientation. A rule was therefore established to describe the orientation of a building and its façades based on the angle between due north and a given building element such as the external wall highlighted in Figure 7.4.

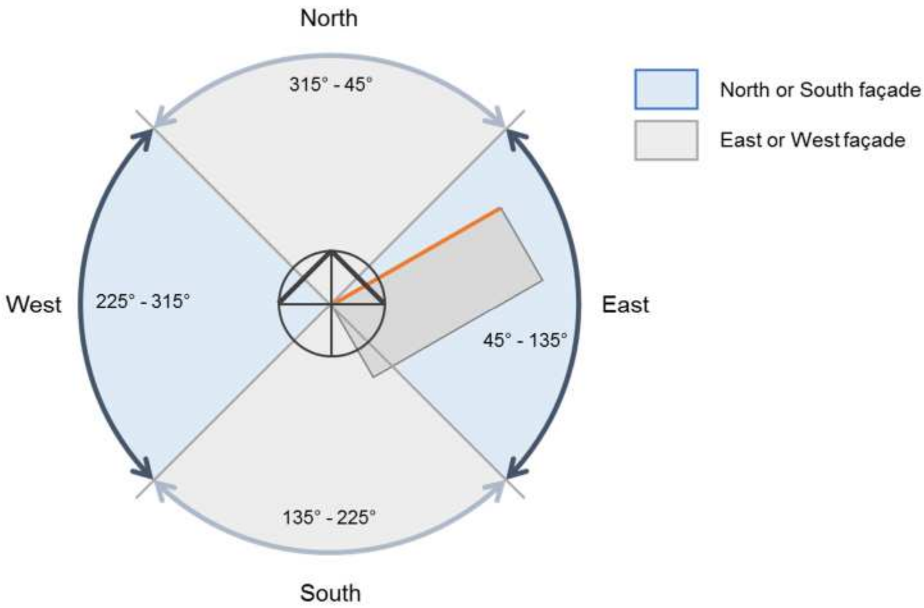

Figure 7.4 Diagram of determination of orientations of façades and buildings

As shown in Figure 7.4, four quadrants were established based on the angles of lines taking north as zero degrees. The circle at the centre indicates the four cardinal directions. The outer circle was divided in to 90 degree quarters and used as a basis for determining the orientation of a façade or a building. Taking the orange coloured line in Figure 7.4, for example, the angle between the line and north fits into the blue shaded quadrant on the right hand side. The wall was therefore deemed to be closer to the East-West axis than the North-South axis and treated as a north façade. Similar rules were applied to all perimeter walls to establish the orientation of each element.

The orientation of a building was on the other hand measured based on a different rule. Due to the difficulties in establishing the orientation of schools, it was decided that the orientation in this study would refer to how much a building is rotated in relation to due north. On the basis that most buildings have external walls that are orthogonal to each other, such approach would account for variations in the amount of direct solar gains through glazed areas during different times of the day and seasons. To avoid confusion, the angle between walls that are set within the top quartile in Figure 7.4 (between 315 and 45 degrees) and due north was taken as the orientation of a building. The angle was measured by using the Google Earth[19] software. The software provides a function that allows the angle between North and a line that is drawn over a satellite image of a building by a user to be measured (Figure 7.5). Taking the school shown in Figure 7.5, for example, the wall that is highlighted was found to be set at 32.28 degrees relative to North, which was therefore deemed to be its orientation.

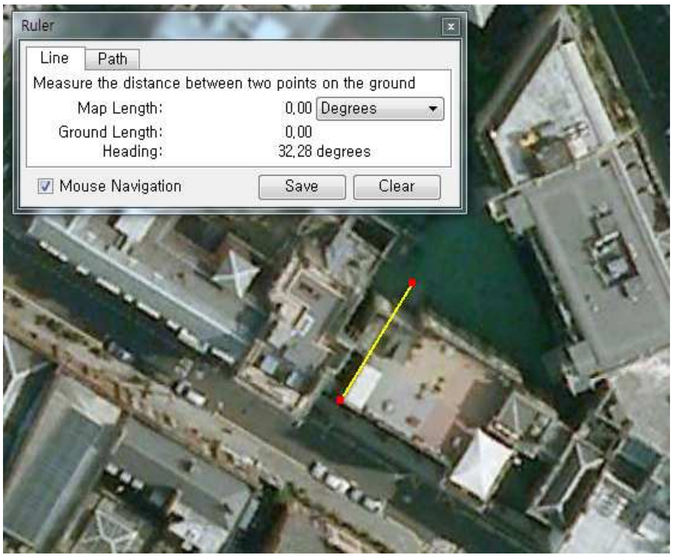

Figure 7.5 An illustration of measuring orientation of a building using Google Earth

Façade adjacency

A site condition that can also affect the pattern of energy use is the extent of surrounding objects such as buildings and vegetation. The density and the proximity of the surrounding objects to the glazed elements of a building could reduce access to the sun, which in turn could increase the demand for space heating as well as artificial lighting. It was therefore deemed important to describe and assess the influence of the surroundings in the vicinity of each façade that could affect access to solar radiation on each façade of a building, hence its energy use.

For the reasons explained previously under the 'Exposure to winds' section, it was deemed more appropriate to describe the surroundings using a categorical variable rather than a numeric variable. The variables that were developed in the study for this purpose were façade

[19] For Google Earth, see: http://www.google.co.uk/intl/en_uk/earth/

adjacencies, which were used to indicate whether there were obstructions near each façade. The adjacency conditions on each façade were assessed based on the surroundings that are approximately one times the height of the building (1H) away from each façade (Figure 7.6).

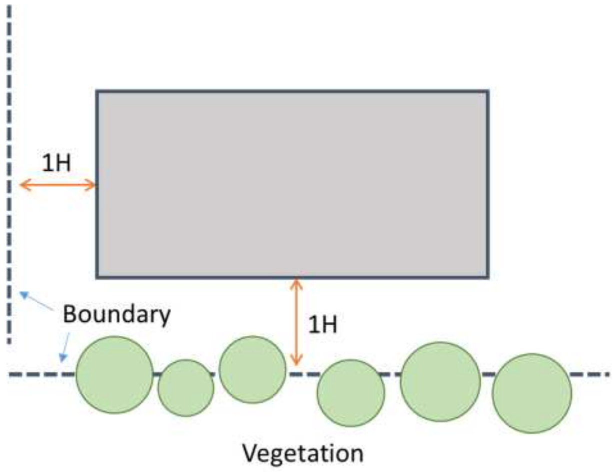

Figure 7.6 Boundary condition for overshadowing from surroundings

Taking the building shown in Figure 7.7, for example, it is clearly visible that the Western and Southern façades are shaded by the vegetation on the South-West side of the building due to their proximity. In this instance the façade adjacency condition was recorded as having obstructions on the South and West.

Figure 7.7 A school surrounded by vegetation

7.1.3.3 Built form

This section explains the process of measurement through which dimensions of building elements were derived in order to calculate parameter values such as the surface-to-volume ratio that describe the form of buildings at an abstract level.

Perimeter and façade lengths

The total and exposed perimeters of buildings were recorded in order to derive the volume and the areas of exposed surfaces. The perimeters were measured separately to differentiate the area of surfaces that are exposed to the weather from party walls with neighbouring buildings that are likely to be occupied, therefore likely to be heated. The lengths of the perimeter of buildings were measured using the Digimap service, which allowed the lengths and areas of buildings to be measured from their footprints (Figure 7.8).

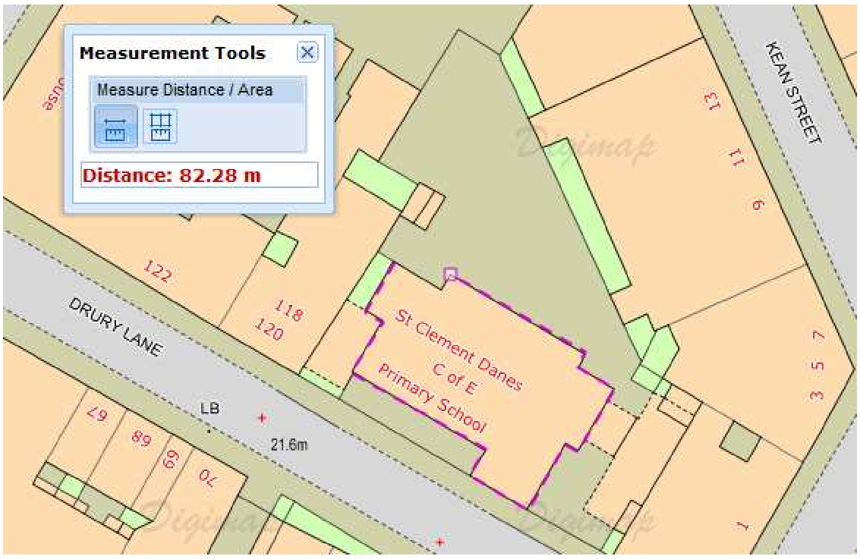

Figure 7.8 Measurement of perimeters of buildings via Digimap

Using the measurement tool embedded in the online platform, a polygon was drawn over the perimeter of a building, which is shown as the dotted pink line in Figure 7.8. The total perimeter length was measured around the entire perimeter regardless of whether any portion of a wall was attached to the adjacent building. The exposed perimeter length on the other hand measured only the walls that were exposed to the external environment.

Lengths of façades with different orientations were measured simultaneously using the same method and used as a basis for deriving the glazing areas on each façade and the overall glazing ratio (described in detail in the 'Glazing percentage' section). Figure 7.9 illustrates how the length of the north wall of a school was measured. In cases where there were walls that were not orthogonal to other façades (e.g. curved walls), such surfaces were either divided into smaller and more distinguishable sections or treated as a single flat angled surface, depending on their curvature.

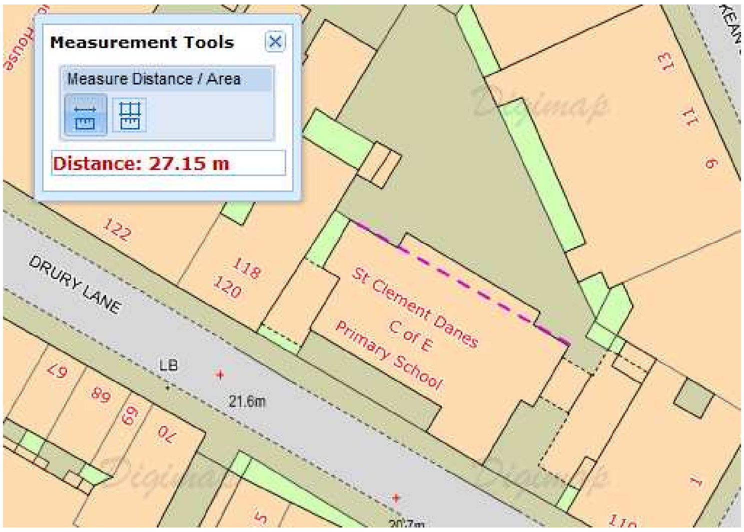

Figure 7.9 Illustration of how façade lengths were measured

Building footprint

A geometrical property that was required to derive the volume and the exposed surface area of a building, in addition to the external wall area, was the roof area. Challenges in measuring the surface area of the roof come from the diverse designs that add complexity. Observations of school buildings using satellite images showed a wide range of roof shapes from the pitched roofs of buildings that were built during the Victorian period to the flat roofs of modern buildings. The constraints in available tools and their abilities however meant that it was difficult to measure the exact surface areas of the pitched or sloping roofs. It was therefore decided that the footprint area would be assumed to represent the surface area of the roof. This was also based on an assumption that walls of buildings were orthogonal to the ground, hence the area of roof would be equal to the footprint of a building.

Figure 7.10 illustrates how Digimap was used to measure the footprint areas of buildings.

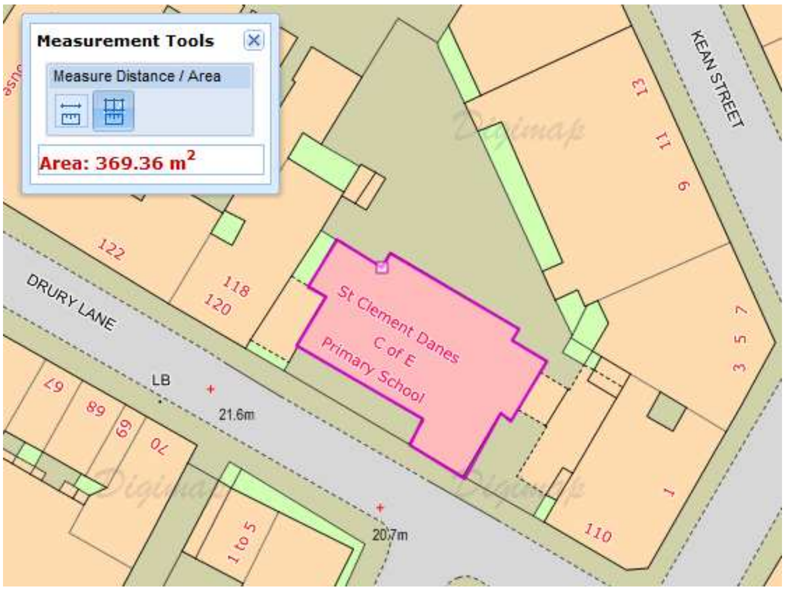

Figure 7.10 An illustration of how footprint area was measured via Digimap

Building height

The height of buildings is a parameter that was measured as part of the survey to describe the geometric shape of buildings. Several methods were explored for acquiring accurate measurements of the height of buildings.

The method that was explored initially was the Geographic Information System (GIS) database from Landmap[20], which provided heights of buildings in major and minor cities across the UK. The database comprises measurements of the height of the terrain and the tops of objects, which in this case were buildings, which were measured using LiDAR[21] technology. Uses of the sophisticated technology led to a belief that the measurements were highly accurate. The data was downloaded from the Landmap website and accessed using ArcGIS[22] software, which allows a user to explore the map and measure the height of buildings that are usually represented as blocks without any context (Figure 7.11b). The measurements from the GIS

[20] For Landmap, see: http://www.landmap.ac.uk/
[21] For LiDAR, see: http://landmap.mimas.ac.uk/index.php/Datasets/Building_Heights/Building-Heights-Download
[22] For ArcGIS, see: http://www.esri.com/software/arcgis/

files were however often found to be questionable. The height of a Victorian school building, for example, was found to be 26.4 metres based on the GIS data (Figure 7.11b). Based on the large windows positioned on the right-hand side of the image shown in Figure 7.11a, the school appeared to be three storeys high. This therefore suggested that the floor-to-floor height of each of these floors was approximately 8 metres, which was deemed extremely high even for the Victorian buildings. Similar uncertainties were also found in modern schools where the height of halls that were clearly greater than the rest of the building from the satellite images were often found to be lower when measured using the GIS data. The uncertainty was therefore deemed to be considerable and an alternative method was explored.

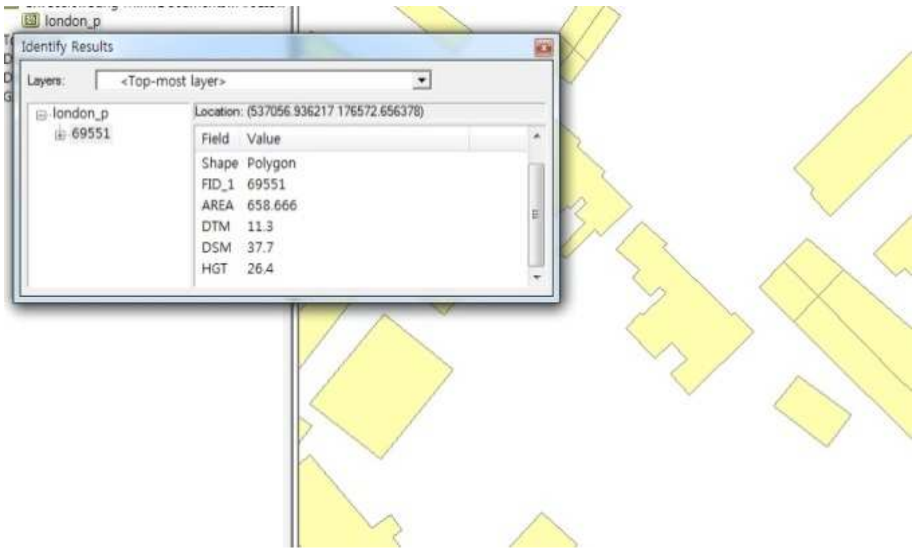

Figure 7.11 Images of (a) a school from a bird's eye point of view and (b) the height of the building acquired from the Landmap GIS dataset

The heights of buildings were derived by multiplying the number of storeys by a figure for the average storey heights of schools in England and Wales of 3.62 m. This approach was deemed the next most feasible method due to the credibility of the statistics and the constraints in time and resources of the research. The measurements came from the Non-Domestic Building Stock project carried out by Steadman, Bruhns, & Rickaby (2000). The project took measurements of external envelopes, in addition to many other parameters, of a large number of non-domestic buildings in four towns in England. The statistic was derived from on-site measurements of floor-to-ceiling heights of schools and was therefore deemed to be the next most accurate measure of the parameter reflecting the characteristics of various school buildings. It should however be noted that the uses of the average height meant that there were limitations in accurately describing the characteristics of buildings. Variations in heights of different spaces in the same school (e.g. classrooms, offices, the halls) and differences in storey heights of Victorian schools compared to modern schools for example, were therefore not well accounted for.

The number of floors was counted based on visual inspection of buildings using the Bing Map's Bird's eye function[23], which provides a 45 degree view of buildings from all directions (Figure 7.11a). Buildings with varying number of floors in different parts were addressed by taking the average of the maximum and the minimum number of floors. These measurements were however only made if a considerable proportion of a building had a different number of floors. This therefore meant that small spaces such as conservatories were not accounted for.

Glazing percentage

The glazed portions of the external walls such as windows and curtain walls are important features that affect the energy efficiency of buildings. While glazed elements are beneficial as they introduce daylight to internal spaces, improve the internal atmosphere and reducing the load on artificial lighting, the high U-values of these units, compared to insulated opaque wall construction, can significantly contribute towards heat gain or heat loss during different

[23] For Bing Maps Bird's eye view function, see: http://www.bing.com/maps/

seasons (CIBSE 2012). The percentages of glazing on each façade relative to the opaque construction were therefore measured to assess their influence on energy consumption.

Data on this characteristic was collected in two steps. Initially, images of all sides of buildings were captured using the Bing map's Bird's eye view function and Google Street View[24]. There were however a number of instances where the view of some façades could not be acquired due to the proximity of neighbouring buildings, other obstructions, or a lack of satellite images. In these cases, the percentages of glazing on the hidden walls were estimated based on the information from the observable façades of buildings such as age, design and orientation.
The images were then imported into a bespoke program that was developed in the programming language Processing[25] by David Hawkins, an Engineering Doctorate student at the UCL Industrial Doctorate Centre in Virtual Environments, Imaging & Visualisation (VEIV)[26]. The tool calculates the percentages of glazing on each wall by drawing polygons on the previously captured images of each façade (Figure 7.12). In the figure, the red polygons indicate the glazed areas in a wall and the blue polygon marks the boundary of the wall.

Figure 7.12 An illustration of how the glazing percentage on facades of buildings were measured using a bespoke tool

[24] For Google Street View, see: http://www.google.com/maps/about/behind-the-scenes/streetview/
[25] For Processing, see: http://processing.org/
[26] For VEIV, see: http://engdveiv.ucl.ac.uk/

Deriving the variables

The various measurements that were taken were then used as a basis for deriving the variables that numerically describe the built form of school buildings (Table 7.3).

Table 7.3 Derived variables and their descriptions

Variable	Description
Surface-to-volume ratio	Exposed surface area divided by volume
Depth ratio	Volume divided by external wall area
Compactness ratio	Perimeter of the building footprint divided by perimeter of a circle with the same area
Glazing ratio	Total glazed area divided by the total external wall area

Types of glazing

In addition to their area, the types of windows or glazed components on external walls play an important role in controlling the heat losses and gains in buildings. The energy efficiency of a glazing component is mainly determined by its construction, which includes the number of layers, and the type of coating as well as the type of window frame (CIBSE 2012). Due to limitations on information with regard to the specification of windows in the study however, the type of glazing was considered only in terms of the number of layers. The commonly used types are single, double and triple glazing. The rate of heat loss through a single glazed window is generally considerably greater than a double glazed window due to the additional insulation provided by the pocket of air between the glass panes. Glazing types were therefore surveyed to assess their impact on the heating consumption of buildings.

As discussed previously, there was no central database that records the type of glazing and the specification of windows in schools. This therefore meant that the type of glazing had to be determined based on educated guesses with the aid of visual inspection of windows and additional factors (Figure 7.13). Initially, close-up images of different facades of buildings were captured using Google Street View. The type of glazing was determined based mainly on the appearance of the frames and the glazing. Taking the images of the window shown in Figure 7.13, for example, the zoomed-in image shows a white window frame with seamless joints, with a particular focus on the grey diagonal lines on the frames (Figure 7.13b), which indicated that the frames were likely to be made of aluminium or a modern material such as PVC that is commonly used with double glazing. Based on the visual inspection, the glazing was therefore assumed to be double.

Figure 7.13 Images of (a) windows and a (b) close-up from the street

In instances where it was difficult to determine the type of glazing due to limitations in acquiring close-up images or insufficient resolution of available images of windows, the construction year of a building was used as a basis for inferring the type of glazing. If a building was constructed in the 1940's and the window appeared to match its age, for example, it was assumed that the windows were highly likely to be single glazed. This decision was based on the historical development of glazing in the UK where double-glazed windows became popular in the 1970's (Double Glazing Team 2012).

Glazing on roof

In modern schools, windows or glazed components are sometimes set in the roof to introduce daylight to spaces such as toilets or corridors that do not otherwise have direct access to natural light. Provision of daylight to deep spaces could reduce the demand for artificial lighting. As with the glazing area on external walls, however, such designs can lead to excess heat gain or heat loss during the cooling and heating seasons, respectively. The characteristic was therefore deemed to be likely to influence the energy consumption and the buildings with these features were recorded.

The presence of roof lights in schools was determined based on satellite images using the Bird's eye function of Bing Maps (Figure 7.14).

Figure 7.14 Satellite image of a school with roof lights

Roof shape

The shape of the roof is a characteristic that was deemed important and effective in distinguishing buildings that were designed and constructed during different periods. An inspection of the roofs from the previous exercise showed that there were three distinct roof shapes: flat roofs, and 'steep' and 'shallow' pitched roofs. Flat roofs were usually found in modern buildings that were constructed in concrete. 'Steep' pitch roofs on the other hand were typically the timber-framed roofs that were generally found in older buildings such as those constructed during the Victorian period, which are commonly found in the stock. The 'shallow' pitch roof type refers to the roofs that are used in steel-framed buildings that are typically sloped at low angles and covered in metal.

External shading

Controlling overheating from excess solar gain during summer through shading is an important feature of buildings that can affect the energy used for mechanical services to provide cooling (CIBSE 2006c). In naturally ventilated buildings, adequate shading plays an important role in providing a thermally comfortable environment during the summer. The shading if not designed adequately can however lead to increased demand for artificial lighting due to the decreased access to daylight. There are various elements of buildings that were built during different periods that provide shading from the sun. These can be the shading provided by recessed windows in Victorian schools, or overhangs or external shading devices such as *brise soleils* that were purposely designed to provide shading in modern buildings. These design features were therefore recorded to assess their implications for electricity consumption.

The provision of external shading was determined based on visual inspections of aerial images from Bing's Bird's Eye View (Figure 7.15). For those schools for which the provision of shading was difficult to assess, a rule was imposed that any form of element that extended over a glazed element on an external wall for more than half the floor-to-floor height was assumed to provide sufficient shading. The presence of shading was recorded on all sides of the building.

Figure 7.15 A school with external shading on the West façade

7.2 Development of a dataset of building and occupant characteristics

The dataset that was used for the study in this chapter was developed by manipulating and collating the previously used datasets with the newly collected data. The development of the dataset involved amalgamating the building characteristics dataset described in Section 7.1.1 with the dataset containing information from Display Energy Certificates (DEC) and the Department for Education (DfE) as described in Section 6.1. The two datasets were merged together using the variable Unique Property Reference Number (UPRN), which is a unique identifier of schools included in the DEC database. A subset of the 554 schools was produced by removing all the records that did not have a matching building characteristics record.

During this phase, the quality of the newly collected data was assessed for its accuracy. Each variable in the merged dataset was inspected for any anomalies that may have occurred from human error during the collection process. Numerical variables were assessed using histograms to identify the variation as well as the outliers that were located far from the median. Categorical variables were inspected also for any typological errors or input values that were in wrong cells.

7.3 Methods of analysis

Various forms of multivariable analyses have been used in assessing the impact of multiple parameters on the energy performance of non-domestic buildings. Multiple regression models are a form of multivariable analysis that has been used and proven to be robust over the past decade. In the US, Sharp (1996, 1998) has used multiple linear regression models to assess the impacts of various building and operational characteristics on energy use in offices and schools. Similar methods were also used in Hong Kong (Chung et al. 2006), Taiwan (Lee 2008; Lee & Lee 2009) and the UK (Hong, Pang, et al. 2013; Spyrou et al. 2014) to assess and identify significant characteristics that influence the pattern of energy use.

The other form of multivariable method is the neural network method that has been explored in recent years. A comparison of the accuracy of predicting the EUI of commercial buildings by multiple linear regression models compared with Artificial Neural Networks (ANNs) by

Yalcintas and Ozturk (2007) found the ANN method to make more accurate predictions. ANNs were also found to be suitable for assessing determinants of energy use in university and school buildings (Hawkins et al. 2012; Hong, Paterson, et al. 2013).

The ANN models have shown considerable potential in assessing the impact of multiple characteristics of buildings on their energy use. This is largely due to the fact that an ANN model, although it is close to being a black-box, learns and modifies itself in relation to the data, even when the relationships between the independent and dependent variables are unknown. Despite the potential however, the experience in dealing with ANNs via collaborative studies showed a number of uncertainties (Hong et al., 2013). The key uncertainty came from the fact that the accuracy of the results from ANN models was found to be highly sensitive to the quality of the input data and the method that was used to train them. The problems in determining the most effective way to train the models have led in the present study to a decision, instead of ANNs, to adopt multiple regression analysis, which has also been widely used in the field.

This section describes the process by which the multiple regression analysis was carried out to assess the influences of the building and operational characteristics on the energy performance of primary and secondary schools. The section is presented in two parts. The first section describes the process through which the building and occupant characteristics of schools were assessed and filtered. This is followed by a description of the methods that were used to develop and refine the regression models and the underlying assumptions.

7.3.1 Assessment and selection of adequate independent variables

Prior to carrying out multiple regression analyses, a set of statistical analyses were carried out to identify and remove extreme outliers, and to establish and examine the relationships between the dependent variables (the electrical and fossil-thermal Energy Use Index (EUI) of schools) and the independent variables (the building and occupant characteristics that were described in Section 7.1). The process was undertaken to remove those characteristics that were not significantly related to energy consumption from the multiple regression analyses.

The list of all possible independent variables and their types are listed in Table 7.4. Initially, the characteristics in the dataset were divided into categorical and continuous variables to ensure that their significance was assessed using adequate statistical methods.

Table 7.4 List of all variables and their values and types

#	Characteristic	Variable type
1	Total useful floor area (m^2)	Continuous
2	Building age	Continuous
3	Site exposure	Categorical
4	Orientation (degrees)	Continuous
5	Façade adjacency	Categorical
6	Glazing type	Categorical
7	Roof shape	Categorical
8	External shading	Categorical
9	Presence of an atrium	Categorical
10	Presence of windcatchers	Categorical
11	Surface-to-volume ratio	Continuous
12	Depth ratio	Continuous
13	Compactness ratio	Continuous
14	Glazing ratio	Continuous
15	Servicing strategy	Categorical
16	Main heating fuel	Categorical
17	Pupil density	Continuous
18	Occupancy level	Categorical
19	Annual cooling degree-days (CDD)	Categorical
20	Annual heating degree-days (HDD)	Categorical

7.3.1.1 Continuous variables

The relationships between these variables and the electrical and fossil-thermal EUIs were examined using a number of statistical methods.

Initially, lists of variables that were deemed to be related to each type of fuel were established. This was due to the distinct ways in the way electricity and fossil-thermal energy are used in buildings. For example, the exposure ratio is a variable that expresses the proportion of the surface area of a building that is exposed to the prevailing weather conditions. The mild climate in the UK means that the more exposed a building is, the more fossil-thermal energy it is likely to require for heating the spaces to provide an adequate environment for the occupants. The exposure ratio would therefore be expected to be correlated to the fossil-thermal energy use but not to electricity due to the prevalence of the uses of natural gas and oil as the sources of heating in school buildings (Hong & Steadman 2013). On the other hand, there were variables that were related to both electricity and fossil-thermal energy uses. The influence of varying density of pupils was for example assessed for both electrical and fossil-thermal EUI. On one hand, schools with a higher density of pupils would be expected to use more electricity due to more intense uses of ICT equipment. The internal heat gain from an increased density of pupils in the classrooms, on the other hand, would be expected to reduce the demand for space heating.

The analyses were carried out in two steps. Initially, scatter plots were used to visually inspect the relationships and identify any trends or outliers. This was then followed by correlation analyses to quantify the strengths and the significance of the relationships.

Scatterplots between each independent variable and the dependent variables (EUIs) were drawn to determine the type of relationship and identify the presence of any outliers that could affect the analyses.

Correlation analyses were carried out to quantify and evaluate the relationships between the independent and the dependent variables. The correlation was quantified by using the Spearman's correlation coefficient rather than the parametric counterpart, Pearson's correlation coefficient. This was due to the non-normal distribution of the dependent variables, which was assessed previously. The Spearman's test is a non-parametric statistic that is used to assess the correlation when the sample has a non-normal distribution (Field & Miles 2010). Under the Spearman's test, the observations were first ranked in order of magnitude of a variable (e.g EUI). The correlation coefficients between the independent and the dependent variables and the associated statistical significances were then calculated using SAS 9.3.

Correlations between the combined energy use and building and occupant characteristics were initially explored due to the close relationship between the end uses that consume electricity and the demand for space heating (Table 7.5). In theory much of the electricity used by end uses such as lighting or computers is converted into useful heat. This internal heat gain would in turn influence the amount of heat the heating system would need to supply in order to maintain comfortable indoor temperature for occupants. This is particularly true for new buildings that have been designed to higher thermal standards in which the useful heat gain from electrical equipment may reduce the demand for heating considerably.

Table 7.5 Spearman's correlation coefficients between the combined EUI and the continuous variables for primary and secondary schools

School type	N	Spearman Correlation Coefficients Prob > |r| under H0: Rho=0									
		Floor area (m^2)	Building age	Orientation	Surface-to-volume ratio	Depth ratio	Compact-ness ratio	Glazing-to-wall ratio	Pupil density	Annual CDD	Annual HDD
Primary school Combined EUI (kWh/m^2)	497	**-0.1123**	0.0062	-0.0276	**0.2121**	**-0.1870**	**0.1339**	0.0104	**0.1457**	0.0385	0.0463
		0.0122	0.8908	0.5396	**<.0001**	**<.0001**	**0.0028**	0.8164	**0.0011**	0.3917	0.3031
Secondary school Combined EUI (kWh/m^2)	53	**-0.2777**	0.1530	-0.1076	**0.2911**	**-0.3564**	0.0958	0.1268	**0.4788**	0.0851	0.1882
		0.0441	0.2740	0.4432	**0.0345**	**0.0088**	0.4949	0.3656	**0.0003**	0.5444	0.1772

The analysis showed that there were significant correlations between the consumptions of primary and secondary schools and the intrinsic features of buildings. In order to acquire a deeper understanding of relationships between these building characteristics and energy consumption, additional analyses were carried out by fuel type (Table 7.6 and Table 7.7).

Table 7.6 Spearman's correlation coefficients between the electrical and fossil-thermal EUIs and the continuous variables for primary schools

Spearman Correlation Coefficients, N = 497	Prob > |r| under H0: Rho=0									
	Floor area (m^2)	Building age	Orientation	Surface-to-volume ratio	Depth ratio	Compact-ness ratio	Glazing-to-wall ratio	Pupil density	Annual CDD	Annual HDD
Electrical EUI (kWh/m^2)	**-0.3412**	**-0.3288**	0.0031	0.7928	0.0556	**-0.1866**	**-0.1716**	**0.3814**	-0.0278	-
	<.0001	**<.0001**	0.9447	0.0777	0.2163	**<.0001**	**0.0001**	**<.0001**	0.5361	-
Fossil-thermal EUI (kWh/m^2)	-0.0070	**0.1249**	-0.0364	**0.2048**	**-0.2300**	**0.2091**	0.0741	0.0164	-	0.0453
	0.8763	**0.0053**	0.4182	**<.0001**	**<.0001**	**<.0001**	0.0992	0.7159	-	0.3130

Table 7.7 Spearman's correlation coefficients between the electrical and fossil-thermal EUIs and the continuous variables for secondary schools

Spearman Correlation Coefficients, N = 53	**Prob > |r| under H0: Rho=0**									
	Floor area (m^2)	Building age	Orientation	Surface-to-volume ratio	Depth ratio	Compact-ness ratio	Glazing-to-wall ratio	Pupil density	Annual CDD	Annual HDD
Electrical EUI (kWh/m^2)	**0.3323**	**-0.4085**	-0.0278	-0.1403	0.1803	-0.1633	-0.1183	0.0239	-0.1220	-
	0.0151	**0.0024**	0.8433	0.3162	0.1964	0.2428	0.3988	0.8650	0.3844	-
Fossil-thermal EUI (kWh/m^{yy})	**-0.4900**	**0.4360**	-0.1390	**0.4154**	**-0.4462**	0.2249	0.1717	**0.4996**	-	0.1832
	0.0002	**0.0011**	0.3208	**0.0020**	**0.0008**	0.1054	0.2188	**0.0001**	-	0.1892

The coefficient from the analyses expresses the covariance of the variables of interest as a standard unit. The resulting coefficient, which is a value lying between -1 and 1, was used as a basis for evaluating the strength of the correlation between the independent and dependent variables. The predictor variables that were found to have a statistically significant relationship with the response variables at a significance level of 5% ($p < 0.05$) were deemed suitable for the multiple regression analyses.

7.3.1.2 Categorical variables

Following the assessment of the continuous variables, the categorical variables were also examined as part of the initial filtering process. Hypothesis tests were carried out to assess whether there were significant differences in the pattern of energy uses of buildings that belonged to different sub-categories under each categorical variable. The statistical significance of the differences in EUIs of buildings between the sub-categories in each category was used as a basis for identifying and filtering variables that were not valuable for further consideration.

The non-normal distribution of the dependent variables (consumption of electricity and fossil fuels), as shown in Section 6.3, meant that non-parametric tests were more suitable for the analyses. Initially, categorical variables were split into two groups according to the differences in the levels of measurement. The variables that have two categories were separated from those that have more than two categories, so that appropriate hypothesis tests could be carried out (Table 7.8).

Table 7.8 List of all categorical variables and the respective levels of measurement

#	Characteristic	Range	Number of Categories	Level of measurement
1	Site exposure	Exposed, semi-exposed and sheltered	3	Nominal
2	Façade adjacency (North, South, East and West)	Obstruction or no obstruction	2	Binary
3	Glazing type	Single or double	2	Binary
4	Roof shape	Flat, ‘steep’ or ‘shallow’ pitch	3	Nominal
5	External shading (South, East and West)	Yes or no	2	Binary
6	Presence of an atrium		2	Binary
7	Presence of Windcatchers		2	Binary
8	Glazing on roof	Yes or no	2	Binary
9	Servicing strategy	Natural ventilation or mechanically assisted ventilation	2	Binary
10	Occupancy level	Standard or extended	2	Binary

The significance of the differences between buildings under the sub-categories of binary and nominal variables were tested using two different types of test. The significance of the differences in binary variables was tested using the Wilcoxon rank-sum test under a null hypothesis that there are no significant differences in the pattern of energy use of buildings with varying characteristics (e.g. the pattern of energy uses between schools with standard and extended occupancy hours). Nominal variables that have more than two sub-categories were analysed in two steps. Similar to the binary variables, Kruskal-Wallis tests were first used to identify whether there were any significant differences between any of the sub-categories. This test was followed by post hoc analyses using Wilcoxon rank-sum tests to identify which sub-categories were significantly different from each other. Where Wilcoxon two-sample tests were required more than once, Bonferroni corrections were made by reducing the level of significance at which results were considered to be statistically significant, to prevent the Type 1 error rate from increasing (Field & Miles, 2010). The level of significance ($p <.05$) was divided by the numbers of Wilcoxon rank-sum tests that were carried out for each variable. The differences in the pattern of energy use for a variable that required three tests for example would be reported to be statistically significant only when the p value was less than 0.017.

In cases where a statistically significant correlation was found only between two sub-categories in variables with three or more categories, the categories with the insignificant differences were revised and modified into one category. The tests of the differences in the EUI between schools with different servicing strategies as shown in Section 6.3, for example, showed that there was a significant difference between naturally ventilated buildings and mechanically ventilated buildings. There were however no significant differences in electrical EUIs of buildings that were designed with different levels of mechanical ventilation system. The findings therefore led to the variable 'Internal environment' being refined to a binary variable with a distinction only between the buildings with natural ventilation and mechanically assisted ventilation strategies. It should be noted that the hypothesis tests were not carried out on those variables that were tested and analysed previously in Section 6.3, such as the servicing types and the phase of education of buildings. This was due to the fact that the previous analyses of these variables were based on a significantly larger sample size and therefore were considered to give a better representation of the school stock.

Once the statistically significant categorical variables were identified and refined, the binary variables were converted into numeric codes, 0 and 1. Indicator or dummy variables were created to model those categorical variables with three or more categories. The variables comprised a set of binary inputs each taking on values of 0 or 1 as shown in Table 7.9.

Table 7.9 An indicator coding example for the site exposure variable

Category	Dummy variable 1	Dummy variable 2
Exposed	0	0
Semi-exposed	1	0
Sheltered	0	1

Table 7.10 shows the list of variables that were identified as having a statistically significant relationship with the electrical (Elec) and fossil-thermal (Heat) EUI of primary and secondary schools.

Table 7.10 The list of statistically significant variables for electrical and fossil-thermal EUIs of primary and secondary schools

Variables	Data range	Primary		Secondary	
		Elec	Heat	Elec	Heat
Continuous					
Floor area	861 - 15396 m^2	●		●	●
Building age	3 to 185 years	●	●	●	●
Surface-to-volume ratio	0.17 - 0.85		●		●
Depth ratio	2.11 - 14.02		●		●
Compactness ratio	1.01 - 4.44	●	●		
Glazing percentage	5.66 - 50.24	●			
Pupil density	0.04 - 0.43 pupils / m^2	●			●
Categorical					
Glazing type	0 = Single, 1 = Double	●	●	●	●
Façade adjacency North	0 = Open, 1 = Obstruction		●		
Façade adjacency South	0 = Open, 1 = Obstruction		●		
External shading South	0 = No shading, 1 = Shading	●		●	
External shading East	0 = No shading, 1 = Shading	●			
External shading West	0 = No shading, 1 = Shading	●		●	
Glazing on roof	0 = No glazing, 1 = Some glazing	●			
Servicing strategy	0 = Natural ventilation, 1 = Mechanically assisted ventilation		●	●	

7.3.2 Development of the multiple regression models

The second part of the analyses involved the development of multiple regression models. This involved exploring ways of selecting the independent variables and diagnosing the appropriateness of the models.

A typical equation for a multiple regression model is written as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{7}$$

where y denotes the dependent variables (electrical and fossil-thermal EUIs), x_1 and x_2 denote the values of independent variables, β_0 denotes the intercept of the regression plane, β_j, j = 1, 2, ….., k, denote the regression coefficients of each independent variable, and ε denotes the difference between the predicted and actual values of a dependent variable.

The models were developed separately for primary and secondary schools due to the significant differences in the patterns of energy use shown in Section 6.3. For each school type, two separate models were developed (electrical and fossil-thermal EUI) due to the inherent differences in the way the fuels are used in buildings. Electrical and fossil-thermal EUIs (kWh/m^2) were used as dependent variables instead of the total annual energy consumption (kWh/yr) due to the significance of the correlation of energy performance with floor area as shown in Section 6.3.

The parameter estimates β_0 and β_j were calculated using the ordinary least squares (OLS) method. The principle of the method is that it finds the parameter estimates that minimise the squared distance between the actual EUI and the EUI predicted by the models (SAS Institute Inc. n.d.).

A key focus of this study was to find a subset of variables or a model that best estimates the electrical and fossil-thermal EUIs of schools. The model of 'best-fit' was defined as the model that is most accurate and simplest (Bozdogan 1987). The selection of the best fitting model was therefore based on three aspects: how well the model predicts the energy performance, how many independent variables are included in the model, and the significance of the model.

The two statistics that informed the selection were the coefficient of determination, denoted as R^2, and the Akaike's information criterion (AIC). The R^2 is a statistic that is often used to determine how well a model predicts the dependent variable. It measures how much of the variation in the dependent variable is explained by the independent variables in the model, hence larger R^2 values indicate better fit. Relying only on this statistic for selecting the best fitting model however can lead to the issue of overfitting, as increasing numbers of variables are bound to improve the R^2. Overfitting is an issue that occurs when a multiple regression model comprises independent variables that are not necessary. The issue can lead to increased possibilities for undetected errors, and worsen the prediction (Hawkins 2004). To avoid this issue, the Akaike's information criterion (AIC) statistic was assessed for all potential models. The AIC is a statistic that measures the inaccuracy and complexity of a model, which is used to find models with the least number of variables which at the same time fit the data well (Bozdogan 1987). The model of best-fit was therefore deemed to be a model that comprise a subset of independent variables with the minimum AIC.

The significance of the models was assessed based on the F-ratio and its statistical significance. The model was deemed to be statistically significant if the F-ratio was found to be greater than that of the critical values for the corresponding F-distribution. The null hypothesis that the model does not significantly improve the predictions was rejected if the significance of the model was below 0.05. Models were also assessed for the presence of multicollinearity and generalizability, to ensure that the results are reliable and that results can be used to draw conclusions about the wider school stock outside of the sample.

Multicollinearity is a problem that stems from independent variables that have strong linear relationships between each other in a multiple regression model. The presence of such a problem in the model is said to have potentially serious effects on the precision with which the regression coefficients are estimated through the least-squares method (Montgomery et al.

2012; Field & Miles 2010). It was therefore necessary to examine the relationships between the independent variables in models of best-fit to detect the presence of multicollinearity and to resolve these problems if there were any. The presence of the multicollinearity was examined by using a collinearity diagnostic variance inflation factor (VIF). The VIF is a useful diagnostic tool, as it quantifies the degree to which the variance of an estimated regression coefficient increases due to collinearity. Throughout the study, VIF values of independent variables that are less than 10 were deemed to be a sign that there was no multicollinearity with other independent variables (Montgomery et al. 2012; Field & Miles 2010).

The generalizability was assessed by checking whether two key assumptions are met: the normality of residuals and the homoscedasticity of variance (Field & Miles 2010). The distribution of the residuals was assessed for normality based on a quantile-quantile or normal probability plot and a histogram with a superimposed normal distribution curve. Diagrams that showed signs of deviation from normal distribution were deemed to violet the assumption. The homoscedasticity of variance was on the other hand assessed by using a scatter plot of the residuals and the predicted values. A diagram that shows random and evenly distributed pattern of residuals were deemed to be an indication that the model meets the assumption of homoscedasticity (Field & Miles 2010).

The regression analyses was carried out in four steps. Initially, regression models for primary and secondary schools and for electrical and fossil-thermal EUIs were created. These models comprised all variables that were found to have a significant correlation with electrical and fossil-thermal EUIs (Table 7.10), and were used as baselines. In the following step, models with the minimum AIC were found from a group of models that were produced by using the R^2 selection method of SAS. Through the R^2 method, regression analyses was performed on all possible combinations of up to 10 independent variables, which resulted in a vast number of models that could be evaluated. Although computationally costly, this method provided opportunities to find models with the minimum AICs under the consideration of all possible options, which would not have been possible with forward, backward, or stepwise selection methods.

In the cases where the model of ‘best-fit’ does not meet the assumptions for generalisation, additional steps were taken in order to resolve the issue. The initial approach was to remove the outliers from the dependent variable. Outliers were identified and removed from the data by using the interquartile ranges, rather than standard deviations, to take into account the skewed nature of the energy consumption. For each school and fuel type, 1.5 times the interquartile range below the lower quartile and above the upper quartile were used as a boundary for identifying outliers (see Figure 5.3 for details). If removing outliers did not resolve the issue, transformation of the data was taken into consideration. Transformation of data is a method that can be used to reduce the skewness of data. Commonly used methods of transformation are to take the logarithm or square root of the dependent variable, or to divide one by each score so that large values reduce to a greater extent than small values, hence reducing skewness.

Once the model of ‘best-fit’ was found and its accuracy was deemed adequate, the importance of independent variables was evaluated based on the partial regression coefficients, denoted as β. This means that the coefficient of each variable represents an expected change in the dependent variable y per unit change in the independent variable, when all of the remaining variables are held constant. The coefficients of independent variables are however often not directly comparable, due to differences in the units of measurement of variables. The standardised version of the coefficients, which are independent of the units, was therefore deemed adequate for comparing the magnitude that each independent variable had over the dependent variable. The standardised correlation coefficient presented in the study would indicate the number of standard deviations of the dependent variable (e.g. electrical EUI) subject to one standard deviation change in the input variable (e.g. age).

7.4 Results

This section presents the results from the multiple regression analyses. A summary is given of the statistics that describe the overall fit of the four regression models. This is followed by detailed information on each of the models and descriptions of the variables that were included in the models and the parameter estimates.

Table 7.11 Overall fit of the regression models for electrical and fossil-thermal EUIs of primary and secondary schools

Dependent variable	N	R^2	R^2_{Adj}	Root MSE (kWh/m²)	F	Pr > F
Primary school						
Electrical EUI (kWh/m²)	478	0.24	0.23	12.22	24.90	<.0001
Fossil-thermal EUI (kWh/m²)	"	0.09	0.09	38.71	12.27	<.0001
Secondary school						
Electrical EUI (kWh/m²)	48	0.38	0.36	16.24	14.06	<.0001
Fossil-thermal EUI (kWh/m²)	53	0.44	0.41	31.83	13.01	<.0001

The R^2 values presented in Table 7.11 represent the proportions of the variation in outputs that were explained by each of the models. The models for primary schools were able to explain 24% and 9% of the variation in electrical and fossil-thermal EUI respectively. The models for secondary schools were found to explain a considerably larger variation in electrical and fossil-thermal EUIs of 38% and 44% for each fuel type respectively. The differences in the performance between the models for primary and secondary schools suggest that there may be a greater variability in building and operational characteristics of primary schools compared to the secondary schools. There is also the considerable differences in sample sizes, which may have introduced less variability for secondary schools. This remains to be explored further in the future.

Overall, it can be seen that the R^2 of the models from this study ranges between 0.09 and 0.44, which is relatively low compared to previous work by Sharp (1998), which applied multiple regression analysis to the relationships between the electrical EUI of schools in the US and building characteristics. That study found the R^2 of multiple linear regression models to range between 0.35 and 0.89, depending on the census division. Although the values were not directly comparable for fossil-thermal EUIs, the differences in R^2 values indicated that the electrical EUI models produced from this study were not as accurate as the study by Sharp (1998), which may be due to a more homogenous nature of the American school stock.

There are a number of factors that are likely to have caused such differences. There is firstly the uncertainty associated with the way buildings are used and operated by the occupants. Based on the principles of building physics and engineering, one would expect to see a reasonable correlation between the building characteristics tested in the study and the energy use, since building fabric plays an important role in mitigating or utilising the prevailing weather conditions. The low levels of R^2 value, particularly with regards to the fossil-thermal EUI of primary schools (R^2 = 0.09), may therefore indicate that buildings are being used in unexpected ways. Lighting for example may be used in class rooms regardless of the availability of daylight. In addition, there is the list of independent variables that were used for the regression analyses. Although great efforts were put in to describing the building characteristics, the focus of the study was mostly on the external characteristics such as built form and other design features. There is however a plethora of parameters, which could not be collected for the study, such as the efficiency and size of building services including boilers, or the installed lighting capacity, that may help explain the variation in EUI better. Lastly there is the uncertainty associated with the parameters that were collected using the desk-top approach. The use of an average storey height to derive numerous parameters that describe the built form, for example, may have reduced the variation in the built form that actually exists in the sample, hence the correlation.

Despite the relatively low R^2 values however, the F-values of the four models were found to be statistically significant ($p < .0001$), indicating that the predictions that were made using the models were significantly better than using the mean to predict the energy performance. This therefore suggested that the findings from these models could be used as a basis for identifying the variables that have significant partial relationships with the EUI of primary schools, and their magnitude.

The root mean squared error (RMSE) indicate the accuracy of the models in the units of the dependent variables EUI. The comparison of the RMSE shown in Table 7.11 to that of the artificial neural networks (ANN) that were trained on the same dataset by Hong et al. (2013), which presented RMSEs of 11.6 kWh/m^2 and 32.0 kWh/m^2 for electrical and fossil-thermal EUI respectively, suggested that ANN methods were more accurate in predicting the EUIs of schools, except for the fossil-thermal EUI of secondary schools.

Figure 7.16 below shows the standardised regression coefficients of the independent variables that were in the final model for electrical EUI of primary schools. Note that the variables are arranged in descending order of magnitude of the coefficients from the left hand side of the graph.

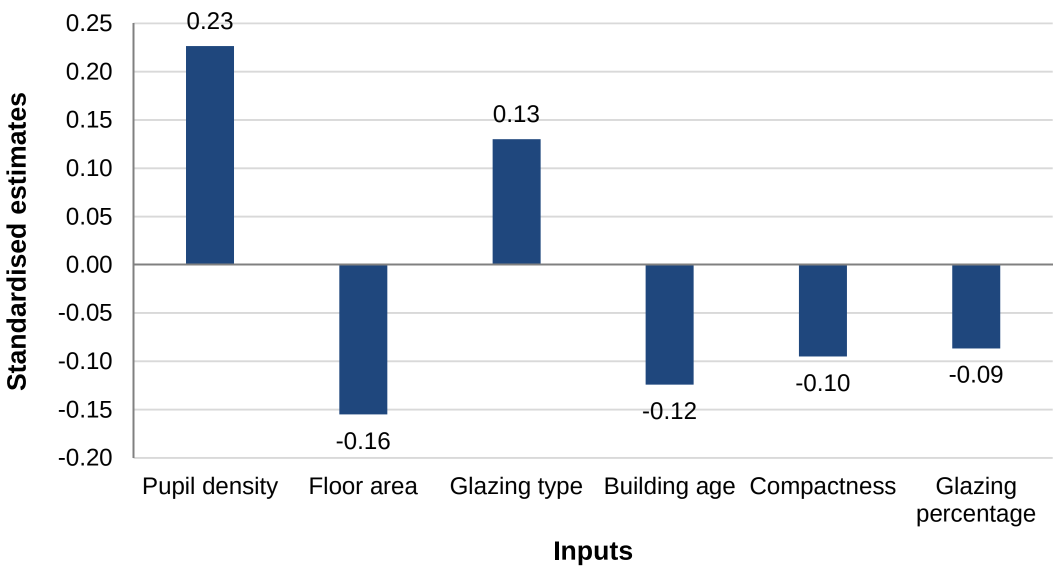

Figure 7.16 Standardised regression coefficients from the final multiple linear regression model for electrical EUI of primary schools

The final model developed using the stepwise method showed that there were six independent variables that were found to contribute significantly towards improving the accuracy of the regression model in predicting the electrical EUI of primary schools. The density of pupils was found to be the most influential independent variable. The positive relationship indicated that schools with a higher density of pupils tended to be more intensive in electricity consumption. This is likely to be due to the increase in uses of ICT equipment such as laptops or tablets that are used for teaching purposes. The floor area of schools was also found to be noticeably important, which indicated that schools with greater floor areas tended to be less intensive in electricity consumption. Larger schools are likely to have greater proportions of the floor area dedicated to ancillary facilities such as sports halls, circulation spaces or storage that are likely to require less energy due to requirements for environment and occupancy compared to the core facilities. The glazing type of schools were also found to be an influential characteristic that was positively correlated to the electrical EUI. This indicated that schools with double glazed windows were more intensive in electricity use. The reduced transmittance of daylight through the windows may have led to increased uses of artificial lighting, hence the electricity consumption. The negative correlation between the building age and electrical EUI indicated that schools that were built a longer time ago tended to be less intensive in electricity use. This is perhaps due to increasing specifications of building services and equipment in modern buildings, which would have increased the demand. Lastly, the two variables with the negative relationship indicated that schools with less compact footprint or schools that have greater percentages of glazing on external walls were less intensive in electricity use. Schools with less compact shape are likely to have more opportunities for introducing daylight to deeper spaces as buildings become more exposed to the external environment. Greater glazing area means that there is increased access to daylight. It is therefore reasonable to assume that these schools would have less demand for artificial lighting.

Table 7.12 Parameter estimates and collinearity statistics of the multiple regression model for the electrical EUIs of primary schools

Variable	**Parameter estimates**			**Collinearity statistics**	
	β	Standard error β	Standardised estimate	Tolerance	VIF
Intercept	52.329	4.407			
Pupil density	66.953	13.529	0.226	0.770	1.298
Floor area	-0.003	0.001	-0.155	0.749	1.335
Glazing type	3.635	1.261	0.130	0.793	1.261
Building age	-0.055	0.020	-0.124	0.786	1.273
Compactness	-2.767	1.269	-0.095	0.848	1.179
Glazing percentage	-0.171	0.081	-0.087	0.970	1.031

Table 7.12 shows the details of the parameter estimates as well as the collinearity statistics for the independent variables in the final model. It can be seen that the tolerance values are

well above 0.2, which is the threshold considered to be of concern, and the variance inflation factors (VIF) are well below 10. There were therefore no signs of multicollinearity in the model.

Figure 7.17 shows the standardised regression coefficients for the independent variables in the final multiple regression model for fossil-thermal EUIs of primary schools.

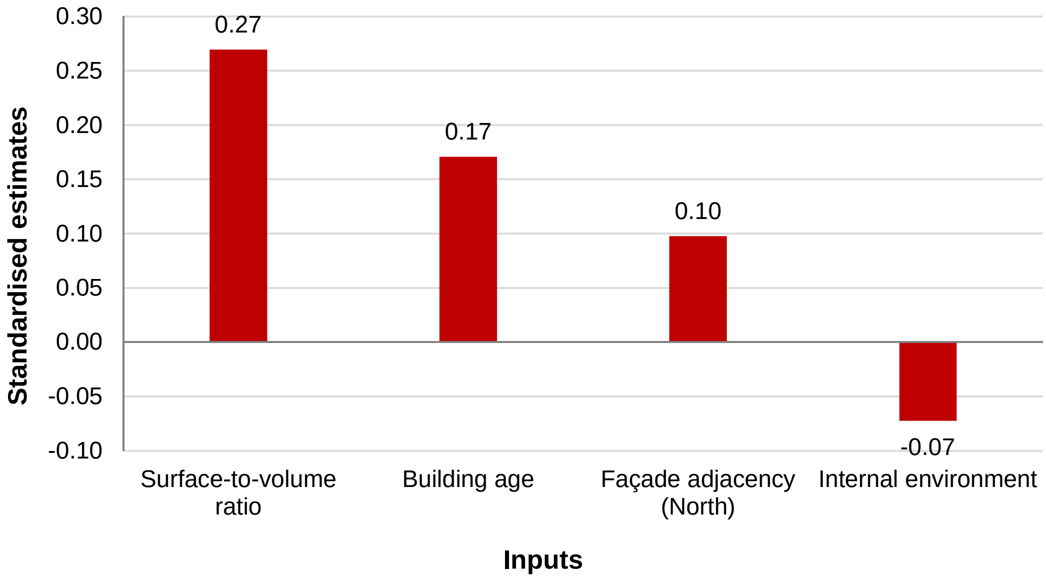

Figure 7.17 Standardised regression coefficients from the final multiple linear regression model for fossil-thermal EUI of primary schools

The final model for predicting the fossil-thermal EUI of primary schools comprised four independent variables. The independent variable that was found to have the most impact on heating consumption of primary schools was the surface-to-volume ratio. The positive relationship means that schools with greater exposed surface area are likely to have a higher demand for heating. In the UK where the weather is mild, the greater exposure to the prevailing weather conditions is likely to lead to an increased heat loss through the fabric, hence the higher demand. The age of buildings was also found to be positively correlated to the uses of fossil-thermal energy. This is likely due to the improvements in thermal performance of buildings over the past decades that would have reduced the requirement for heating compared to the older buildings that were compliant with less stringent standards or built prior to the implementation of Building Regulations. The presence of obstructions on the north side of buildings was also found to have some impact on the heating energy use of primary schools.

Based on principles of building physics, such a correlation is difficult to explain, as glazing on northern façades generally introduces diffused light, which does not contribute towards reducing space heating loads. The results represent correlations, which perhaps means that there may be characteristics common between the buildings with an obstruction on the north façade that influence the heating energy use. Lastly, the schools that are ventilated via mechanical systems were found to have less requirement for fossil-thermal EUI. Naturally ventilated buildings are highly dependent on operable windows for providing fresh air to the occupants. Frequent uses of windows or other means of natural ventilation means that there are greater chances of losing heat via ventilation (Chatzidiakou et al. 2014).

Table 7.13 Parameter estimates and collinearity statistics of the multiple regression model for the fossil-thermal EUIs of primary schools

Variable	Parameter estimates			Collinearity statistics	
	β	Standard error β	Standardised estimate	Tolerance	VIF
Intercept	75.95	10.40			
Surface-to-volume ratio	117.85	20.31	0.27	0.89	1.13
Building age	0.22	0.06	0.17	0.90	1.12
Façade adjacency (North)	12.29	5.52	0.10	1.00	1.00
Internal environment	-9.92	6.08	-0.07	0.97	1.03

The tolerance and the VIF of the independent variables in the model indicates that there were no signs of multicollinearity in the model.

The equations of the multiple regression models for primary schools are thus written as

Electrical EUI (kWh/m²) = 52.33 + 66.95(PD) – 0.003 (FA) + 3.63 (GT) - 0.05 (BA) – 2.77 (CR) – 0.17 (GP) (8)

Fossil-thermal EUI (kWh/m²) = 75.95 + 117.85(SVR) + 0.22(BA) + 12.29(FaN) – 9.92(IE) (9)

Table 7.14 List of abbreviations used in equations 8 and 9 above and the descriptions

Abbreviation	Descriptions
BA	Building age
CR	Compactness ratio
FA	Floor area (m^2)
FaN	Façade adjacency North
GP	Glazing percentage
GT	Glazing type
IE	Internal environment
PD	Pupil density
SVR	Surface-to-volume ratio

Secondary Schools

The following section presents the results from multiple regression analyses of the electrical and fossil-thermal EUIs of secondary schools.

Figure 7.18 shows the independent variables in the final model for the electrical EUI ranked by the magnitude of the standardised estimates in descending order from the left hand side of the graph.

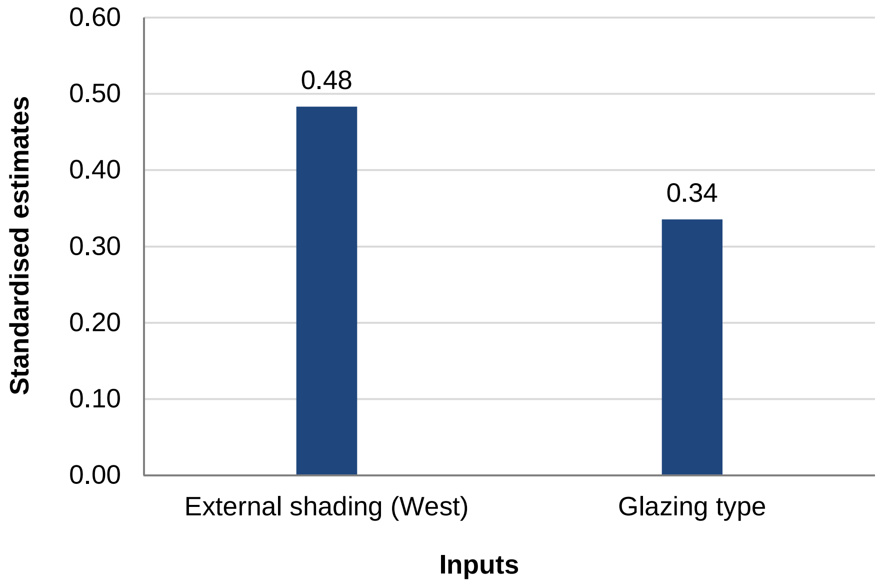

Figure 7.18 Standardised regression coefficients from the final multiple linear regression model for electrical EUI of secondary schools

The regression analyses showed that two independent variables were found to be significantly correlated to the electrical EUI of secondary schools. The results indicated that schools with purposely designed external shadings on the Western façade tended to be more intensive in electricity use. Schools with double glazed windows were also found to have considerable correlation with the electrical EUI. There are two potential explanations for such correlations. First, the most obvious end-use that is likely to be influenced by these characteristics is lighting. These schools for example, may have classrooms that are oriented towards the West, which means that shading on that façade would increase the requirement for artificial lighting due to reduced access to daylight because of the decreased angle of the visible sky. As with the primary schools, more intensive electricity use in schools with double glazed windows could be due to the reduced transmittance of daylight through the windows, which would also increase the requirement for artificial lighting. Whether such implications could lead to such strong influences is however, questionable. There could possibly be other factors, which were not collected in this study, that were correlated with these features. For example, these are characteristics that can be found in modern schools and the presence of external shading suggests that these are likely have been designed to reduce carbon emissions. It is therefore possible that there is a common feature that exists in these modern schools.

Table 7.15 Parameter estimates and collinearity statistics of the multiple regression model for the electrical EUI of secondary schools

Variable	Parameter estimates			Collinearity statistics	
	β	Standard error β	Standardised estimate	Tolerance	VIF
Intercept	55.11	4.22	-	-	-
External shading (West)	29.30	7.14	0.48	0.48	1.01
Glazing type	14.51	5.09	0.34	0.34	1.01

Table 7.15 shows the detailed summary of the parameter estimates and the collinearity statistics of the final model for electrical EUIs of secondary schools. It can be seen that the tolerance values and the VIF are both within the predefined thresholds for identifying multicollinearity.

The following section presents the results from the regression analysis of the fossil-thermal EUIs of secondary schools. The standardised parameter estimates of the final model are shown in Figure 7.19.

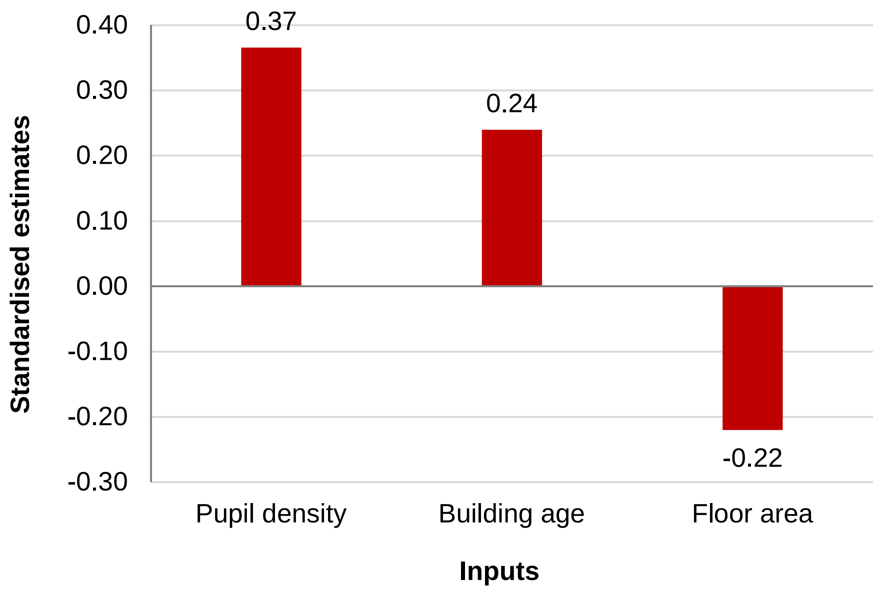

Figure 7.19 Standardised regression coefficients from the final multiple linear regression model for fossil-thermal EUIs of secondary schools

Three independent variables were found to be significantly correlated to the fossil-thermal EUIs of secondary schools. The density of pupils was the most important characteristic that was correlated with the way schools use energy for heating. The positive nature of the relationship means that schools with a higher density of pupils per unit floor area tended to use more energy for heating purposes. The correlation is likely to be related to the energy used for domestic hot water that is typically designed according to the number of occupants. An increased density of pupils would therefore mean that the demand for hot water was also likely to be higher, hence the higher fossil-thermal EUI. The next most important variable was the building age. The positive relationship means that building that are older tended to require more energy for heating. As with the primary schools, this is likely due to the reduced heat loss through the building fabric in modern buildings, which are likely to more air-tight and have better thermal performance. Lastly, the floor area was found to have a negative relationship with heating energy use. This indicated that larger schools tended to use less energy for heating. This is likely due to larger schools having ancillary facilities such as sports halls that are not heated as extensively as classrooms due to intermittent occupancy.

Table 7.16 Parameter estimates and collinearity statistics of the multiple regression model for the fossil-thermal EUIs of secondary schools

Variable	**Parameter estimates**			**Collinearity statistics**	
	β	Standard error β	Standardised estimate	Tolerance	VIF
Intercept	109.273	24.147			
Pupil density	221.917	77.475	0.366	0.696	1.436
Building age	0.424	0.218	0.240	0.746	1.340
Floor area	-0.003	0.002	-0.220	0.640	1.563

The collinearity statistics tolerance and VIF shown in Table 7.16 indicated that there was no multicollinearity between the independent variables in the final model.

The equation of the multiple regression models for predicting the electrical and fossil-thermal EUI of secondary schools are thus written as

$$\textit{Electrical EUI (kWh/m}^2\textit{)} = 55.11 + 29.3\ (ESW) + 14.51\ (GT) \quad (10)$$

$$\textit{Fossil-thermal EUI (kWh/m}^2\textit{)} = 109.27 + 221.92\ (PD) + 0.42\ (BA) - 0.003\ (FA) \quad (11)$$

Table 7.17 List of abbreviations used in multiple regression models for secondary schools

Abbreviation	**Descriptions**
BA	Building age
ESW	External shading West
FA	Floor area
GT	Glazing type
PD	Pupil density

7.5 Chapter summary

This chapter described how multiple regression analyses were carried out to assess and identify building and operational characteristics that have significant correlations with patterns of energy use of primary and secondary schools in England.

Below are key findings from the analyses:

- Empirical data on electrical and fossil-thermal EUIs were found to be correlated with building and operational characteristics. Correlations were found between electrical EUIs and characteristics such as the density of pupils, floor area, and presence of external shading. The heating energy use of primary and secondary schools on the other hand was found to be related to surface-to-volume ratio, building age and density of pupils. These results indicated that the demand for energy in schools are influenced by these intrinsic features.
- The regression models for primary and secondary schools were found to comprise different set of characteristics. This suggested that the patterns of energy use of buildings with different types of activities are likely to be influenced by different intrinsic features.
- The experience in developing the building characteristics dataset highlighted that there is a lack of centralised database in the UK that stores detailed information on schools. The data collection exercise was also found to be extremely resource intensive.
- The relatively low R^2 values of the models indicated that the pattern of energy use is not always directly dependent on the principles of building physics. Occupant behaviour and the restricted range of variables that were used in the analyses were presumed to be the main factors that led to low R^2 values. There is therefore scope to explore the correlations further with additions of details on other factors such as building services, controls and the management of schools.

- Despite the increased level of granularity, the data were found to be insufficient to fully explain the relationships and their magnitude. This is largely due to the lack of detailed information about various other aspects of buildings.

In summary, the study in this chapter has shown that the demand for energy in schools is influenced by features such as the shape of buildings and the density of pupils, which are independent of how efficiently buildings are being operated. This means that the current approach to benchmarking, which does not provide any means to take into account the influence of these intrinsic features, is likely to result in feedback that is less relevant. A school that is designed such that it is considerably more exposed to the prevailing weather conditions, for example, is likely to require more energy to provide an adequate indoor environment. This means that buildings that are less exposed would appear to be operated more efficiently despite the differences in factors that determine the demand for heating energy. It is therefore highlighted that there is a case for using these parameters for benchmarking purposes in order to assess the operational energy efficiency with greater comparability.

The analysis provided insights that complement the findings from the previous chapter in that greater understanding was acquired of the relationships between a broader range of characteristics and the energy performance of schools. The limitations of the study with regards to the data and the subsequent difficulties in understanding the reasons behind these correlations however suggested that further analyses based on more refined information are needed to fully understand the factors that influence energy consumption in schools.

Chapter 8 Bottom-up Analysis of English Schools

This chapter aims to acquire yet deeper insights into the patterns of energy use in schools and the determinants of energy use by analysing data of much finer granularity. This final phase of the research incorporates empirical data from post-occupancy evaluations of a small number of modern secondary schools in England. End-use energy consumption and detailed information on various types of equipment are analysed in relation to the intrinsic or extrinsic factors.

8.1 CarbonBuzz database

The descriptions of schools and data on their detailed energy consumption were acquired from the online platform CarbonBuzz[27]. The platform was developed by a collaboration of various organisations headed by the Chartered Institution of Building Services Engineers (CIBSE) and the Royal Institute of British Architects (RIBA) and launched in 2013. The platform aims to support the industry in managing the energy consumption of non-domestic buildings in the UK and to help reduce the gap between their design stage estimation and their operational energy performance. The main function of the platform is to allow various stakeholders in the industry such as architects and engineers to upload information during the design and in-use stages of the projects. The data accumulated from various projects will then enable stakeholders to improve understanding of the energy performance of their buildings by comparing the design stage performance to the in-use performance as well as to other buildings with a similar type of activity.

In 2013, a dataset of 300 records that relate to 163 primary and secondary schools, which were uploaded onto the CarbonBuzz database, was acquired from the Building Research Establishment (BRE). An initial inspection showed that there were numerous records that did not provide useful information about the operational performance of schools, in particular they lacked breakdowns of end-use consumption. As mentioned previously, CarbonBuzz is used

[27] For CarbonBuzz, See: http://www.carbonbuzz.org/

by various organisations to upload not only operational energy consumption data but also design and benchmarking information. This therefore means that there were records of energy performance certificates (EPC) and design stage estimations that were made via dynamic thermal simulation tools. In addition, the database comprised records that were uploaded during the development phase for testing various aspects of the platform. Moreover, the level of completeness of the records in the dataset was also found to vary considerably. This therefore meant that it was necessary to identify and remove records that did not report the operational energy use with a breakdown of end uses.

The following steps were taken to clean and filter the data:

- Initially, records that did not appear to be valid were removed from the dataset based on an assumption that valid records should at least provide metered annual electricity and non-electric energy consumption figures.
- Secondly, the variable 'RecordName' that describes the nature of each record was inspected to eliminate records that were either uncertain in their nature or not related to operational energy performance. This involved removal of records that did not have any input value, which therefore meant that it was extremely difficult to verify the nature of the records. Records with names that were difficult to judge (e.g. xxx) or that were not likely to provide operational performance data on buildings (e.g. test, EPC) were also removed during this process.
- Thirdly, records that provided sufficient information on the end-use consumption of schools were identified and a subset extracted from the dataset. This involved searching for records that had inputs in the end-use categories corresponding to the main building subsystems such as lighting and space heating but also unregulated consumption such as small power, which it would not be possible to measure separately without a sub-meter.
- Lastly, the validity of the remaining records was assessed based on the reliability of the data source.

The changes in the number of records and the schools in the dataset after each of these processes are shown in Table 8.1 below.

Table 8.1 Changes in the number of records and schools in the CarbonBuzz dataset

#	Description	No. of records	No. of Schools
1	Raw dataset	300	163
2	Removal of records without annual energy consumption figures	205	82
3	Dataset free of blank, uncertain and unsuitable records	40	24
4	Sub-metering information available (based on small power consumption)	15	11
5	Validation of data sources	9	9

The validation process applied to the energy consumption data showed that the selected nine records have been uploaded with sufficient levels of completeness and were entered by two reliable sources.

The data on four out of the nine secondary schools were obtained from the Building Performance Evaluation (BPE) project[28], which was developed and sponsored by the Technology Strategy Board (TSB) in 2012. The programme aimed to help the industry to deliver more efficient buildings that performed as intended. The main objective of the project was to collect data and document information throughout the design, construction and operation phases of various non-domestic buildings and to disseminate the findings from the studies to industry. Funding was provided by TSB to individual companies or organisations in the industry, which are working on a new or recently completed buildings, to carry out BPE to capture detailed information such as design strategies, ventilation and air tightness, and occupancy patterns (TSB, n.d.).

The remaining five records were all secondary schools that were case studies presented in a PhD thesis by Pegg (2007). The records uploaded on to CarbonBuzz provided detailed

[28] For BPE, see: https://connect.innovateuk.org/web/building-performance-evaluation

information on energy performance as well as some building characteristics. The thesis itself was consulted to acquire further information on the buildings such as layouts and descriptions of building services that were not collected by the online platform.

Table 8.2 below shows the list of schools that were selected for the present study and their descriptions. It should be noted that the schools were kept anonymous for confidentiality reasons.

Table 8.2 General description of the case study schools

School	Phase of education	Location	GIA (m^2)	No. of pupils	Completion
1	Secondary	Illford	14,610	1,850	01-Apr-10
2	Secondary	London	12,886	1,200	01-Jul-07
3	Secondary	Stockport	10,419	1,150	01-Jan-09
4	Sixth form college	Nantwich	2,843	1,357	19-Jul-10
5	Secondary	London	10,529	1,350	01-Sep-02
6	Secondary	London	10,627	1,200	01-Sep-03
7	Secondary	Bristol	12,957	1,265	01-Sep-04
8	Secondary	Liverpool	7,900	900	01-Sep-05
9	Secondary	Nottingham	7,715	900	01-Sep-04

It can be seen that the schools used for the study were all secondary schools except for school 6, which was a sixth form college.

8.2 The end-use energy consumption of the case study schools

Data on the energy performance of the nine schools was acquired from the CarbonBuzz database, recorded according to the Chartered Institution of Building Services Engineers' (CIBSE) *TM22* method (CIBSE 2006a). *TM22* is a method that was developed by CIBSE to aid building professionals in assessing the energy performance of buildings during the design and in-use stages. The method was originally developed in 1999 based on earlier work such as the PROBE studies and *Energy Consumption Guide 19* (Cohen et al. 2001; Action Energy 2003). The energy performance data which were obtained for the study were collected using a new version of *TM22* that was developed for the TSB's BPE project for the purposes of gathering energy and systems data (TSB, 2012).

Figure 8.1 shows a tree diagram, which provides an overview of the structure of data collected according to the *TM22* method. The diagram shows how the energy consumption of buildings could be collected and analysed at varying levels of granularity.

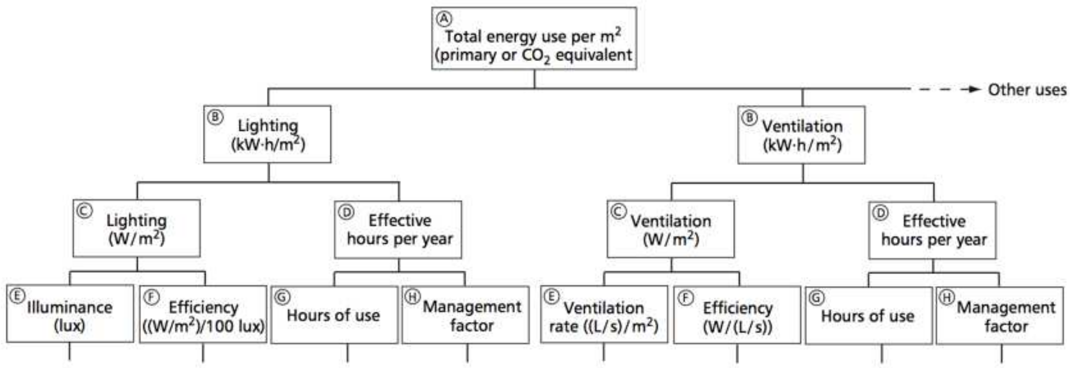

Figure 8.1 A tree diagram example (CIBSE 2006a)

As shown in the diagram, the *TM22* files obtained from CarbonBuzz database included energy consumption at building, end-use and, for some schools, system level. At the building level, annual energy consumption was recorded separately for electricity and non-electrical energy uses. These were reported in the form of energy use intensities (EUIs). The files also contained information from sub-meters, which were installed to measure the energy used by major building sub-systems such as lighting, space heating, and any other equipment that consumes energy such as small power or ICT. The system-level information refers to the specifications of equipment such as power ratings and hours of use as illustrated in Figure 8.1. This information was reported as part of the *TM22* assessment where component level energy use was analysed in order to understand how energy is used by various components of building subsystems. The levels of energy use of various components and equipment reported in *TM22* files were however not meter readings, due to the limitations in sub-metering, but consumption calculated based on information recorded by the assessors during their site visits. In addition to the types of equipment and numbers of pieces, their power rating, the load and usage factors, and hours of use were used as a basis to estimate the energy use by each type of equipment, which was then reconciled with the sub-meter level measurement for validation. Taking the end-use category ‘small power’ for example, the numbers of computers and laptops were reported along with more details such as their power ratings, hours of use and load factors.

The list of end-use categories and examples of equipment which were found under each of the categories is shown in Table 8.3.

Table 8.3 List of building systems included in the TM22 files and the fuel types

Building system	Description
Space heating	
Hot water supply	
Refrigeration	
Fans, pumps and controls	
Internal lighting	Teaching spaces, corridors etc.
External lighting	Security lights, sports lights etc.
Small power	Projectors, CCTV, cleaning equipment etc.
ICT equipment	Computers, laptops, server rooms etc.
Vertical transport	Lifts
Catering – central	Ovens, freezers, food display etc.
Catering – distributed	Kettles, small fridges, microwaves etc.
Laboratory equipment	

8.3 Detailed building and occupancy information

In addition to the detailed energy consumption data from the *TM22* files, information on various aspects of the buildings, the occupants and operational characteristics was obtained via the 'contributing factors' section of CarbonBuzz and the pre-visit questionnaire (PVQ) files.

The 'contributing factors' section of the platform allows users to record information on various factors that can potentially influence the patterns of energy use of buildings. The information recorded in the section covers building design, management, special energy uses, occupancy levels and operating hours, IT infrastructure, and appliances. The design section describes the details of the building such as construction type, air tightness, and details of facades (including the surface area and the U-value). The management section provided a general description of the management strategy, presence of a BMS, types of controls etc. There is also a section that provides details on the end uses that are uncommon in typical buildings such as server rooms or bakery ovens. The occupancy and operating hours section provides information on the varying number of occupants and their schedule throughout the year. Any additional details on server rooms or appliances are described under the IT infrastructure and Appliances sections.

The PVQ files were questionnaires that were distributed to the project teams that were part of the BPE project with the aim of collecting information on various aspects of the buildings in question. The questionnaire was divided into several themes, each designed to describe the schools in considerable detail including descriptions of the fabric, building services, catering services, and equipment. These files were however only available for four schools that were part of the BPE project. In addition, inspection of the inputs in these files showed that the level of completion of the questionnaires tended to vary considerably. It was therefore deemed appropriate only to use the variables that were generally filled out in the four schools unless there was a way of acquiring the missing information through another source.

Another set of information that was collected for the analyses covered variables that describe the built form of schools, which did not exist in either *TM22*, PVQ or the PhD thesis by Pegg (2007). Abstract variables such as the compactness and plan depth ratios were calculated using the desktop approach that was described in Section 7.1.1. The variables that were derived are described in Table 8.4 below.

Table 8.4 Descriptions of the building characteristics of the case study schools that were derived for analyses

Building character	Description
Compactness ratio	Perimeter of exposed facades compared to the circumference of a circle with the same area as the building footprint.
Glazing to solid wall ratio	Glazing area divided by area of the area of solid wall on all facades

The compactness ratio was derived by measuring the perimeter of each school and comparing it to the perimeter of a circle with the same area as the building. Using the technique described in Section 7.1, the perimeter length of the building footprint was measured using the online mapping portal Digimap[29].

The ratio between the glazed and solid components of the fabric of buildings was derived as a means to utilise what was available from the Pegg PhD thesis. Unlike the data obtained from CarbonBuzz, there was limited level of information on schools reported in the thesis. Due to the small sample size from CarbonBuzz, it was therefore necessary to utilise the ratios that were reported in the thesis for the present study. Consequently, the areas of the fabric, which were obtained from the PVQ files, were used to derive the glazing ratios for the four schools.

8.4 Methods of analysis

This section describes the process through which the high resolution data was analysed. The methods that were used to analyse the data and the underlying assumptions are described in detail.

The patterns of energy use of the case study schools were analysed in the following steps. First, the energy performance of each of the case study schools was analysed at the building level using descriptive statistics. This involved comparing the proportions of electricity and fossil-thermal energy use in schools and also how well these schools perform against their peers. Secondly, the energy consumption of each fuel type was disaggregated into different end uses and analysed separately. Descriptive statistics were used to analyse the variance of end-use consumption for each fuel type. Attributions of the equipment to each of the end-uses were then made.

As discussed in the previous sections, the case study schools that were used for this study were designed and built in the past 5 to 6 years. This therefore means that they were built to

[29] For Digimap, see: http://digimap.edina.ac.uk

comply with the recent Building Regulations requirements that focus on improving energy efficiency through improvements in thermal performance as well as the efficiency of services. To understand how these schools perform within the wider context, the annual electricity and fossil-thermal energy use of the schools was compared to the cumulative frequency distribution of the performance of secondary schools in England (Figure 6.2 and Figure 6.4). To compare the energy performance of these schools to the stock accurately however, as discussed in Section 6.1, it was necessary to normalise energy performance to a standard weather condition in the UK so that the influence of seasonal and regional variations in weather was taken into account.

The heating degree-days (HDD) that were used for the adjustment were acquired using two methods. The records from CarbonBuzz for HDD were acquired through the information acquired from the central information point (CIP) based on the locations of buildings and the dates when the measurements were taken. The dates of measurement of the energy consumption of the schools, which were acquired from the PhD thesis, were not on the other hand available. Moreover, the HDD records from the CIP began when the Display Energy Certificate (DEC) scheme was implemented in 2008, which would not have been useful even when the dates were available. The document did however indicate the typical HDD (base 15.5°C) of the regions in which the schools were located. These HDD figures were therefore assumed to be representative of the weather conditions of those regions at the time the schools were monitored.

Once the HDD values were obtained, the fossil-thermal energy use of the case study schools used was adjusted using equation (4) shown in Section 6.1. Unlike the previous section however the adjustments were made to the actual energy used for space heating, rather than adjusting the fossil-thermal EUI of the case study schools based on an assumption that 80% of fossil-thermal energy was used for space heating purposes.

Once normalised, the energy performance of the case study schools was compared to the adjusted *TM46* benchmarks appropriate to each school. The adjusted benchmarks were obtained from the CarbonBuzz database. The energy performance of the case study schools was also compared against the energy performance statistics of secondary schools which were presented in Section 6.3.

Following the analyses of whole-building energy performance of the case study schools, the breakdowns of electrical and fossil-thermal energy consumption were analysed to understand the trend in energy consumption in schools in greater detail. Descriptive statistics such as mean and standard deviations were used to assess the distribution of various end-uses amongst the schools. The analyses of end uses for each fuel type was also intended to improve understanding of the contribution of each end use towards the overall energy performance of schools. This was further intended to examine whether the claims that had been made with regards to the percentage of fossil-thermal energy use that is for space heating purposes in the previous sections were accurate (Section 6.1). In addition, the variation of the pattern of energy use was expressed in the form of median absolute deviation (MAD) rather than the standard deviation which is frequently used and is based on the mean when the data is normally distributed. MAD is the median of the absolute deviations from the median (equation 12) which therefore is less sensitive to outliers (Malinowski 2009; Falk 1997).

$$MAD = Med \{ |X_i - med_n| : 1 \leq I \leq n \} \tag{12}$$

Note that the recording of the distribution of end-use consumption may have been affected by the way the sub-meters were installed. Taking the energy consumption of phones for example, it could have been metered from a sub-meter for ICT equipment, since phones are communications devices. There is however the possibility of the equipment being included under a small power sub-meter, as it is not part of the building services system.

Various end-use categories were analysed in further detail for those schools for which detailed information on equipment was available. This analysis aimed to develop a broader understanding of how end-use consumption is further disaggregated into various types of equipment. The component level information was acquired from *TM22* files, which provided a list of pieces of equipment and their energy consumption. The assessment involved simplifying the list of equipment under each of the end-use categories. This is due to the varying levels of labelling of various equipment by different assessors. Taking ICT equipment for example, some records would report the numbers and energy consumption of different types of printers separately, whereas others would report it as a single item ‘Printer’. It was therefore necessary to aggregate similar types of equipment into smaller number of categories for analysis.

For each end-use category, analyses were carried out to examine the relationship between detailed building and occupant characteristics and the end uses. This was intended to identify the features that significantly affect the energy consumption of the case study schools. Using SAS 9.3[30], scatter plots and correlation coefficients were used initially to assess the strength of the relationships and filter out insignificant variables. The small size of the sample used in this study meant that it was difficult to assess the normality of the sampling distribution. It was therefore decided that non-parametric methods rather than parametric methods would be used wherever necessary to analyse the data. With regards to the correlation coefficient the Spearman’s coefficient was used rather than the Pearson’s coefficient, due to the difficulty of establishing the normality of the data owing to the small sample size.

The relationship between building features that can be expressed numerically such as the normalised U-value of the building fabric and the end-use consumption, which in this case would be space heating, was analysed using scatter plots to assess the shape of the relationship.

For those variables that were found to have significant correlations with specific end-uses, regression analyses and hypothesis tests were carried out, similar to those described in Section 6.2, to quantify the significance.

Regression analyses involved uses of simple and multiple linear regression models to quantify how much the end-use consumption varied in relation to variation in the regressor variables.

[30] For SAS, see: http://support.sas.com/documentation/93/index.html

The coefficient of determination of the models, expressed as R^2, and its significance was used as a basis to assess the strength of the significance.

For categorical variables such as the type of controls for lighting, hypothesis tests were carried out to examine whether there was a statistically significant difference in the pattern of energy use between schools with different features.

Of all end uses, ICT and small power were analysed jointly due to the differences in classifying various electronic equipment into end-use categories. The difference stems from the definition of what constitutes Information Communication Technology (ICT) equipment. In the *TM22* data, equipment such as desktops, monitors or laptops were reported under the ICT equipment category in addition to the equipment that forms the IT infrastructure such as that in server and hub rooms.

It should be noted that end-use consumption was analysed only where empirical data was available. The figures that were estimated, due to sub-meters not being available, were excluded. Taking the domestic hot water (DHW) consumption for example, a sub-meter for hot water supply was found to be unavailable during the site observation.

The analyses were carried out in several steps. Firstly, the overall energy consumption of the case study schools was assessed against other schools to put it in context. This was then followed by analyses of each of the end uses in relation to various characteristics of the schools such as built form and number of pupils. Lastly, energy use by each type of equipment, which had been approximated using the bottom-up approach as illustrated in *TM22*, was assessed to further improve the understanding of how energy is used in these schools.

8.5 Results

Figure 8.2 shows the annual energy performance of the case study schools. Note that fossil-thermal energy consumption was corrected to account for the impact of seasonal and regional variation in weather.

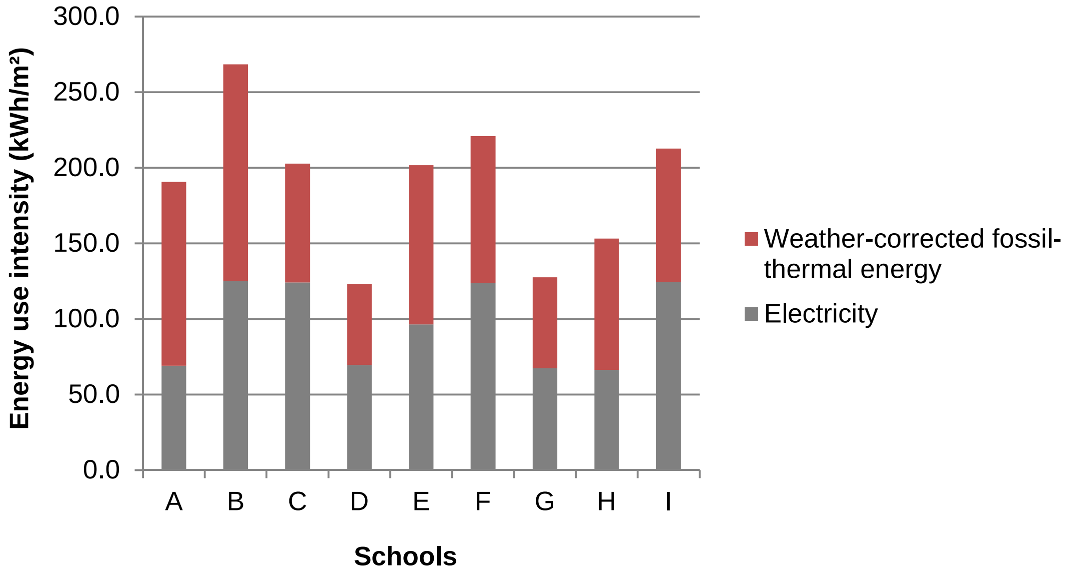

Figure 8.2 Stacked bar chart of the annual energy performance of the case study schools

The figure shows that there is considerable variation in the patterns of energy use in the case study schools, despite the similarity of the activity. The chart shows that there are two groups of schools that have similar levels of electrical EUI. Schools B, C, F and I were all found to be considerably more intensive in electricity use with consumption between 124 and 125 kWh/m^2, compared with schools A, D, G and H that were found to use between 66 and 69 kWh/m^2 of electricity. It is however not clear why there is such a sharp division in the pattern of energy use between these groups as they are all secondary schools, which should mean similar levels of demand for energy use. There was also a large variation in fossil-thermal energy use despite the corrections made to account for the effects of weather conditions. These variations therefore suggest that there are factors other than the activity that determine the pattern of energy use in schools, which will be explored further in the following sections.

A school that requires careful attention is school D, which only houses sixth form students who are in years 12 and 13. The difference in the range of students and their classes in school D means that the pattern of energy use may differ from those schools that comprise the whole range of secondary school students from year 7 to year 13.

Table 8.5 shows descriptive statistics for the energy performance of the case study schools by fuel type. Note that both the raw fossil-thermal EUI and the weather-corrected figures are illustrated for comparison purposes. The 95% level confidence intervals of the median and the median absolute deviation (MAD) are shown to illustrate the variability of the sample.

Table 8.5 Descriptive statistics for the electrical and fossil-thermal EUIs of the case study schools

Fuel type and benchmarks	**Energy consumption (kWh/m^2)**			
	Min.	Median (95% CL)[a]	Max.	MAD[b]
Modern secondary schools				
Electricity	66.2	96.3 (67.4, 124.3)	125.0	27.8
Raw fossil-thermal energy	54.3	96.7 (55.2, 109.0)	111.2	9.5
Weather-corrected fossil-thermal energy	53.6	88.4 (60.0, 121.1)	143.4	17.1
CIBSE TM46				
- Typical electricity consumption		40		
- Typical fossil-thermal energy use		150		
Analyses from Section 6.3				
- Median electricity consumption		50		
- Median fossil-thermal energy use		111		

[a] Distribution-free confidence limits of medians
[b] Median absolute deviations

The statistics for electricity use in the case study schools (Table 8.5) showed that electricity consumption is considerably higher than the energy benchmarks in CIBSE *TM46* and the statistics on recent trends in energy consumption of schools from Section 6.3. What is more, the maximum consumption was found to be more than twice the median of the large sample, and even the least intensive of the case study schools was found to be more intensive than a typical older school. Taking into consideration that these schools were building in 2002 or later, and that 6 in 7 existing stock comprise schools that were built more than 25 years ago, the difference indicates how electrically intensive the modern schools are becoming despite the efforts to design low energy schools (Global Action Plan 2006).

A considerable variation was also observed in the weather-corrected fossil-thermal energy use of the case study schools, with a median absolute deviation of 17.1 kWh/m². In general however the median heating consumption of these schools suggested that they were significantly less intensive than the *TM46* benchmark of 150 kWh/m² and somewhat less than the statistics from Section 6.3. This is more clearly shown in Figure 8.3 where the electrical and weather-corrected fossil-thermal EUIs of the case study schools were plotted on a cumulative frequency distribution curve generated based on the secondary schools that were analysed in Chapter 6.

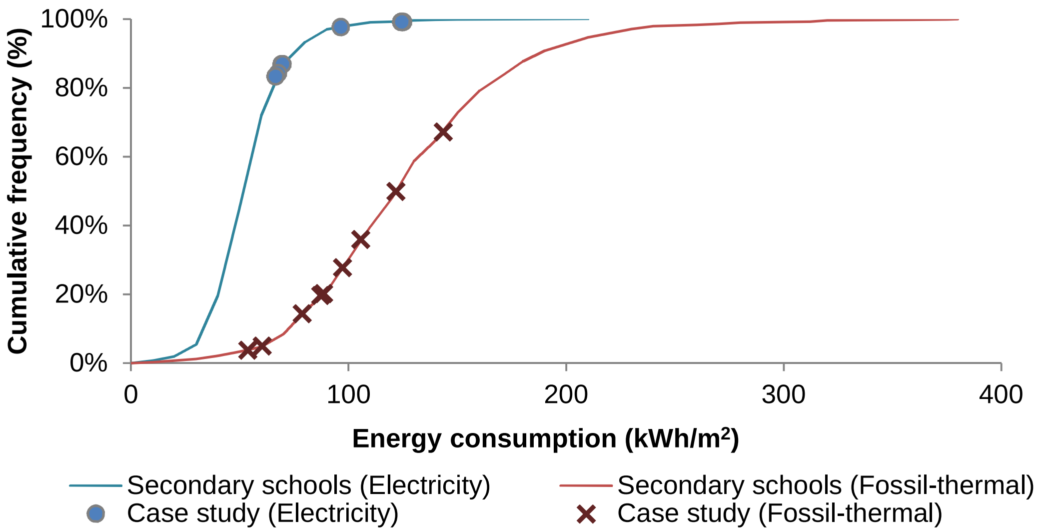

Figure 8.3 Annual electrical and fossil-thermal EUIs of the case study schools compared to the cumulative frequency distribution of the school stock

High levels of electricity consumption can be clearly be seen in Figure 8.3 where all case study schools are positioned above the 80th percentile with some reaching up to the 99th percentile. This comparison suggests that schools that were built in recent years are likely to be considerably more intensive in electricity use than older secondary schools. The energy used for heating on the other hand were generally less intensive than the stock but found to vary considerably. The school with the least heating energy use was placed at the 4th percentile while the school with the highest consumption was positioned at the 67th percentile. The large variation in heating energy use is rather surprising as these schools would have been designed to higher thermal performance standards, hence a reduced demand for heating. This suggests that the improved building standards in these modern buildings do not necessarily dictate how the schools are heated. Nevertheless, the intrinsically higher thermal performance of these buildings means that benchmarking their energy performance of the stock would not yield an accurate measure of how efficiently the buildings are being operated. If the fossil-thermal performance of these schools was compared to the Victorian schools for example, Victorian schools would have a greater demand for heating due to the leaky building envelope. It is therefore highly probable that the operational energy efficiency of Victorian school would appear to be inefficient even when it is being operated efficiently when the modern school is not.

Analyses of individual end uses

The following sections present results from the analyses of the electricity and fossil-thermal energy uses by various end-use categories.

Figure 8.4 shows the breakdown of electricity consumption in the case study schools into major end-use categories including the unregulated energy uses.

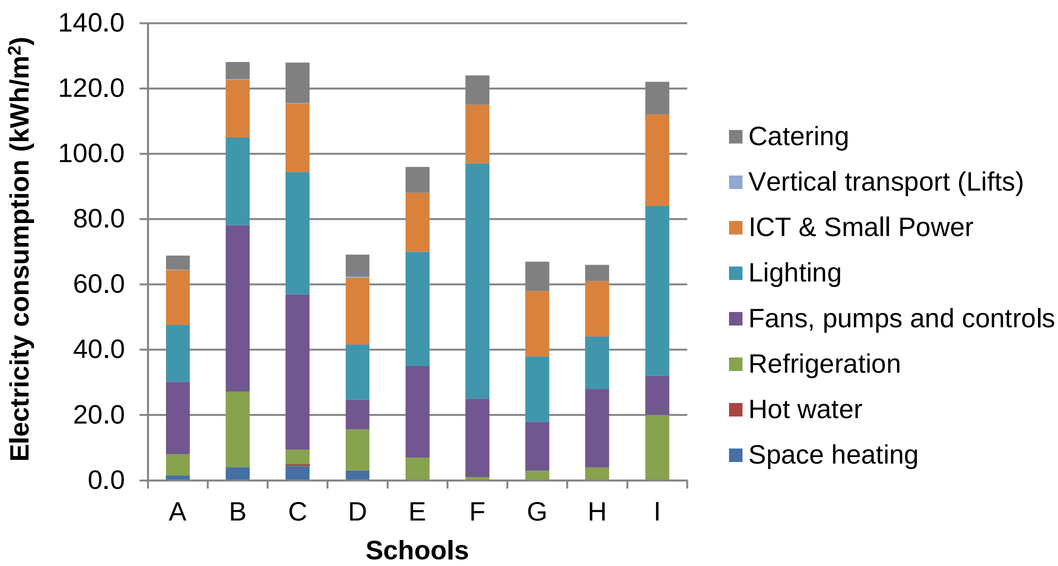

Figure 8.4 Breakdown of electricity consumption of the case study schools by end-use categories

The disaggregation of total electricity consumption shows that there is a considerable variation in how electricity is used by end-use categories in schools that have similar total consumption

(Figure 8.4). The variation in electrical EUI, despite all case study schools being modern secondary schools with academy status, shows just how complex and diverse the patterns of energy use can be even within the same activity group. It also highlights the importance of understanding the factors that introduce these variations and whether the variation is due to intrinsic features or the inefficient operation of buildings.

Table 8.6 shows statistics for the electrical energy used in each end-use category. The table also presents the confidence intervals, which are reported at the 95% level of confidence. It should however be noted that the upper and lower confidence limits were not reported for electric space heating, domestic hot water supply or vertical transport due to the majority of schools having no energy use in those categories.

Table 8.6 Electricity consumption statistics for the case study schools by major end-use categories

End-use category	Electricity consumption (kWh/m^2)			
	Min.	**Median (95% CL)[a]**	**Max**	**MAD[b]**
Space heating	0.0	0.0 (-, -)	4.4	-
Hot water	0.0	0.0 (-, -)	0.6	-
Refrigeration	1.0	6.4 (3.0, 20.0)	23.2	3.4
Fans, pumps and controls	9.0	24.0 (12.0, 47.5)	50.9	9.0
Lighting	16.0	26.9 (17.0, 52.0)	72.0	9.9
ICT & Small Power	16.9	18.0 (17.0, 21.0)	28.0	1.1
Vertical transport	0.0	0.0 (-, -)	0.4	-
Catering	4.3	8.0 (5.0, 10.0)	12.3	2

[a] Distribution-free confidence limits of medians
[b] Median absolute deviations

As shown in Table 8.6, the energy used to light internal spaces such as classrooms and corridors and external spaces such as car parks and sports grounds was the most intensive end use with a median of 26.9 kWh/m^2. The next most intensive end use was the fans, pumps and controls, which cover the energy used by equipment in the plant rooms that form the core of the HVAC system. The energy used by equipment to maintain adequate levels of indoor air quality and thermally comfortable environment to the occupants was found to be 24.0 kWh/m^2. There was however a large variation in the pattern of these end-uses where the most intensive was an order of a magnitude greater than the least intensive.

The end-use category with the third most intensive energy use was the ICT and small power equipment including desktops and monitors as well as equipment found in server and hub rooms. In contrast to the energy used for lighting and fans, pumps and controls, the level of energy use by these types of equipment was much more constant between schools with a median of 18.0 kWh/m^2 and a median absolute deviation of 1.1 kWh/m^2. At the other end of the spectrum, the energy used to provide hot water for toilets and showers, and to operate vertical transport or lifts was found to account for less than 1% of total electricity consumption on average. In schools A, B, C and D, portable electric heaters were used to provide heating locally to the staff or students, which accounted for up to 4% of total electricity consumption.

Table 8.6 also shows that there are five end-uses – lighting, fans, pumps and controls, ICT & small power, catering, and refrigeration – that together account for more than 95% of total electricity consumption of these schools. This suggests possibilities of improving the comparability of benchmarking in an efficient manner by identifying the key factors that are correlated to these end-uses.

The following sections present results from a more detailed analysis of each of the electrical end uses. Each of the end-use categories was explored further using the equipment-level energy uses derived using the bottom-up method, wherever information was available. The results from correlation analyses of the end uses and the building and occupant characteristics are also presented.

8.5.1 Internal and external lighting

Figure 8.5 shows the energy used for lighting in the case study schools. Schools A, B, C and D show a further breakdown of the end use into energy used for internal and external lighting. It should be noted that these figures were based on a combination of sub-metered data and the data derived using the bottom-up approach whereby energy uses for internal and external lightings were estimated based on observations from the site visits including the power rating, number of fittings and usage factors, which were then calibrated against the total meter reading for validation.

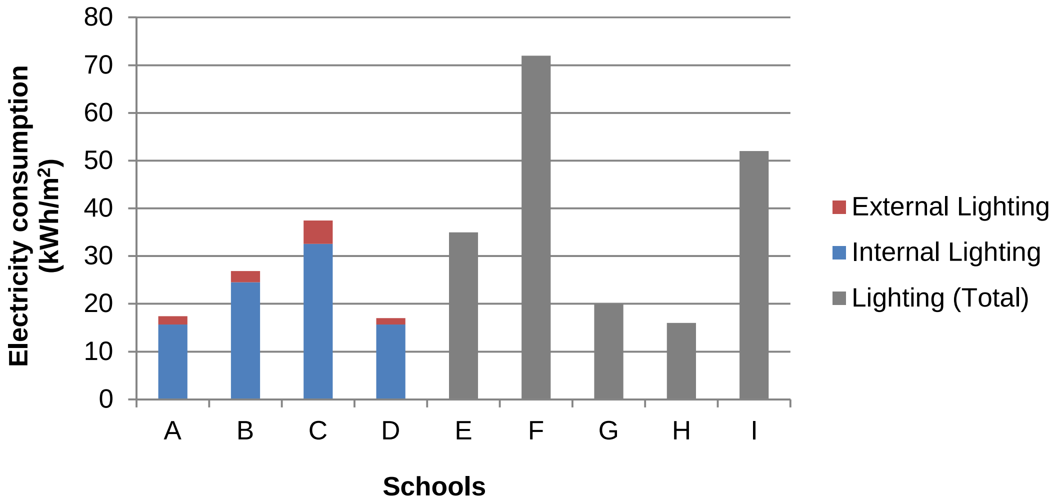

Figure 8.5 Electricity consumption for lighting in the case study schools

A comparison of the lighting end uses between the schools shows that there is considerable variation in the intensity of energy used for lighting both internal and external facilities (Figure 8.5). The disaggregated lighting consumption in schools A, B, C and D shows that approximately 90% of the energy was used for lighting the internal spaces of schools such as classrooms and corridors, and the rest was used to light external spaces such as car parks, sports grounds and roofs.

Schools F and I were the most intensive of all with consumption of 72 and 52 kWh/m^2, which accounted for 58% and 42% of the total electricity consumption of these schools respectively. The consumption of school F in particular was found to be more than four median absolute deviations away from the median of 26.9 kWh/m^2, an unusually high figure. Among various features of these buildings, schools E, F and I were the only schools that had manual switches for lights in all areas, which meant that the energy use was highly dependent on the way the lights in the classrooms and corridors were controlled by the staff and pupils. In his thesis Pegg (2007) highlighted that the high levels of consumption in these schools were due to the constant use of lights in classrooms and circulation spaces during unoccupied hours and even when ample daylight was available. He also noted that the lights in schools that had automated controls via presence and daylight sensors were being operated more efficiently than the lighting in schools with manual controls.

The combined dataset of the five schools from the thesis and the four recently built schools from Carbon Buzz provided an opportunity to assess whether the findings from the previous study by Pegg (2007) applies to the larger sample. A hypothesis test was therefore carried out to assess the potential relationship between the lighting control types and the electricity used for lighting. Prior to the assessment, schools with different control types were categorised into two groups. Schools with manual switches were grouped separately from those with one or more automated control mechanisms using presence, absence and photocell sensors. A null hypothesis was formulated where insignificance of the test result would mean that there was no significant difference in the pattern of lighting energy use between schools with and without manual controls. The result of the hypothesis test is shown in Figure 8.6.

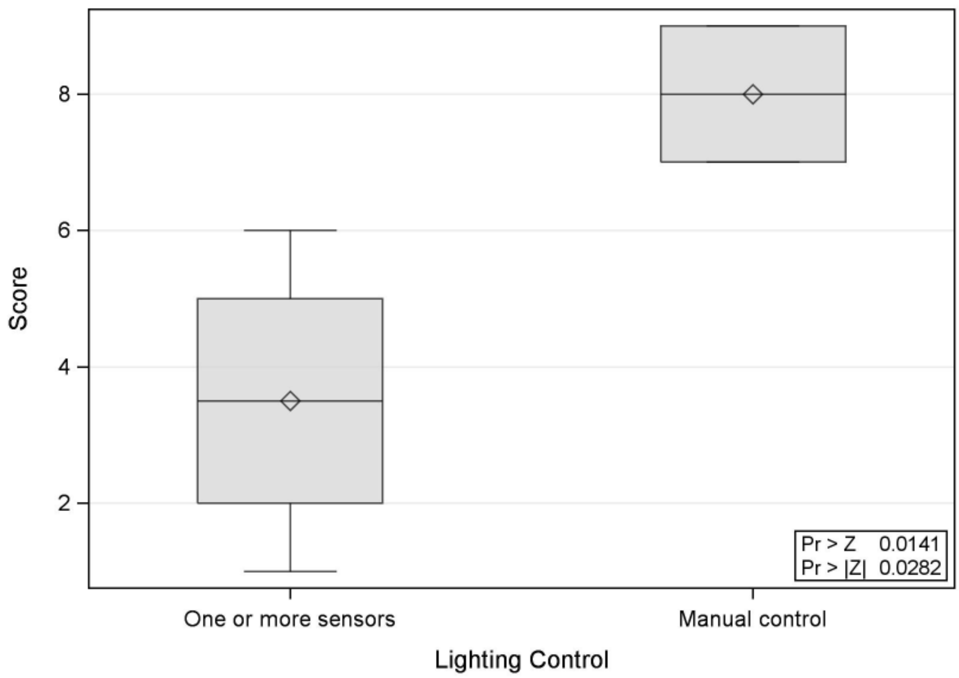

Figure 8.6 Wilcoxon rank-sum test results of lighting consumption of schools with different control strategies

The result showed that the difference in energy consumption for lighting between these schools was statistically significant ($p < 0.05$). This suggested that schools with more sophisticated control strategies that involve automated controls on internal lighting in classrooms and other occupied spaces have the ability to be more energy efficient. This suggests that lighting may not be controlled as efficiently as it should be in schools that are equipped with manual controls. It is therefore likely that the lights are left on, even when the spaces are not occupied or when enough daylight is available. Considering however that the result was based on a small sample, and that the total lighting consumption was inclusive of both internal and external lighting, further investigation would be needed to validate this finding.

In addition to the hypothesis test, correlation analyses were carried out to assess the relationships between lighting consumption and building characteristics. Based on the previous findings however, it was decided that schools with manual controls would be excluded from the analysis due to the independence of manual lighting control from the external conditions. The results are shown in Table 8.7.

Table 8.7 Correlation analysis of total lighting consumption and geometrical building characteristics

Variables	**Spearman Correlation Coefficients, N = 6 Prob > |r| under H0: Rho=0**	
	Coefficient	p-value
Surface-to-volume ratio	-0.83	0.04
Glazing to solid wall ratio	0.03	0.96
Depth ratio	0.31	0.54

The analysis showed that there was a strong negative relationship (-0.83) between the lighting EUI and the surface-to-volume ratio of the case study schools, which was statistically significant (p, < 0.05). This suggested that the schools with greater exposed surface area were using less energy for lighting than those that were less exposed to the external environment (Figure 8.7). It is conceivable that schools with greater surface area relative to their volume would have greater opportunities to use day lighting, provided that the buildings were designed with adequate glazed areas.

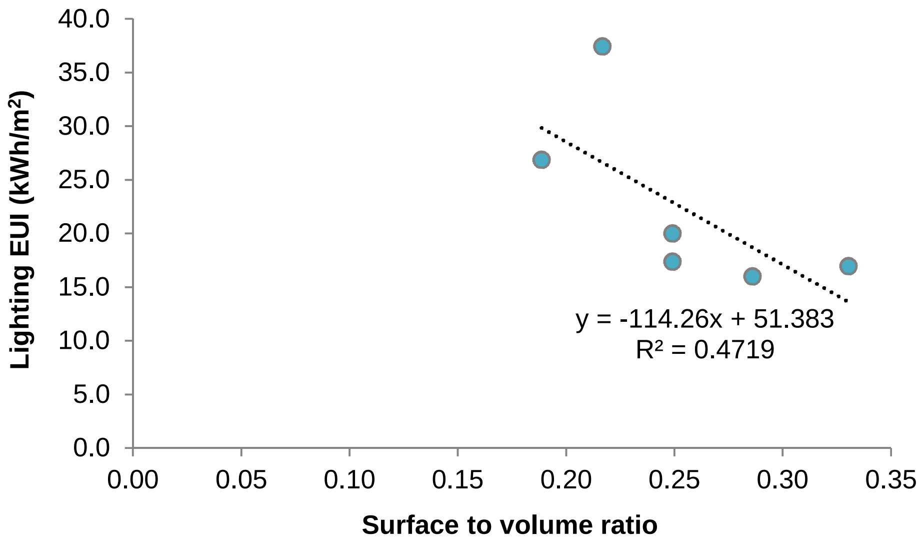

Figure 8.7 Scatter plot of the surface to volume ratio and the total lighting EUI of schools with daylight sensors

The analysis also showed that there was hardly any correlation (0.03) between the lighting EUI and the area of glazing relative to the solid proportion of the external walls. This suggests that the lighting controls were not necessarily responding to the availability of daylight. There was also no significant relationship between the depth of the floor plan of buildings and the lighting EUI (p, > 0.05). The lack of correlation is likely due to the way light fittings are designed and controlled in schools. Taking the classrooms in school G for example, Pegg (2007) observed that the light fittings were installed and controlled in rows perpendicular to the windows. This therefore meant that the lights near the windows were being controlled based on the illuminance levels of areas deep in the classrooms, which therefore led to the lights not being dimmed at all.

Figure 8.8 shows the lighting energy use in schools A, B, C and D broken down into different types of floor space. It should be noted that the figure was based on the estimated energy use of lights in different parts of schools. These were derived based on the specifications of equipment such as wattage and luminaire type, and assumptions about management and usage factors that were acquired during the site visits. There is therefore an element of uncertainty here and the results are only intended to provide a picture of where the lighting energy is likely to be used in schools.

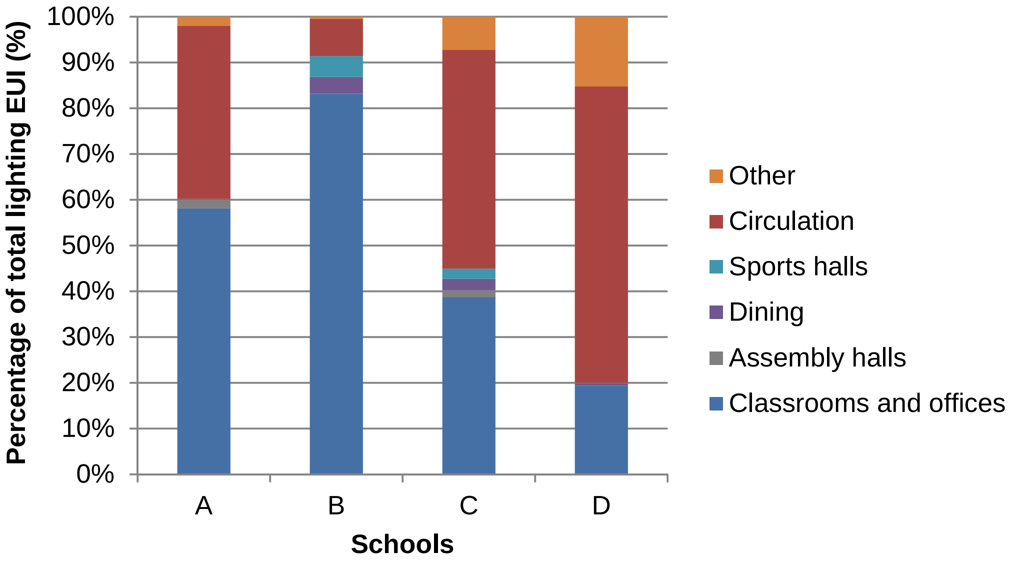

Figure 8.8 Estimated internal lighting consumption divided into different spaces in schools

The disaggregation of the lighting EUI into different space types shows a considerable variation between the schools. This is likely due to the differences in the way schools are designed and operated where the allocation of spaces and the occupancy would vary considerably from school to school. In general, the estimated lighting energy use for classrooms, office spaces and circulation spaces accounted for more than 80% of the total lighting energy use in all schools.

What was interesting was the amount of energy used for lighting the circulation spaces. Although these are estimated figures, the energy used for lighting stairs and corridors accounted for 38 to 65% in schools A, C and D except for school B in which the estimation was very low at 8%. A closer examination of the assumptions made during the bottom-up calculation of the lighting energy uses showed that lighting in stairs and entrances accounted for a considerable proportion of the lighting use in circulation spaces. This is likely due to the 24-hour operations of these lights, which are kept on for security reasons.

8.5.2 Fans, pumps and controls

In schools, fans, pumps and controls form the core of HVAC systems. The following section presents results from the analysis of the energy used in plant rooms.

The energy consumption by the equipment is shown in Figure 8.9. Note that this end use in schools A, B, C and D was broken down further, based on the estimated consumption figures which were calibrated to the metered energy use.

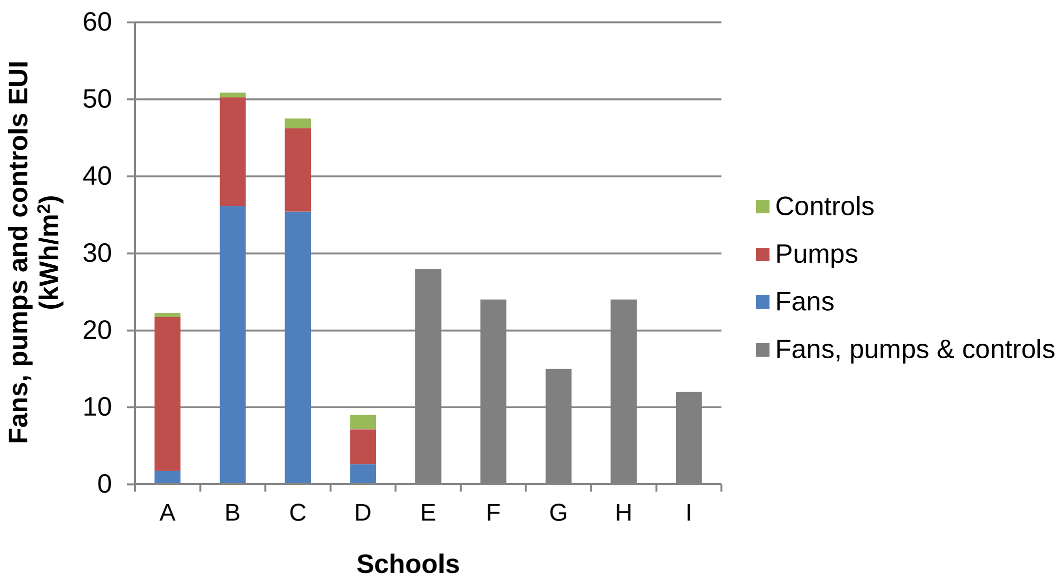

Figure 8.9 EUI of fans, pumps and controls of the case study schools and their breakdown

The bar chart shows that there is a large variation in the combined energy use of fans, pumps and controls (Figure 8.9). The end-use consumption was found to be the most intensive in schools B and C with consumption of 51 and 48 kWh/m^2, which accounted for 41% and 38% of the total electricity consumption. This is likely due to the significantly high proportion of areas that were mechanically ventilated compared to the other schools. In schools B and C, approximately 90% of the occupied spaces were understood to be mechanically ventilated, which is considerably greater than the other schools where the estimated percentage of the areas being mechanically ventilated ranged between 20 to 60%. This would have resulted in the increased load on fans, pumps and controls, hence the noticeably higher energy use. The implications of having high levels of mechanical ventilation can be observed further by the differences in the energy used by fans. It can be seen that fans in the mechanically ventilated schools (B and C) accounted for 71 and 75% of the end-use in comparison with school A in which up to 80% of the spaces were being naturally ventilated. School D was also a mechanically ventilated building but the low consumption figures for both fans and pumps suggested that sixth form colleges may have different patterns of use, hence the different demand. An examination of the core operating hours showed that school D was operating for noticeably fewer hours at 1,564 per year compared with schools B and C that operate for 2,503 and 2,816 hours per year. It was also found that the energy used by fans, pumps and controls was closely related to the core operating hours of the schools (Figure 8.10).

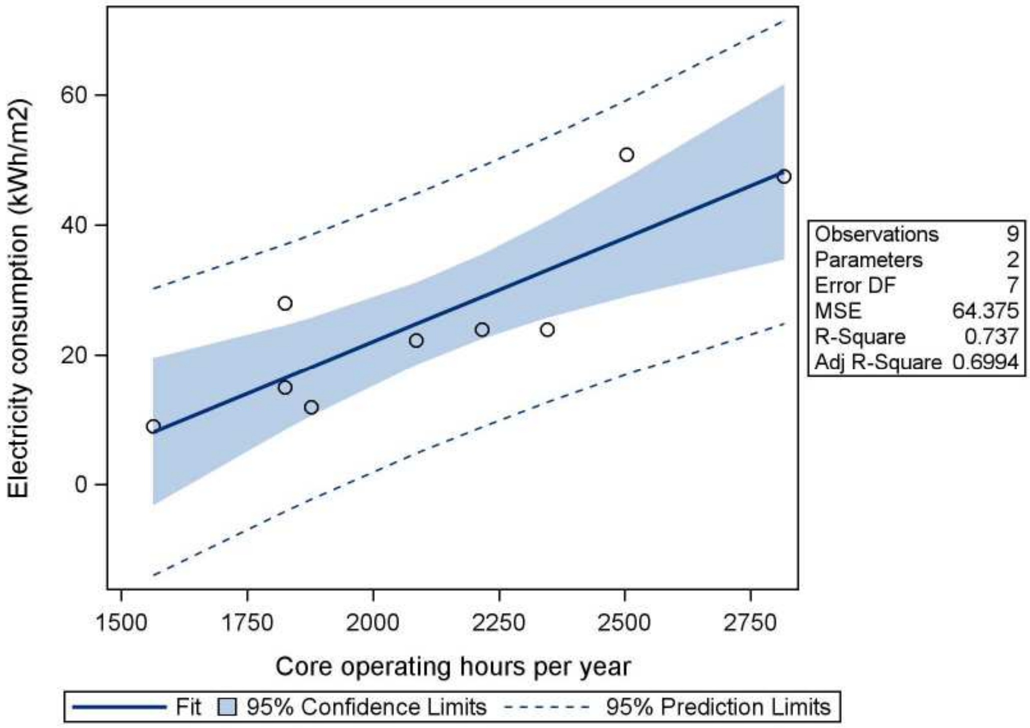

Figure 8.10 Scatter plot of core operating hours of schools and the fans, pumps and controls EUI, and line of best fit

The energy used to operate fans, pumps and controls was also found to have a statistically significant relationship with the depth ratio (Spearman, $p < .05$). The relationship was positive with a correlation coefficient of 0.78, which suggested that buildings with deeper floor plans were using more energy to operate the HVAC system. This makes sense as buildings with deep floor plans are likely to have greater needs for mechanical ventilation and perhaps cooling due to difficulties in adopting natural ventilation strategies. It is also likely that buildings with greater plan depth would have increased energy demand for supplying air due to increased lengths of ductwork.

8.5.3 ICT and small power equipment

The following section presents results from the analysis of the energy used by information and communications technology (ICT) and small power equipment.

Figure 8.11 shows the plug loads from various ICT and small power equipment in the case study schools. The electrical plug loads, which were shown in Table 8.6, were separated into the energy consumption by equipment in server and hub rooms, and general ICT and small power equipment. The plug loads in server and hub rooms include the energy used by equipment that provides networking, stores electronic data and integrates the curriculum and management functions of schools. The general ICT and small power equipment includes computing devices such as desktops and laptops, and also office and teaching equipment such as printers, photocopiers, projectors and speakers.

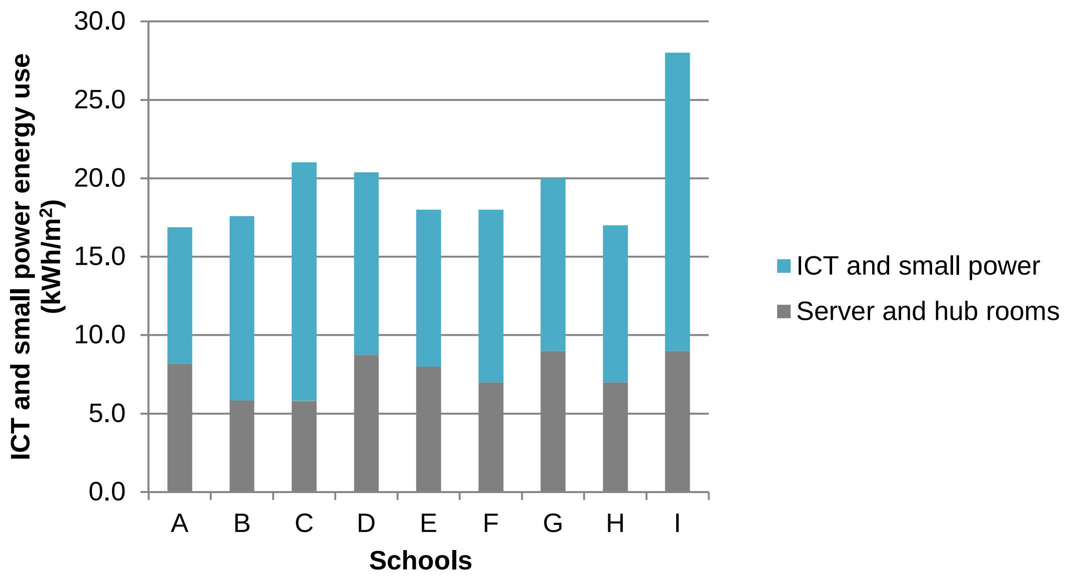

Figure 8.11 Breakdown of electricity use for ICT equipment in nine case study schools

The plug loads for operating the ICT and small power equipment show a relatively similar pattern across all schools. The energy used by computing devices and office equipment was found to account for approximately 60% of the total plug load and 13% of total electricity use on average. The electricity consumption by the general ICT and small power equipment was found to be reasonably similar in all schools, except for school ‘I’, which showed an unusually high level of energy use of 19 kWh/m^2 (Table 8.8).

Table 8.8 Statistics of the plug load from various ICT and small power equipment

Equipment	**Electricity consumption (kWh/m^2)**			
	Min.	Median (95% CL)	Max.	MAD
All ICT and small power equipment	16.9	18.0 (17.0, 21.0)	28.0	1.1
- Server and hub rooms	5.8	8.0 (5.9, 9.0)	9.0	1.0
- ICT and small power equipment	8.7	11.0 (10.0, 15.2)	19.0	1.0

A closer examination of the general ICT and small power consumption of school ‘I’ showed that the energy use was more than 7 MAD away from the median, indicating the significance of its deviation from the other schools. The lower granularity of information on school ‘I’ meant that it was difficult to identify what might be causing such a high level of consumption. The description of the facilities and equipment in the school however indicated that it was due to the specialism of the school, which was in ICT. In his thesis, Pegg (2007) described that most students in school ‘I’ were provided with laptops and that these were actively used for teaching purposes. The higher levels of equipment and the active use of the technology was therefore likely to have contributed to such a high intensity. This also highlights the importance of taking into account the changes in demand for electricity according to variations in curriculums or specialisms of schools. These are intrinsic features of schools necessary for education of pupils, and therefore assessing the operational efficiency without considerations for the difference would provide misleading feedback.

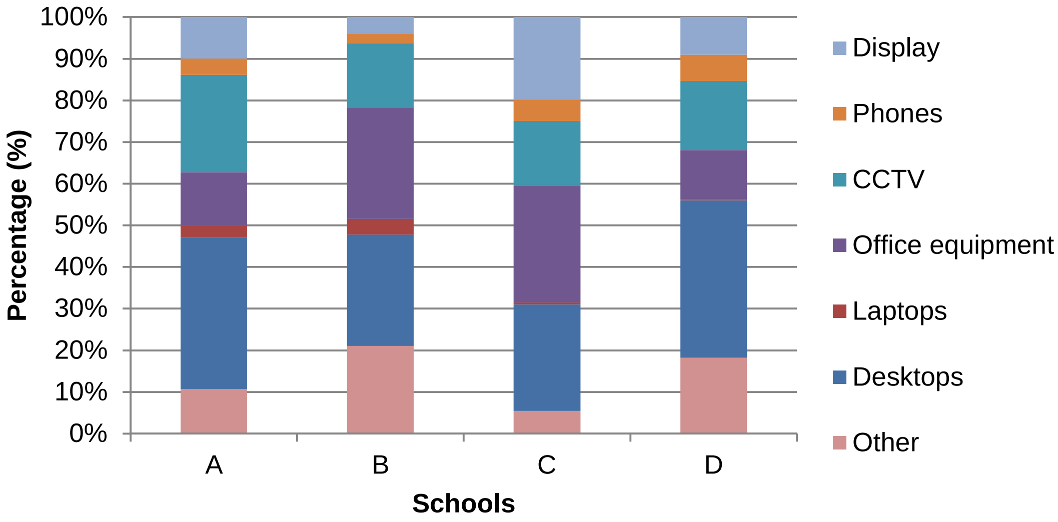

Figure 8.12 Estimated energy use by ICT and small power equipment of schools A, B, C and D

The estimated energy uses of equipment suggested that computers were likely to be the most intensive users of electricity (Figure 8.12). The consumption of the desktops was however estimated to be significantly greater than the laptops. This is due to the differences in the assumed power ratings between the two types of device where the rating of desktops was much greater than that of laptops at 61W and 6W respectively. There were also differences in the provision of ICT equipment whereby there were many more desktops present in schools A, B, C and D than laptops (Figure 8.13).

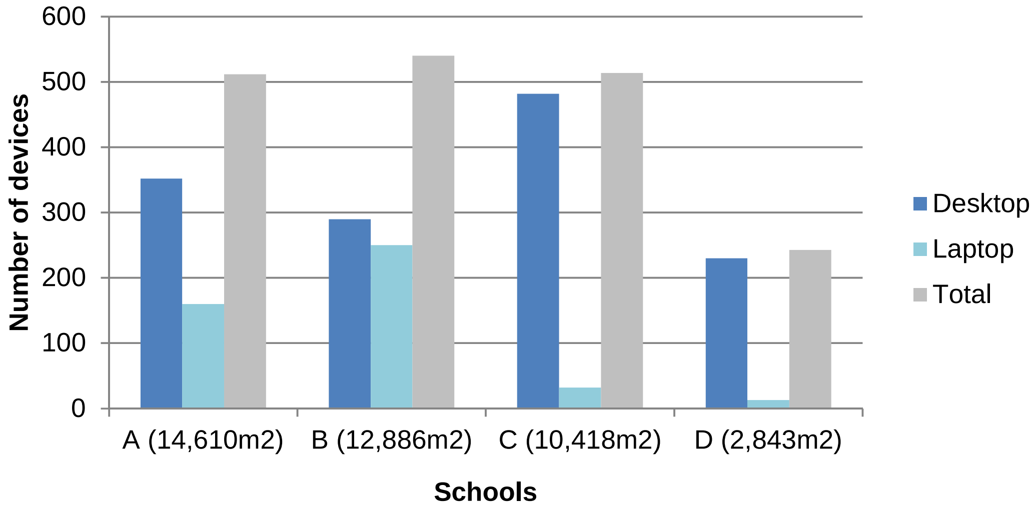

Figure 8.13 Distribution of the numbers of computers in schools A, B, C and D (floor area)

The provision of computers in schools A, B, C and D, although limited in numbers, was compared to the historical changes shown in Figure 8.14 (Hall 2004). The comparison showed that the mean number of pupils per computer in schools has decreased continuously over recent years and that the figures for A, B, C and D were considerably lower than shown by the latest survey which was carried out in 2004. This suggested that the pupils in the case study schools were provided with much better access to ICT, and that the integration of ICT equipment into teaching and learning in schools has increased gradually over the past decade. Considering however that the four schools were all academies, further investigation is needed to identify whether the provision of computers is similar in other types of schools.

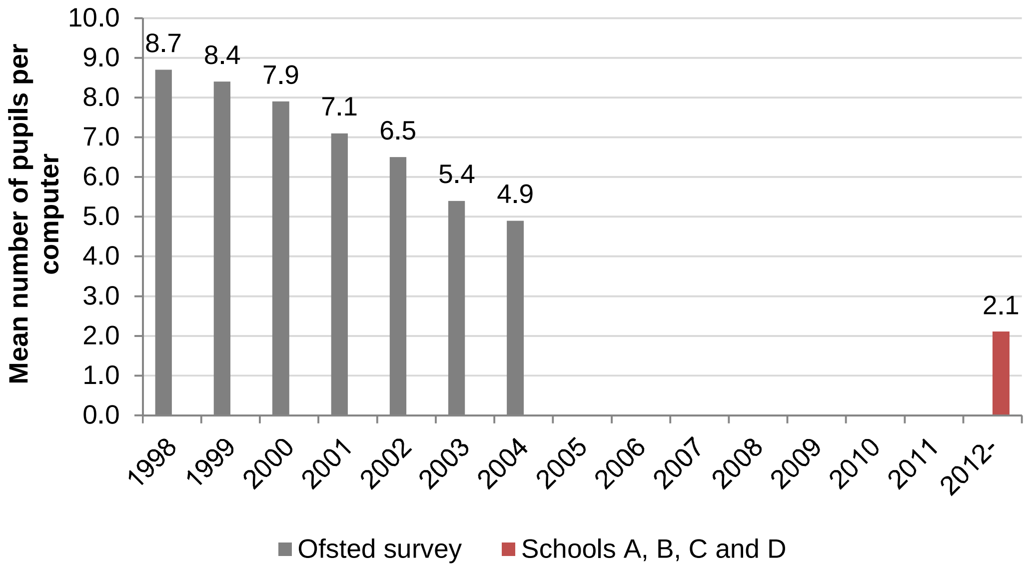

Figure 8.14 Comparison of the mean number of pupils per computer in schools A, B, C and D against historical changes in other secondary schools

As shown in Figure 8.12, there were also noticeable plug loads from office equipment and CCTV. CCTVs were found to account for up to 10% of the ICT and small power equipment energy use and between 1 and 3 % of total electricity consumption. A closer examination showed that the number of security cameras was directly correlated to the size of schools. The energy consumption of office equipment also accounted for considerable energy use. The pattern of energy use of the equipment however could not be analysed in a meaningful way due to the diversity of equipment and provision.

In addition to general ICT and small power equipment, the server and hub room equipment was also found to account for a noticeable proportion of the overall end use (Figure 8.11). The energy used by equipment in server and hub rooms showed a median of 8.0 kWh/m^2 with a small MAD of 1.0 kWh/m^2, which suggested that the modern schools have been designed with similar levels of server and hub room equipment. These accounted for approximately 39% of the ICT and small power equipment and 9% of total electricity consumption (Table 8.8). A closer examination of the operational data from *TM22* showed that the equipment in the server rooms of these schools was noticeably more energy-intensive, where the combined power rating of the equipment would frequently exceed 20kW. The equipment was also found to operate for 24 hours, hence the significant energy use. The existence of server and hub rooms in all schools also highlighted the prevalence of such facilities in modern secondary schools, as result of recent developments in technology and its integration into teaching. Considering that the study by Hall (2004) found that approximately 70% of the staff of secondary schools were using ICT regularly for teaching and learning in 2004 it is likely that most schools would have such facilities. The density of equipment and its variation however remains to be investigated further as more information becomes available in the future, especially for primary schools.

8.5.4 Refrigeration

The following section presents results from the analysis of the energy used by the HVAC systems providing cooling to different parts of the schools.

Figure 8.15 below shows the distribution of the cooling EUI in the case study schools. Note that the energy used for refrigeration in schools A, B, C and D was disaggregated based on the figures derived using the bottom-up approach.

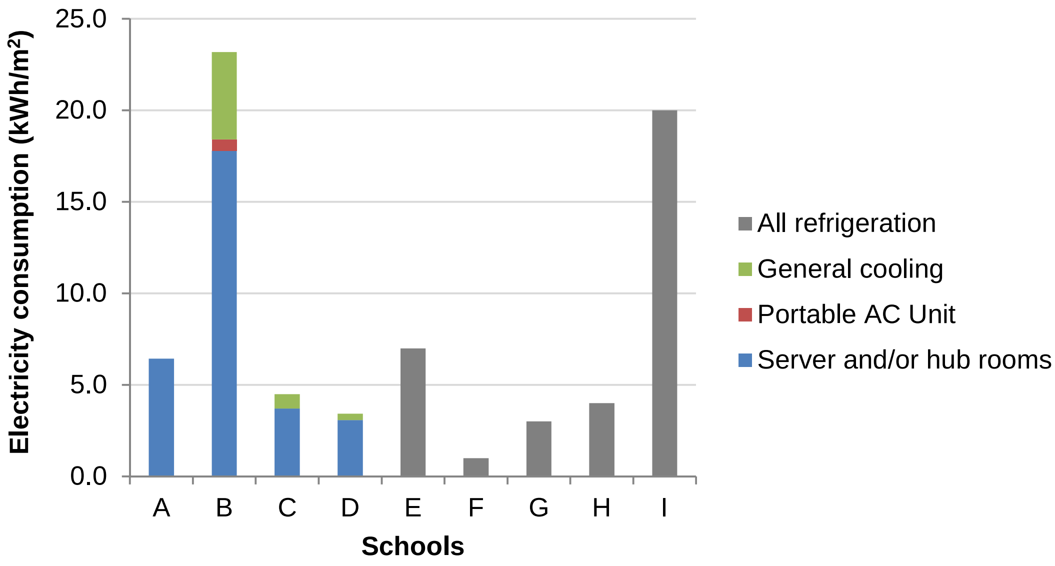

Figure 8.15 Comparison of refrigeration energy use in all case study schools

The comparison of cooling energy consumption of all nine schools show a large variation. Schools B and I were found to be significantly more intensive than the other schools, with the energy consumption going as high as 23.2 kWh/m^2. In schools B, D and I, these energy uses accounted for between 16% and 19% of total electricity consumption.

A disaggregation of the refrigeration end use of schools A, B, C and D showed that a significant proportion of all of the cooling consumption was being used for air-conditioning the server and hub rooms, which accounted for 77% to 100% of the cooling load. This was largely due to the significantly longer hours of operation of the equipment in these rooms, which were constantly running 24 hours a day for the whole year. The equipment, which is sensitive to temperature and humidity, would therefore have required the environment to be maintained at adequate conditions. A close examination of the specification of cooling equipment showed that its capacity was very high. The information acquired from the *TM22* data showed that the capacity of the chillers providing cooling to the server rooms could be as high as 65.5 kW. Uses of such equipment throughout the year would therefore result in considerable energy consumption.

The following sections present results from the analyses of end-uses of fossil-thermal energy. The overview of total fossil-thermal energy use is followed by analysis results for each of the main end uses.

Figure 8.16 shows the metered consumption of four end uses that constitute the total fossil-thermal EUI of the case study schools.

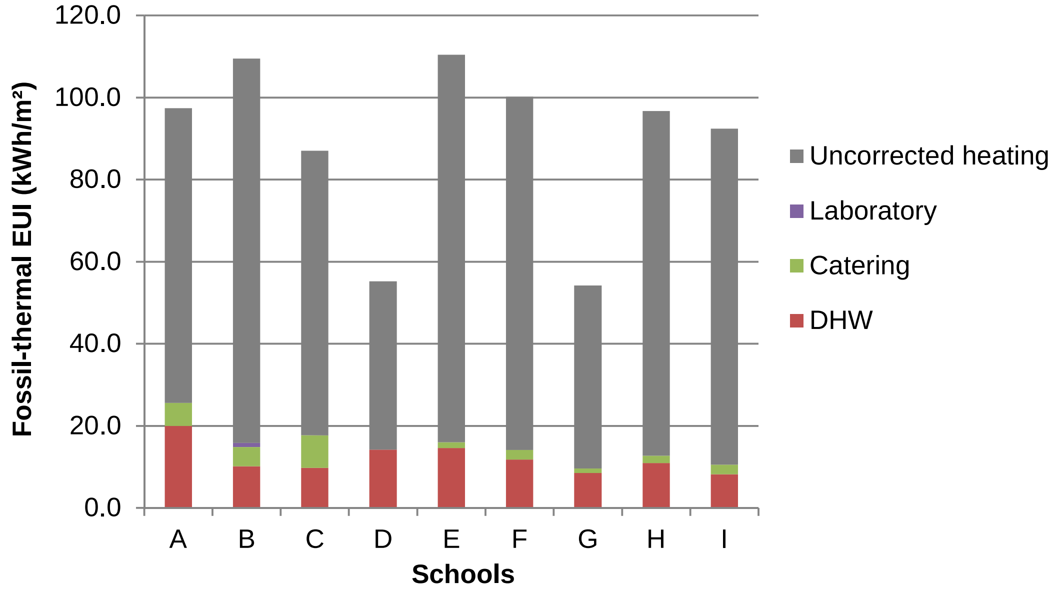

Figure 8.16 Fossil-thermal energy use of the case study schools broken down into different end uses

The figure above shows that fossil-thermal energy consumption mostly comprises energy used for heating the indoor spaces in all schools. On average, space heating was found to account for 82% of the total fossil-thermal energy use of the case study schools. Unlike the overall intensity of energy use, which was found to vary considerably, the percentages that space heating accounted for were relatively consistent. This suggested that the assumption made in Section 6.2, where the fossil-thermal energy use of the stock was corrected based on an assumption that 80% of it would be used for space heating, was likely to be reasonable. The extent to which this percentage may be similar to other schools such as primary schools and also secondary schools that were built decades ago remains however, to be validated in the future when more data becomes available.

Table 8.9 Descriptive statistics for the fossil-thermal energy consumption of the case study schools by major end-use categories

End-use category	Fossil-thermal EUI (kWh/m^2)			
	Min	**Median (95% CL)***	**Max**	**MAD**
Raw space heating	41.1	81.9 (44.6, 93.6)	94.4	11.7
Weather-corrected space heating	39.5	77.9 (50.4, 95.5)	124.5	16.7
DHW	8.2	10.9 (8.5, 14.6)	20.0	2.4
Catering	0.0	2.3 (1.1, 5.6)	7.9	1.2
Laboratory	0.0	0.0 (0.0, 0.0)	1.0	-

* Distribution-free confidence limits

Both Figure 8.16 and Table 8.9 shows that the large variation in the total fossil-thermal EUIs (Table 8.5) was largely due to the variation in the intensity of energy used for heating indoor spaces. Considering that these schools were all secondary schools and that they were built to modern building regulations standards suggests that there are likely to be other factors that are influencing the demand for space heating.

8.5.5 Space heating

Table 8.10 below shows the area-weighted U-value and glazing to solid wall ratios of façades in the case study schools. It should be noted that the U-value of schools E, F, G, H and I were calculated based on the figures from the study by Pegg (2007).

Table 8.10 Area weighted U-values and glazing to solid wall ratios on facades of all case study schools

Schools	Area weighted U-value of facades ($W/m^2 \cdot K$)	Glazing to solid wall ratio
A	0.73	0.32
B	0.85	0.44
C	0.62	0.29
D	0.54	0.16
E	1.21	0.60
F	1.14	0.45
G	0.75	0.35
H	0.68	0.43
I	1.12	0.43

A correlation analysis of the above building characteristics with the space heating energy use of the case study schools showed that there were statistically significant correlations (Table 8.11). It should be noted that uncorrected space heating EUI was used, rather than weather-corrected consumption, to prevent any uncertainties associated with the heating-degree corrections.

A strong positive relationship (0.93) was found between the ratio between glazed and solid wall on the facades of the case study schools and the energy used for heating indoor spaces. This is due to the increased rate of heat loss through the glazed components of the external fabric that have much higher conductivity than solid walls. This finding is supported by the strong positive relationship between the area weighted U-value and the space heating EUI, which confirms that greater glazed areas lead to increased heat loss and therefore increased heating load.

Table 8.11 Spearman's correlation coefficient between the space heating EUI and the area weighted U-values and glazing to solid wall ratios

Variables	**Spearman Correlation Coefficients, N = 9 Prob > |r| under H0: Rho=0**	
	Coefficient	p-value
Glazing to solid wall ratio	0.93	0.0003
Area weighted U-value	0.77	0.02

Figure 8.17 shows the relationship between the two variables and the line of best fit. The R^2 value of 0.684 of the line indicates that approximately 68% of variance in the space heating EUI of the case study schools is explained.

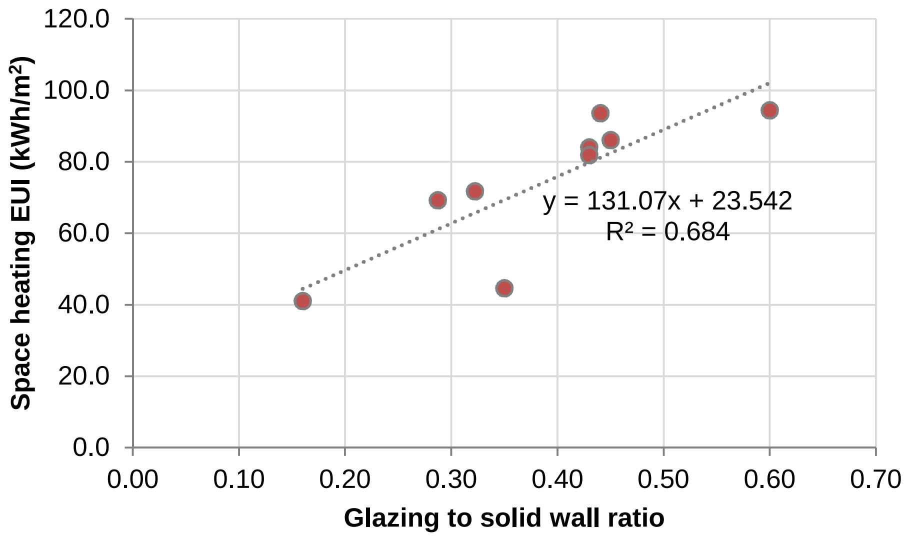

Figure 8.17 Scatter plot of glazing to solid wall ratio and uncorrected space heating EUI

8.5.6 Domestic hot water supply

The energy used for providing hot water for facilities such as kitchens, showers and toilets was found to be the next most intensive fossil-thermal end use. The median consumption for the hot water supply of the case study schools was 10.9 kWh/m^2, which accounted on average for 14%, and up to 26% of total fossil-thermal energy use.

Table 8.12 below shows the results from the correlation analyses between domestic hot water energy consumption, floor area, and number of pupils. Note that the correlations were assessed in relation to annual energy consumption (kWh/yr), rather than the EUI.

Table 8.12 Spearman's correlation coefficients between the annual domestic hot water supply consumption (kWh/yr) and building size and the number of pupils

Variable	Spearman Correlation Coefficients, N = 9 Prob > |r| under H0: Rho=0	
	Coefficient	p-value
Floor area (m^2)	0.85	0.004
Number of pupils	0.93	0.000

Statistically significant correlations (Spearman, $p < 0.05$) were found between the amount of gas used for heating water and both the size of schools and the number of pupils. The strong correlation is likely due to the similar pupil densities in the case study schools, where floor area per pupil ranged between 8 and 10 m^2. The stronger correlation between annual energy consumption and number of pupils is likely due to the fact that the design of hot water systems is usually based on an estimated number of occupants (CIBSE 2004). The high levels of correlation therefore suggests that the hot water supply is probably being used as intended during the design stage and that it remains generally constant in schools. This also explains why the relationship between the intensity of energy use for hot water supply, expressed in kWh/m^2, and the number of pupils was not statistically significant.

The regression model in Figure 8.18 shows that number of pupils can explain more than 80% of the variation in annual energy consumption for hot water supply.

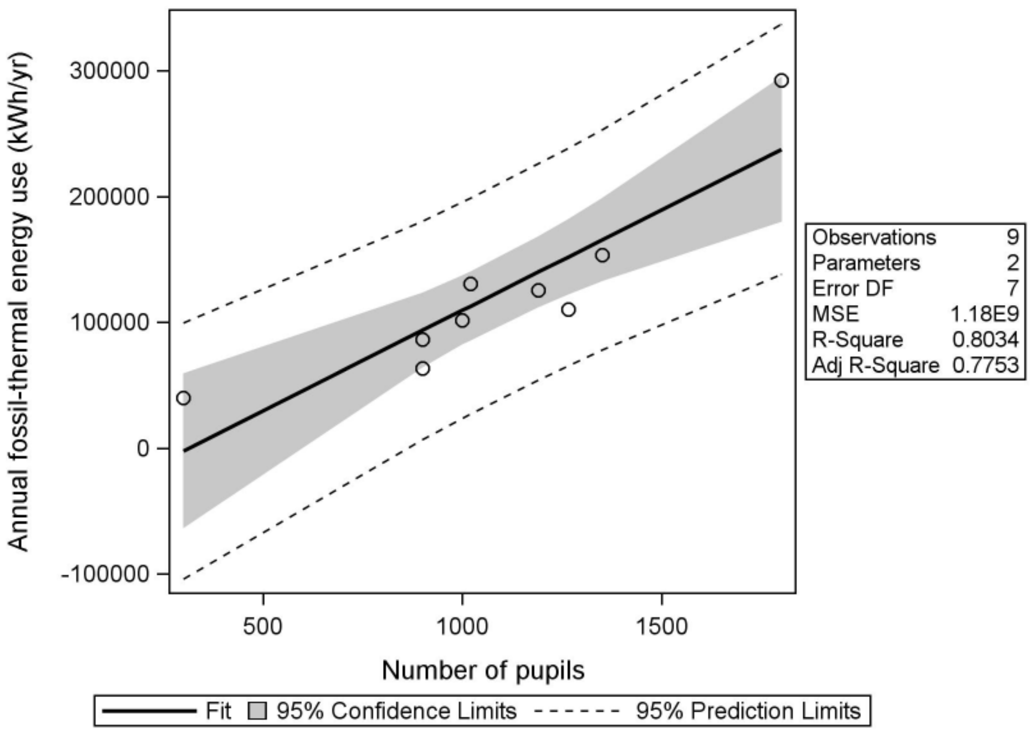

Figure 8.18 Regression model of the number of pupils with the annual fossil-thermal energy use for the domestic hot water supply

8.5.7 Catering

The EUI for catering was analysed separately from other end uses as it usually involves using both electricity and fossil-thermal energy. This is due to the mixture of equipment used in kitchens and canteens for preparing, cooking and storing food. Figure 8.19 shows the distribution of different types of energy used to cater for pupils and staff in the case study schools.

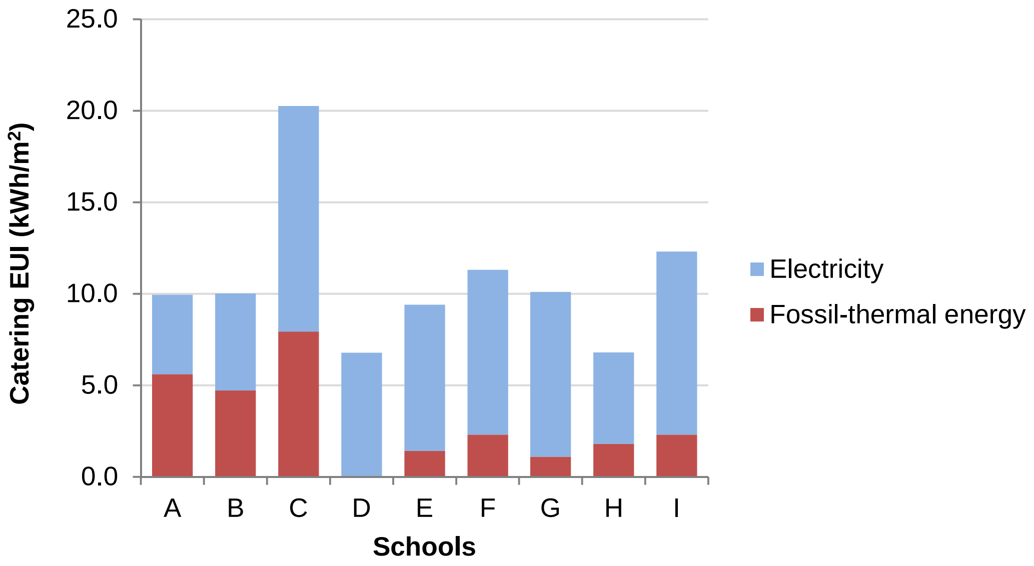

Figure 8.19 Stacked bar chart of catering EUI by fuel type

It can be seen that electricity is used widely in all schools by contrast with the use of gas that varies considerably. The intensity of electricity use was generally higher than fossil-thermal energy use where the median consumption was 8.0 kWh/m^2 and 2.3 kWh/m^2 respectively, which represented on average 8% and 2% of total electricity and fossil-thermal energy consumption, respectively. The information available on the catering equipment in schools A, B, C and D indicated that meals were generally cooked using a mixture of gas and electricity in ovens and microwaves. There were however many more items of electrical equipment such as refrigerators, dish washers and mixers used for food storage and the general operation of kitchens.

The relationship between the characteristics of occupants and the energy used for catering was first explored by assessing the correlations between total catering energy use and number of pupils as well as number of meals served.

Table 8.13 Spearman's correlation coefficients between the combined catering EUI, number of pupils, and number of meals served

Variable	N	Coefficient	p-value
Number of pupils	9	0.10	0.797
Number of meals served	3	1.00	< .0001

The correlation analyses showed that there was a weak relationship between catering energy use and the number of pupils (Spearman, $p > 0.05$). This is likely due to the fact that there is a variety of practices in the schools, which serve meals at different times of the day. In addition, it is unlikely that all students in schools will have meals provided by the school throughout the day. This therefore suggests that the volume of food cooked in the kitchens in the form of the number of meals may be better correlated with how much energy is used for catering. Out of nine schools, the approximate number of meals served during the week was available only for schools A, C and D. Despite the very small sample size however (Table 8.13), a statistically significant relationship was found between the number of meals served in canteens throughout the day and total electricity and fossil-thermal energy used in the kitchens (Spearman, $p < .0001$). A scatter plot of the two variables is shown in Figure 8.20. The R^2 values of the line of best fit of 0.9885 indicated that the regression model could explain up to almost 99% of the variation in catering energy use. The test result was however based on an extremely small sample size and therefore needs to be evaluated with a larger set of data to confirm the relationship.

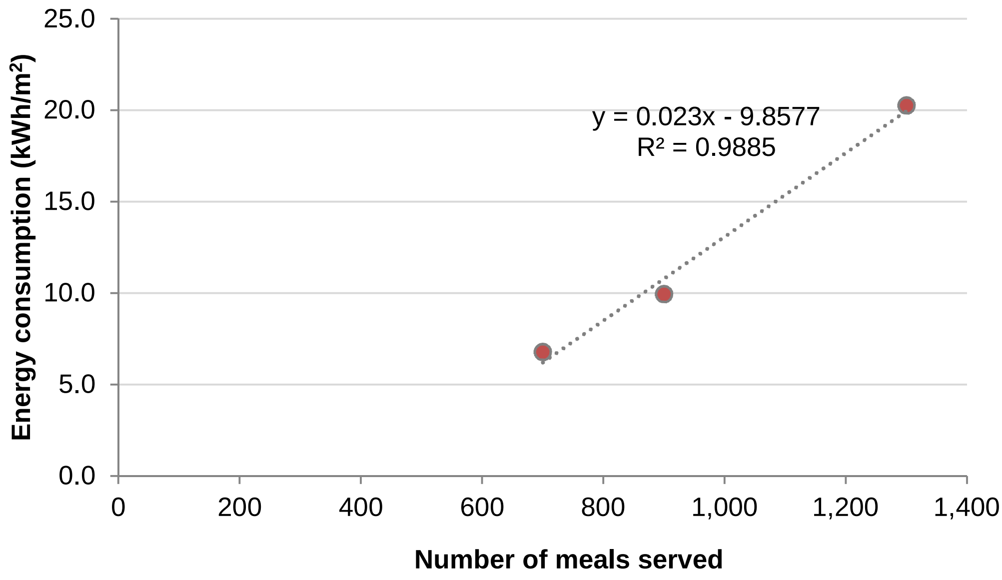

Figure 8.20 Scatter plot of the number of meals served and the total catering EUI

8.6 Chapter summary

In this chapter, the end-use consumption of nine modern secondary schools was assessed in finer detail. The main objectives of the chapter were to assess the disaggregated energy consumption of schools and to observe the relationships between intrinsic features of school buildings and the end-use energy consumptions.

Summary of the findings are below:

- Out of 300 records in the Carbon Buzz database, only nine were found to provide reasonably accurate information on the end-use energy consumption of secondary schools. This highlighted yet again the difficulties in obtaining a large quantity of empirical data, especially with fine granularity.
- *TM22* data and PVQ files were found to provide ample details on energy consumption, built form, specifications of building systems and various types of equipment, and occupancy patterns, which were very useful in improving the understanding of how energy is used in these schools.
- The case study schools were found to be considerably more intensive in electrical EUI compared to the school stock, which suggested that modern schools with an academy

status tended to be highly intensive in electricity. The fossil-thermal EUI on the other hand was found to be generally less intensive than the stock, likely owing to improved thermal performance. These findings suggested that the operational energy efficiency of modern schools would be assessed with greater accuracy if their energy performance were compared to those with similar thermal performance.

- A large variation in the breakdown of end-use energy consumption was found between the schools in question, even between those with similar total consumption. This demonstrated the intricacy of the patterns of energy use in schools, which could not be assessed using the top-down approach used in previous chapters. The variation in end-use energy consumptions also emphasised that there are various factors that influence each of these end uses.

- Analyses of each of the end uses, particularly the energy uses associated with fixed building services such as the HVAC system, lighting, and space heating, showed that the pattern of energy use was usually related to intrinsic features of buildings such as the depth of floor plan, exposed surface area, and the thermal performance of the fabric. These relationships clearly demonstrated that the energy performance of the case study schools was influenced by the intrinsic features of buildings.

- The school with the specialism in ICT was found to be considerably more intensive in the ICT end-use consumption, which was attributed to extensive uses of laptops for teaching purposes. This finding suggested the demand for energy can also be affected by curriculum of schools that have not previously been considered.

- Findings from exploratory and inconclusive results suggested a number of factors that could potentially improve the comparability of benchmarking. The number of meals served for example, was found to be related to the catering EUI.

- Server rooms were found in all case-study schools with similar levels of EUI. This suggested that these equipment are likely to be a common feature of modern teaching and that there is no justification to introduce a separable item.

- Space heating was found to account for approximately 80% of total fossil-thermal energy uses on average. This figure raised the possibility that the proportion of space heating adjusted for the variation in weather conditions under the DEC scheme may be disproportionate.

In summary, this study showed that assessment of the energy consumption of sub-systems is effective in explaining and identifying the factors that are likely to have caused the variation in the patterns of energy use of the case study schools. This is in clear contrast to the feedback from top-down approaches to benchmarking that provide indications of whether buildings are intensive users of energy or not, but not why. A building that appears to be highly energy-intensive to a whole building benchmark for example, would not show which of the sub-systems is likely to be causing the inefficiency. Uses of the bottom-level data for benchmarking could however resolve this issue where energy benchmarks for each end use would provide opportunities to isolate an area of problem and provide a sense of direction.

The availability of greater detail on schools also showed that there are many more intrinsic factors that are correlated with individual end uses. The correlations between the variables that express the intrinsic characteristics of buildings such as the U-values and the plan depth clearly emphasised the need to improve the comparability of benchmarking if the operational energy efficiency of buildings is to be evaluated accurately. The high electrical EUI of the ICT specialist school demonstrated that the demand for energy can be influenced by ‘soft’ factors such as the specialism of schools. Under the current scheme, it is likely that schools with more equipment would receive worse grades due to increased energy consumption. Such feedback would however ignore the fact that these equipment were intended to increase the effectiveness of teaching. It is therefore evident that the implications on the demand for energy from primary functions of schools should be taken into account when benchmarking their operational energy efficiency.

Chapter 9 Discussion

This chapter reflects on the findings from the previous four chapters and discusses the robustness of current UK benchmarking practices and their implications for the development of a robust benchmarking system for evaluating the operational energy efficiency of buildings across the non-domestic stock. Based on the outcome of the discussion, recommendations for work by CIBSE and others are made at the end of the chapter.

9.1 Approaches for benchmarking operational energy efficiency

In recent decades, energy benchmarks in the UK have been derived predominantly using the top-down approach based on descriptive statistics as representations of the energy performances of similar buildings in the stock. Assessments of the energy performance of schools using top-down (Chapter 5 and Chapter 6) and bottom-up (Chapter 8) approaches have revealed the benefits and limitations of using the top-down approach for benchmarking the operational energy efficiency of UK non-domestic buildings.

As shown in Chapter 6, statistics derived using a top-down approach such as those in CIBSE *Guide F* or *TM46* show that this is an effective way to describe the actual energy performance of the existing school population. Such a characterisation of the stock presents opportunities for building operators or managers to put their buildings' performance into a broader context. Comparing the performance of modern secondary schools to whole-building energy benchmarks that represent the distribution of the school population in Chapter 8 for example, showed that this is effective in identifying how efficient a given group of buildings is in relation to similar buildings in the stock. With regards to schools, such feedback would be beneficial for local authorities or county councils who have energy efficiency as part of their agenda. Moreover, such feedback would provide motives for improving the energy efficiency of buildings based on peer pressure rather than absolute levels of energy efficiency. For other building types such as commercial offices, where reputation is of crucial value, such peer-driven feedback may generate stronger motives to improve energy efficiency.

The simplicity of the method that is used to derive the current energy benchmarks is also beneficial in that there is a minimal requirement for information both to derive the benchmarks and to evaluate the performance of buildings. As demonstrated from the DEC scheme, the information that is required is annual metered energy consumption, floor areas, occupancy levels, location of a building to take into account the regional and seasonal variation in weather, and knowledge of any separable energy uses if they exist. Such low granularity data is more likely to be obtainable through utility bills or regular meter readings, although this may not apply for floor areas or the separables. It is therefore relatively less intensive in resources than the bottom-up approaches, which often require activities such as post-occupancy evaluation (Hong et al. 2014).

A key challenge in using the top-down approach however, lies with the fact that it is often difficult to obtain even the low granularity data in sufficient quantity to represent the stock in reasonable detail. In historical work 50 or 100 samples have often been quoted as sample sizes that can derive benchmarks which are reliable representations of the stock (CIBSE 2012; Jones et al. 2000; Jones 2014; Bruhns et al. 2011). As highlighted in Section 3.4 however, there were no evidences to support these claims. The boot strapping analyses of sampling distributions in Section 6.3 on the other hand showed that these sample sizes may not be sufficient for estimating a reliable statistic. The analyses showed that 95% confidence intervals ranged between 20 and 25% of the estimated parameter when medians were derived from 50 samples (Figure 6.6 to Figure 6.9). Although the study was limited to primary and secondary schools, these results clearly showed that benchmarks based on sample sizes of 50 or 100 were not likely to be reliable as previously believed. Conversely, the study found that the confidence interval was found to reduce to approximately 10% of the estimated parameter when the sample size increased to approximately 200 (Figure 6.10). While the analysis provide evidence upon which the reliability of future benchmarks can be assessed, it also highlights that a considerably larger sample than previously believed to be adequate is required to derive benchmarks that are representative of the stock. Difficulties in acquiring such sample sizes was shown by the analysis in Chapter 5 where just 10 out of 29 benchmark categories had sample sizes greater than 200. Similarly, examples of energy benchmarks that were derived from small sample sizes can be found in CIBSE's *Guide F* (2012). In tables 20.4, 20.5 and 20.6 the sizes of samples that were used to derive the benchmarks can be seen to vary considerably, where some benchmarks were based on sample sizes as small as nine.

The other drawback of the approach is that feedback from using these simple top-down benchmarks is not likely to indicate clearly whether a building is being operated efficiently or not. First, whole-building energy benchmarks, although separated for main fuel types, do not provide fine detail for identifying why a building is assessed as inefficient. Difficulties found in interpreting the patterns of energy use and the underlying factors with certainty in Chapter 5 and Chapter 6 are examples of such drawbacks in using top-down approaches. The analyses of the bottom-up end-use energy consumptions in Chapter 8 on the other hand, provided valuable insights in interpreting and identifying areas of concern in modern secondary schools, which can potentially complement the top-down approach. Second, the empirical nature of the top-down approaches means that building operators acquire relative levels of energy efficiency that are defined by the buildings in a sample. Although peer pressure can be a strong motive, such a reference point may not be aspirational for those building operators who aim to achieve absolute levels of energy efficiency. In these instances, benchmarks or baseline performances estimated by using bottom-up approaches may be more appropriate (Federspiel et al. 2002). Recently, Bordass et al. (2014) explored the possibility of estimating whole-building benchmarks that are inspirational by aggregating end-use consumption using the CIBSE *TM22* method and prescribing specifications of building services and their use. While the underlying concept of using the bottom-up approach provided a new perspective, the underlying method was incomplete and lacked robustness, particularly in estimating the demand for space heating and cooling. Similarly, Hong et al. (2014) found that dynamic thermal models that are refined for the actual operational characteristics of an existing building have the potential to produce baseline figures that closely resemble the intrinsic features of individual buildings. Although the study demonstrated the concept of baseline benchmarks, its application to the wider building stock remains to be explored.

Overall, the most beneficial aspect of the top-down approach to benchmarking is that it is empirical in the sense that these benchmarks are inclusive of the complex interaction between surrounding environments, buildings, occupants, which can relate to a wider group of buildings. The different perspectives that can be acquired through the bottom-up approach also suggest possibilities of utilising both approaches in a complementary manner (Mathew et al. 2010; Hong et al. 2014). Until the limitations and uncertainties associated with bottom-up approaches are explored further however, top-down approaches are likely to be more appropriate for benchmarking the operational energy efficiency of the non-domestic stock.

9.2 Improved benchmarking comparability

In the UK, benchmarking practices have seldom considered taking into consideration the influences of intrinsic building and operational features on the energy demand of buildings. It is only in recent years that, under the current DEC scheme, top-down energy benchmarks are normalised for a set of parameters to account for variations in a number of contextual features of individual buildings such as weather and occupancy hours. Compared to historical benchmarks where actual energy consumption was directly compared to energy benchmarks, these adjustments contribute towards improving the comparability of the features that determine the intrinsic demand for energy. The analyses of the patterns of energy use in buildings based on these characteristics showed however that there were uncertainties associated with methods that underpin these procedures.

The analyses of buildings claiming extended occupancy hours showed that a considerable proportion of buildings had claimed to be occupied for extended hours, which suggested that the definition of ‘standard’ occupancy hours may have become outdated (Figure 5.10). Moreover, the analyses of the energy performance of local and central government offices that had claimed extended hours showed that there were almost no correlations with the consumption (Figure 5.11 and Figure 5.12). Similarly, correlations between occupancy hours and electrical and fossil-thermal EUI of primary and secondary schools were found to be insignificant (Section 7.3.1.2). Although the correlation analysis was carried out just for two types of public sector offices and schools, the lack of correlation suggested that there must be issues associated with how the extended hours of occupancy are currently counted and validated.

In Chapter 7, correlations between fossil-thermal energy use and annual heating degree-days were found to be statistically insignificant, which is likely due to poor operation of the heating system. Moreover, the analysis of the end-use consumption that composes the fossil-thermal energy use found that space heating generally accounts for 80% rather than 55%, which is the current assumption for adjusting the benchmarks to account for variation in influence of weather conditions. The percentage was originally derived from a small sample of schools that are neither representative of the stock nor primary schools. The noticeable difference between the two figures however, suggested that the current assumption of 55% may be an inaccurate representation of the proportion of fossil-thermal energy used for space heating in schools, which would make it more difficult for buildings in colder regions to achieve better grades.

While these procedures are currently central to providing more relevant feedback to building operators on their operational energy efficiency, such uncertainties highlighted a need to provide empirical evidences to validate these processes. The hybrid approach adopted in Chapter 7 on the other hand showed that there is a plethora of intrinsic features that influence the energy demand of schools, which are currently not accounted for by the current approach.

The multiple regression analyses showed that characteristics such as floor area, glazing percentage, presence of external shading and the type of glazing were significantly related to how electricity was used in schools (Figure 7.16 and Figure 7.18). The surface-to-volume ratio and age of buildings on the other hand were found to be related to how schools are heated (Figure 7.17 and Figure 7.19). The exploration of the bottom-up data in Chapter 8 also found significant correlations between the building features and end-use energy consumption. Characteristics such as surface-to-volume ratio, the depth ratio, and the glazing to solid wall ratio were found to have significant correlations with end-use energy uses such as lighting, mechanical ventilation, and space heating. These correlations clearly show that the intrinsic demand for energy is influenced by the intrinsic building characteristics. Consequently, this suggests that there is a need to change the benchmarking culture which currently does not take into account the implications of these characteristics.

There were also significant relationships between the operational or ‘soft’ characteristics and the pattern of energy use. In Section 6.3, the number of pupils was found to account for considerable variation in electricity and fossil-thermal energy use in schools (Table 6.6 and Table 6.7). Similarly, pupil density was found to be the most influential characteristic correlated to the electrical and fossil-thermal EUIs of primary and secondary schools respectively (Figure 7.16 and Figure 7.19). The exploratory analyses of the relationships between the end-uses and various characteristics that were only available for small numbers of schools also revealed significant relationships (Chapter 8). There was a strong relationship between the number of meals served and the catering consumption. There was also a strong correlation between the domestic hot water supply and the number of pupils (Figure 8.18). Another feature of schools that has developed in recent years but has not yet been explored in depth is the variation in energy demands of schools with different specialisms that come with academy status. Among the case study schools, the school specialising in ICT was found unsurprisingly to have an unusually high level of consumption associated with ICT and small power equipment (Figure 8.11). These are relationships that were to be expected but not analysed in other research. Although based on a small sample, the findings from the detailed end-use consumption suggest possibilities for further exploring various factors for which information was not available that may intrinsically influence the demand for energy in schools.

These findings clearly show that the demand for energy in schools is influenced by a broad range of intrinsic building and operational characteristics, which show possibilities for improving the comparability of benchmarking the operational energy efficiency. Moreover, differences in the determinants of energy demand between primary and secondary schools suggest that there is likely to be a particular set of parameters which influence the demand that are specific to each building type. A study focussing on identifying the drivers of electricity and gas demand in large food retail buildings in the UK for example, found key drivers of energy demand that are completely different from schools (Spyrou et al. 2014). The Better

Buildings Partnership on the other hand carried out an initiative to develop a benchmarking method based on commercial buildings where the division of energy used by landlords and tenants is of critical importance (BBP 2012). It is therefore evident that a more bespoke and context-driven approach to benchmarking is needed in order to provide a fairer and more precise evaluations of the operational energy efficiency for buildings in the stock with a diverse range of activities and characteristics.

9.3 Implications of adopting hybrid approaches

As highlighted in the previous section, the current top-down approach does not provide sufficient means to assess, identify and normalise energy benchmarks for multiple intrinsic characteristics. The multiple regression analyses used in Chapter 7 demonstrated on the other hand that hybrid approaches can be adopted for assessing and identifying the key parameters for obtaining a more precise indication of operational energy efficiency. The empirical nature of the approach, combined with opportunities to improve the comparability, therefore show potential for improving the robustness of benchmarking without fully committing to the bottom-up approach. This method has also been used in practice to support the US ENERGY STAR scheme over a decade, which adds confidence to the method. There are also hybrid approaches that use more advanced methods such as Artificial Neural Networks (ANN) that have been explored for similar purposes (Hong et al. 2014; Hawkins et al. 2012; Yalcintas & Ozturk 2007; Yalcintas 2006). In addition to the improved comparability, adopting these advanced methods would also allow the parameters that are currently used to adjust the benchmarks under the DEC scheme to be assessed and incorporated into the benchmarking process if they are found to have significant correlations with patterns of energy use. Despite their benefits however, experience from the present study suggests that employing a hybrid approach is likely to come at a cost.

The most obvious challenge is the increased burden of acquiring data with sufficient granularity to support these complex methods. Difficulties in acquiring data of finer granularity on a large scale were highlighted throughout the case study of schools. In chapter 6, searching for publicly available databases that provide additional information on the school stock other than the number of pupils proved to be challenging and ineffective. In chapter 7, using the desk-top approach to gather information on the built form proved to be extremely time and resource intensive. Similarly, the process of gathering data for the analyses in Chapter 8 revealed how difficult it is to collect detailed end-use energy consumption data due to technical problems such as faulty sub-meters, despite the project being overseen by the Technology Strategy Board (TSB). What is more, post-occupancy surveys are highly demanding and therefore unlikely to be carried out on a large scale unless initiatives such as the Building Performance Evaluation (BPE) project by TSB continue in the future. Based on this experience, it is possible to anticipate that collecting sufficient data for all UK non-domestic buildings would be extremely challenging and costly in the current state of knowledge.

The introduction of hybrid approaches would also increase the complexity of the process through which the operational energy efficiency of buildings is benchmarked. Unlike the simple top-down approach which requires inferences to be made from a sample distribution as demonstrated in Chapter 6, these complex methods will require time and resources in order to develop and validate the underlying models before they are implemented for benchmarking purposes. To carry out such procedures on a regular basis for all building types however would require considerable time and resources that would result in increased operation costs.

To summarise, it is clear that adopting hybrid approaches for benchmarking the UK non-domestic stock in the short-term is likely to be difficult and costly. Without adopting a hybrid approach however, it is also likely that the benchmarking practice in the UK will continue to lack robustness in assessing operational energy efficiency. As demonstrated by the US ENERGY STAR scheme, these advanced approaches are likely to become feasible once a robust framework is established. It is therefore clear that there is a need to develop long-term plans to establish a policy framework that would allow hybrid approaches to be adopted, if benchmarking practices in the UK are to become more robust in the future.

9.4 Changes in the pattern of energy use over time

Analyses of the empirical energy performance data from the DEC scheme and the case studies provided unprecedented opportunities to assess the latest patterns of energy use in public sector non-domestic buildings. The analyses of the latest DEC data (Chapter 5) showed that the levels of energy use in various public buildings were considerably different from the energy benchmarks in CIBSE *TM46*. Buildings under a majority of the benchmark categories tended to be more intensive in electrical EUI and less intensive in fossil-thermal EUI relative to the *TM46* benchmarks, which suggested that findings from the previous review of DECs by Bruhns et al. (2011) remain true. It was also found that the deviations were generally greater than 10% from the benchmarks in the majority of benchmark categories, indicating that the benchmarks were no longer representative of the latest patterns of energy use in the stock.

The longitudinal study of the energy performance of buildings from 2009 to 2011 suggested that these deviations were likely to have occurred due to continuing changes in patterns of energy use (Figure 5.13 and Figure 5.14). Similar patterns were found when the energy performance of schools was analysed separately in more detail in Chapter 6. Both primary and secondary schools were found to have higher electrical and lower fossil-thermal EUIs in relation to the *TM46* benchmarks, and such tendencies were becoming more extreme. Comparisons of the latest performance figures of schools with historical benchmarks also showed that similar trends are likely to have existed for over a decade (Table 6.4 and Table 6.5). A detailed analysis of the electrical EUI of modern secondary schools showed that provision of ICT equipment had gradually increased over the years, which suggested that increased uptake of ICT equipment is likely to have contributed to increases in electrical EUI (Figure 8.14). Similar findings from studies by Godoy-Shimizu et al. (2011) and Jones (2014) not only raised confidence about the reality of the trends observed in the current study but also the possibility of finding similar trends in other sectors and countries. These findings indicated that the patterns of energy use in schools continue to change in relation to developments in technology (e.g. fixed building services and end-user equipment such as ICT), and other unknown factors, and that the representativeness of energy benchmarks is influenced by these changes.

This brings the focus to the static nature of the current benchmarks in CIBSE *TM46*. Since the implementation of the DEC scheme in 2008, these benchmarks have remained untouched despite initial plans to review and update them in the light of the first years' DECs (Bruhns et al. 2011). What is worse is that these benchmarks were based mostly data that were collected around the 1990s and were already old (CIBSE 2008). Consequently, these uncertainties have led private organisations to launch initiatives that are aimed at developing benchmarks that are up-to-date. Julie's Bicycle[31] for example is a private organisation that has been formed to support the development of benchmarks for entertainment buildings in the creative industry. Although such initiatives are positive movements for the general improvement of energy efficiency of non-domestic buildings, particularly those in the private sector which are currently not required to lodge DECs, it is clear that the *TM46* benchmarks are losing credibility.

The findings therefore clearly show that there is a need to explore ways to keep the benchmarks up-to-date, if the DEC scheme is to play a key role in improving the energy performance of the UK non-domestic stock. One such way would be to create a framework to update the benchmarks at regular intervals. An example of a well-maintained framework is the US ENERGY STAR scheme. The benchmarks that underpin the scheme are derived from the Commercial Building Energy Consumption Survey (CBECS). The survey, which was initiated in the 1970's, has been carried out every 3 to 4 years with the latest round starting in 2013 (Energy Information Administration (EIA) n.d.). Consequently, the benchmarks are refreshed after each cycle to reflect the latest trends in the energy performance of the stock.

Applying a similar approach to the DEC scheme may be beneficial but may also introduce complications. The positive aspect of regularly updating energy benchmarks is they will be more relevant to how energy is used in the stock, which can also maintain credibility with the building operators. Complications arise however, due to the ways in which energy performance is assessed under the current scheme. As described in Chapter 2, a key feature of the certificate is a bar chart illustrating historical changes in the DEC rating over the previous three years. As with energy certification systems for home appliances such as fridges, this

[31] For Julie's Bicycle, See: http://www.juliesbicycle.com/

means that incentives to improve operational energy efficiency comes not only from achieving high grades that demonstrate efficient operation but also from improving upon previous years, which can have a positive effect on the reputations of organisations. Making such improvements visible would however require the underlying benchmarks to remain fixed over a period of time, as frequent updating of energy benchmarks would ‘move the goal posts’. This would make it more difficult for building operators to achieve better grades and, as a consequence, would be likely to reduce their motivation. As proposed by Bruhns et al. (2011) in their consideration of the mechanism of the DEC scheme, three to five years is likely to be a reasonable frequency for carrying out such revisions. Considering however that there would be greater changes in trends over longer periods, three years would be preferable.

More generally however, the current study has shown that a more dynamic approach is required to provide top-down benchmarks that represent the latest trends in the energy performance of the stock. This is because considerable change in the patterns of energy use, and the factors that contribute towards demand, can take place within a three-year period. These changes could result from phenomena as small as increased adoption of ICT equipment uses in schools (Figure 8.14) or from those as large as the recent economic recession that could have implications on the energy demand of an entire sector in a very short period of time. It is therefore possible to anticipate a framework that is more flexible than the current best practice so that benchmarks depict the latest patterns of energy use at any given time. The possibilities and benefits of flexible benchmarks can be seen in existing frameworks such as Carbon Buzz, which was launched in 2013. The strength of the platform comes from the web-based configuration which can be navigated by users to acquire various types of information from the underlying database. The link between the web platform and the underlying database means that benchmarks which reflect the latest patterns of energy use in buildings in the database can be promptly derived. Moreover, developments in automated meter-reading technologies, recent changes in Building Regulations for mandatory installation of sub-meters, and the integration of public and private databases such as shown by the NEED project all point towards possibilities for developing a more flexible and dynamic benchmarking system (DECC 2013b).

9.5 Appropriate grouping of buildings

Grouping buildings into appropriate classifications plays an important role in ensuring that the energy performance of various types of non-domestic buildings is compared against benchmarks that are representative of buildings with similar demands for energy. The processes of preparing and analysing data in the present study showed that there were shortcomings associated with the activity classification system of *TM46*.

Assessment of the latest DEC records in Chapter 5 revealed large variations in operational ratings, which were in most cases heavily positively skewed by small numbers of energy-intensive buildings (Section 5.5). A closer analyses of these buildings revealed that their activity type, hence the demand for energy, differed considerably from other buildings under the same benchmark category. A building that was extremely energy-intensive under the 'Workshop' category for example was identified as a crematorium. The range of building types that is allocated to the benchmark category however raised uncertainties as to whether or not this comparison was relevant. This was due to the fact that the benchmark category comprises a variety of building types such as garages or communications facilities that are highly likely to have greatly differing demands for energy from a crematorium. These cases highlighted that there are numerous cases where building types are inappropriately allocated to benchmark categories which do not reflect their intrinsic energy demand.

The process of extracting DEC records of primary and secondary schools also found evidences of misclassification of buildings. Under the 'Schools and seasonal public buildings' category numerous building types were found such as 'speedways' or 'day centres' that were neither 'schools', 'public' nor 'seasonal'. These are very different types of activities which should not belong under the same benchmark category. Benchmarking the operational energy efficiency of these building types would therefore result in feedback that is irrelevant.

There were also problems associated with building types classified at different levels of specificity. As discussed in Section 6.1, there were several building types relating to schools such as 'School' or 'State school' that are ambiguous and can cause confusion. Similar problems can be found in other benchmark categories. The ‘General office’ category for example not only comprises simple building types such as ‘Offices’ but also building type descriptions that refer to building services such as ‘Offices, cellular, naturally ventilated’. This categorisation was found by Hong & Steadman (2013) not to correspond in many cases to the actual servicing strategy that is separately reported as part of the DEC.

On a broader scale, a review of the *TM46* classification by Hong & Steadman (2013) found that similar issues associated with classifications could be found in other benchmark categories. Currently these issues may not be important, as building types are only intended to guide the DEC assessors in allocating their buildings to the correct energy benchmarks. These classification issues are critical however when the data collected according to these classifications is to be used for assessing and developing future energy benchmarks. As it was shown in Table 6.1 for example, there were 755 records that were discarded from the analyses of schools due to the ambiguity caused by the inappropriate levels of specificity of building types. As shown from the boot strapping analysis (Figure 6.10), this is a large sample size that could otherwise improve the reliability of energy benchmarks.

In the previous review of DEC records on the other hand, Bruhns et al. (2011) explained that it was anticipated that some building types might come to justify the use of separate benchmarks. Due to limitations in data and time, the review was not however able to validate and justify introducing new benchmarks. Under the current classification, primary and secondary schools are allocated to the ‘Schools and seasonal public buildings’ category, which means that the energy performance of these types of school are compared to the same benchmark. The comparison of the latest energy performance of primary and secondary schools however, showed that secondary schools were significantly more intensive in electricity use than primary schools (Figure 6.2). This meant that secondary schools are more likely to appear less energy-efficient, irrespective of their levels of operational efficiency, due to their intrinsically higher demands for electricity. What is interesting is the fact that historical benchmarks such as those presented in *Energy Consumption Guide 73* and CIBSE *Guide F* previously separated primary and secondary schools (BRECSU 1996b; CIBSE 2012). It is therefore evident in the cases of schools that the aggregation of the two building types into the single activity type 'schools' was not specific enough, and that the existing classification should be revised into two categories to improve the robustness of the scheme.

As with schools, CIBSE *Guide F* provides energy benchmarks for numerous building types at finer levels of aggregation than *TM46*, which suggests that similar approaches could be applied for wider range of building types. Taking fire stations and police stations for example, these building types currently belong to the 'Emergency service' *TM46* benchmark category. Under the public buildings category in Table 20.1 of *Guide F* however, energy benchmarks for fire stations and police stations show 'typical' fossil-thermal EUIs of 385 kWh/m^2 and 295 kWh/m^2 respectively, which are significantly different. Similar differences can also be found in Northern Ireland (Table 20.4 CIBSE *Guide F*). Although they remain to be tested, these noticeable differences suggest possibilities for finding significant differences that could lead to separate benchmarks being established for these building types.

The analyses of the patterns of energy use in electrically-heated buildings also suggested that there are cases for providing separate benchmarks for these buildings. Comparisons of the energy performance between buildings that use electricity as the main heating fuel and more conventional buildings that use fossil-thermal energy for heating in Chapter 5 showed that there were distinct differences in the patterns of energy use across numerous benchmark categories (Table 5.9). Although the combined carbon emissions may not differ in many categories, the fact that their demand for energy could differ due to uses of electrical heaters rather than conventional gas boilers suggest that these buildings deserve benchmarks on their own merit. Similar distinctions have been made in the work by Jones et al. (2000) and Jones (2014) where separate benchmarks are proposed for public buildings in Northern Ireland.

Overall, it is clear that there are issues associated with the current classification system of *TM46* that make it inappropriate not only for buildings that currently require DECs but also for rest of the non-domestic buildings. The issues of misclassification and confusing levels of specificity, and the need to assess and refine the benchmark categories for schools and electrically-heated buildings from this study, suggest that there is a need to re-examine the adequacy of the whole classification system of benchmark categories and the associated building type classifications.

9.6 Provision of adequate data

In the UK, it is only in recent years that the energy performance of such large numbers of schools has become available for benchmarking purposes. This is due to the implementation of the DEC scheme, which enforced the monitoring of the actual energy performance of non-domestic buildings and established a centralised database to collect the data in a systematic manner. The accumulation of the metered energy consumption data from various public sector buildings on an annual basis means that the opportunities to derive energy benchmarks that are representative of the stock have been greatly improved. Despite the improvements however, this research found that there are limitations in policies and frameworks to provide sufficient data to implement top-down or hybrid approaches and to robustly benchmark the operational energy efficiency for the UK non-domestic stock.

The analyses of DECs in Chapter 5 showed there were small sample sizes in numerous benchmark categories, highlighting the difficulties in using DECs to derive reliable benchmarks even for public sector buildings. The difficulty is exacerbated when considering buildings in the private sector whose carbon emissions account for approximately 60% of total emissions of the non-domestic stock (Carbon Trust 2009). The fact that these buildings are currently not mandated to lodge DECs means that acquiring sufficient data for benchmarking private sector buildings will be even more challenging. In addition to the limited coverage, the floor area threshold for DECs also poses difficulties. As described in Chapters 5 and 7, most of the DEC records that were assessed in the study were greater than 1,000m^2 due to the current threshold. This means that data accumulated through the DEC scheme currently does not represent buildings smaller than the threshold. The recent introduction of a lower threshold of 500m^2 through the recast of the EPBD in 2014 is a positive change that would certainly improve the coverage of the scheme (Department for Communities and Local Government (DCLG) 2012a). A substantial flaw of the new threshold however is the fact that DECs for buildings smaller than 1,000m^2 would be valid for 10 years rather than 12 months. This means that data for smaller buildings will be updated only at 10-year intervals, during which patterns of energy use would have changed considerably.

An obvious way to tackle this challenge would be to make amendments to the current DEC framework so that the coverage is extend to the private sector and the validation period of DECs for smaller buildings is aligned to 12 months. The benefits of extending the scheme across the non-domestic buildings are immense. First, the extended scheme would provide the necessary framework to acquire data from a wider range of building types. The comprehensive coverage of such framework would allow the reliability of existing benchmarks to be assessed and, reliable and representative benchmarks derived when required. Moreover, the mandatory nature of the scheme would also ensure that sufficient data is collected annually from across the non-domestic stock as long as compliance with the scheme is enforced rigorously. This comprehensive data on energy performance could also aid policy makers in assessing and developing strategies for the future. The challenge however lies with the fact that there is currently insufficient evidence to claim confidence for benchmarks for activities that are likely to be found in the private sector (e.g retail, hotels).

An alternative solution to the lack of data would be to utilise data from numerous initiatives that have the potential to complement the DEC scheme without having to extend its coverage. The Carbon Reduction Commitment (CRC) energy efficiency scheme, which requires organisations in both the public and private sectors to report their annual carbon emissions might be considered for acquiring data on private sector buildings. The CRC is however currently targeted at large organisations that use more than 6,000MWh of electricity per year, which means it is unlikely to be helpful for deriving benchmarks that represent the wide range of buildings in the stock (Carbon Trust 2014). The Building Energy Efficiency Survey (BEES), the National Energy Efficiency Data framework (NEED), and the non-domestic component of NEED (ND-NEED), which are all being developed by the Department for Energy and Climate Change (DECC 2013a; DECC 2013b; DECC 2014) on the other hand, are examples of government initiated projects that aim to acquire reliable and comprehensive data on the energy performance of building across the entire non-domestic stock. It would be possible to integrate the data from databases that are developed under initiatives such as Julie's Bicycle or CarbonBuzz. There are also databases managed by organisations such as the Better Buildings Partnership that collect and analyse the energy performance data from properties managed by companies such as British Land. A key challenge in utilising data from these diverse range of sources however is the compatibility of classifications and measurements with other databases.

Historically, most classification systems used for benchmarking purposes have been based on the types of activities that take place in buildings. These classifications also use the building envelope as a boundary for evaluating the energy performance of buildings. Such a method of classification is ideal for benchmarking operational energy efficiency, as the demands for energy are determined on a building level based on complex interactions between the surrounding environment, the building fabric, and the occupants (Chapters 7 and 8).

In Chapter 5 however, difficulties in comparing the floor area statistics from DECs with those from the non-domestic building stock database (NDBS) were raised due to differences in classification systems. Benchmark categories such as 'General office' for example comprise a wide range of office types from law courts to central government offices. It was therefore difficult to directly compare the floor area statistics from DECs based on benchmark categories. It could be argued that the building type classification can be used instead to improve compatibility. As discussed earlier however, issues associated with levels of specificity and aggregation of building type classifications make this difficult. Moreover, the list of building types under the DEC scheme currently does not provide a sufficient range of building types to cover buildings in a number of economic sectors such as manufacturing and warehouses (Hong & Steadman 2013). Difficulties were also raised from the differences in the basic spatial units in each case (Section 3.5.1). The boundary of an entity in the NDBS is defined as a premise or hereditament rather than a building (Section 3.5.1). Comparing statistics for buildings to those for premises, which could be located over a floor, a building, or in multiple buildings, was therefore not only difficult to reconcile but also irrelevant.

Consequently, it is evident that although the current activity classification provides an adequate basis for benchmarking purposes, it may not be fit for acquiring and deriving benchmarks for the entire UK non-domestic building stock. It is also clear that there is a need to explore ways in which compatibility with other databases could be improved, particularly those that have the potential to provide data at the national level in the future. The project that sheds most light on linking building level data with premises is work on the 3D stock model by the UCL Energy Institute (2014). The project is currently being carried out with an aim to automate the process of bringing together building level data with premise data, which would result in a database of a 3D model of floor space that contains information on both energy use and building form and its attributes. A pilot study currently focusing on non-domestic buildings in Camden, London, United Kingdom was found to be a success, and there are plans to test the methodology on other regions (Evans et al. 2014).

Overall, it is clear that the current mandatory data-collection framework of the DEC scheme provides an invaluable basis for developing reliable benchmarks for UK non-domestic buildings. As it stands however, the scheme was found to provide insufficient coverage for assessing and deriving reliable energy benchmarks for buildings in the public sector let alone across the non-domestic stock as a whole. It is also clear that there is a need to explore the possibilities for harnessing the data from a diverse range of databases.

9.7 Recommendations for future work by CIBSE

Discussion of the findings from the current study has shown that the current DEC scheme lacks robustness for benchmarking the operational energy performance of buildings across the non-domestic stock. Moreover, it was evident that there is a need to revise the underlying framework to improve and sustain the effectiveness of the benchmarking in the future. Based on the outcome of the discussion, recommendations are made to CIBSE for achieving a benchmarking system that is robust and sustainable for the entire UK non-domestic stock.

9.7.1 Context-driven benchmarking

Positive aspects of using the current top-down approach for deriving benchmarks were identified during the discussion. The strength which was in its simplicity was however also found to be its weakness due to insufficient means for taking into account the variation of intrinsic features that influence the demand for energy in buildings.

In the light of these findings, CIBSE should consider adopting hybrid benchmarking approaches that would allow evaluation of operational energy efficiencies that are bespoke to the circumstances of individual buildings. As discussed, there are challenges for adopting a more complex approach. There is also a gap in knowledge about the feasibility of adopting such methods in practice within the existing context. A sensible step would therefore be to carry out further research to improve the understanding of the cost implications.

The project should aim to develop a working platform that can be used for benchmarking the operational energy efficiency of a building type. As part of the process, a scoping study would be carried out on the methods, policies and sources of data. Analysing the process of developing such a platform would allow CIBSE to develop a better understanding of the benefits and barriers. Findings from the project would also assist in determining the feasibility of adopting such an approach in the future, and in planning future strategies.

9.7.2 A dynamic and sustainable framework

One of the key findings from the current study was that the patterns of energy use in buildings continue to change over time and that statistical benchmarks are bound to become outdated sooner or later. This means that there is a need to establish a framework to allow benchmarks to be kept up-to-date, and to continue to carry out such a process.

The short-term objective should be to update current energy benchmarks to reflect the latest patterns of energy use as soon as possible. Considering that there is sufficient data accumulated in the central register over the past five years, revising the benchmarks at least for public sector buildings would be a reasonably simple task. For benchmark categories that do not have sufficient sample sizes (< 200) to derive reliable benchmarks, other databases should be explored and consulted to ensure that the revised benchmarks are reliable. In the instances where such option is not feasible, building type categories with similar demand for energy could be amalgamated to achieve larger sample sizes. Moreover, information about the underlying sample and methods should be made transparent for improved clarity and credibility of the DEC scheme.

In parallel, it is also recommended that the interval at which the benchmarks are updated is established as soon as possible. As the study showed, patterns of energy use in buildings continue to change over time. At present this means that the extensive consulting work that is occasionally carried out merely to 'patch' the outdated benchmarks not only incurs considerable cost but also becomes obsolete rather quickly in the following years.

A substantial proportion of these problems could be resolved by utilising the existing Carbon Buzz platform for maintaining the DEC data and updating the *TM46* benchmarks. The platform is embedded with algorithms that allow DEC data from underlying databases to be extracted and analysed instantly without requiring much human involvement. This means that the financial burden associated with involving consultants for updating the benchmarks would be considerably reduced or even avoided. Moreover, benchmarks that relate to the latest patterns of energy use could be produced based on the latest set of DEC records when requested without waiting for the *TM46* benchmarks to be updated.

To utilise the platform however would require CIBSE to explore the possibility of establishing a link between the central register and the Carbon Buzz platform. Establishing a secure and private structure and protocols to manage the DEC data and the benchmarks separately from the current public platform would also need to be explored.

9.7.3 Refinement of the classification system

The activity classification system is perhaps the aspect of the DEC scheme that requires the most attention. This study has identified numerous issues associated with classification of buildings in the current scheme and shown that there is a need for the classification to become more flexible for it to remain effective in the future.

CIBSE should determine whether the current level of specificity of benchmark categories is sufficient for the building types. Taking the benchmark category ‘Schools and seasonal public buildings’ for example, separate benchmarks should be provided for primary and secondary school building types. The method of hypothesis tests could be used to identify further building types that deserve their own benchmarks. A sample size of 200 could be used as a basis to ensure that these separate benchmarks are reliable representations of the stock.

Corrections should also be made to relocate the building types that currently belong to the wrong benchmark category. The relocation of building types should be based on empirical evidence to ensure that the buildings with similar demand for energy are grouped together. There is also a need to revise building types that are included for no apparent reason and only cause confusion. Numerous building types allowed presently for primary and secondary schools for instance, should be condensed into four categories: ‘State primary school’, ‘Private primary school’, ‘State secondary school’, and ‘Private secondary school’. Hong & Steadman (2013) discuss how other similar issues may be tackled in more detail.

Apart from the short-term objectives, CIBSE should carry out studies on implications that future changes in policies or legislation may have for the current benchmarking system, and develop strategies in preparation. This could be done by carrying out a scoping study with the aim of taking an overview of existing classifications for the private sector in comparison with the current activity classification system. Such a study would also be useful in highlighting and preparing the data that would be needed to prepare energy benchmarks for these building types. In addition, CIBSE should also explore possibilities for linking the activity classification with other more comprehensive classifications that underpin national databases such as NEED. Making the classifications compatible with one another would not only allow initial energy benchmarks for the private sector to be developed based on ND-NEED but also allow DECC to utilise the data from DECs in return for creating an evidence base for their policies.

9.7.4 Reassessment of the current adjustment procedures

CIBSE should revise the definitions and specifications of the current set of adjustment procedures as part of the broader revision of the DEC framework.

The current definition of ‘standard’ occupancy hours should be examined to assess whether what was previously deemed to be typical remains applicable. The mechanism underpinning how extended hours of occupancy are counted should also be assessed and validated. Under the current method, a building is deemed occupied if there is more than 25% of the nominal maximum occupancy. The implications for energy consumption between a building that is occupied by 25% of the staff and 50% or even 80% could be very different due to differences in use of equipment or fixed building services such as computers or hot water use that depend more on occupants than floor area. It would therefore be sensible to seek ways to adjust the benchmarks proportionally to the occupant density.

The proportion of the fossil-thermal energy use pro-rated to account for regional and seasonal variation in weather conditions should be revised. Although the figure remains to be validated on a larger and representative sample, the figure of 55% was found to be very low compared to what was found to be on average 80% in modern secondary schools. Such revision would require surveys of existing data on the end-use consumption of both primary and secondary schools. Currently however there may be difficulties in acquiring data to provide sufficient evidence for the stock.

9.7.5 Amendments to the DEC framework

The study has shown that one of the most effective ways to improve the robustness of the DEC scheme would be to amend the current framework, which is currently limited to the public sector and for an unreasonably long renewal period for smaller buildings. CIBSE should therefore continue to make calls for extending the DEC scheme to the private sector, and aspire to revise the validation period of DECs for buildings that are smaller than 1,000m^2 from the current 10 years down to 12 months.

9.7.6 Strategic framework for the future

In this research, it was found that multivariable methods for benchmarking provide ways to assess and identify key parameters that can improve the comparability of benchmarking for each building type. In addition, individual end-use consumption levels were found to be correlated with different intrinsic features that were more relevant in the context of building physics. Based on these findings, it is possible to anticipate an approach where a hybrid approach is adopted for deriving end-use energy benchmarks. Such an approach would allow benchmarking to provide deeper insight into how efficient each system is being used, which would benefit the building operators in identifying the causes of inefficiency and setting directions to improve their operational energy efficiency. The correlations between intrinsic features and individual end uses would also allow end-use energy benchmarks to be normalised based on a more robust set of parameters.

In the current state of affairs, acquiring sufficient data at such high levels of granularity is likely to be extremely challenging as discussed earlier. The introduction of requirements for energy metering of end-use consumption in the 2010 version of approved documents L2A and L2B of the Building Regulations for new and existing non-domestic buildings however offers a future where such data may become widely available (HM Government 2010b; HM Government 2010c).

Chapter 10 Conclusion

This chapter provides a summary of the research by describing its aims, methodology and the key findings which were discussed in the previous chapter. The contribution to existing knowledge, suggestions for further work, and research limitations are described.

10.1 Conclusions of the research

This research aimed to explore ways in which the operational energy efficiency of UK non-domestic buildings could be benchmarked in a robust manner. The main objectives were to improve the understanding of the latest patterns of energy use in non-domestic buildings and acquire a deeper insight into factors that influence the demand for energy. The research was designed in several stages to acquire a holistic view of patterns of energy use and determinants of energy demand. Initially, the latest DEC data were analysed to assess the latest trends in energy use of public sector buildings and the robustness of the *TM46* energy benchmarks. The following sections involved a case study of English schools, which was carried out in three stages involving analyses of data of varying granularity.

Key findings from the study are summarised below:

- The energy benchmarks that underpin the DEC scheme are no longer representative of the stock, hence inadequate for benchmarking the operational energy efficiency of UK non-domestic buildings. Continued changes in patterns of energy use in buildings owing to technological changes and the uncertainties associated with varying sample sizes were found to be key factors that influence the robustness of top-down energy benchmarks.
- The current top-down approach for deriving benchmarks was found to be beneficial in providing an opportunity for building operators to put their performances in a broader context. The method was relatively simple, hence did not require substantial resources. Differences in the intrinsic features that are correlated to the patterns of energy use between primary and secondary schools however suggested that hybrid

approaches to benchmarking would need to be adopted to improve the comparability of benchmarking in the future.

- Numerous issues that reduce the effectiveness and have the potential to lead to misleading feedback were found in the activity classification system. Misclassifications of buildings that were allocated to benchmark categories that have building types with similar demand for energy were identified. The building type classifications were riddled with confusing categories that were deemed to hinder the potential for utilising the DEC data for developing future energy benchmarks.
- Statistically significant relationships were found between various intrinsic building and operational characteristics of English schools and their energy performance. Multiple regression analyses showed that pupil density and surface-to-volume ratio were the most influential characteristics for the electrical and fossil-thermal EUI of primary schools respectively. For secondary schools, the presence of external shading on the western façade and pupil density were found have the strongest correlations with electrical and fossil-thermal EUI. Exploratory analyses also revealed previously unexplored correlations such as between number of meals served and catering energy consumption.
- There was a general lack of data to maintain and develop reliable energy benchmarks for buildings across the non-domestic stock. The data accumulated under the current DEC framework was found to be inadequate for deriving benchmarks for the entire UK non-domestic stock. In addition, the current 10 year validity of DECs for buildings under 1,000m^2 meant that benchmarks derived from DECs would not be representative of the patterns of energy use of buildings of smaller sizes.

This research clearly showed that there were shortcomings in the current approach to benchmarking the operational energy efficiency of the non-domestic stock in the UK. The research therefore concludes that the current DEC scheme does not provide sufficient means to acquire a precise evaluation of the operational energy efficiency for public sector buildings in the UK. Moreover, it concludes that a holistic revision on how benchmarks are derived and maintained and buildings are classified are central to achieving a benchmarking system that is robust and sustainable for the future. In addition, the move towards context-driven and dynamic benchmarking and the development of a national database, that provides an evidence base for UK non-domestic buildings not just for benchmarking but also for policy development, were identified as key elements in achieving these goals.

10.2 Contribution to existing knowledge

Below are contributions to knowledge in the field stemming from this research:

1) A comprehensive analysis of the patterns of energy use of primary and secondary schools in England in this study has identified and provided empirical evidence in relation to the parameters that are required to achieve a robust and sustainable benchmarking system.

2) The benefits and limitations of current benchmarking practice and the policy framework in the UK were identified, and proposals were made for directions that CIBSE should take in order to achieve a more effective benchmarking system in the future.

3) The research has explored and provided details of a framework through which the influences of previously unexplored intrinsic features of buildings such as building shape or activity specialism on the patterns of energy use can be collected and explored.

10.3 Research limitations

As described in Section 4.2.4, this research was carried out under a set of constraints in order to address the proposed research questions within the duration of the research programme. Consequently, there were limitations in effectively addressing the research questions within the context of the entire non-domestic stock.

Below are the key limitations:

- Using empirical data of varying granularity to assess the latest patterns of energy use and the correlations between intrinsic features and the energy performance were found to be highly effective in acquiring a holistic view of how energy is used in buildings. Limitations in availability of data of finer granularity and the coverage which was limited to schools however, allowed correlations to be explored but the findings could not be generalised across the non-domestic stock.
- There were assumptions that were made in measuring the built forms of schools in Chapter 7, particularly the heights of buildings, which may have introduced elements of uncertainty to the analyses.
- Due to the empirical nature of this research, methods that are used elsewhere for deriving benchmarks, particularly bottom-up approaches, were not explored to gain insights into their benefits and limitations on benchmarking the operational energy efficiency of buildings. Similarly, methods of benchmarking that are used in other fields of studies such as health sciences or economics were not explored in this research.
- Closer interpretation of the trends in energy use in public sector buildings was not possible due to insufficient information on finer details of their operations.

10.4 Suggestions for further work

Although the original research questions were addressed and answered, further research topics that could deepen the knowledge of benchmarking the energy performance of buildings were discovered.

Below are summaries of these topics:

- ***Development of a dynamic and context driven benchmarking system:*** the next logical step stemming from this research would be acquiring insights into the benefits and limitations of a working system to provide energy benchmarks that depict the latest trends of energy performance of the stock at any given time, and are able to take into consideration the context of individual buildings.

- ***Validation of the measurements of built form using empirical data:*** assessment and validation of the accuracy of the measurements of built form that were taken in this study would allow the method to be developed and adopted for wider use in research and industry for surveying building characteristics.
- ***Assessing correlations between a comprehensive range of intrinsic features and patterns of energy use***: The significance of the correlations found in this study remains to be assessed in conjunction with other parameters such as those demonstrated in Chapter 8. The significance of the intrinsic features that were identified in this study remains to be assessed in relation to those that have not been tested.
- ***Exploration of methods used in other fields of study:*** The methods that are used in other fields of study such as health sciences or business studies, and their feasibility for use in the built environment remains unknown. Insights acquired from such studies may provide ideas for revolutionising the way operational energy efficiency of non-domestic buildings is benchmarked.
- ***Scoping study to explore the possibilities of reconciling TM46 classifications with VOA classifications:*** establishing the link between the two classifications is vital for acquiring sufficient data on the patterns of energy use for private sector buildings. Compatibility with ND-NEED would be critical for deriving benchmarks that are representative of the stock for private sector buildings, until sufficient records are accumulated through the DEC scheme once it is extended to the private sector.

References

Action Energy, 2003. *Energy Consumption Guide 19: Energy use in offices*. Department of the Environment, Transport & the Regions. London, UK.

Bannister, P., 2009. Why Good Buildings Go Bad, While Some Are Just Born That Way. *Ecolibrium, the Journal of the Australian Institute of Refrigeration, AC and Heating*, pp.24–32.

Better Buildings Partnership (BBP), 2012. *BBP Position Paper: Voluntary DECs and Landlord Energy Certificates*. London, UK.

Birt, B. & Newshame, G.R., 2009. Post-occupancy evaluation of energy and indoor environment quality in green buildings : a review. *3rd International Conference on Smart and Sustainable Built Environments*. Delft, the Netherlands, 15-19 June 2009.

Bordass, B., Cohen, R., et al., 2001. Assessing building performance in use 3: energy performance of the Probe buildings. *Building Research & Information*, 29(2), pp.114–128.

Bordass, B., 2001. *Flying blind: Things you wanted to know about energy in commercial buildings but were afraid to ask*. Available at: http://www.usablebuildings.co.uk/ [Accessed 4 May, 2011].

Bordass, B., 2005. *Onto the Radar : How energy performance certification and benchmarking might work for nondomestic buildings in operation, using actual energy consumption*. Available at: http://www.usablebuildings.co.uk/ [Accessed 4 May, 2011].

Bordass, B. et al., 2014. Tailored benchmarking and its application to design and actual energy use. *CIBSE-ASHRAE Technical Symposium*. Dublin, Ireland, 3-4 April 2014.

Bordass, B., Cohen, R. & Field, J., 2004. Energy performance of non-domestic buildings: closing the credibility gap. *Building Performance Congress*. Frankfurt, 19-24 April 2004.

Bordass, B. & Field, J., 2007. *Scoping Study: Energy and CO_2 emissions benchmarks for non-domestic buildings*. [Unpublished document], London.

Bordass, B., Leaman, A. & Ruyssevelt, P., 2001. Assessing building performance in use 5: conclusions and implications. *Building Research & Information*, 29(2), pp.144–157.

Bozdogan, H., 1987. Model Selection and Akaike's Information Criterion (AIC): The General Theory and Its Analytical Extensions. *Psychometrika*, 52(3), pp.345–370.

BP, 2012. *BP Energy Outlook 2030*, London. Available at: http://www.bp.com/sectiongenericarticle800.do?categoryId=9037134&contentId=7068677 [Accessed 13 February, 2012].

BRECSU, 1994. *Good housekeeping in swimming pools - a guide for centre managers*, Watford, UK: Building Research Energy Conservation Support Unit.

Bruhns, H., 2000. Property taxation data for nondomestic buildings in England and Wales. *Environment and Planning B: Planning and Design*, 27(1), pp.33–49.

Bruhns, H., Steadman, P., Herring, H., et al., 2000. Types, numbers, and floor areas of nondomestic premises in England and Wales, classified by activity. *Environment and Planning B*, 27, pp.641–666.

Bruhns, H., Jones, P. & Bordass, B., 2011. Benchmarking for Display Energy Certificates. *CIBSE Journal*, May, pp.28–31.

Bruhns, H., Jones, P. & Cohen, R., 2011. *CIBSE Review of Energy Benchmarks for Display Energy Certificates - Analysis of DEC results to date*. Available at: http://www.cibse.org/content/Technical_Resources/Technical_Reports/Technical Report_CIBSE Report on 45000 DECs.pdf [Accessed June 11, 2011].

Bruhns, H., Steadman, P. & Herring, H., 2000. A database for modeling energy use in the non-domestic building stock of England and Wales. *Applied Energy*, 66(4), pp.277–297. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0306261900000180.

Building Construction Authority (BCA), 2014. *BCA GREEN MARK*. Available at: http://www.bca.gov.sg/greenmark/green_mark_buildings.html [Accessed June 23, 2014].

Building Research Establishment (BRE), 2014. BRE Group: *SBEM: Simplified Building Energy Model*. Available at: http://www.bre.co.uk/page.jsp?id=706 [Accessed June 24, 2014].

Bull, J., Gupta, A., Mumovic, D., Kimpian, J., 2014. Life cycle cost and carbon footprint of energy efficient refurbishments to 20th century UK school buildings. *International Journal of Sustainable Built Environment*, 3(1), pp.1–17.

Camp, R.C., 1989. *Benchmarking: The Search for Industry Best Practices That Lead to Superior Performance*. White Plain, NY. Quality Resources.

Carbon Trust, 2009. *Building the future today - Transforming the economic and carbon performance of the buildings we work in (CTC765)*, United Kingdom: Carbon Trust.

Carbon Trust, 2014. *CRC Energy Efficiency Scheme - Carbon Trust*. Available at: http://www.carbontrust.com/resources/guides/carbon-footprinting-and-reporting/crc-carbon-reduction-commitment [Accessed August 13, 2014].

Carbon Trust, 2006. *Energy Saving Fact Sheet* | *The Climate Change Levy (CCL)*. London, UK.

Carbon Trust, 2010. *Hospitals - healthy budgets through energy efficiency*. London, UK.

Carbon Trust, 2012. *Schools sector overview (CTV019): Learning to improve energy efficiency*. Available at: http://www.carbontrust.com/media/39232/ctv019_schools.pdf [Accessed January 17, 2013].

CCC, 2008. *Building a low-carbon economy – the UK's contribution to tackling climate change*, London, UK. Committee on Climate Change.

Chatzidiakou, L. et al., 2014. A Victorian school and a low carbon designed school: comparison of indoor air quality, energy performance, and student health. *Indoor and Built Environment*, 23(3), pp. 417-432.

Chung, W., Hui, Y. & Lam, Y., 2006. Benchmarking the energy efficiency of commercial buildings. *Applied Energy*, 83(1), pp.1–14.

CIBSE, 2003. *CIBSE Briefing 6: The Energy Performance of Buildings Directive*. London, UK: Chartered Institution of Building Services Engineers.

CIBSE, 2011. *CIBSE Briefing The Recast Energy Performance of Buildings Directive* (Article 10), p.16. Available at: http://www.cibse.org/index.cfm?go=page.view&item=721 [Accessed July 3, 2011].

CIBSE, 2012. *CIBSE Guide F: Energy efficiency in buildings*. 3rd edn., London, UK: CIBSE Publications.

CIBSE, 2004. *CIBSE Guide G: Public health engineering*. London, UK: CIBSE Publications.

CIBSE, 2006a. *CIBSE TM22 Energy assessment and reporting method*. London, UK: CIBSE Publications.

CIBSE, 2006b. *CIBSE TM41: Degree-days: theory and application*. London, UK: CIBSE Publications.

CIBSE, 2008. *CIBSE TM46 Energy benchmarks*. London, UK: CIBSE Publications.

CIBSE, 2009. *CIBSE TM47 Operational Ratings and Display Energy Certificates*. London, UK: CIBSE Publications.

CIBSE, 2006c. *Design for improved solar shading control*. London, UK: CIBSE Publications.

Climate Action, 2011. *Climate change*, Available at: http://bookshop.europa.eu/sl/climate-change-pbML3111102/ [Accessed May 12, 2011].

Cohen, J., 1992. Statistical Power Analysis. *Current Directions in Psychological Science*, 1(3), pp.98–101.

Cohen, R. et al., 2001. Assessing building performance in use 1: the Probe process. *Building Research & Information*, 29(2), pp.85–102.

Cohen, R. et al., 2008. *Implementation of EPBD Article 7.3 in Germany and the UK : Comparison of Methodologies and Procedures*. Improving Energy Efficiency in Commercial Buildings (IEECB) conference, 10-11 April, 2008. Frankfurt.

Creswell, J., 2008. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches,* Third Edn. California: SAGE Publications, Inc.

CSO, 1980. *Standard Industrial Classification*. London, UK: HMSO.

Davies, H., 2013. *Tracing the continuing development of Part L*. Available at: http://www.modbs.co.uk/news/fullstory.php/aid/12062/Tracing_the_continuing_development_of_Part_L.html [Accessed September 28, 2013]

DCLG, 2007. *The Energy Performance of Buildings (Certificates and Inspections) (England and Wales) Regulations 2007*. London, UK: HMSO.

DCLG, 2008. *A guide to Display Energy Certificates and advisory reports for public buildings*. Available at: http://www.communities.gov.uk/documents/planningandbuilding/pdf/20.pdf [Accessed May 24, 2011].

DCLG, 2012a. *A guide to display energy certificates and advisory reports for public buildings*. Available at: https://www.gov.uk/government/publications/display-energy-certificates-and-advisory-reports-for-public-buildings [Accessed 9 October 2013].

DCLG, 2012b. *A guide to energy performance certificates for the construction, sale and let of non-dwellings*. Available at: https://www.gov.uk/government/publications/energy-performance-certificates-for-the-construction-sale-and-let-of-non-dwellings--2 [Accessed 15 July 2014].

DECC, *CRC Energy Efficiency Scheme*. Available at: http://www.decc.gov.uk/en/content/cms/emissions/crc_efficiency/crc_efficiency.aspx [Accessed February 13, 2012].

DECC, 2009. *Energy Security : A national challenge in a changing world*. London, UK: Department of Energy Climate Change.

DECC, 2011. *What measures does the Green Deal cover?*. London, UK: Department of Energy Climate Change.

DECC, 2013a. *DECC Non-domestic building energy use project phase I*. Available at: https://www.gov.uk/government/publications/decc-non-domestic-building-energy-use-project-phase-1 [Accessed August 14, 2014]

DECC, 2013b. *National Energy Efficiency Data-Framework (NEED) - GOV.UK*. Available at: https://www.gov.uk/government/collections/national-energy-efficiency-data-need-framework [Accessed August 14, 2014].

DECC, 2014. *The non-domestic National Energy Efficiency Data-Framework (ND-NEED)*. Available at: https://www.gov.uk/government/statistics/the-non-domestic-national-energy-efficiency-data-framework-nd-need [Accessed September 3, 2014].

Demanuele, C., Tweddell, T. & Davies, M., 2010. Bridging the gap between predicted and actual energy performance in schools. *Low Energy Architecture*, (September), pp.1–6.

Department for Business Innovation and Skills (BIS), 2010. *Low Carbon Construction Executive Summary*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/31774/10-1266es-low-carbon-construction-igt-executive-summary.pdf [Accessed August 14, 2011].

Department for Education (DfE), 2013. *Education and Training Statistics for the United Kingdom : 2013*, Available at: https://www.gov.uk/government/publications/education-and-training-statistics-for-the-uk-2013 [Accessed March 22, 2014].

Dooley, K., 2011. Linking energy to people in order to measure and control. *CIBSE Technical Symposium*. 6-7 September, 2011. De Montfort University, Leicester, UK.

Double Glazing Team, 2012. *History of Double Glazing*. Available at: http://www.doubleglazingprices.org.uk/history-of-double-glazing/ [Accessed 16 April, 2012].

Efron, B., 1993. An Introduction to the Bootstrap, London: Chapman & Hall.

EIA, 2011. International Energy Outlook 2011, Available at: http://www.eia.gov/forecasts/ieo/pdf/0484(2011).pdf [Accessed 8 February, 2012].

EIA, *Energy Information Administration (EIA) - Commercial Buildings Energy Consumption Survey (CBECS)*. Available at: http://www.eia.gov/consumption/commercial/ [Accessed June 10, 2012].

Environmental Protection Agency, 2011. *ENERGY STAR ® Performance Ratings Technical Methodology*. Available at:

http://www.energystar.gov/ia/business/evaluate_performance/General_Overview_tech_methodology.pdf [Accessed June 8, 2011].

European Commision, 2010. *The EU climate and energy package*. Available at: http://ec.europa.eu/clima/policies/package/index_en.htm [Accessed 19 December, 2011].

European Commision, 2006. *The European Climate Change Programme*. Available at: http://ec.europa.eu/clima/policies/eccp/index_en.htm [Accessed 11 May, 2011].

European Parliament, 2003. Directive 2002/91/EC of the European Parliament and of the Council. *Official Journal of the European Union*, L001, 4.1.2003, pp. 65-71.

European Parliament, 2010. Directive 2010/31/EU of the European Parliament and of the Council. *Official Journal of the European Union*, L153, 18.6.2010, pp. 13-33.

Evans, S., Liddiard, R. & Steadman, P., 2014. A 3D geometrical model of the non-domestic building stock of England and Wales. *Building Simulation and Optimization 2014 Conference*. London, UK.

Falk, M., 1997. Asymptotic independence of median and MAD. *Statistics & Probability Letters*, 34(4), pp.341–345.

Fausett, L., 1994. *Fundamentals of Neural Networks*. New Jersey: Prentice-Hall.

Federspiel, C., Zhang, Q. & Arens, E., 2002. Model-based benchmarking with application to laboratory buildings. *Energy and Buildings*, 34(2002), pp. 203-214.

Field, A. & Miles, J., 2010. *Discovering Statistics Using SAS*, Sage Publications Ltd.

Filippin, C., 2000. Benchmarking the energy efficiency and greenhouse gases emissions of school buildings in central Argentina. *Building and Environment*, 35(2000), pp.407–414.

Gakovic, B., 2000. Areas and types of glazing and other openings in the nondomestic building stock. *Environment and Planning B: Planning and Design*, 27(5), pp.667–694.

Gardiner, J. & Lane, T., 2013. *Green for Growth. Building Magazine*. Available at: http://www.building.co.uk/story.aspx?storyCode=5048252 [Accessed February 17, 2013].

Global Action Plan, 2006. *UK Schools Carbon Footprint Scoping Study*. Available at: http://www.sd-commission.org.uk/data/files/publications/GAP-Final-Report.pdf [Accessed July 31, 2013].

Godoy-Shimizu, D. et al., 2011. Using Display Energy Certificates to quantify schools energy consumption. *Building Research & Information*, 39(6), pp.37–41.

Hall, L., 2004. *ICT in Schools Survey 2004 Findings from a survey conducted in Spring 2004*. London: HMSO.

Harwood, E., 2010. *England’s schools : history, architecture and adaptation*, Swindon: English Heritage.

Hawkins, D. et al., 2012. Determinants of energy use in UK higher education buildings using statistical and artificial neural network methods. *International Journal of Sustainable Built Environment*, 1(1), pp.50–63.

Hawkins, D.M., 2004. The problem of overfitting. *Journal of chemical information and computer sciences*, 44(1), pp.1–12.

Hernandez, P., Burke, K. & Lewis, J.O., 2008. Development of energy performance benchmarks and building energy ratings for non-domestic buildings: An example for Irish primary schools. *Energy and Buildings*, 40(3), pp.249–254.

Herring, H., Hardcastle, R. & Phillipson, R., 1988. *Energy use and energy efficiency in UK commercial and public buildings up to the year 2000*. Energy Efficiency Office, Department of Energy. London: HMSO.

HM Government, 2007. *The Energy Performance of Buildings (Certificates and Inspections) (England and Wales) Regulations 2007*, Available at: http://www.legislation.gov.uk/uksi/2007/991/contents/made [Accessed 25 May, 2014].

HM Government, 2010a. 2050 Pathways Analysis. Available at: https://www.gov.uk/2050-pathways-analysis [Accessed 19 December, 2011]

HM Government, 2010b. *The Building Regulations 2000 Approved Document L2A: Conservation of fuel and power in new buildings other than dwellings*. London: HM Government.

HM Government, 2010c. *The Building Regulations 2000 Approved Document L2B: Conservation of fuel and power in existing buildings other than dwellings*. London: HM Government.

HM Government, 2011. *The Carbon Plan*, Available at: http://www.decc.gov.uk/en/content/cms/what_we_do/lc_uk/carbon_plan/carbon_plan.aspx.

HM Government, 2012a. *Central Government Property and Land including Welsh Ministers estate. - Datasets* | *data.gov.uk*. Available at: http://data.gov.uk/dataset/epims [Accessed May 13, 2013].

HM Government, 2012b. *The Energy Performance of Buildings (Certificates and Inspections) (England and Wales) (Amendment) Regulations 2012*, http://www.legislation.gov.uk/uksi/2012/809/contents/made [Accessed 25 May, 2014].

Hong, S.-M. et al., 2014. A comparative study of benchmarking approaches for non-domestic buildings: Part 1 – Top-down approach. *International Journal of Sustainable Built Environment*, 2(2), pp.119–130.

Hong, S.-M., Pang, S., et al., 2013. Identifying determinants of energy use of schools in England for benchmarking purposes. *CIBSE Technical Symposium*. Liverpool, UK, 11-12 April 2013.

Hong, S.-M., Paterson, G., et al., 2013. Improved benchmarking comparability for energy consumption in schools. *Building Research & Information*, 42(01), pp.47–61.

Hong, S.-M. & Steadman, P., 2013. *An Analysis of Display Energy Certificates for Public Buildings 2008 to 2012*. Available at: https://www.bartlett.ucl.ac.uk/energy/news/display-energy-certificates [Accessed February 11, 2014].

International Energy Agency (IEA), 2010. *Energy Performance Certification of Buildings*, Available at: http://www.iea.org/publications/freepublications/publication/policy-pathways--energy-performance-certification-of-buildings.html [Accessed 27 June, 2014].

IPCC, 2007. *Climate Change 2007: The Physical Science Basis*. Available at: http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf [Accessed 3 January, 2012].

Isaacs, N., Baird, G. & Donn, M., 1990. Energy Audits and Their Effect on Improving Energy Management. *Building Research and Practice*, 18(5), pp.279–283.

Jones, P. et al., 2000. Energy benchmarks for public sector buildings in Northern Ireland. *Proceedings of CIBSE National Conference*. Dublin. pp. 1–8.

Jones, P.G., 2014. A review of energy benchmarks in the Northern Ireland public estate. *CIBSE-ASHRAE Technical Symposium*. Dublin, Ireland, 3-4 April 2014.

Lee, W., 2008. Benchmarking the energy efficiency of government buildings with data envelopment analysis. *Energy and Buildings*, 40(5), pp.891–895.

Lee, W.-S. & Kung, C.-K., 2011. Using climate classification to evaluate building energy performance. *Energy*, 36(3), pp.1797–1801.

Lee, W.-S. & Lee, K.-P., 2009. Benchmarking the performance of building energy management using data envelopment analysis. *Applied Thermal Engineering*, 29(16), pp.3269–3273.

Liddiard, R., 2008. *A Review of Non-Domestic Energy Benchmarks and Benchmarking Methodologies*. Available at: http://re.jrc.ec.europa.eu/energyefficiency/pdf/IEECB08/IEECB08 proceedings/070_Liddiard_final.pdf [Accessed April 29, 2011].

Longwell, H.J., 2002. The future of the Oil and Gas Industry : Past Approaches, New Challenges. *World Energy*, 5(3), pp.100–104.

Malinowski, E.R., 2009. Determination of rank by median absolute deviation (DRMAD): a simple method for determining the number of principal factors responsible for a data matrix. *Journal of Chemometrics*, 23(1), pp.1–6.

Mathew, P. et al., 2010. Advanced benchmarking for complex building types: laboratories as an exemplar. *Proceedings of the 2010 ACEEE Summer Study on Energy Efficiency in Buildings*. Pacific Grove, CA, pp. 15–20.

Mathew, P. et al., 2004. Rating Energy Efficiency and Sustainability in Laboratories : Results and Lessons from the Labs21 Program Energy Benchmarking. *ACEEE Summer Study of Energy Efficiency in Buildings*. Washington, DC.

Mavrogianni, A., Wilkinson, P., Davies, M., Biddulph, P., Oikonomou, E., 2012. Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings. *Building and Environment*, 55, pp.117–130.

Montgomery, D.C., Peck, E.A. & Vining, G.G., 2012. *Introduction to Linear Regression Analysis* 5th Edn., Hoboken: John Wiley & Sons.

Monts, J. & Blissett, M., 1982. Assessing energy efficiency and energy conservation potential among commercial buildings: A statistical approach. *Energy*, 7(10), pp.861–869.

Mortimer, N.D., Elsayed, M. & Grant, J.F., 2000. Patterns of energy use in nondomestic buildings. *Environment and Planning B: Planning and Design*, 27(5), pp.709–720.

Mumovic, D. & Santamouris, M., 2009. *A Handbook of Sustainable Building Design and Engineering* First Edn., London, UK: Earthscan.

National Environment Agency (NEA), 2008. *Energy Smart Labeling Scheme*. Available at: http://www.nea.gov.sg/cms/ar2008/3-1-4.html?expandable=0 [Accessed June 27, 2012].

Office of Environment and Heritage (OoEH), 2011a. *Fact Sheet 4: Preparing for NABERS office rating applications*. Available at: http://www.nabers.gov.au/public/WebPages/DocumentHandler.ashx?docType=3&id=15&attId=0 [Accessed June 22, 2013].

Office of Environment and Heritage (OoEH), 2011b. *Fact Sheet 5: Preparing for NABERS hotel rating applications*. Available at: http://www.nabers.gov.au/public/WebPages/DocumentHandler.ashx?docType=3&id=16&attId=0 [Accessed June 22, 2013].

Office of Environment and Heritage (OoEH), *An introduction to NABERS*. Available at: http://www.nabers.gov.au/public/WebPages/ContentStandard.aspx?module=10&template=3&include=Intro.htm&side=EventTertiary.htm [Accessed June 22, 2013].

Ofsted, 2011. *ICT in schools 2008–11*. Available at: http://www.ofsted.gov.uk/resources/ict-schools-2008-11 [Accessed 16 February, 2014]

Oxford Dictionaries, *Definition for Benchmark*. Available at: http://oxforddictionaries.com/definition/benchmark [Accessed February 29, 2012].

Pegg, I., 2007. *Assessing the Role of Post-occupancy Evaluation in the Design Environment – A Case Study Approach*. EngD Environmental Technology Dissertation. Brunel University.

Ratti, C., Baker, N. & Steemers, K., 2005. Energy consumption and urban texture. *Energy and Buildings*, 37(7), pp.762–776.

Rickaby, P. & Gorgolewski, M.T., 2000. A classification system for services in nondomestic buildings. *Environment and Planning B: Planning and Design*, 27(5), pp.695–708.

Santamouris, M. et al., 2007. Using intelligent clustering techniques to classify the energy performance of school buildings. *Energy and Buildings*, 39(1), pp.45–51.

SAS Institute Inc., *Introduction to Statistical Modeling with SAS/STAT Software: Least Squares :: SAS/STAT(R) 9.2 User's Guide* Second Edn. Available at: http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_intromod_a0000000342.htm [Accessed April 24, 2014].

SAS Institute Inc., 2014a. *The BOXPLOT Procedure: Styles of Box Plots :: SAS/STAT(R) 9.22 User's Guide*. Available at: http://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#statug_boxplot_sect017.htm#statug.boxplot.schematic [Accessed March 10, 2014].

SAS Institute Inc., 2014b. *Unrestricted Random Sampling :: SAS/STAT(R) 12.1 User's Guide*. Available at: http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_surveyselect_a0000000154.htm [Accessed March 26, 2014].

Sharp, T., 1998. Benchmarking Energy Use in Schools. *ACEEE 1998 Summer Study on Energy Efficiency in Buildings*. Washington, DC: ACEEE, pp. 305–316.

Sharp, T., 1996. Energy benchmarking in commercial office buildings. *Proceedings of the ACEEE 1996 Summer Study on Energy Efficiency in Buildings*. pp. 321–329.

Spyrou, M.S. et al., 2014. An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation. *Energy and Buildings*, 68, pp.172–182.

Steadman, P., Bruhns, H.R., Holtier, S., et al., 2000. A classification of built forms. *Environment and Planning B: Planning and Design*, 27(1), pp.73–91.

Steadman, P., Bruhns, H. & Rickaby, P., 2000. An introduction to the national Non-Domestic Building Stock database. *Environment and Planning B: Planning and Design*, 27(1), pp.3–10.

Steadman, P., Bruhns, H.R. & Gakovic, B., 2000. Inferences about built form, construction, and fabric in the nondomestic building stock of England and Wales. *Environment and Planning B: Planning and Design*, 27(5), pp.733–758.

Steadman, P., 2014. *Building types and built forms*, Leicestershire, UK: Matador

Technology Strategy Board (TSB), *Building Performance Evaluation - innovateuk*. Available at: https://connect.innovateuk.org/web/building-performance-evaluation/ [Accessed November 28, 2013].

Technology Strategy Board (TSB), 2012. *Building Performance Evaluation, Non-Domestic Buildings: Technical Guidance*, Available at: https://connect.innovateuk.org/web/building-performance-evaluation/project-execution-templates [Accessed 28 Nov, 2013].

The UCL Energy Institute, 2014. *Energy use in the UK building stock: new empirically based models*. Available at: http://www.bartlett.ucl.ac.uk/energy/research/themes/buildings/energy-use-in-the-uk-building-stock [Accessed August 14, 2014].

UNFCCC, 2011a. *An introduction to the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol*. Available at: http://unfccc.int/files/press/backgrounders/application/pdf/unfccc_and_kyoto_protocol.pdf [Accessed 14 July, 2011].

UNFCCC, 2011b. *Kyoto Protocol*. Available at: http://unfccc.int/kyoto_protocol/items/2830.php [Accessed 14 July, 2011].

Yalcintas, M., 2006. An energy benchmarking model based on artificial neural network method with a case example for tropical climates. *International Journal of Energy Research*, 30(14), pp.1158–1174.

Yalcintas, M. & Ozturk, U.A., 2007. An energy benchmarking model based on artificial neural network method utilizing US Commercial Buildings Energy Consumption Survey (CBECS) database. *International Journal of Energy Research*, 31(April 2005), pp.412–421.

Yang, L., Lam, J. & Tsang, C., 2008. Energy performance of building envelopes in different climate zones in China. *Applied Energy*, 85(9), pp.800–817.

Zhou, P., Ang, B.W. & Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189(1), pp.1–18.

Appendices

Appendix A - List of variables in the Department for Education data

Appendix A List of variables in the Department for Education data

Table A-A.10.1 Description of variables in the EduBase[32] data

Variable	Description
URN	Unique Reference Number of a school
UKPRN	A reference number issued by the UK Register of Learning Providers (UKRLP)
Description of a school	Details about the head teacher, address, postcodes etc.
Type of establishment	Academy, community school, further education etc.
Establishment status	Open or closed
Open and close date	Dates when a school opened or closed
Phase of education	Primary, secondary etc.
Number of pupils	Number of boys and girls by age group
School capacity	Number of pupils for which the school is organised to make provision
Specialism	Description of the main and secondary specialisms of a school
Free school meal percentage	Number of pupils known to be eligible for and claiming free school meals
Boarders	Boarding school, children's home etc.
Sixth form	Whether or not a school has a sixth form
PFI	Part of a private funding initiative or not
SEN	e.g. ASD - Autistic Spectrum Disorder, SpLD - Specific Learning Difficulty
GOR	Government Office Region
LLSC	The Local Learning and Skills Council
Super output areas	Middle layer SOA (MSOA) and Lower layer SOA (LSOA)

[32] For EduBase, see: http://www.education.gov.uk/edubase/home.xhtml