DECARBONISING THE ENGLISH RESIDENTIAL SECTOR

MODELLING POLICIES, TECHNOLOGIES AND BEHAVIOUR WITHIN A HETEROGENEOUS BUILDING STOCK

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AUTHOR DECLARATIONS

This dissertation is the result of my own work and includes nothing that is the outcome of work done in collaboration except where specifically indicated in the text. Material included in this thesis has also been published within the following journals:

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During the period of registered study in which this thesis was prepared, the author has not been registered for any other academic award or qualification. The material included in this thesis has not been submitted wholly or in part for any award or qualification other than that for which it is now submitted.

This dissertation does not exceed the regulation length, including footnotes, references and appendices.

Scott Kelly
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ABSTRACT

The residential sector in England is often identified as having the largest potential for emissions reduction at some of the lowest costs when compared against other sectors. In spite of this, decarbonisation within the residential sector has not materialised. This thesis explores the complexities of decarbonising the residential sector in England using a whole systems approach. It is only when the interaction between social, psychological, regulatory, technical, material and economic factors are considered together that the behaviour of the system emerges and the relationships between different system components can be explained giving insight into the underlying issues of decarbonisation.

Building regulations, assessments and certification standards are critical for motivating and driving innovation towards decarbonising the building stock. Many existing building performance and evaluation tools are shown to be ineffective and confound different policy objectives. Not only is the existing UK SAP standard shown to be a poor predictor of dwelling level energy demand but it perversely incentivises households to increase CO_2 emissions. At the dwelling level, a structural equation model is developed to quantify direct, indirect and total effects on residential energy demand. Interestingly, building efficiency is shown to have reciprocal causality with a household's propensity to consume energy. That is, dwellings with high-energy efficiency consume less energy, but homes with a propensity to consume more energy are also more likely to have higher energy efficiency.

Internal dwelling temperature is one of the most important parameters for explaining residential energy demand over a heterogeneous building stock. Yet bottom up energy demand models inadequately incorporate internal temperature as a function of human behaviour. A panel model is developed to predict daily mean internal temperatures from individual dwellings. In this model, socio-demographic, behavioural, physical and environmental variables are combined to estimate the daily fluctuations of mean internal temperature demand. The internal temperature prediction model is then incorporated in a bottom-up engineering simulation model. The residential energy demand model is then used to project decarbonisation scenarios to 2050. Under the assumption of consistent energy demand fuel share allocation, modelling results suggest that emissions from the residential sector can be reduced from 125 $MtCO_2$ to 44 $MtCO_2$ after all major energy efficiency measures have been applied, the power sector is decarbonised and all newly constructed dwellings are zero carbon. Meeting future climate change targets will thus not only require extensive energy efficiency upgrades to all existing dwellings but also the complete decarbonisation of end use energy demand. Such a challenge can only be met through the transformation of existing building regulations, models that properly allow for the effects of human behaviour, and flexible policies capable of maximising impact from a heterogeneous residential building stock.

For Nana

"Essentially all models are wrong, but some are useful" – ***George E.P Box***

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NOMENCLATURE

ADEPT	Annual Delivered Energy, Price Temperature model
ANOVA	Analysis of Variance
ASHRAE	American Society for Heating Refrigeration and Air-Conditioning Engineers
BPEC	Building Performance Evaluation and Certification
BRE	Building Research Establishment
BREDEM	Building Research Establishment Domestic Energy Model
CA	Canonical Analysis
CARB-HES	Carbon Home Energy Survey
CCC	Committee for Climate Change
CIBSE	Chartered Institute for Building Services Engineers
$CO_{2(eq)}$	Equivalent CO_2 includes CO_2 and other green house gases
DEA	Domestic Energy Assessor
DECC	Department of Energy and Climate Change
DEFF	Domestic Energy Fact File
DEFRA	Department for Environment, Food and Rural Affairs
DER	Dwelling Emission Rate
DOE	Department Of Environment
ECF	Energy Cost Factor
EHCS	English House Condition Survey
EHS	English Housing Survey
EI	Environmental Impact Rate
EM	Expectation Maximisation
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificates

EST	Energy Saving Trust
EU	European Union
FE	Fixed Effects
FES	Fuel and Energy Survey
FIT	Feed In Tariff
GDP	Gross Domestic Product
GFI	Generalised Fit Index
GHG	Green House Gas
GLS	Generalised Least Squares
HDD	Heating Degree Days
HEED	Housing Energy Efficiency Database
HEFF	Housing Energy Fact File
HHLD	Household
HLP	Heat Loss Parameter
HTCC	Heat Transfer Convective Coefficient
IAM	Integrated Assessment Model
IEA	International Energy Agency
LED	Light Emitting Diode
LEED	Leadership in Energy and Environmental Design
LSOA	Lower Super Output Area
MLR	Multiple Linear Regression
MS	Member States of the European Union
NEED	National Energy Efficiency Data Framework
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
PCSE	Panel Corrected Standard Errors
PR	Pooled Regression

PV	Photovoltaic
RdSAP	Reduced Data Standard Assessment Procedure
RE	Random Effects
RHI	Renewable Heat Incentive
RSLs	Registered Social Landlords
RMSE	Root Mean Square Error
SAP	Standard Assessment Procedure
SEM	Structural Equation Modelling
SDLT	Stamp Duty Land Tax
SHWS	Solar Hot Water Systems
TLI	Tucker Lewis Index
TRV	Thermostatic Radiator Valve
UK	United Kingdom
UNEP	United Nations Environment Programme
U-Value	The overall heat transfer coefficient representing the rate of heat transfer through a physical boundary given in $W/K.m^2$.
WBCSD	World Business Council for Sustainable Development

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Introduction

1.1 Motivation

It is now widely accepted that the residential sector offers significant potential for carbon mitigation. This is true for both the overall magnitude of emissions reductions and the cost per tonne of $CO2_{(eq)}$ mitigated. However, both the scope and scale of potential carbon mitigation pathways remain controversial. The pace of decarbonisation is also openly debated. Examples of some of these contentions include: centralised versus decentralised energy supply; energy efficiency versus low carbon generation; demolition versus renovation of the existing building stock and behaviour change versus technological solutions. Incontrovertibly, any one of these seemingly apparent tensions is not mutually exclusive, and the ultimate decarbonisation pathway will likely consist of most if not all of these proposed solutions being implemented to some varying degree.

Despite the significant potential for carbon mitigation in the built environment, deep cuts have not yet materialised. It is argued that this lack of progress stems from a poor understanding of the highly complex socio-economic, socio-dynamic and technical physical systems that underpin energy use in dwellings. Modelling this requires novel methods capable of capturing the complexities that arise from government policies, physical processes and technologies, human behaviour and economics. Moreover, as the effects of climate change are directly caused by the global stock of $CO_{2(eq)}$ in the atmosphere, the pace of decarbonisation is pivotal. New methods may prove important for representing the interactions that occur between technological sub-systems but also for modelling how the system may change over time, including feedbacks and delays endogenous to the system. The motivation for this thesis aims to explore decarbonisation opportunities from the residential sector by adopting an integrated systems perspective whilst maintaining the complexity and heterogeneity that naturally exists within the residential sector and between people.

1.2 Research questions

This research aims to gain deeper insight into the realistic carbon mitigation potential from the residential sector in the United Kingdom by taking into account: the systemic impacts of building performance and certification standards; the physical and thermodynamic limitations of building energy efficiency; the economics of energy demand; the role of human behaviour in the mitigation of $CO_{2(eq)}$ and the technological potential for carbon mitigation from heterogeneous dwellings.

The first section aims to understand the role of social systems, rules and regulations as they pertain to the energy performance of residential buildings and their role in reducing emissions. Questions answered in this section specifically ask about the limitations of existing organisational, legal and social systems (e.g. energy performance certificates) established to motivate individuals to improve the performance of the building stock over time. The success of building performance standards and energy certification in the UK are compared to a number of international examples. The role of path-dependence in the development of building performance standards, namely the development of the Standard Assessment Procedure (SAP) will be scrutinised. The following research questions will be answered for this chapter.

> How have historical building performance and evaluation standards developed in the UK building sector?
>
> Is there evidence of legacy or lock-in within present day building standards?

Are existing building performance and evaluation standards (such as BREDEM, SAP and RdSAP) capable of representing the diversity within the existing building stock?

Are building performance and evaluation standards most effectively estimating building performance and what, if any, improvements can be made to estimating building performance?

What lessons can be learnt from best practice in Europe to improve UK building performance and evaluation standards?

What does the UK SAP standard actually measure?

Are there any potential improvements to be made to Energy Performance Certificates (EPCs) to maximise energy and $CO_{2(eq)}$ mitigation?

The next chapter seeks to explain demand at the individual dwelling level. Specifically, the magnitude and significance of different causal factors known to influence dwelling energy consumption will be examined. This section uses a structural equation model (SEM) to combine factors such as the physical characteristics and efficiency of dwellings as well as the socio-demographic and behavioural factors of occupants. In particular, the relationships between different variables (e.g. direct and indirect effects) for explaining residential energy consumption are explored. This section establishes the hypothesis that energy consumption within the domestic stock is complex and consists of many different confounding factors spanning several research disciplines (e.g. sociology, psychology, engineering and economics). For this chapter the following research questions will be answered:

Is a systems based approach to modelling energy and emissions from the built environment appropriate?

Are there any mediating factors that help to explain dwelling level energy demand?

What are the direct and indirect effects that explain dwelling level energy demand?

What is the relationship between energy efficiency and energy demand?

> Is there a non-recursive relationship between energy efficiency and energy demand?

Internal temperature is considered one of the most important factors determining residential energy demand. A panel model is therefore developed to answer a number of questions about the role of different socio-demographic indicators, behavioural characteristics and physical attributes of buildings to explain and predict internal temperature. The natural heterogeneity of dwellings results in a wide variety of different buildings being used for different purposes. Thus, the distribution of internal temperatures between dwellings and over time is important for developing much more accurate models of energy demand. For this chapter the following research questions will be answered:

> Is it possible to use internal temperatures as a proxy for behaviour to improve estimates of dwelling level energy demand?
>
> Can internal temperatures be used to link behavioural and engineering based models?
>
> What are the relative estimated effects of socio-demographics, human behaviour, weather and the physical properties of a dwelling on internal temperature?
>
> What socio-demographic and behavioural characteristics are most influential in explaining high internal temperatures?

There are now several bottom-up building stock models predicting energy and emissions from the UK residential sector with varying strengths and weaknesses. Many of the models identified make unrealistic assumptions about internal temperatures and therefore inadequately account for the role of human behaviour in predicting energy consumption. Adopting a bottom-up approach, it is possible to analyse the effect of different decarbonisation strategies across different subsectors of the economy. In particular, it allows the effects of technology penetration rates to be modelled. The decarbonisation potential from a number of technologies is then compared as well as any interaction effects that occur between different technologies. For this final chapter the following questions will be answered:

How can the typical bottom-up engineering building stock model be improved?

How can the thermal mass of a dwelling be incorporated more scientifically within existing building stock models?

What is the total amount of emissions reductions that can be achieved from the application of different end-use technology benchmarks within the building stock?

What is the difference between using the portfolio approach and the individual technology approach?

Is it possible to meet the present UK carbon budgets under existing decarbonisation policies?

1.3 Contribution

This thesis makes several important contributions to the literature. As a thesis, it applies a systems perspective for decarbonising the residential sector. It is no longer acceptable to adopt a unilateral or myopic perspective to model energy and emissions from buildings. This thesis therefore brings together many ideas from different research disciplines and applies them in novel and interesting ways to model energy demand. By adopting this approach, deeper insight into the interaction between different system elements can be brought to light and new strategies developed.

In Chapter 4 a critical review of existing UK building performance evaluation and certification (BPEC) tools are presented. The chapter begins by bringing together historical literature on building performance standards in the UK to reconstruct the historical line of events in their development. This is interesting as it shows that existing building evaluation tools have deviated little from the early models, suggesting path-dependence and lock-in, despite significant advances in computing power, new data sets and new modelling methods. The main conclusion from this chapter is that existing rating standards (e.g. SAP) are not fit for purpose and are therefore in need of major overhaul. Deficiencies of the standard are discussed in depth, but most importantly the standard confounds several government policy objectives and performs inadequately overall. Perversely, the SAP standard is shown to incentivise households to increase emissions in some circumstances. Several suggestions are provided for how to improve UK domestic BPEC tools.

Chapter 5 describes the implementation of a structural equation model to ascertain the causal factors giving direct, indirect and total effects on dwelling level energy consumption. The contribution from this chapter is that it adopts well-understood econometric modelling techniques and uses these to explain residential energy demand in England. This is important because it shows the interplay between different variables and therefore allows different causal factors to be untangled and estimated. Perhaps most importantly, the model shows SAP has a reciprocal relationship with energy consumption. That is – all else being equal – the efficiency of a building (SAP) decreases energy consumption, but the propensity for a dwelling to consume energy has the effect of increasing dwelling efficiency improving its SAP rate. It is only when both effects are considered together that the true dynamics of the system emerge.

In a similar fashion, Chapter 6 – for the first time – applies panel regression methods to predict internal temperatures over heterogeneous dwellings in England. Panel methods are superior for modelling the heterogeneity over cross sections as well as over time. The breakthrough here is that it provides a method to predict internal temperatures on a daily basis. This is advantageous, as internal temperatures are not averaged out over long periods as they are in other similar models. For the first time it is now possible to capture human behaviour and social demographics through their effect on internal temperature within bottom up building energy models. An important output of this model is its ability to make important statistical inferences about the magnitude of different variables and their effect on dwelling level internal temperatures.

Perhaps the most significant contribution of this thesis is the development of a new bottom up building stock model of the English residential sector. The superiority of this model over other building stock models is its capability to represent the heterogeneity within the existing building stock. Thus, it is able to represent the true underlying diversity within the building stock, not simply represent the building stock from a small number of representative building archetypes. The model includes more detail at higher temporal resolution than any other model built to date. It predicts mean daily internal temperatures using the equations derived in Chapter 5 and therefore is able to capture the vagaries of human behaviour. Using the bottom up building stock model, decarbonisation of the existing building stock is modelled until 2050. Carbon abatement potentials from different technology benchmarks are quantified and compared.

1.4 Thesis organisation and structure

The introductory chapter opens with dialogue on the importance of conducting residential energy modelling and the contributions made in this thesis. A short section is included to describe the philosophical standpoint of this thesis - a section often neglected in theses adopting a modelling based approach.

The second chapter provides a short description about the historical context and evolution of energy demand and energy efficiency in the residential sector. The sheer scale of the challenge to decarbonise residential buildings is contextualised before ending with an examination of existing government policy aimed at decarbonising buildings.

The third chapter presents a literature review of the major developments in residential energy modelling over the last forty years. Fundamental differences between bottom-up and top-down approaches are discussed. Recent developments using neural networks, conditional demand analysis and index decomposition methods are all compared. Several international models are reviewed before models developed for use within a UK context are brought into focus. The chapter concludes with a discussion on the strengths and weaknesses of different modelling approaches, gaps and opportunities for future residential modelling and concludes with several suggestions for how different modelling approaches can be taken forward in this thesis.

In the fourth chapter, Building Performance Evaluation and Certification (BPEC) standards are critically reviewed within a UK context. This chapter highlights the importance of social and legal frameworks such as building regulations, performance standards, Energy Performance Certificates (EPCs) and building simulation models for encouraging innovation and investment in energy efficiency. Several international examples are compared before suggestions are made for improving UK based standards and regulations.

The fifth chapter seeks to quantify the causal explanatory factors of household energy demand. A SEM is developed where direct, indirect and total effects on household energy demand are quantified. This chapter lays the foundation and provides evidence for why it is necessary to adopt a complex systems approach for modelling energy demand.

The sixth chapter develops a panel model for predicting the diversity of mean daily internal temperatures over a heterogeneous building stock. Internal temperatures are one of the most important and least understood variables when used to explain residential energy demand. Using this model it is possible to predict the distribution of internal temperatures over time and over different buildings.

The seventh chapter develops a bottom-up building stock model for estimating energy and emissions from 16,217 dwellings. Five end-use energy demand categories are estimated for each dwelling. These are space heating, hot water, lighting, appliances and cooking. An analytical thermodynamic heat balance equation is derived to estimate energy loss through the building envelope. Heating degree-days are estimated on a daily basis using predicted mean daily internal temperature and daily mean external temperature for each region.

The eighth chapter extrapolates decarbonisation strategies for the building stock out to 2050. The penetration of different technology benchmarks are modelled using a set of derived logistic s-curves. Final energy demand and $CO_{2(eq)}$ emissions reductions are calculated for a number of different technological benchmarks.

The ninth chapter discusses the main findings of this research. Important implications for the development of future policy are emphasised in the context of meeting future carbon targets. The chapter concludes with a section on future research opportunities.

1.5 Research philosophy

1.5.1 Ontological and epistemological foundation

Often neglected in theses using quantitative methods is an explanation or appreciation of the ontological and epistemological foundations that underpin the assumptions made during the research; the outlook and framing of research questions; the methods applied; and the interpretation of results. This is an oversight as the philosophical basis used in developing a model (whether understood by the modeller or not) has important ramifications for the types of questions that can be asked; the methods used to answer these questions and the implications that the findings may have for the future advancement of knowledge (Corbetta, 2003, p.10).

It is important to understand the philosophical standpoint from which research is derived as it moulds and shapes the questions asked, the methods used and the direction of investigation as it evolves over the course of the research. The following section is provided to give the reader an ontological framework from which this research has been derived and developed. It is included to remind the reader (and the author) about the importance of philosophy in shaping a frame of reference, the limitations of modelling, and therefore the capacity for models, as an abstraction of reality, to contribute to existing knowledge.

1.5.2 All models are wrong

"Essentially all models are wrong, but some are useful" – George E.P Box (1976)

This quote was originally coined by Box (1976) and concisely sums up the science, art and philosophy of modelling, and remains as pertinent today as it did when it was formulated. Although the quote is often used in jest by modellers and non-modellers alike, few might realise the deeper philosophical meaning it carries. The quote affirms that 'all' models are wrong, and by definition implies that no model is correct. It therefore recognises that all models are merely a manifestation of reality and by definition, makes all models incorrect in one respect or another. However, the quote qualifies this statement and makes clear that just because models are a mere representation of reality, it does not necessarily follow that they are not useful. In contrast, it would be naïve to think that because models are wrong they are useless. The quote therefore endorses a constructivist view of the world stating the world is only knowable through the meanings and understanding attributed to it by individuals. Constructivism focuses on how theories are generated and described. Constructivists believe theory to be an act of generation rather than formalisation of the underlying reality. Constructivists propose a paradigm for knowledge and truth that is based on inter-subjectivity instead of classical objectivity and viability instead of truth (Geertz, 1973). A constructivist's approach requires that the researcher approach the object without prejudices or pre-conceived theories. Thus constructivism is a view held by many philosophers of science (Routledge, 2000) and is often considered to be a pragmatic view of the world. There is also a strong connection between constructivism and the importance of modelling and simulation to understand the world i.e. through simplified constructions of the world through models.

The ontological and epistemological perspectives adopted by the researcher not only reflect the researcher's view of reality but also the subject matter being researched. The philosophical dichotomy between the natural sciences and the social sciences is clearly articulated by Wilhlem Delthy (Hodges, 1969) and Max Weber (Weber and Miller, 1963). In the natural sciences – it is argued – reality can be explained through cause and effect relationships but in the social sciences – according to Delthy (1969) – can only be interpreted by an observer through empirical observation. Such distinctions become blurred in interdisciplinary research when methods from both branches of science are used simultaneously. This is even more problematic in the development of models that are, themselves, an abstraction of reality and therefore a construct for how the modeller understands and views the world.

Several models are developed in this thesis. The econometric models developed in the first several chapters are best described as postpostivist as they rely on the scientific method, the falsification of hypothesis and can probabilistically describe reality using empirical data. The engineering model – although deterministic in nature – adopts a moderate constructivist approach. This is for several reasons. Firstly, as the engineering model is a simulation of reality it does not measure reality itself, and therefore by definition it is a construction. Secondly, although as a modeller I strive to use the best available theory, methods and data available, theory will always evolve, new and improved methods will always be developed and data will never be perfect. Thus, a model that aims to simulate reality will never produce results that are an objective truth of reality. Thirdly, as a modeller I strive for objectivity, but in the process, this is limited by my own intellectual capacity and understanding. However hard I try to remove my own personal bias, judgements and pre-conceptions they will inevitably have an effect on how I choose to construct the model and interpret the findings. Fourthly, my view of the world is unique and therefore relative to my own reality (relativism). If many different people were to develop a building stock model of the residential sector, each would be unique and none would represent an objective representation of reality. Nor would it be true that the probabilistic outcome of many simulation models would be able to produce an objective truth (because the personal biases of each modeller would change the probabilistic outcome). Compounding this further is the inclusion of a human behavioural model that is used within the engineering domestic building stock model. This pushes the model even further into the realm of constructivism.

In sum, the econometric models may be classified as postpostivist in nature as they are able to produce falsifiable and testable hypothesis that may explain social reality. In contrast, the engineering simulation model is classified as constructivist. It is likely that my philosophical standpoint is in opposition to other building stock modellers. It is difficult to know the ontological and epistemological view of other building stock modellers as their views are never described and therefore can only be guessed from the language used when authors describe their own models. Adopting a constructivist view accepts that absolute truth cannot be attained by a simulation model but tendencies, trends and relationships can be interpreted to gain insight into how the world might work. It therefore provides a means to test what changes might be necessary to change the way reality manifests as our relative interpretation of reality also changes.

1.5.3 Ethical principles

A model is a model is a model. Almost every field of modern research involves the development of a model to help understand, simulate, forecast or communicate knowledge and ideas about the nature of physical, environmental, social and behavioural subjects. Although models of some description have been around since humans started painting on cave walls, recent advances in computing hardware and software tools (such as statistical packages) have introduced important ethical questions about the role and use of complex models in modern society. There is no doubt models are able to provide insight into many of the economic, environmental and technical problems that society is presently saddled with (or will be in the future). However, naïve claims about the accuracy or ability of models can often lead to spurious conclusions and therefore legitimacy concerns about the essence of the model for describing reality (Williamson, 2010). Likewise, inappropriate applications or assumptions made during the modelling process may lead to erroneous allocation of resources and incoherent policy decisions. The ethics of modellers wishing to contribute to the advancement of human knowledge or future policy is therefore paramount. This research has thus adhered to the ethical principles demanded by the scientific community and deserved by the public.

Thus, when using models, it is important to acknowledge the limitations of the model and the questions that can and cannot be answered. Responsibility lies with the modeller to provide this information but also with the users of model outputs to demand it. In summary, models need to be seen for what they are: an interpretation or construction of the reality they attempt to represent.

1.5.4 The scientific method

The scientific method was first developed in the 17th Century and often credited to al-Hasan ibn Al-Haytham (Gorini, 2003). However, classical writers such as Aristotle, Galileo, Grossteste, William of Occam, Kepler, Bacon and Popper have all emphasised the importance of practicing good science and the pitfalls of not following sound scientific methods. Of important note is the iterative nature of learning derived from the development of hypothesis, conjecture and ideas towards practice, data and facts (Box, 1976). Thus, existing knowledge leads to new hypothesis where data is collected and new hypotheses are tested. Matters of fact lead to tentative theories and discrepancies induce new theories that can be tested against hypotheses at which point the process repeats itself.

Originally developed for use in the natural sciences, the scientific method requires systematic observation, measurement, testing and experiment. This process is usually repeated in a closed loop until no known knowledge is able to falsify the theory put forward. In other words, no theory can ever be considered certain as new evidence disproving it may still be discovered. Critical rationalism as developed by Popper (Popper, 2002) claims there is no method for ascertaining the truth of a scientific hypothesis only to reject it.

1.5.5 Criticism, self-criticism and flexibility

If the iterative process as outlined above is to work efficiently, then feedback between deduction, hypotheses testing and induction must be unhampered. Model builders must not fall in love with their model and therefore remove objectivity (Tillman, 1978). It is important to remain critical about ones work and question discrepancies as and when they occur throughout the modelling process. It is only through self-criticism and acceptance of criticism from others that a model can become a legitimate tool for interpreting the world.

1.5.6 Parsimony

The principle of Occam's razor is attributed to William of Ockham a 14th century English logician (Zahálka and Železný, 2011). In its original form, it simply states that "Entities should not be multiplied unnecessarily" (Ambrose and Lazerowitz, 2004, p.112) or more precisely "when you have two competing theories that make exactly the same predictions, the simpler one is the better" (Mills, 2011, p.11). Unfortunately, it is often mistakenly used to suggest that simpler explanations are better than complicated ones. Nowadays it is often referred to as the law of parsimony and implies when two theories or models are equal, the burden of proof rests with the more complicated model to show it is able to make better predictions. Using Solomonoffs inductive inference method it is possible to derive a mathematical proof for Occams razor (McCall, 2004). However, under the principles of the scientific method, Occam's razor is not considered an irrefutable principle, but can be used as a heuristic to guide the modelling process.

As discussed above, the philosophical views held by the modeller can have serious implications for the type of methods; the development of the model and the interpretation of the results produced by the model. The following section will therefore carefully articulate the overall research methodology adopted for this thesis. Although it is not possible to completely eliminate the effects of philosophical perspective, human error and bias entering the modelling process through the modeller, an effort is made to describe the research methodology in such a way so that the reader can gain an appreciation for the philosophical perspective and approach of the modeller. At the very least, this will allow the reader to understand the perspective of the modeller from which this research was undertaken.

1.6 Research methodology

Surprisingly, energy and emissions from the residential sector remain largely misunderstood. This is demonstrated by the significant discrepancy shown to exist between predicted energy demand and actual energy consumed. Such discrepancies exist because the majority of models fail to adopt a systems approach when modelling the inherent complexity of residential energy demand. This point is continuously re-iterated within the literature which argues residential energy consumption is a socio-technical phenomenon arising from the interaction between people and technology (Royal Commission, 2007; Crosbie and Baker, 2010; Lomas, 2010; Wall and Crosbie, 2009). That is, energy consumption is caused just as much by the physical characteristics and construction methods of the building as it is by the social, cultural and behavioural characteristics of the inhabitants.

The idea that people matter as much as buildings, and that psychological, social, economic and behavioural aspects must be considered alongside the physical properties of the building was pioneered by Lutzenhiser (1992). Given the strong arguments in favour of adopting a more systems based approach, it is surprising to find most bottom-up energy demand models discount or ignore large portions of important information from other disciplines. Engineering based models such as BREDEM and BREHOMES do not take account of human behaviour, yet they are still widely used to estimate residential energy demand and still feature prominently behind a large number of government policies. At the other end of the spectrum, top-down aggregate models, such as the Domestic Energy Fact File model (DEFF) or the Annual Delivered Energy, Price and Temperature model (ADEPT) treat the residential building stock as a homogenous group and therefore are only capable of measuring incremental adjustments to average consumption over the entire building stock. As top-down models model energy consumption at the macro level they provide insufficient information about energy consumption occurring at the micro-level and cannot model the complex interactions that exist between socio-technical systems (Swan and Ugursal, 2009). Top-down models fail to model the effect of new technologies and human behaviour and therefore cannot differentiate amongst effects occurring within and between different subsectors or groups.

More recently, building on the work of Meadows and Meadows (1972), Lovins (2002) overtly argues for a more complex systems approach for modelling all types of energy systems. For the residential sector, this requires going further than merely thinking outside the box, but also requires modelling the interaction and feedback between the physical built environment and the behavioural considerations of people. Complexity as distinguished from complicatedness is used to characterise a system that has many parts connected and operating together in an intricate arrangement. In its broadest definition, complex systems therefore attempt to explain, model or calculate the interrelatedness and complexity of a particular subject, object or field.

In contrast to reductionism, systems thinkers recognise that the behaviour of the whole cannot be determined by studying each of the individual separate parts that make up the system. Rather the outcome of the system can be explained as a property of the relationships and interconnectedness of the different parts acting together. Thus, complex systems give rise to collective behaviour where the response of the system is often an emergent, non-linear property of the system as a whole (Meadows, 2009).

Adopting a systems view of domestic energy use leads to the conclusion that no single action to address the problem can be carried out in isolation. Policy makers, practitioners, technical experts, engineers, social scientists, etcetera must all consider broader performance issues, while research carried out in this field must acknowledge residential energy demand as a multidisciplinary problem that needs to be addressed in new ways. While a narrow view may be able to solve specific problems in some circumstances, it will fail, overall, to address real problems at the whole system level. Therefore, new methods capable of addressing the complexity at a whole systems level whilst acknowledging the importance of the heterogeneity of the building stock were kept as central tenets of the research methodology adopted during this thesis.

In this introduction, I have described why it is important to have prior understanding for the philosophical standpoint of the modeller and their perspective of the world. Using this framework I then articulate the research methodology used in this thesis. In particular, I emphasise why I have adopted a whole systems perspective rather than focusing on economics, engineering or behaviour to model energy demand. Keeping this broad epistemic approach in mind, I show how it is possible to construct a building stock model of the residential sector in England to estimate energy and emissions.

2

Background and context

2.1 Chapter summary

This chapter provides context and background for this thesis and explains why emissions from the built environment are critical to decarbonisation and must therefore be understood thoroughly. Trends in energy and emissions from the UK between 1970 and 2010 are presented providing an historical basis for the evolution of energy, emissions and energy efficiency technologies over five end-use categories. If future climate change targets are going to be met and runaway climate change is to be avoided, then the UK building stock (representing the highest source of CO_2 emissions) will need to be completely decarbonised by 2050. The chapter concludes with a discussion on the role of existing UK government policy and the incentives and mechanisms required to put the residential sector on a trajectory to meet future energy and emissions targets.

2.2 Climate change

Climate change is now widely accepted as an anthropogenic phenomenon (Bernstein et al., 2008). Preventing catastrophic climate change will thus require decisive, bold and immediate action (IPCC, 2008). Global trends indicate energy consumption is expected to grow, with fossil fuels remaining the dominant source of energy well into the foreseeable future (IEA, 2012). Global energy demand is predicted to grow by no less than 35% between 2005 and 2035[1], with coal remaining the largest source of electricity generation to 2035 (IEA, 2010). Unlike population growth which is predicted to level-off at around 9.3 billion people by 2050 (UNFPA, 2007), energy consumption is expected to keep growing, with ever-increasing quantities of $CO_{2(eq)}$ being released into the atmosphere, predicted to jump from 29 Gt in 2008 to 35 $GtCO_{2(eq)}$ in 2035 (IEA, 2010). Similarly, global electricity demand is projected to double between 2000 and 2030, growing at an annual rate of 2.2% between 2008 and 2035, with over 80% of this increase occurring in non-OECD countries. This is faster than any other final energy source (IEA, 2010) .

Many researchers now argue that energy efficiency is fundamental to the global fight against climate change (IPCC, 2008). If energy efficiency does not lead to a decrease in fossil fuel demand, the chance of achieving the IPCC's most relaxed $CO_{2(eq)}$ mitigation scenario will be unlikely (IPCC, 2008). In the summary report of IPCC AR4 Working Group III it is acknowledged that different technologies for emissions reductions will vary over time, region and stabilisation level, however, energy efficiency always plays a key role across all scenarios for most regions and at all time-scales (IPCC, 2007, p.16). In addition, McKinsey (2009) have shown that energy efficiency can contribute the largest abatement potential between now and 2030 with 14 $GTCO_{2(eq)}$ of savings coming from energy efficiency measures alone, compared with 12 $GTCO_{2(eq)}$ from low carbon energy supply, 12 $GTCO_{2(eq)}$ from better management of forestry resources and 9 $GTCO_{2(eq)}$ from technical and behavioural changes. UNEP (2006) have predicted that without serious energy efficiency gains, GHG emissions will more than double by 2030 in China, Brazil and India.

One of the largest opportunities for energy efficiency resides in the built environment where it is estimated that 40% of total final energy is consumed by all OECD countries (IEA, 2008a). In a recent report on energy efficiency submitted to the G8 (IEA, 2008a) it was shown that carbon savings from energy efficiency is both cost effective and substantial if implemented decisively. If implemented globally and without delay, proposed efficiency gains are estimated to save around 8.2 $GTCO_{2(eq)}$/year by 2030 (IEA, 2008a). Furthermore, the IEA estimate that 34% (IPCC estimates 29%) of total carbon savings will need to come from the built

1. This prediction uses the 'New Policies Scenario' as described in the World Energy Outlook 2010, assumes cautious implementation of policy commitments, and plans to reduce GHG emissions.

environment alone to meet international climate change targets. Decarbonisation of the built environment thus forms a crucial component for any decarbonisation plan aiming to mitigate the effects of catastrophic climate change.

2.3 Residential energy consumption in the United Kingdom

In the UK, all buildings account for 46% of total $CO_{2(eq)}$ emissions and 40% of primary energy demand (DECC, 2011a). In London this is even higher where buildings account for 67% of all emissions (DEFRA, 2008a; Clarke et al., 2008; McKinsey, 2009). When buildings from the residential sector are considered in isolation, dwellings are shown to account for 27% of total emissions and 29% of total primary energy consumption (Wood et al., 2007). In 2011, Over 60% of all energy consumption in the residential sector is for heating, around 18% for hot water 19% for lighting and appliances and 3% for cooking (DECC, 2011a).

While space heating is responsible for the largest overall share of domestic energy consumption and emissions (WWF, 2007) demand for electricity – driven by increased plug load – is growing faster than any other final energy source (Energy Saving Trust, 2006a) (see Figure 2.2). In the UK electricity has the highest $CO_{2(eq)}$ emissions per kWh of energy delivered when compared against all main fuel types. Furthermore, the average delivered energy-efficiency of electricity is just 35% compared with approximately 90% for natural gas when used for heating[2]. The carbon intensity of electricity consumed in England is also much higher than natural gas with average carbon emissions from the national grid[3] measured at 0.537 kg/$CO_{2(eq)}$ per kWh (2009), compared with natural gas estimated to be 0.185 kg/$CO_{2(eq)}$ per kWh (The Carbon Trust, 2008). Over time, as additional renewable electricity generation is added to the national grid, electricity emissions factors will adjust accordingly. This demonstrates the non-trivial relationship between energy consumption and carbon emissions for different technologies and energy carriers over time.

2.4 Historical trends in residential energy consumption

Before any substantive modelling was completed, important historical trends occurring in the UK residential sector between 1970 and 2010 were investigated. The

2. This assumes direct electric resistance heating not heat generated through heat pumps.
3. This figure represents the average CO_2 emissions from the UK national grid per kWh of electricity delivered to site. The factor presented is the five year rolling average with a final measurement taken in 2008.

identification of discontinuities, unusual deviations and important trends for different energy service categories helped establish important historical factors behind residential energy demand. Figure 2.1 is an area plot showing the relative changes in energy demand between 1970 and 2010 for five different residential energy service categories. The Figure shows overall energy demand has increased in the residential sector and the overall dominance of space heating when compared against all other end-use categories.

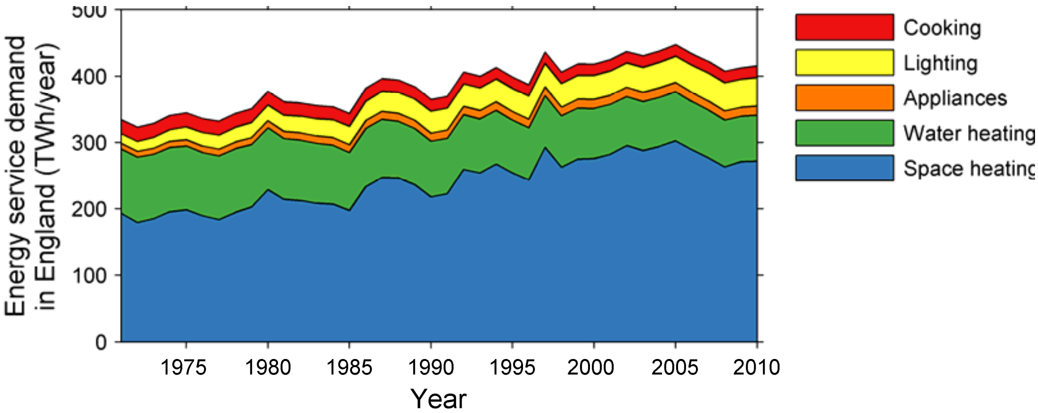

Figure 2.1: Energy service demand by service category in England

Data source: graph created from DECC domestic energy statistics (DECC, 2011a)

In Figure 2.2 energy demand was indexed to 1970 to identify the relative rate of change from each energy service category. Although energy demand for lighting and appliances start from a lower absolute base, the rate of increase has grown much faster than any other final energy demand. Electricity demand from appliances grew by over 300% increasing from 16.75 TWh/year to 51.1 TWh/year between 1970 and 2010. Projections from the Energy Saving Trust indicate that growth in energy consumption from all sources will slow and then level off at around 80 TWh/year by 2020. Overall energy demand for space heating has risen over the same period but with a sharp decline in demand from around 2005. This might have been caused by several factors such as an increase in energy prices (which occurred over this same period) or the start date of efficient boiler mandation and CERT increases. This suggests government policy may play an important role This contrasts with cooking and hot water, where energy demand has been steadily declining since 1970 most likely due to the improvement in energy efficiency of these systems.

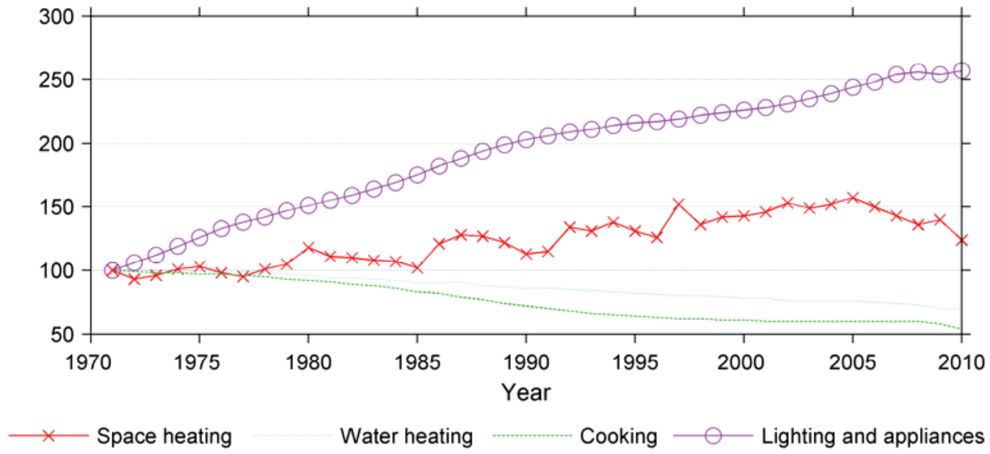

Figure 2.2: Domestic energy demand by energy demand category
Data source: graph created from DECC domestic energy statistics (DECC, 2011a)

In 2008, the EU Commission mandated that old incandescent light bulbs would be phased out by 2012, leaving room for the diffusion of new energy efficient light bulbs. This is now starting to have a measurable impact on demand. Since 2007, the total energy consumed by lighting in the UK has declined sharply (Figure 2.3). Presently lighting in the UK consumes around 13.1 TWh/year, if present trends continue this will drop to below 8 TWh/year by 2020.

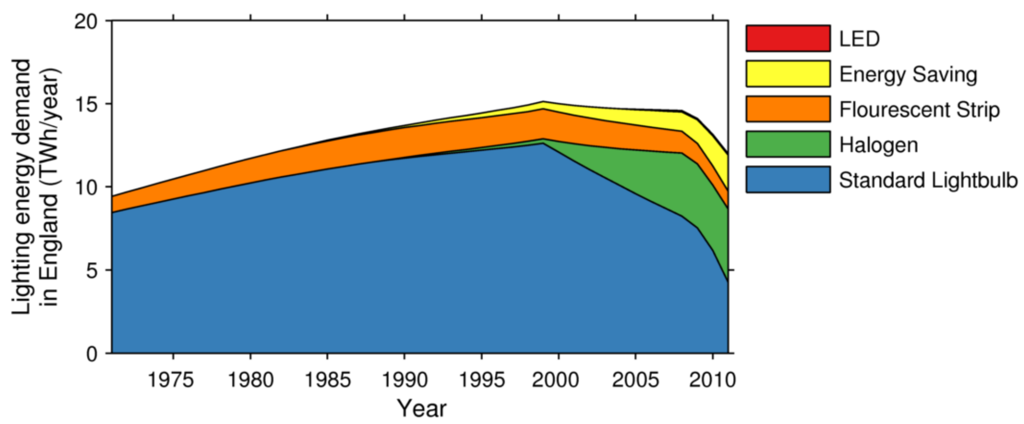

Figure 2.3: Evolution of lighting demand in England
Data source: Graph created from Market Transformation Programme data tables

Some of the biggest historical transitions in end-use energy consumption are from cold and wet appliances. From around 1975, fridge freezers exploded onto the market and have dominated final energy demand from all appliance categories ever since (Figure 2.4). Interestingly the energy consumed by cold appliances peaked around the year 2000 and then started to decline due to improved energy efficiency product standards and market saturation. This will likely continue into the future as efficiency standards continue to have an effect, and old appliances are replaced with new.

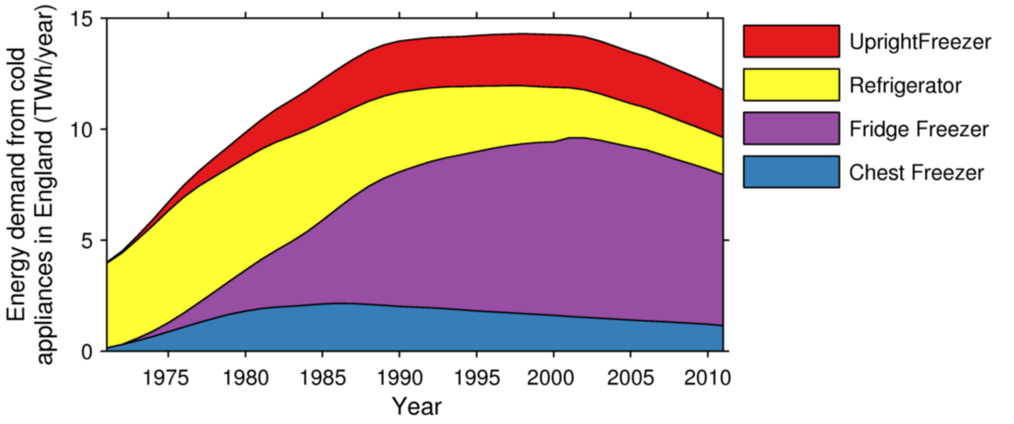

Figure 2.4: Evolution of energy demand from cold appliances in England
Data source: Graph created from Market Transformation Programme domestic appliance statistics (DECC, 2011a)

For wet-appliances, the growth in energy demand from washing machines stagnated from the 1990's, most likely due to appliance saturation and marginal changes to appliance efficiency (Figure 2.5). However, any lack in growth was taken up by the expansion of tumble-driers, dishwashers and combined washer-driers as shown in Figure 2.5. In 2010, energy consumed by tumble-driers exceeded the energy consumed from typical washing machines with tumble driers remaining the fastest growing energy consuming wet-appliance.

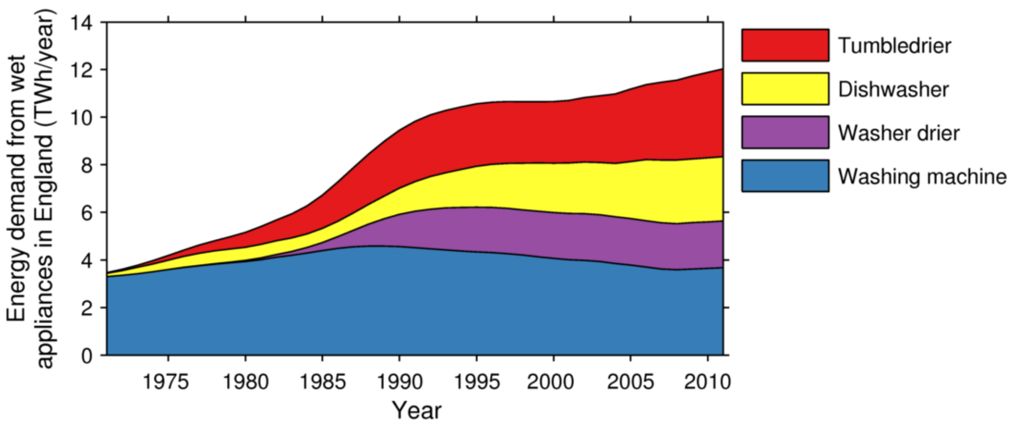

Figure 2.5: Evolution of energy demand from wet appliances in England
Data source: Market Transformation Programme domestic appliance statistics (DECC 2011)

Since the 1970's demand for consumer electronics increased rapidly and is now the largest of all end-use appliance categories. Home computing has similarly expanded rapidly from the 1980's and now consumes almost 6 TWh/year with the dominant share of total energy demand coming from desktop computers (Figure 2.7).

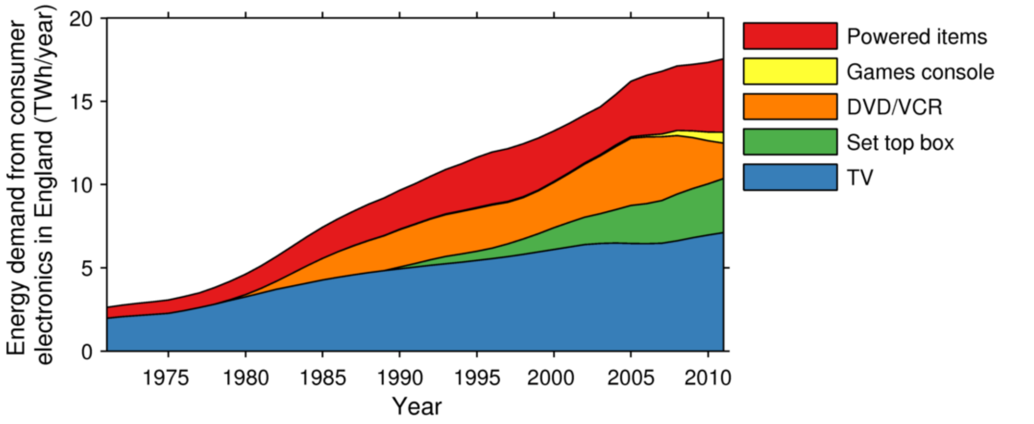

Figure 2.6: Evolution of energy demand from consumer electronics in England
Data source: Market Transformation Programme domestic appliance statistics (DECC 2011)

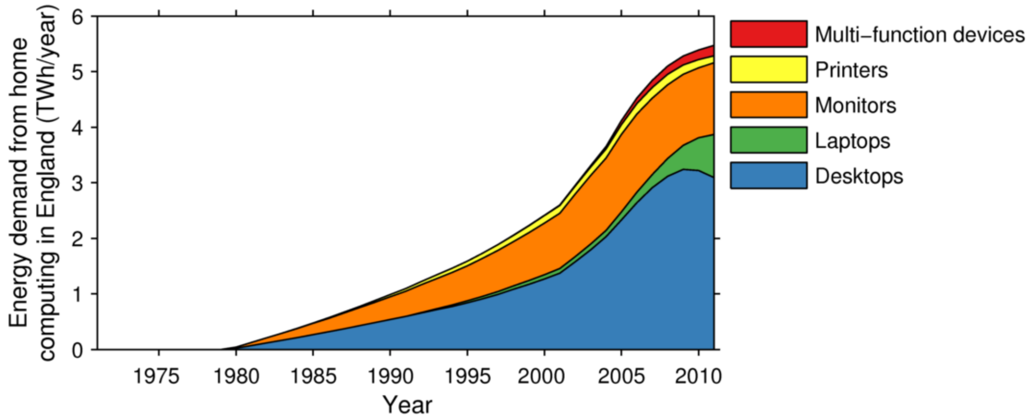

Figure 2.7: Evolution of energy demand from home computing in England
Data source: Market Transformation Programme domestic appliance statistics (DECC 2011)

Energy used for cooking (ovens, microwaves and kettles) accounts for approximately 5% of overall energy consumption from English dwellings. The energy consumption from gas and electric ovens has been in steady decline due to efficiency gains and consumers switching to specialist cooking appliances such as rice-cookers and bread-makers. This is indicated in Figure 2.8 where a decrease in demand in the use of ovens is taken up by an increase energy demand from more energy efficient microwave ovens. There has also been a steady and marked increase in the use of energy consumed by kettles, which may indicate a transition from gas-top traditional kettles (which are not captured in these statistics) to electric kettles.

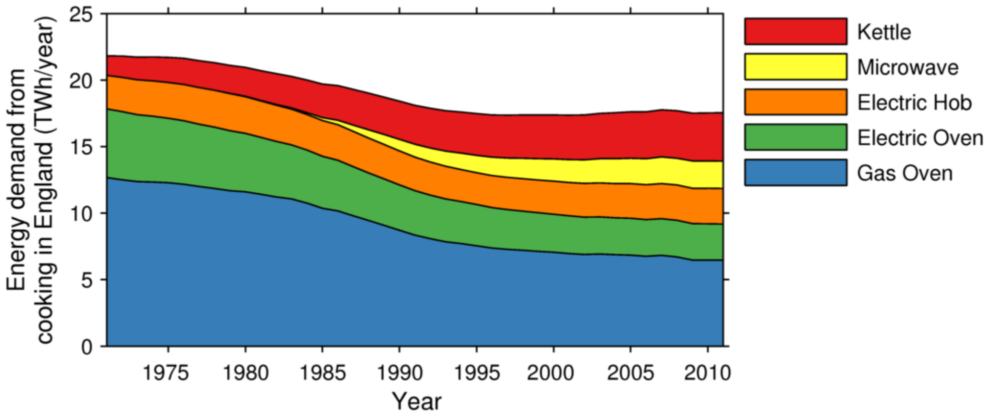

Figure 2.8: Evolution of energy consumed from cooking appliances in England
Data source: Market Transformation Programme domestic appliance statistics (DECC 2011)

2.5 Historical trends in home energy efficiency

In the UK, the SAP standard is the dominant method for evaluating the performance of a building. Over the last forty years, SAP ratings improved substantially, rising from an average of just 18 in 1970 to 54 in 2010 (DECC 2011). If this trend continues, the average SAP rating of the UK building stock will increase to 88 by 2050. This is equivalent to an average dwelling reducing its energy bill in real terms from £720/annum to £192/annum[4] (£2005). Although the trend for increasing SAP rates is promising, the corresponding rate of increase in energy consumption remains uncertain, especially as real household disposable income is expected to rise. Furthermore, electricity is the fastest growing end-use energy carrier and presently has the highest carbon intensity. Not surprisingly, the growth in residential energy consumption is largely matched by the growth in new dwellings over the period 1970-2004. However, from 2004 onwards residential energy consumption appears to decouple from the growth in new dwellings. One plausible explanation for this sudden decoupling is the rapid rise in the real price of gas and electricity, motivating consumers to cut energy spending (see Figure 2.9). It is notable the real price of gas and electricity is only 20%-30% more expensive in real terms than in 1970. Moreover, the largest increase in energy price over this period has occurred in the last five years.

4. The SAP2009 methodology is used to estimate energy consumption. The analysis assumes an average dwelling with a SAP rate of 55 and area of 60m^2 consumes 15.5MWh/annum for heating using natural gas @ 3.1p/kWh and consumes 1.55MWh/annum of electricity @ 11.46 p/kWh. By 2050 the same home is estimated to improve its SAP rate to 88 giving an annual energy consumption of 4.2MWh/annum from heating using natural gas and 2MWh/annum from electricity using constant 2005 prices (£2005).

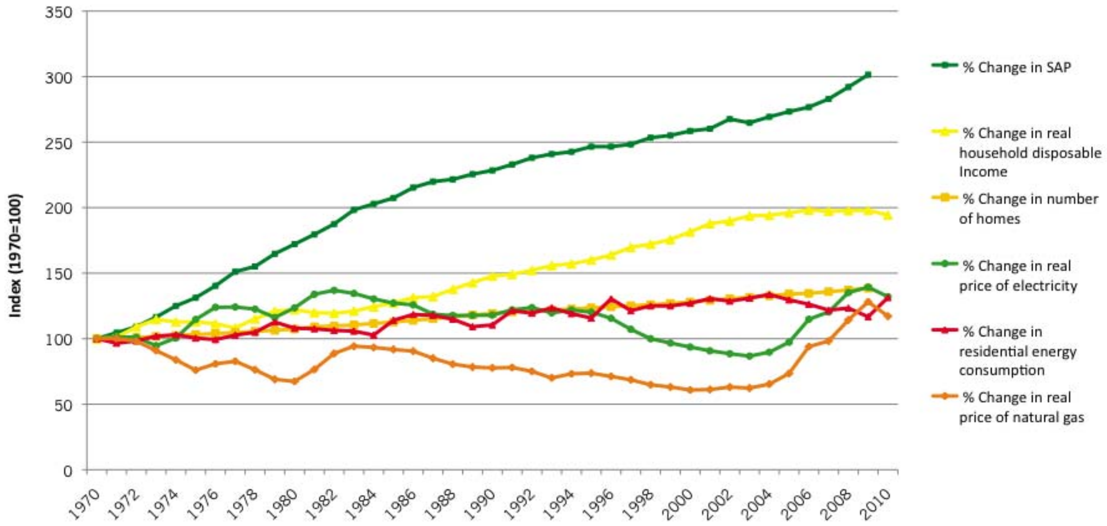

Figure 2.9: Relative changes in factors that affect household energy consumption and SAP
Data source: DECC Domestic Energy Consumption in the UK Tables

Figure 2.10 shows significant growth in loft insulation thickness between 1976 and 2008. Over 80% of all dwellings in the UK are now listed as having at least some level of loft insulation. This suggests policies such as Warm Front and CERT may have had an impact on increasing loft insulation thickness. It is estimated by DECC that some 5.8 million homes have installed some level of loft insulation under EEC or CERT (DECC, 2011a).

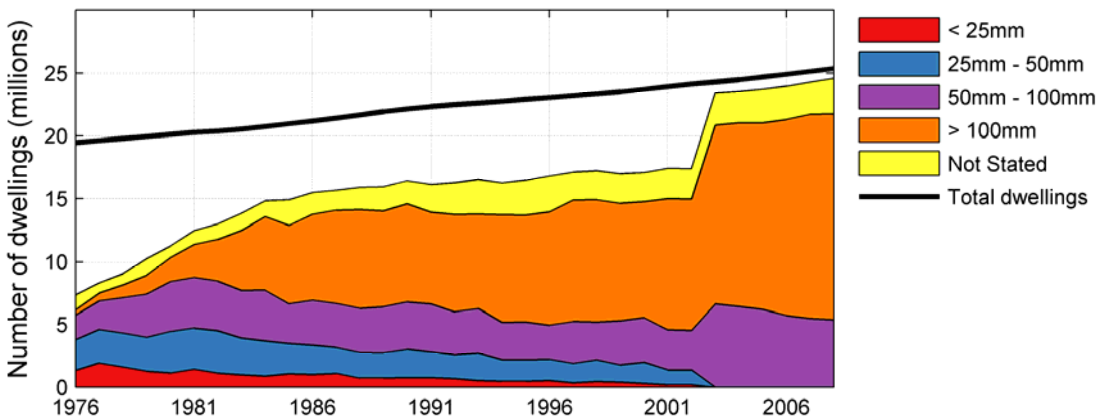

Figure 2.10: Loft insulation thickness penetration rates[5]
Data source: DECC Great Britain's Energy Fact File

The adoption of cavity wall insulation has grown steadily from the early 1970's and by 2010 approximately half of all eligible homes had had their cavities filled (Figure 2.11). Similarly, the historical uptake of double-glazing has transformed the

5. The large jump occurring 2003 in Figure 2.10 is due to changes in data collection and recording procedures and not the direct result of an increased number of homes installing loft insulation.

residential sector with over 80% of all dwellings having had 80% or more of their rooms fitted with double-glazing (Figure 2.12).

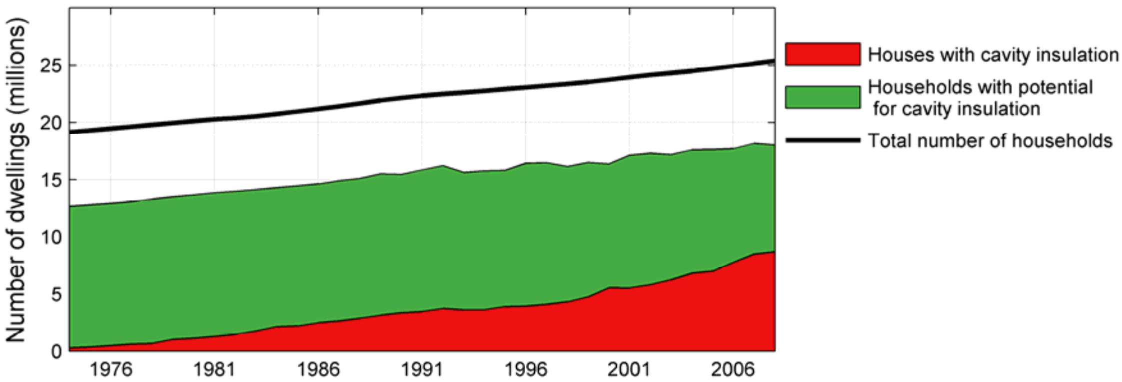

Figure 2.11: Evolution of cavity wall insulation penetration
Data source: DECC Great Britain's Energy Fact File

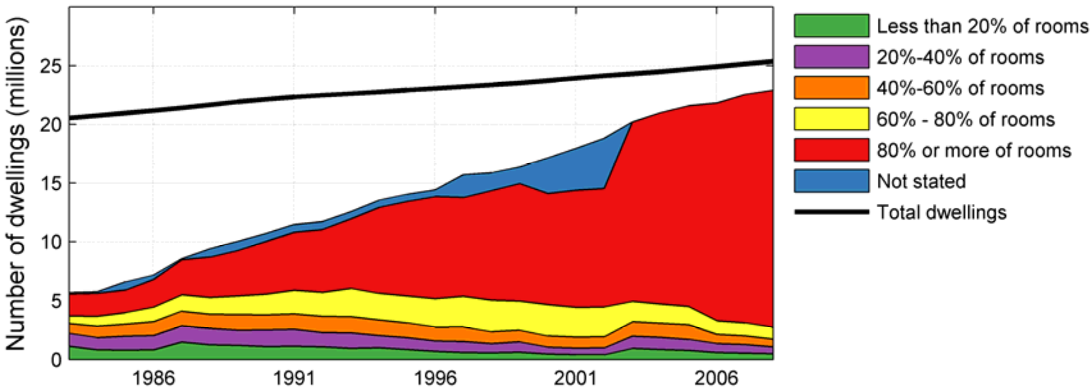

Figure 2.12: Evolution of double glazing penetration
Data source: DECC Great Britain's Energy Fact File

There are two clear messages that have emerged from reviewing these historical trends. First, energy consumption in the residential sector has been steadily increasing over the last forty years. Most independent assessments indicate that growth rates will start to slow and decline in many end use categories. The second important message is that a good proportion of the 'low hanging fruit' for decarbonising the residential sector have already been adopted. At first appearance, this suggests the potential for much needed carbon savings from domestic buildings might be more limited than originally anticipated. However, with over half of all residential dwellings having an energy efficiency rating of "D" or less, the potential for reducing emissions even further must still exist, even if this comes at a much higher cost. Indeed, meeting the next round of carbon budgets will require much more co-ordinated policy across the entire energy sector. Furthermore, there is significant uncertainty about the level of technology benchmarks required within the building stock to meet future carbon budgets. What is starting to become clearer is that each dwelling will need to maximise its own carbon mitigation potential if future carbon targets are going to be met.

2.6 The scale of the challenge

The residential sector is repeatedly identified by government departments (Communities and Local Government, 2006; DECC, 2009a; Energy Efficiency Partnership, 2008; Communities and Local Government, 2007); commercial organisations (Mckinsey, 2008; McKinsey, 2009), nongovernmental organisations (Centre for alternative technologies, 2007; WWF, 2007) and by academia (Boardman et al., 2005; Levine and Urge-Vorsatz, 2008; World Business Council for Sustainable Development, 2009) as having the largest potential for emissions reduction at some of the lowest overall costs. Still, there remains significant debate about the best approach for reducing the $CO_{2(eq)}$ emissions now imminently required.

In 2008, the UK emitted approximately 152.6 $MtCO_{2(eq)}$[6] from the residential sector (DECC, 2011b). According to the independent Committee on Climate Change (CCC) if the UK is to reach its target of achieving 80% reductions in $CO_{2(eq)}$ emissions on 1990 levels by 2050; emissions from households will have to be eliminated almost entirely (DECC, 2008a). Additionally the CCC claim technical potential exists to reduce emissions by almost 40 $MtCO_{2(eq)}$. Over half of this comes from negative cost energy efficiency improvements and lifestyle changes, with the remainder costing much less than the forecast price of carbon estimated at £40/$tCO_{2(eq)}$. This is in stark contrast to the department of Communities and Local Government (2006) who claim it may only be possible to reduce emissions from the existing stock by 9-18 $MtCO_{2(eq)}$, with an additional 4 $MtCO_{2(eq)}$ savings from new buildings. This suggests a disappointing 15% reduction in emissions from the residential sector from a business as usual scenario[7] by 2050. This is clearly insufficient and will not meet the government's ambitious 80% emissions reduction target by 2050.

Achieving the level of CO_2 emission reductions will require year-on-year improvements to the building sector. These include: the implementation of zero carbon residential new buildings post 2016, higher standards for household

6. This figure includes both direct and indirect emissions such as the supply of electricity to homes.
7. The business as usual scenario assumes that emissions from the residential sector remain stable to 2050. This allows for growth in electricity consumption but with lower overall emissions factors.

appliances and significant efficiency upgrades to almost all existing dwellings (Clarke et al., 2008). Regrettably, there is insufficient empirical research quantifying the complex interdependent relationships between all of the major driving forces purporting to explain residential energy consumption. Furthermore, there still remains a number of barriers and market failures which undermine much needed investment in energy efficiency in the residential sector (IEA, 2008b, p.33).

2.7 Existing government policy

In 2007, the UK government put in place a National Energy Efficiency Action Plan (NEEAP) to reduce emissions from the UK housing stock by 31% on 1990 levels by 2020. Following this, the UK government introduced The Climate Change Act and thus became the first country in the world to pass legislation for reducing GHG emissions. The UK is now legally bound to reduce emissions by 80% on 1990 levels by 2050 (HM Government, 2008). Interim budgets established by the Committee on Climate Change (CCC) require 50% cuts by 2027; 35% cuts by 2022; and 29% cuts by 2017 (CCC, 2010). While it is likely the interim budget to reduce emissions by 23% on 1990 levels by 2012 will be met, this did not result from good governance alone. Rather, the emissions reductions primarily came from the ‘dash for gas’ during the 1990’s (UKERC, 2009, p.17) and the recent financial crisis that saw total emissions drop by some 10% in 2009 alone (CCC, 2011, p.4). For the UK to meet the next set of carbon budgets, reductions in emissions from the residential sector are pivotal. This position is acutely expressed by the CCC declaring net emissions from buildings in 2050 will need to be almost entirely eliminated if future emissions targets are going to be met (CCC, 2010, p.237). Meeting such a target will only be possible through radical reductions in energy consumption and necessary but strategic changes to energy supply and delivery.

The UK Government has also implemented a number of policies to encourage building energy efficiency. One of the most successful energy efficiency policies has been the mandatory use of condensing boilers when a boiler is replaced (Eyre, 2012). Although UK energy use is falling and Eyre (2012) argues that more could be done to improve energy efficiency policy for UK buildings. New product standards such as the Carbon Emissions Reduction Target (CERT) have been effective at delivering cost-effective measures they will not be able to deliver a complete low-carbon transformation (*ibid*). Supplier led measures such as Energy Efficiency Standards of Performance (EESOP) and the Energy Efficiency Commitment (EEC) are aimed at driving increases in energy efficiency within existing homes. Between 2002 and 2004 the overall cost effectiveness of EEC was a saving of £150/tC with priority given to customers in the 'priority group' of low-income households (Oxera, 2006). Government led initiatives such as HEES and Warm Front target those households who are in fuel poverty and is therefore not a panacea for reducing emissions.

Government policy could be used to remove market failures and barriers to investment enabling progress to be made towards meeting future targets. The Green Deal, Feed In Tariffs (FITs) and Renewable Heat Incentive (RHI) are all government-backed policies designed to meet the policy objectives of the energy trilemma[8]. Recent backtracking by the government (e.g. minimising the penetration of FITs and decreasing investment in renewables may have jeopardised business confidence, increased market uncertainty and may be preventing future investment from the commercial sector in increased energy efficiency and low carbon technologies.

Building on the background presented in this chapter, the next chapter will review the existing literature on energy demand modelling, highlighting gaps and potential opportunities for further research. Research will then analyse existing building performance and evaluation tools used in the UK to ascertain whether existing UK building standards are fit for purpose.

8. The energy policy trilemma describes three overlapping policy objectives as being environmental degradation, energy security, energy price (energy poverty).

3

Literature Review

3.1 Chapter summary

This literature review provides an overview of methods and approaches used to model residential energy demand and emissions. This chapter is confined to describing existing models. Firstly, Integrated Assessment Models (IAM's) are introduced in the context of E3 modelling (Energy, Environment and Economy). Following this, major differences between bottom-up and top-down modelling methods are established. Several examples of the strengths and shortcomings of top-down methods are presented before the same is done for bottom-up methods. Two bottom-up methods are introduced and discussed in detail: the engineering method and the statistical or econometric method. Several reasons for the lack of robust bottom-up econometric methods are provided. The chapter concludes with a short description of several UK residential sector energy models.

3.2 Integrated Assessment Models (IAM) and E3 Modelling

Integrated Assessment Models (IAM's) are defined very broadly as any model combining scientific and socio-economic factors for assessing and evaluating policy options. The importance of climate change has seen IAM's being applied to measure and assess the impacts of different mitigation options for minimising the effects of climate change. Integrated assessment models are representational and interdisciplinary and can perform analysis either: ex post or ex ante with the ability to also perform counterfactual analyses (Parson and Fisher-Vanden, 2003). Weyant et al. (1996) describes integrated assessment modelling in broad terms as any research which draws on multiple disciplines. In general, IAM's can be distinguished into two broad classes: policy optimisation models (such as DICE[9]), which seek to optimise policy strategies, and policy evaluation models (such as IMAGE[10]) which assess the effects of specific policy choices. Under this broad definition, the dynamic macro-economic models developed under Dr Terry Barker et al. (2003)can be considered as IAM's, however, the models developed by Barker et al (2003) rarely feature in any comparison or assessment of IAM's within the literature (Alberth and Hope, 2006; Weyant et al., 1996; Bohringer, 2006). This is most likely because these models are primarily macro-economic models adapted to incorporate and measure GHG emissions from economic activity – not the other way around. The Cambridge E3 models are therefore better thought of as hybrid, dynamic, E3 (energy-environment-economy) models which can be used to prognosticate a large number of variables related to economic activity including GDP, employment, interest rates, energy, and importantly $CO_{2(eq)}$ emissions (among others).

MDM-E3 is an example of an E3 model, which was first developed during the 1970's and is now one of the most established macro-economic models of the UK economy (Barker and Kohler, 2006). MDM-E3 uses the non-optimising dynamic simulation approach and since it is based on time-series data, it has the advantage of a strong connection with historical trends. Unlike other top-down models, sub-models can be expanded and compared with top-down outputs and procedures. Interestingly, the two approaches can feed into one another providing opportunities for modelling the complexities of the real world.

3.3 Bottom-up, top-down and hybrid modelling methods

Two broad approaches exist for modelling the interaction between energy, economy, and environmental systems and technology (Van Der Zwaan et al., 2002). The top-down approach uses macroeconomic principles and the interaction between the energy sector and the economy at large, and relies on aggregate economic behaviour

9 . DICE stands for Dynamic Integrated Model of Climate Change and the Economy. It is a model that attempts to use the tools of modern economics to determine efficiency strategy for coping with the threat of global warming.

10. IMAGE is an IAM model with a particular focus on land use, reporting information information on seven crop yields in 13 regions from 1870 to 2100.

based on observed historic trends to predict future changes in energy and $CO_{2(eq)}$ emissions. Bottom up methods on the other hand, take a disaggregated approach and tend to focus on energy demand using highly disaggregated, technical, physically-based, engineering-type methods to model in detail, the technology type, energy demand and supply sectors involved (Hoogwijk et al., 2008; Johnston, 2003). The data input for these models largely consists of quantitative data of physically measureable variables i.e. the thermal performance of a wall, the efficiency of a space heating system etc. This data is then used to describe the past, present and future stocks of energy technologies within particular sectors of the economy (Johnston, 2003). Even with this level of disaggregation and detail, many bottom-up models still do not have the capacity to calculate important economic variables such as income and price effects. According to Herring (1999), purely bottom-up models are still widely criticised and have been the subject of a long-running debate between energy economists about their inability to incorporate other macro-economic effects such as rebound effects, economic co-benefits and the various barriers to the realisation of energy efficiency. Figure 3.1 shows a graphical representation of both modelling approaches for estimating demand for energy services and $CO_{2(eq)}$ emissions.

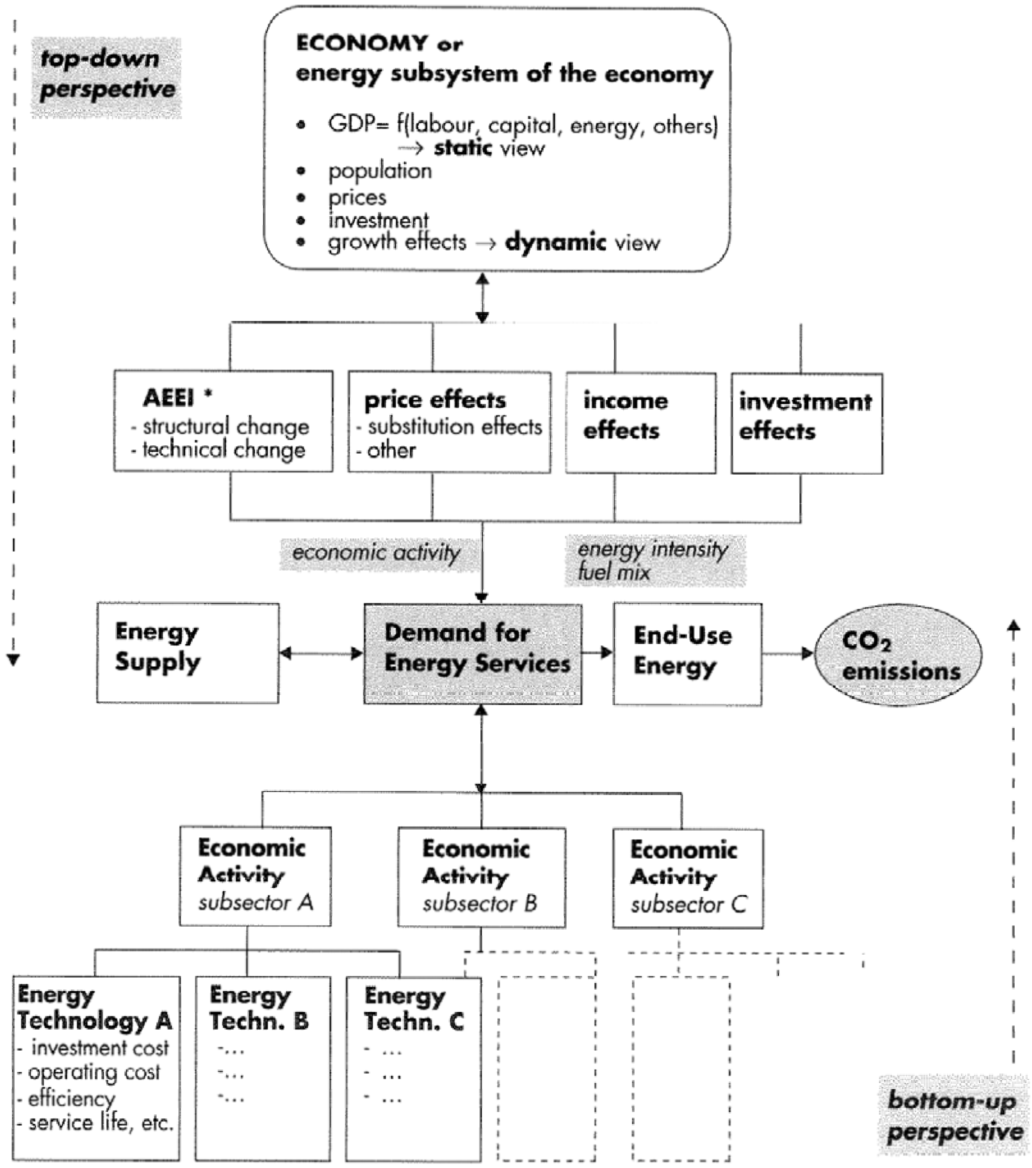

Figure 3.1: Diagrammatic representation of bottom-up vs. top-down modelling

Reproduced from (IEA, 1998, p.18)

As identified by Hoogwijk et al. (2008) the differences between these two fundamental approaches are not definitive but at the same time, they are also not exclusive. The bottom-up approach adds technology detail and is therefore well suited to test policy instruments; however, it pays little attention to the various barriers that may prevent technology adoption. In top-down approaches technology detail is limited but system integration and barriers to adoption can be incorporated – to some extent – within the model. Similarly, disaggregation of different technologies or the effects on different sub-sectors are sometimes difficult to ascertain in top-down models. To this end, these two different approaches will lead to very different model properties and therefore model results, these effects are most widely noticed in the analysis of emissions and mitigation costs for climate change (Jacobsen, 1998).

The advantages of incorporating top-down macroeconomic techniques with bottom-up engineering methods was first identified in older studies such as (Hoffman and Jorgenson, 1977) but more recently by Barker (1995) who argue that the two approaches are more complementary in nature rather than substitutable. Similar to models completed by Nakicenovic & Riahi (2003) (2004) which are based on the linkages between top-down and bottom-up approaches, Barker (2006) ascertains that "our approach avoids the typical optimistic bias attributed to bottom-up engineering methods and unduly pessimistic bias attributed to typical macro-economic approaches – page 4". The advantages of such approaches are reviewed more fully in the following literature (IEA 1998; Grubb et al. 2003)

3.4 Bottom-up and top-down and hybrid modelling methods as applied to the residential sector

Over the last two decades there has been a plethora of national level domestic energy models that vary in data requirement, disaggregation level, socio technical assumptions and the scenarios or predictions that can be made (Kavgic et al., 2010). Since the advent of computers, many national level models have been developed to assist in the prediction and analysis of domestic energy consumption. Most authors agree that the majority of models generally take two broad epistemic approaches described as being either top-down or bottom-up. Advances in recent years have seen the development of sophisticated hybrid models that integrate both of these approaches into a single model. In parallel with these integrated techniques, a number of advances have been made in machine learning, new statistical approaches and GIS methods which are now capable of modelling the interaction between energy, economy, environmental systems and technology within the built environment (Rylatt et al., 2003). For example, a neural-network based national energy consumption model was developed for the Canadian residential sector (Aydinalp et al., 2003) and other innovative statistical techniques such as decision tree analyses are being used to model residential energy consumption at the national level in Hong Kong (Tso and Yau, 2007).

Due to the fact that several relatively recent publications provide excellent reviews on different residential sector modelling techniques, this section has purposefully been kept brief (Tso and Yau, 2007; Strachan and Kannan, 2008; McFarland et al., 2004; Kavgic et al., 2010; Jebaraj and Iniyan, 2006; Aydinalp-Koksal and Ugursal, 2008; Böhringer and Rutherford, 2009; Swan and Ugursal, 2009).

3.5 Top-down residential sector energy modelling

The top-down approach uses macroeconomic principles and the interaction between the energy sector and the economy at large, relying on aggregate economic behaviour based on observed historic trends to predict future changes in energy and $CO_{2(eq)}$ emissions. Top-down methods use econometrics and more specifically, multiple linear regression methods to explain variance between dependent and independent covariates related to residential energy demand. For example, econometric top-down models use aggregate level data such as income, fuel prices and average dwelling efficiency to explain the variance of aggregate energy consumption from the residential sector. Such models are often criticised for lacking detail about present and future technologies with an inability to allow for future events when environmental, social and economic conditions may be entirely different from what was experienced in the past (Kavgic et al., 2010). These models tend to neglect the socio-technical and behavioural considerations of energy use at the household level and instead make general conclusions about aggregate or average energy consumption across the building stock. As argued by Hitchcock (1993) energy consumption patterns are a complex technical and social phenomenon and to be understood appropriately must be tackled from both engineering and social science perspectives concurrently.

Several models have been developed that implement top-down regression methods for modelling aggregate residential energy demand from the UK residential sector (Summerfield et al., 2010a; Shorrock, 2003; Azadeh et al., 2010). One of the first top-down regression based methods was developed by the Building Research Establishment (BRE) and used data from the domestic energy fact file (DEFF) to predict aggregate housing stock energy consumption. The obvious limitation of this method is the homogenous treatment of UK dwellings with a limited number of independent variables averaged over the UK on an annual basis. Although the power of the model to predict total energy consumption from the residential sector appears robust when compared with historical trends, the model cannot isolate regional, local or individual household effects. It also fails to isolate important explanatory variables that may have an effect on energy consumption such as fuel type, growth in appliances, changes in relative wealth and energy prices. Thus, it does not explain consumption in sufficient detail to quantify the effects of different policy measures (Kavgic et al., 2010). On the back of the DEFF model, an improved version was created using decomposition analysis to explain the various factors contributing to $CO_{2(eq)}$ emissions between 1990 and 2000 in the UK residential sector (Shorrock 2003). More recently, the model was improved again (Summerfield et al., 2010a; Lowe, 2007) by adding inflation adjusted energy price to the equation thus creating the annual delivered energy and price model (ADEPT). The model still suffers from the same limitations as the DEFF model, and similar to other aggregate regression models cannot explain consumption characteristics at the household level nor model the specific effects of technologies, policy options or behaviour.

3.6 Bottom-up residential sector energy modelling

Although aggregate regression methods help to show trends in energy consumption patterns across the building stock, they cannot explain the various components that contribute to energy consumption at the household level. For this type of analysis investigations at the micro or dwelling level are necessary. Bottom up methods take a disaggregated approach and estimate energy and emissions using high resolution data that can use any combination of physical, social, behavioural or demographic properties of a household (Hoogwijk et al., 2008; Johnston, 2003). The empirical data requirement for bottom-up models is significantly more demanding and therefore requires large quantitative datasets that contain specific characteristics for each dwelling. Such variables include physically measured variables, demographic information and sometimes details about the energy consuming behaviour of the occupants (BRE, 2005). Bottom-up methods allow the modeller to combine, or aggregate micro-level estimates to draw conclusions about the entire dwelling stock.

Two types of bottom-up methods are identified within literature and the method chosen is contingent on the data and structure of the analysis required. These two approaches are the engineering method and the statistical method. The engineering method uses a sample of houses and technologies to represent the national housing stock. In this approach, thermodynamic equations are employed to balance the energy requirements of a dwelling. Such models therefore require physically measurable variables such as information on different building components (floors, roofs, walls, windows etc), building type, building location and the efficiency and type of heating systems in operation. Given the modeller has access to a sufficient level of empirical data on the physical properties of a building and well grounded assumptions on the heating systems and behavioural patterns associated with a buildings operation, it suggests it is possible to estimate the energy consumption and therefore the emissions from the building.

Because estimates are conducted at the micro-level, such models have the potential to model the impact of various policy and technology options. For instance, as every home has a unique set of technology options for carbon mitigation it is only by aggregating bottom-up estimates that the true mitigation potential from the residential sector can be gauged. A top down approach would implement marginal changes to the average level of mitigation therefore giving a very different answer. Unlike top-down methods, bottom-up methods allow assessment for the effects of new technology options and the penetration of different technologies into the building stock. They also allow the properties of the system to emerge from the interaction between different technologies.

3.6.1 Bottom-up econometric methods

Similar to top-down models, regression techniques can also be employed for bottom-up analysis. Given the widespread use and adoption of the general linear model in all branches of social science research, it is somewhat surprising more models have not been developed that use this technique for estimating residential energy demand. While one or two models were developed in the UK during the 80's and 90's using large statistically powerful datasets (Baker et al. 1989) the full potential of these models has never genuinely been realised. More recent developments using bottom-up methods rely on data obtained from very small localised datasets representing just a small subset of the population, with perhaps, a few hundred representative cases (Baker and Rylatt, 2008). The main reason for such a significant gap within literature might be explained by the serious lack of nationally representative, high quality, high-resolution data at the household level combining energy consumption data with dwelling characteristics and occupant behaviour. Indeed, there are many benefits of multiple regression including their simplicity and adaptability to almost any problem. A downside of this approach is the assumption that a single dependent variable is a linear function of multiple independent variables. It is also difficult to ascertain the underlying causal mechanism behind the model as standard multiple regression techniques only provide evidence that the explanatory variables collectively have an effect on the response variable and sometimes can suffer from multicollinearity.

3.6.2 Bottom-up engineering models

There are now hundreds of programs and tools developed for calculating energy consumption within the built environment. For instance, the US Department of Energy hosts an online Building Energy Software Tools directory[11] with over 360 software tools submitted by individuals and organisations around the world for measuring, identifying and evaluating energy efficiency, renewable energy and sustainability of buildings (U.S Department of Energy, 2012). The directory is a collection of both commercial and open source software packages freely available for download and evaluation. Because the energy tools directory includes databases, spreadsheets, system analysis tools as well as whole-building energy performance and simulation programmes it provides an overall picture of current engineering best practice for modelling energy use and efficiency within the built environment (US Department of Energy, 2009).

The sheer scale of the building services industry has led to the establishment of two prominent multi-national professional bodies that together set standards and best practice philosophy for designing and implementing energy systems within the built environment. In the USA, this is the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE, 2009) and in the UK, this is the Chartered Institution of Building Services Engineers (CIBSE, 2009). Both organisations provide a vast and comprehensive body of information and procedures for calculating and indeed modelling energy use within the built-environment.

Although the tools identified above focus on measuring and sizing engineering equipment at the individual building scale, the physical engineering principles associated with computing energy demand can be used to estimate building stock energy demand through the aggregation of building level energy demand calculations. Indeed, this method is the one adopted by the vast majority of bottom-up residential energy models. With the development of such models and the application of emissions factors, it is then possible to compute $CO_{2(eq)}$ emissions.

In the UK for example, BREDEM (Building Research Establishments Domestic Energy Model) is the most widely used model for calculating the energy requirements of a single domestic building. The model itself uses a series of heat

11. http://apps1.eere.energy.gov/buildings/tools_directory/

balance equations and forms the basis of the Governments' (SAP) used for the energy rating of dwellings (BRE, 2005). One major weakness of building physics models relates to the assumptions made regarding the behavioural factors that contribute to energy consumption, which are known to be significant (Boardman et al., 2005, p.57; Hitchcock, 1993). Another failing of physical models is a failure to allow for economic factors and as a direct consequence, fail to describe and account for the purchase of different energy technologies in the home and more generally, the energy choices made by households. One way to overcome these deficiencies is to supplement these methods with a bottom-up econometric model.

3.7 United Kingdom domestic building stock models

BREHOMES (Shorrock, 2007) is probably the most important bottom-up building stock model in the UK as it used widely in the development of new government policy. The model brings together a number of data sources developed since 1970s. It uses a number of building archetypes to make energy and emissions extrapolations for the residential sector. BREHOMES (Shorrock and Dunster, 1997) uses BREDEM (Anderson et al., 2001) for its energy calculation procedure, first developed in the 1980's. The purpose of BREHOMES is to calculate annual required energy for three main areas, specifically: space heating; water heating, and; appliances and lighting. Other inputs into the model include U-values for different standards of insulation, floor areas by building category, heating patterns, water heating system, heating system efficiencies, lights and appliance use, cooking use, number of occupants, external temperature (degree days) and average internal demand temperature over the heating season. Using this information energy demand from each dwelling archetype can be computed. Unfortunately, the model does not include any economic dimension and the underlying data is copyrighted to GfK. This severely limits the accessibility of the model for validation purposes and the extent to which information can be released for further scrutiny (Shorrock, 2007). A further shortcoming of this model is the crude assumption made about internal temperatures assumed to remain constant over long periods.

Johnston's Model (Johnston, 2003) was developed as a PhD research project from 2001-2004. Developed as a bottom-up engineering model it aimed to predict the energy and $CO_{2(eq)}$ emissions from the UK residential sector. There are two principal components within the model: a data model and the BREDEM-based energy and $CO_{2(eq)}$ emissions model. Although demand oriented, it also includes a simple supply side model. The BREDEM model then calculates energy and $CO_{2(eq)}$ emissions for each “notional” building type (there are only two) this is then scaled up to reflect the total housing stock in the UK. It does this for each year in question between 1996 and 2050. Although this is one of the more advanced domestic energy sub-models, it still contains several weaknesses. There is no allowance for human behaviour and the economic decision making of agents. There is also no disaggregation by region, fuel type, fuel price, technology type or efficiency rating and it only uses two “notional” dwelling types, a typical pre 1996 dwelling and a typical post 1996 dwelling. A further limitation of the model is that it uses 1996 as the base year making it difficult to do ex-post or counterfactual analysis pre 1996.

UKDCM (Boardman et al., 2005) was developed by Boardman et al. at the Environmental Change Institute (ECI) in Oxford and is a bottom-up residential sector model for the UK and was developed after both Johnston’s Model and BREHOMES. Unlike BREHOMES which uses an average dwelling to predict future trends from a stock of 1000 dwelling types, UKDCM uses a disaggregated approach that gives around 20,000 different dwelling types by 2050 with an appropriate weighting, it then uses this data to describe the overall carbon emissions profile of the housing stock given a particular future scenario. The resulting housing stock is highly disaggregated with datasets from nine geographical regions, seven age classes, and ten types of construction that are then divided by tenure, number of floors, and construction. For the period 2005-2050, decadal age classes are added to allow for improving building classes. A clear weakness of this model is the absence of cost and economic data justified because of the difficulties it provides in modelling (Boardman et al., 2005). A well known publication called “40% house” (Boardman et al., 2005) was developed during the project and explicitly sets out what decisions are required to reduce energy consumption in homes by some 60%.

DECarb was first developed in 2001 and proposed to remove the requirement for increasing quantities of disaggregated data that are either unavailable or unrealistic to measure at the level of disaggregation required. Natarajan notes: “one of the key challenges for modelling the housing stock is to reconcile the requirement for real and diverse future stock with the limited information that can be fed into such models to measure future trends” (Natarajan and Levermore, 2007, p.5719). DECarb proposed to solve this dichotomy by using historical back casting to test the model results. The model uses BREDEM algorithms to perform energy calculations.

Included within the model is information on the housing stock incorporating six historical age classes, seven internal variables (wall type, house type, insulation etc) and giving 8064 unique combinations for each age class. As has been shown by others (Natarajan and Levermore, 2007) averaging is not a good technique for representing the existing building stock as it removes the inherent variability from the existing stock distribution. Instead, DECarb uses the heat balance method used by several other models including Shorrock and Dunster (1997) and Johnston (2003).

The DEMScot model was developed by Cambridge Architectural Research to model green house gas emissions from housing in Scotland (Cambridge Architectural Research, 2009). The aim of the model was to show the impact of different Scottish government policy interventions aimed at reducing $CO_{2(eq)}$. The model is based in Excel and draws extensively on data from the Scottish House Condition Survey. It is a bottom-up engineering model and uses standard BREDEM12 assumptions to estimate energy and emissions from each dwelling contained within the sample.

The Housing Energy Fact File was also developed by Cambridge Architectural Research (CAR) and is not so much a model as it is a collection of important data representing household energy consumption in England (Palmer and Cooper, 2011). Two important tools were developed by CAR. **The Cambridge Housing Energy Model** uses a similar approach to **DEMScot** and estimates building performance independently for each house using data from the English Housing Survey. **The Cambridge Housing Tool** is a convenient lookup tool that is able to query English Housing Survey data to find statistics about the existing building stock.

3.8 E3 Hybrid models incorporating residential energy as a sub-model

The MARKAL domestic sector model (Kannan and Strachan 2009) is an optimisation model that has an advantage over other domestic stock models because it incorporates wider macro-economic effects. The trade-off in this regard is that it treats the residential sector as a single sector within the broader economy. The MARKAL model is a bottom-up, dynamic, linear, optimisation model. As an optimisation model, it minimises total energy system cost by choosing the investment and operation levels of all interconnected system elements. Participants within the model are assumed to have perfect inter-temporal information and knowledge about future policy and economic developments. Hence, under these input assumptions it delivers an economy wide solution of least cost. Within the domestic model, end-use technologies are characterised in detail with energy service demands imposed exogenously (Kannan and Strachan 2009). In order for the model to be optimised under realistic engineering and economic frameworks a range of constraints are imposed.

The DTI model (UK Parliament, 1999) is the UK Government's econometric partial equilibrium model of the UK energy market. The model's key inputs include fossil fuel prices, economic growth and demographics. The residential final energy demand is driven by real disposable income, domestic energy prices, number of households, external temperature and the uptake of appliances. The model consists of 130 econometric equations made up of 65 fuel share equations, 20 stock equations and 50 demand side equations. Each of the final user sectors consists of a suite of econometric equations. Energy demand is disaggregated into 13 sectors (services, domestic, iron and steel, agriculture, transport and eight industrial subsectors). Each of the final user sectors consists of a number of econometric equations to explain past energy demand as a function of other variables such as prices and income or output levels, based on the historic relationship between these variables and historic trends in efficiency (UK Parliament, 1999).

3.9 Strengths and shortcomings of UK residential sector energy models

Except for MARKAL (which has limited residential sector modelling capacity) none of the residential sector energy models reviewed account for economic effects such as the price of energy or the cost of installing new appliances or elasticities of demand. Nor do any models incorporate the behaviour of occupants. As identified by Kannan and Strachan (2009) achieving carbon reductions is not just a technical challenge it is also an economic challenge. Decisions for improving building efficiency are made at the dwelling level, thus being able to predict when people invest in efficiency or switch to low carbon technology is central to this type of modelling. Modelling this type of behaviour is difficult for the reasons already discussed. A further weakness is that most models ignore the interactions between different carbon mitigation strategies within buildings but also across other parts of the economy. For instance most of the models assume an exogenous emission factor (or energy mix) ignoring the dynamics of a changing power sector over time. None of the models identified (except for Johnston where a crude attempt was made) take an integrated approach to modelling energy supply and demand, instead each model treats the built environment as independent from other sectors of the economy and then predicts how it will perform in isolation. As will be shown, only by taking a complex systems approach can the true dynamics of residential energy demand be properly understood.

Many residential energy models have been developed to model energy, efficiency and emissions from the residential sector. Most of the models presented in this section have unique input assumptions including data, calculation methods and time scales over which the model is applied. The importance of using a disaggregated model for capturing the heterogeneity within the building stock is emphasised and will be the approach followed when designing and constructing a model for this research. While aggregate models are able to capture economy wide trends in energy and average efficiency levels across the entire building stock, they fail to represent the diversity within the building stock and therefore miss opportunities for more targeted reductions. A primary purpose of the model developed will be to capture this diversity. In addition, many of the aggregate models previously discussed cannot model the impact of specific technologies or the effects of human behaviour. These shortcomings will also be addressed in the new model. Disaggregated bottom-up models make it possible to capture the natural diversity between dwellings. However, these models are still deficient because they do not adequately incorporate the behavioural characteristics of occupants and the interactions people have with the physical thermodynamic processes of the buildings on a daily basis. This is particularly evident for how these models incorporate internal temperature profiles. The model presented in this thesis proposes new methods to overcome these deficiencies. Most models fail to situate the residential sector within the much broader context of energy supply and demand. As micro-generation technologies proliferate and smart grid technologies are embedded within the energy system, the distinction between supply and demand will become increasingly blurred. As identified by Bergman and Eyre (2011) microgeneration may play an important role in decarbonisation efforts offering indirect 'soft' benefits despite it being a more expensive technology. Building stock models that fail to situate the residential sector within this broader energy systems context will therefore miss opportunities for energy demand reduction and further decarbonisation. A model that offers insight into the system wide benefit will therefore be an extremely useful policy tool.

4

Building performance evaluation and certification in the UK: a critical review

4.1 Chapter summary

Improving the efficiency and performance of the UK residential sector is now necessary for meeting future energy and climate change targets. Building Performance Evaluation and Certification (BPEC) tools are vital for estimating and recommending cost effective improvements to building energy efficiency and lowering overall emissions. In the UK, building performance is estimated using the Standard Assessment Procedure (SAP) for new dwellings and Reduced SAP (RdSAP) for existing dwellings. In this chapter, many opportunities for improving the effectiveness of BPEC tools are identified. If the residential sector is going to meet future energy and climate change targets, the process used to measure and evaluate building performance will need to improve. Building performance standards across Europe are therefore compared to highlight the most effective strategies.

In the UK, the large variance between estimated and actual energy performance may be preventing the adoption of bottom-up energy efficiency measures. Despite popular belief, SAP and RdSAP do not estimate building energy efficiency per se but instead attempt to estimate the cost effectiveness of efficiency measures and thus create perverse incentives which may lead to an overall increase in $CO_{2(eq)}$ emissions. In this regard, the SAP standard confounds cost-effectiveness, energy efficiency and environmental performance giving an inadequate estimate of all three policy objectives. Several opportunities for improving measurement, analysis, synthesis and certification of building performance characteristics are therefore provided.

4.2 Aim and scope of chapter

The objective of this chapter is to identify the characteristics of existing policy that are working well, and what factors might lead to more rapid improvement of the building stock. An appreciation for how building certifications are conducted is required but also an appreciation for the inner workings of the wider system, consisting of: tenants, property owners, estate agents, government regulators and other independent or related commercial entities. For example, existing government targets require all new buildings to be zero carbon by 2016 whilst simultaneously making significant improvements to the existing building stock (although there are no concrete targets yet in place for the existing stock). The effectiveness of policy therefore rests on adequate implementation of the following criteria:

i) a universally accepted and implementable definition of zero carbon;

ii) accurate calculation procedures for assessing the performance of buildings;

iii) a widely understood building rating standard for the comparison and assessment of heterogeneous buildings;

iv) a sufficient number of well trained and competent assessors to carry out inspections;

v) a credible certification programme that motivates individuals to improve the energy efficiency of their homes, and;

vi) investment in research looking into the dynamics of both the social and technical dimensions of building performance and the role for policy to meet future energy and emissions targets.

Thus, a successful national BPEC strategy will have at its heart: an accurate and reliable set of calculation procedures for assessing buildings; trained and competent assessors; an understandable and well-respected building performance and certification standard; and finally, high level research that maximises the use of rich datasets that feed back into policy discourse and close the loop on building performance improvements. The need for a reliable measurement and verification system was demonstrated in the US through an analysis of the wide variance of energy and carbon performance of buildings under the LEED programme. Wedding and Brown (2007, 2008) found the variance between estimated and actual energy consumption was caused precisely by the lack of measurement and verification in assigning green credentials.

The current chapter is novel in its outlook and presents an original critique of building performance standards in the UK. It therefore offers an important but timely contribution to the development of policy for improving BPEC, thus leading to well informed policy targeted at rapidly transforming the UK building stock. This chapter is separated into four main sections. The first section looks at the development of BPEC calculation procedures in the UK. It is argued that lock-in and path dependence from early BREDEM models has led to inefficient and ineffective building standards (e.g. SAP and RdSAP) bringing into question the power of existing SAP calculation routines to deliver the changes necessary to meet future energy and climate change targets. The second section looks at the development of the EPBD and compares the different building standards implemented across Europe. Several improvements and strategies are identified for implementation within a UK context. Thirdly, the central role of Energy Performance Certificates (EPCs) for driving bottom-up transformation of the building stock is discussed. Finally, the weaknesses of SAP and RdSAP are reviewed with suggestions offered for how the underlying calculation procedures may be improved, increasing the reliability of estimates and therefore the predictability of end-use energy savings to drive future carbon reductions.

4.3 The importance of building performance evaluation and certification (BPEC)

Not only is a sound evidence base for the potential contribution in emissions reductions from the residential sector important, but also, the right policies and incentives are in place to ensure these reductions are achieved. One of the first steps required to meet future emissions related targets is to ensure a robust measurement and certification procedure is in place. There are many benefits for implementing a national building performance and certification scheme, several of these are discussed below.

A large statistically robust dataset containing details on the condition of the building stock allows detailed modelling to be carried out on the performance of many discrete heterogeneous buildings. Data can then be aggregated in different ways to determine the performance of buildings belonging to different groups. For example, buildings can be broken into income deciles, building typology, ownership category or location greatly enhancing opportunities for decarbonisation.

A large database containing information about each specific dwelling thus makes it possible to target whole boroughs, communities and streets for simultaneous improvement. Targeting the best improvements on a street-by-street basis means that resources can be pooled, transaction costs reduced and the benefits from economies of scale realised. Street-by-street transformation of the existing stock is a clear strategy supported by several existing studies (GFC, 2009; Kirklees Council, 2009; DECC, 2009a; Lomas, 2010)

A national building performance and certification scheme provides a common standard from which all buildings can be compared and measured against. This reduces confusion in the sector and creates a level-playing field for market competition. Thus, national certification schemes expose previously hidden information about the performance of a building making the information more openly available to buyers and future tenants. In Europe, it was not until the European Performance of Buildings Directive (EPBD) came into force that certification requirements were extended to all existing buildings across the EU. A primary function of implementing this standard was to address the issue of imperfect information and encourage much needed investment in building energy efficiency (European Commission, 2002). In Europe, an EPC needs to be produced every time a new occupier purchases or leases a building. Through the provision of information about a buildings' energy performance, new occupiers are given the opportunity to make well-informed choices about the property thus changing the set of characteristics that drive value in the property market.

As well as resolving information asymmetry, building standards also have the potential to improve fuel poverty statistics. In 2009, at least one-fifth (5.5 million) of UK homes were in fuel poverty (DECC, 2011c). This is exacerbated by the forecasted increase to energy prices (DECC, 2011b). Without detailed information about the performance of buildings classified as being in fuel poverty, it is difficult to determine what strategies may alleviate these pressures. Robust BPEC standards thus allow information to be collected and effective strategies to be developed which may alleviate fuel poverty.

In sum, BPEC standards now represent an integral component of many countries strategies for reducing emissions from the residential sector. However, such benefits only accrue when the BPEC standards are trusted by the users of the information enabling them to act on the information they are given. Unfortunately, this can only happen if building performance tools are able to accurately calculate energy and emissions and therefore give a fair evaluation. In this chapter, many opportunities are identified for improving building performance evaluation and certification through better calculation procedures, targeted incentives and improved policy design.

4.4 Historical development of BPEC in the UK

4.4.1 Building performance and evaluation in a UK context

Presently, the UK relies on a family of models developed by BRE to estimate energy and emissions from UK buildings. All models in this family rely on variations being made to BREDEM standard assumptions. BREDEM was established as an engineering simulation tool for estimating an individual buildings performance. Typically, a trained engineer or energy assessor will perform an audit on the physical characteristics of a building through measurement and identification of energy relevant characteristics within the home. Examples of parameters recorded include the surface area of all floors, walls windows and roofs as well as the materiality of the structure (e.g. insulation thickness and double-glazing). Details about the energy system are also required for calculating heating system efficiency. The calculation routines thus use pre-specified internal and external temperatures to estimate energy demand from a set of heat balance equations (Anderson et al., 2001). As BREDEM is essentially a physical simulation model, the data requirements are substantial.

It is from the early suite of BREDEM models that SAP was used to assess the performance of newly constructed dwellings. The energy performance of existing buildings is estimated using the Reduced Standard Assessment Procedure (RdSAP) and is based on a simplified SAP procedure. In RdSAP, additional standard data tables (which use default values) are added to the model to replace missing or incomplete information. This greatly reduces the data and time requirements for conducting a building performance assessment on an existing building. Unfortunately, this often comes at the expense of accuracy when a building's performance is frequently shown to be different from the category on which default values were based. Given the importance for accurately estimating energy and emissions from the existing building stock, calculations for measuring the performance of the existing stock ought to be more accurate, thus giving an assessor the opportunity to include this information in the assessment.

Although building regulations have been in place for newly constructed buildings for several decades, it is only relatively recently that existing buildings have come under much deeper scrutiny. The UK suffers from an aging building stock where approximately 40% of buildings were built before 1944 (Dixon and Gupta, 2008). Moreover, it is estimated that over 75% of buildings in use today will still be standing in 2050 (Boardman et al., 2005; Sustainable Development Commission, 2007, p.41). Transforming the existing building stock – while maintaining high standards of construction in new buildings – is essential. The importance of existing buildings is emphasised in Figure 4.1 where the cumulative number of EPC lodgements from new dwellings and existing dwellings is compared. If present trends continue, all buildings will have an EPC by the early twenties.

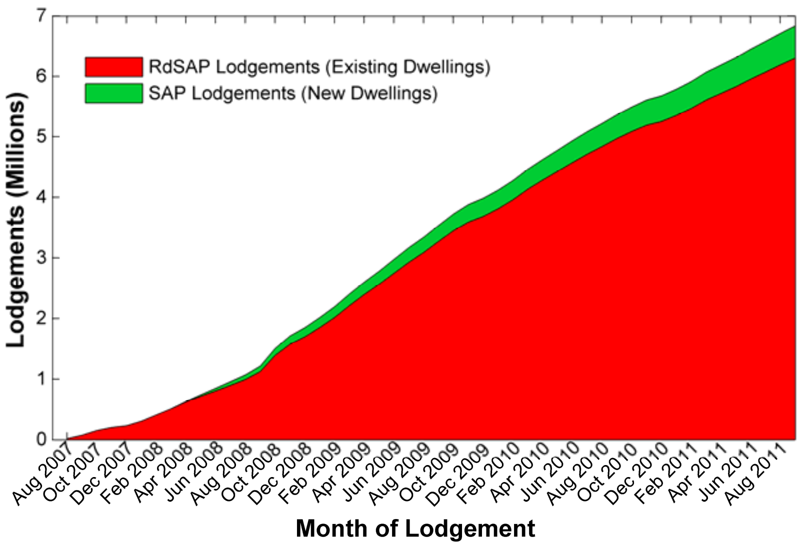

Figure 4.1: Cumulative EPC lodgements in England

Data source: Data received from a Freedom of Information (FOI) request from Landmark (Beschizza and Kelly, 2011)

4.4.2 Historical development of building standards in the UK

The UK Governments SAP was first developed in 1993 as an independent calculation methodology for estimating the performance of buildings across the UK. SAP is now at the heart of Government policy concerning the measurement, identification and improvement of the UK building stock. The SAP routines have since been incorporated in the UK building regulations for meeting the energy requirements of newly constructed buildings (Part L1A) and for measuring the energy performance of existing buildings (Part L1B). It is the chosen method for delivering the EU EPBD and is used in the calculation and creation of Energy Performance Certificates (EPCs). It is used widely for the delivery of many Government policies such as Warm Front, the Carbon Calculator, Stamp Duty Exemption for Zero Carbon homes and The Code for Sustainable Homes among others. In future SAP will increasingly be used for the delivery of new Government policy targeting a reduction in emissions from dwellings across the UK. For example, SAP will likely play a central role in policy instruments such as the GreenDeal and the Renewable Heat Incentive (RHI), where the effectiveness of strategies to reduce energy and carbon will need to be assessed. Additionally, it will be an important measure for identifying and targeting homes requiring priority attention, such as those dwellings classified as being in Fuel Poverty.

The estimated performance of the building stock is also changing. Below, two histograms represent how the estimated performance of the English building stock has evolved over a 10-year period from 1996 to 2006. While it is clear both the mean and the median estimated performance of dwellings has improved over time, there has been very little improvement in the number of dwellings meeting the high performance standard (A or B)[12]. This must change if all buildings are to be zero carbon by 2050 as recommended by the Committee on Climate Change (CCC, 2010, p.237).

12. Changes to the SAP calculation methodology between 1996 and 2006 may be responsible for some of the variation in estimates.

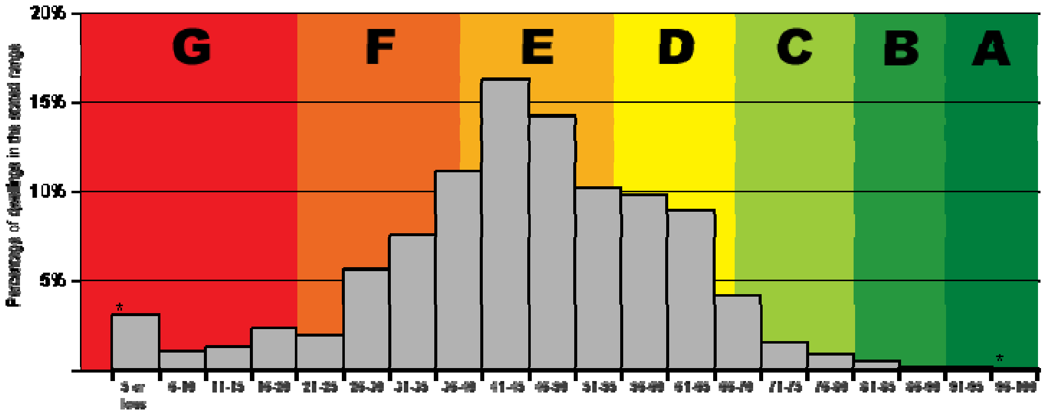

Figure 4.2: Distribution of UK SAP ratings in 1996

Data Source: EHCS 1996, after grossing weights have been applied

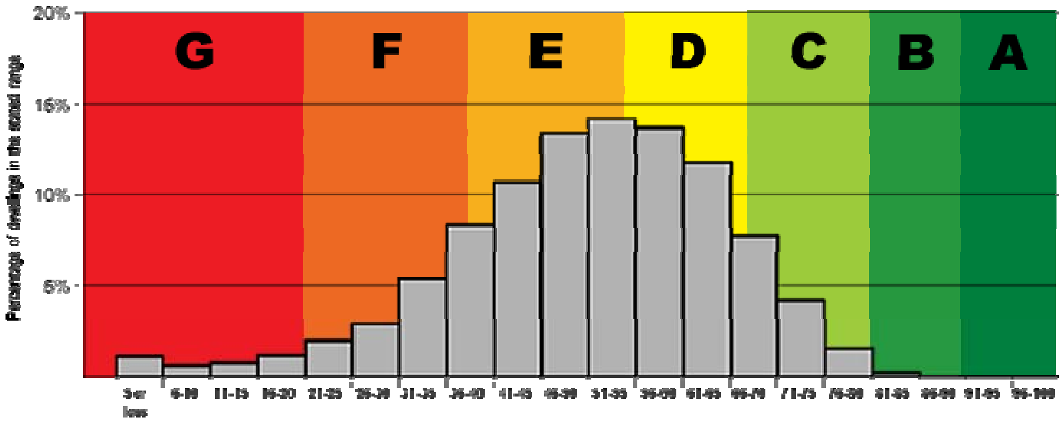

Figure 4.3: Distribution of UK SAP ratings in 2006.

1. Note that the shift to higher efficiency is primarily in the lower-to-middle performing buildings from 1996, not at the upper end of the distribution.
2. Data Source: EHCS 2006, after grossing weights have been applied

Given the importance of meeting future energy and climate change targets and the central role of buildings for meeting these goals, it is crucial that the underlying data and calculation procedures used by SAP are understood, validated and reflect the range of strategies that might be adopted to improve stock performance. Whilst anecdotal evidence from professional and academic circles suggests the efficacy of SAP for measuring building performance may be outdated and inadequate (BRE, 2006; Reason and Olivier, 2006), a gap exists within peer-reviewed literature with the aim of providing an independent critique of BPEC effectiveness for improving building stock emissions. There is also a serious lack of recent experimental analyses testing the validity and robustness of BREDEM and SAP (at least since 1990's) in regard to calculating building performance, especially for low energy buildings (Shorrock, 2011). Such validation tests need to correctly estimate the effect of new efficiency measures on energy consumption while controlling for behavioural and other climatic factors. Furthermore, many newly constructed homes do not meet minimum regulatory compliance standards (Grigg, 2004). This is owed to design errors, building defects and failures in enforcement. This is largely because of poorly developed policy, low understanding from those implementing the regulations and a lack of verification of performance (Reason and Olivier, 2006).

In conclusion, SAP calculation procedures now form the backbone of government policy for estimating building performance in the UK (Dickson et al., 1996). It is the primary method for assessing the efficiency of the building stock and for meeting EU policy directives regarding improvements to building efficiency (Audit Commission, 2009; DECC, 2009b; DEFRA, 2008b). SAP is widely used by government departments, local authorities, architectural practices energy auditors and energy companies for estimating building performance and for meeting minimum compliance regulations. Accordingly, the calculation procedures used by SAP need to correctly reflect the true performance of a building.

4.5 The early BREDEM Models

During the 1980's an Energy World Demonstration project was initiated where 51 homes in the Milton Keynes Energy Park were designed and constructed to be at least 30% more efficient than the building codes of the time. These new building endeavours led to advanced trial and monitoring programmes and the construction of over a thousand new low energy homes across the UK. It represented a milestone in the design and construction of energy efficient buildings. Important advances in whole-house energy calculation procedures were also developed and incorporated in early versions of the BREDEM model.

An early successor to BREDEM was a single zone; bi-seasonal building physics model that utilised mean seasonal temperatures for the calculation of energy demand (Uglow, 1981). This very crude approximation simply found the average external temperature over the entire heating season (October to April inclusive [5.5-7.5°C]) for use in a heat balance equation. Similar crude approximations were adopted for internal temperatures, estimated to be 16.4°C for homes using full central heating and 13°C otherwise for the entire length of the heating season. Unfortunately, these crude temperature approximations introduced significant uncertainty into the model adversely affecting the model's ability to predict energy use in homes. Although these approximations simplified the calculation procedure, it is now widely accepted that internal energy demand is highly sensitive to small changes in both internal and external temperature (Cheng and Steemers, 2011) and that internal temperature is significantly affected by occupant behaviour. This raises important questions about the legitimacy of this model to predict actual energy demand. Furthermore, the sensitivity of this model to varying climatic conditions was never validated, as dwellings used in the construction of the model were all taken from the same geographical location (Uglow, 1981).

Another shortcoming of this early model was its sensitivity to the estimated length of the heating season, producing dramatically different demand estimations for small changes in heating season length. Moreover, the temperatures used in this model were long-term averages with no consideration given to the behavioural effects of occupants. An investigation into the validity [13] of the model showed model estimations were roughly within 20% of measured energy consumption values (Uglow, 1982). Unfortunately, the sample of homes used in the validation consisted of just 42 dwellings with similar characteristics to the homes used during model development, severely limiting the statistical power of the results to be used across different circumstances with different building typologies and locations (Uglow, 1982). The homes used to create the model are thus vastly different to dwellings belonging to the population making it incorrect to draw any conclusions about the building stock as a whole.

A later version of BREDEM was extended to include two zones and incorporate changes to the way internal and external temperatures were handled. Specifically, the model adopted the degree-day method instead of the mean temperature method (Henderson and Shorrock, 1986). The degree-day method is a better approximation of heating demand than the mean temperature method as it more accurately estimates climatic factors from both the duration and extremes of seasonal temperature profiles. Henderson (1986) tested the two-zone version developed in BREDEM-5 against earlier versions of BREDEM and showed that the two-zone model improved the scatter of model estimates of energy consumption, reducing the standard error. As noted by Shorrock (2011) these improvements may have also been explained by other changes that were incorporated into the model at the same time. A further shortcoming of this validation process was that it used the same building dataset as was used by Uglow (1982), and is therefore subject to the same modelling limitations as this earlier version. Such validation exercises raise serious questions about the

13. The model was validated against 42 homes belonging to BRE staff near Garston

robustness of these early models for estimating building performance more generally. Furthermore, Henderson (1986) notes:

"The sample used for this study was dominated by medium to large dwellings with a good standard of heating, so that the good agreement observed should be extrapolated cautiously to other situations – page 91"

Henderson remarks the model should be expanded and validated against a more varied range of dwellings. The paper proposes that fabric heat loss is only loosely related to energy consumption and calls for an assessment method that accounts for the demand for heating instead of an analysis of only building fabric (i.e. a model incorporating human behaviour). A description on the development of BREDEM prior to 1985 is available in a report produced by Anderson et al (Anderson et al., 1985).

In BREDEM-8, the model was upgraded from a two-zone bi-seasonal version to a monthly model. Another validation exercise was completed by Dickson et al (1996) and involved comparing the results of the monthly model and the seasonal model against metered energy measurements and detailed simulation models. The metered energy measurement dataset used for this validation exercise consisted of 19 intensively monitored dwellings from the Milton Keynes Energy Park over two consecutive years (Dickson et al., 1996). All dwellings participating in this study used natural gas for central heating. They were also designed to consume 30% less energy than typical buildings constructed in the UK at that time. Once again, due to the confined geographic location of the sample and the limited sample size, the results from this validation exercise can only be cautiously extrapolated to model buildings from the rest of the UK.

Dickson (1996) found very little difference between results from the bi-seasonal version and the monthly version of BREDEM. The reason for such agreement in model results is most likely due to the similar assumptions made by the two models. For example, the monthly model adopted the same calculation procedure for estimating electricity demand as the seasonal model and simply divided the estimated annual electricity demand evenly over each month in the twelve-month period. Dickson (1996) also showed that BREDEM compared well with more detailed simulation models. Agreement between Dickson's BREDEM model and other building simulation models can be explained by similar assumptions common to most physical building simulation models. For example, building simulation models fail to account for human behaviour and usually just include the physical properties of the building.

The most recent and comprehensive BREDEM model was completed in 2007 and incorporated several important improvements. The model now allows different heating profiles for weekdays and weekends; it has a more thorough allowance of renewable resources; it incorporates monthly demand for electricity from lights and appliances; it allows for the responsiveness of the heating system; and it makes important corrections for the utilisation of hot water. Given the significant developments now incorporated within BREDEM, it is unfortunate that statistically robust validation exercises have not been completed on the model for over fifteen years. As discussed already, even the initial validation exercises conducted on BREDEM raised important questions about their applicability for extrapolation to the rest of the UK building stock. Validation of the model is now of the utmost importance.

If BREDEM were to be statistically validated for the UK housing stock, the model would have to be validated against a sample of approximately 384 dwellings[14]. This has significant statistical implications for the present SAP version of the model when the most recent validation exercises were completed over fifteen years ago against a sample of just 19 dwellings. As far as the author is aware there has never been a validation exercise conducted for BREDEM on a sample larger than 45 dwellings or on a sample spanning any significant geographic or climatic region in the UK. Moreover, recent improvements to building codes have resulted in the construction of many high performance buildings. The energy consumption from high energy efficiency buildings have never been tested against BREDEM and SAP energy performance estimations (Shorrock, 2011).

Figure 4.4 summarises data on the relationship between actual and modelled energy consumption, using the 1996 English House Condition Survey (EHCS) and the 1996 Fuel and Energy Survey (FES). The SAP estimates of energy consumption were taken directly from those recorded in 1996 EHCS. The scatter plot shows 3,756 data-points showing the large variance between estimated and actual energy costs. It is expected that some of the variance can be explained by climatic and behavioural

14. This assumes a confidence level of 95% and a confidence interval of +/-5%.

effects not included in the SAP calculations. However, with such a wide confidence interval[12] and weak statistical significance of slope, the error bars of the model estimates cannot be ignored. This result can only lead to the conclusion that RdSAP is a very poor predictor of actual energy consumption. In sum, the homogeneity and limited sample size of these early building models severely limit the accuracy and robustness of the models for predicting energy demand from a large cross-section of UK dwellings. Therefore statistically robust energy-demand validation exercises for the existing building stock are urgently required.

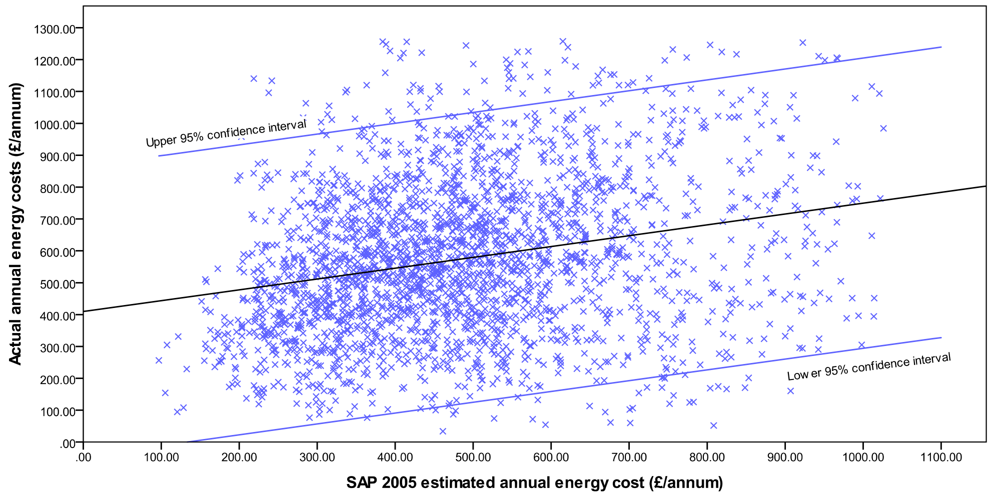

Figure 4.4: Actual versus SAP estimated energy consumption

4.6 The development of SAP for new buildings

One of the most important outcomes from BREDEM was the establishment of a national rating scheme for buildings, now known as the (SAP). The development of SAP was conceived from a desire to provide a national energy-rating label for buildings and to address the confusion that had arisen from several private-sector energy rating schemes (Killip, 2005, p.9). The original purpose of SAP aimed to address the following issues:

i) enhance the role of building energy efficiency for all buildings leased and sold;

ii) use the SAP rate as a trigger for improving the energy efficiency of buildings; and,

iii) introduce minimum SAP requirements into existing building regulations for all newly constructed buildings.

Although SAP is calculated using very similar algorithms as those included in BREDEM, there are several important distinctions between these two methods. First, BREDEM is foremost a tool for estimating the energy demand from a single dwelling. This requires the input of physical building characteristics but also details about occupancy and weather that are generally location specific. The purpose of SAP however, is to give a standardised measure from which the energy performance of a building can be compared with other buildings in the UK. Therefore, as an indicator of relative building energy performance (as opposed to estimating energy consumption directly) SAP rates are estimated independent from occupancy, behaviour and weather characteristics, although, other European countries make very different assumptions about the standardisation of different factors (e.g. France has three different climatic zones in their standard building model).

The first version of SAP was developed in 1993 as a joint project by the Department for the Environment (DOE) and the Building Research Establishment (BRE). It was developed using the annual BREDEM-9 model to independently rate, assess and compare the energy performance over a heterogeneous building stock. By 1994, SAP had been incorporated into part L of the building regulations and marked a step change in how newly constructed buildings were rated and assessed. One of the main outputs of the new rating system was an energy efficiency index, ranging from 1-100, known as the buildings SAP rate. The SAP rate represents an estimate of the annual cost in £/m^2 for providing heating, hot water and lighting to a dwelling. The higher the SAP rate the lower the expected energy cost. As well as being independent of demographic, social and cultural factors, SAP is also independent of the ownership and efficiency of appliances and individual heating patterns and temperature set points applied by the occupants (DEFRA, 2005). However, such factors are known to contribute significantly to actual energy consumption (Kelly 2011a).

A consolidated version of SAP1995 was published in 1998 (SAP1998) with improvements to the methodology being introduced in later versions of the model (SAP2001, SAP2005 and SAP2009). In SAP2001 a carbon index was introduced to demonstrate compliance with new building regulations (BRE et al., 2001); this was later adapted in SAP2005 as the dwelling $CO_{2(eq)}$ Emission Rate (DER) and the Environmental Impact Rating (EI) (RICS, 2005). The dwelling emission rate is calculated from a notional dwelling benchmark based on Part L of the 2002 Building

Regulations (HM Government, 2002). The Environmental Impact (EI) rating is based on a dwelling's $CO_{2(eq)}$ emissions from heating, hot water, ventilation and lighting less any emissions saved from onsite energy generation. The EI rating is calculated using the emissions factors for different fuel types. Like SAP, it is normalised to unit floor area and expressed on a scale from 0-100 so that the building's EI rating is essentially independent of dwelling size. In SAP2005, a supplementary calculation for Stamp Duty Land Tax (SDLT) was added giving exemption of stamp duty for zero carbon homes. In the new version several improvements were made, including additional allowances for the effects of thermal bridging; an update to solar hot water heating calculations; new allowances for renewable energy technologies; the addition of energy used for lighting; and, the adoption of more widely understood energy units (i.e. GJ to kWh).

From April 2006, new building regulations stipulated the use of SAP2005 for all newly constructed buildings. Among other things, the new building regulations replaced the requirement of U-values for estimating household energy efficiency with the Dwelling Carbon Dioxide Emission Rate (DER). At the same time, the new regulations necessitated the need for SAP rates to be displayed inside newly constructed buildings. It was hoped that by conspicuously displaying the energy performance rating of newly constructed buildings, the awareness of energy efficiency for purchasers, sellers, and occupants would increase, and therefore be an important factor in the sale of new dwellings. The intention of this new policy was to ensure that energy efficiency ceased being a hidden factor that was difficult and expensive to determine and would become a transferable, transparent, and simple measurement for making investment decisions in buildings. This principle was extended to existing dwellings and led to the implementation of RdSAP and to the establishment of Energy Performance Certificates (EPCs).

Up until 2006, the focus of building regulations had been on the construction of new buildings, or those buildings undergoing major renovation. With legislation for the construction of new buildings firmly in place, a new rating scheme for existing buildings was urgently required. In 2006, the building regulations were once again amended to comply with the new EPBD (European Parliament, 2002). This led to the introduction of approved document L1A for new build and L1B for existing homes including extensions. The outcome was a new version of SAP specifically targeting existing dwellings. The new assessment procedure, now known as RdSAP (Reduced

Data SAP) substantially lowered the overall data requirement from previous versions of SAP. With this new rating system, average values about the building stock can be used when physical data for a dwelling are missing. Theoretically, this means that every home, no matter how old, can be given a SAP rating from which it is possible to create an energy performance certificate (EPC).

Under new legislation (HM Government, 2007), an EPC must be produced whenever a building is sold, constructed or rented out, showing the energy performance of the property and how it can be improved. The purpose of the new law was to allow buyers to make informed choices about the purchase or lease of a property during the early stages of the transaction, thereby effecting the decision of purchase. However, legislation never stipulated the point during the transaction where the information should be made available. Consequently, new occupants typically receive information about the building's performance well after the transaction has been completed. This significantly reduces the effectiveness of EPC's to inform decisions and change market values based on building efficiency.

Despite widespread use, there is still much confusion about what BREDEM, SAP and RdSAP actually measure. BREDEM is a building physics model that estimates the energy requirements of a dwelling while ignoring the behavioural effects of occupants. SAP uses BREDEM algorithms and therefore also ignores human behaviour but estimates the economic efficiency of a dwelling using standardised data for climate, the number of occupants, internal temperature characteristics and energy prices. RdSAP is similar to SAP but uses a standardised set of assumptions about building characteristics such as age, typology, and heating systems for estimating building performance (Banks, 2008). In sum, BREDEM is used to estimate building energy consumption while SAP and RdSAP are used to estimate building performance.

SAP remains the most important calculation procedure for assessing and certifying the energy performance of new buildings in the UK. It is therefore, imperative that SAP and RdSAP give the right market signals to transform the building sector. This will require methodologies that fairly and accurately measure building performance in an open and transparent way. Figure 4.5 is a timeline showing how BREDEM and SAP have evolved over the last forty years. Instruments such as the GreenDeal, RHI, and FIT's will only lead to greater reliance on BPEC tools and standards in the future.

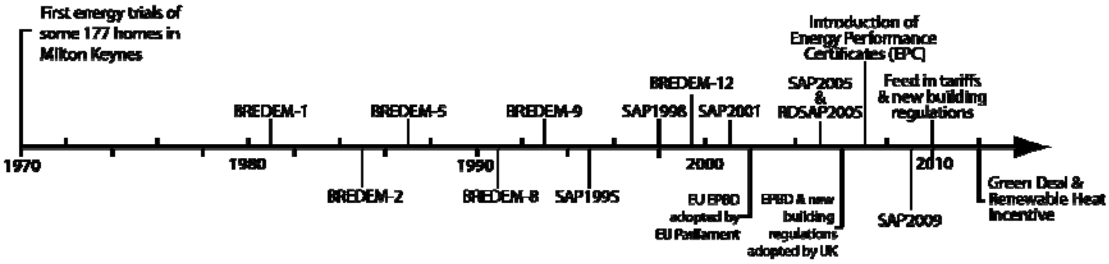

Figure 4.5: Evolution of BREDEM and SAP

4.7 Inter-European comparison of building performance and certification

The EPBD was introduced by the EU Parliament in 2002 and has had a significant influence in bringing about much needed change to building regulations in many Member States (MS). It remains the most important legislative instrument at the EU level for reducing energy consumption from EU buildings (European Parliament, 2002). Despite concerted efforts from EU officials, the long-term trend across the EU27 has remained relatively unchanged. The large difference in emissions between countries as shown in Figure 4.6 can be explained by differences in climate, relative per capita wealth, the relative size of dwellings and the number of occupants per dwelling, all varying greatly between countries.

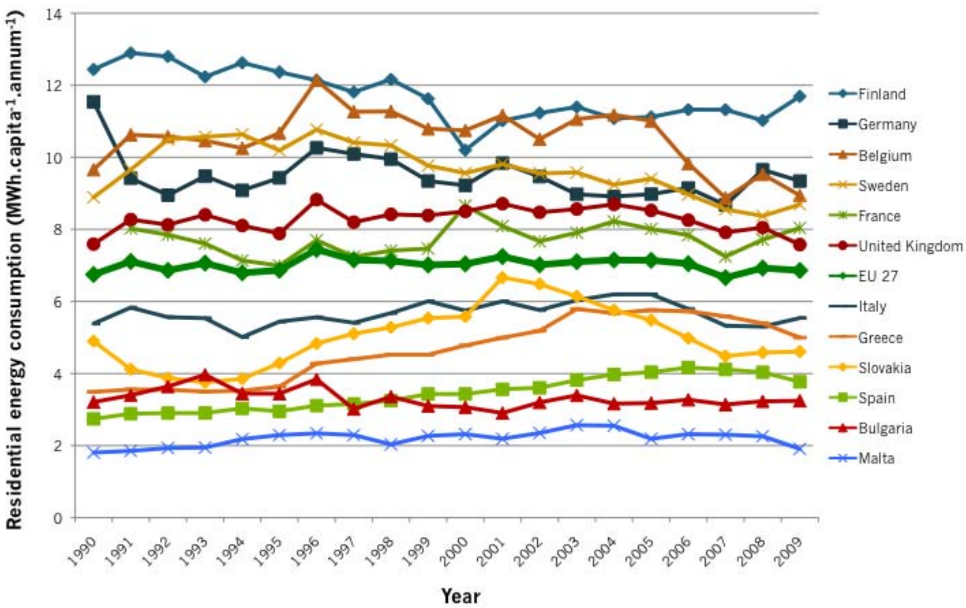

Figure 4.6: Annual per capita residential energy consumption for selected EU countries

Data source: Eurostat 2011

In the UK, the introduction of the EPBD came at a time when public awareness of climate change was increasing, as was political pressure to deal with fuel poverty. Thus, the introduction of a reliable rating scheme for both new and existing dwellings was acutely needed. The following section will compare and contrast policy, and regulations implemented in the building sector for different EU member states, with particular focus on how the UK may learn from European experience.

As outlined by the European Parliament, the EPBD was designed to go beyond simply being a tool for the analysis and comparison of buildings to something that would form the basis of transforming the built environment across Europe. Under the principle of subsidiarity and proportionality, MS were required to develop and implement measurement and certification standards for improving the energy performance of their building stock. Each member state was therefore given freedom to implement BPEC standards to their own accord. The result was a plethora of different BPEC standards across all MS. Some 30 European and 24 International standards were drafted (Roulet and Anderson, 2008). With the benefit of several years of years of hindsight, the strategies adopted by different MS can now be assessed and compared.

A review of these schemes has highlighted some important differences. For example, some countries only consider heating while other countries include cooling needs as well as hot water, plug load, and lighting in calculation procedures. There are also important differences in the level and type of information being collected. For instance, some member states use primary energy while others use final energy. Germany gives both primary energy and final energy statistics on the EPC (Maldonado et al., 2011). While most MS give a grade in energy units (i.e. kWh/m^2 per year) some give additional units (i.e. $CO_{2(eq)}/m^2$ per year). The UK is unique in that it uses the final cost of energy to create a relative scale of building performance from 0-100. All these factors make it difficult to compare ratings across different MS. However, it is possible to look at different schemes across Europe and identify what instruments appear to work well.

When innovative products and technologies are not accounted for within building assessment rules, it acts as a barrier to market uptake (Heijmans et al., 2010). If new technologies and innovations are not included in SAP calculations, there is no motivation to include them in the design, construction or renovation of a building to improve performance (Xing et al., 2011). It is therefore important that SAP procedures explicitly foresee the possibility of new technologies and innovative systems not covered by the standard procedure. Countries like Portugal and Denmark offer loose frameworks, making it much simpler for new and innovative systems to be incorporated in their building standards. However, there are disadvantages to this approach that include inaccuracies between anticipated versus realised energy savings. A further method of dealing with new and complex technologies is the 'equivalence approach' where equivalent technologies are used as proxies for unspecified technologies. To minimise the disadvantages it is beneficial for any building performance standard to regularly make improvements to the calculation procedure or alternatively make allowance for technologies to 'prove' their efficiency levels to be included in future versions of the model. If both calculated and metered energy consumption data were required to estimate dwellings overall performance, the difference between these two values could assist in the determination of actual efficiency improvements offered by new technologies.

An important distinction between several EU schemes is the methodology used in the calculation of building performance. There are two methods. The first method is known as the 'estimation method' and is derived from the physical properties of the building. Average values for buildings of a similar type are sometimes used when information is missing. The second method is the 'measurement method' and uses actual energy consumption data to estimate building performance. Both methods have their own advantages and disadvantages. The estimation method is based on the physical properties of the building envelope and the efficiency of heating systems, thus detailed information about the building allows improvement diagnostics to be carried out. Another advantage of a standardised calculation procedure is that the energy performance from different buildings can be immediately compared. The time required to collect sufficient information about a building for this type of analysis is not negligible, thus making it a much more costly process to implement then the measurement method. The price for carrying out an energy performance evaluation in Europe ranges from €50-€1000 (Maldonado et al., 2011, p.26). In the UK, the estimated cost is much less, estimated to be around £40 making it one of the most affordable schemes in Europe.

The measurement method, on the other hand, is quick and energy saving recommendations directly relate to the real energy consumption of the dwelling. This method however is adversely affected by occupant behaviour and because building certification should supposedly represent an independent estimate of the buildings performance – and not incorporate the behaviour of occupants – standardisation of certification for comparison purposes across different buildings becomes problematic. A further complication of this method is that it makes the identification of building improvements difficult to assess as much less information about the physical materiality of the building is collected and so the contribution from building energy efficiency and occupant behaviour cannot be separated. Clearly, the best approach is to combine both methods. There are presently four countries in the EU that allow users to choose between these two methods these are, Finland, Germany, Luxembourg and Latvia. However, the full potential of combining estimated and measured energy consumption readings has not yet been fully exploited by any country.

Given the apparent success of the EPBD since being introduced in 2002, and the huge potential remaining for improving the performance of buildings across Europe, a new version of the EPBD was recast and ratified by the EU Parliament (2010a). The Recast of the EPBD clarified, strengthened and extended the scope of the existing directive, requiring all new buildings to be 'nearly zero energy' by 2020. The definition of 'nearly zero energy' requires newly constructed buildings to have very high-energy performance with all energy coming from renewable sources produced on-site or in proximity to where the final energy is consumed. This is in stark contrast to the strategy adopted in the UK requiring all new buildings to be zero-carbon by 2016. Given the controversy surrounding the definition of zero-carbon in the UK (Goodchild and Walshaw, 2011) and the difficulty in measurement and certification of zero-carbon policies (Kennedy and Sgouridis, 2011), it is not surprising the EU chose to use energy consumption as the measurement instrument rather than $CO_{2(eq)}$ emissions.

The subtle differences in policy and implementation strategies across Europe raises important questions about the availability of different schemes for meeting energy and climate change targets. While the UK methodology gives a certain amount of freedom for developers to source low carbon energy, it does not necessarily provide sufficient motivation to improve the efficiency of the building. Put another way, a building in the UK may continue to use energy inefficiently as long as it is taken from a low carbon source. This is in contrast to the Recast of the EPBD that calls for clear strategies that focus on energy demand reduction. Although there are no specific targets for existing dwellings, the Recast of the EPBD expects MS to develop policies and take measures that will stimulate the refurbishment of existing buildings and to inform the commission of these national plans.

4.8 Evaluation of Energy Performance Certificates (EPCs)

A necessary and important output of carrying out building performance evaluations is the Energy Performance Certificate (EPC). In the preamble of the EPBD it states that the EPC is to form the basis of a package of integrated policy measures designed to transform the building stock across Europe. The EPC system therefore goes beyond being a simple tool for the comparison of buildings and serves as a policy instrument for reducing carbon emissions and transforming the European building stock. One of the key principles of the EPBD is the stipulation that any building sold, leased or undergoing major renovations within the EU must have an energy performance evaluation and an up-to-date EPC.

The scheme is now functional in all MS and is regarded as being successful in stimulating the transition to a more efficient building stock (Maldonado et al., 2011). There are however, still logistical and economic considerations closely scrutinised by several MS. In the UK, SAP calculations have been mandatory since 1995 for newly constructed buildings and it became compulsory in 2007 for all existing buildings sold or leased to have an EPC (Bell and Lowe, 2000).

The following section will therefore discuss the benefits and disadvantages of different EPC criteria. Figure 4.7 shows the layout of an EPC for England and Wales showing both the SAP rate and the Environmental Impact Rating. The certificate contains a discrete normalised scale with no connection to real units. This is in contrast to the both the German (Figure 4.8) and Italian (Figure 4.9) certificates that give a single continuous scale quoting actual energy consumption (kWh/m^2). The German scale also gives estimates for the energy consumption of both new and existing buildings of the same building type. The Italian EPC shows a range of different building performance measures, (i) cooling performance, (ii) heating performance, (iii) hot water performance, (iv) overall performance. Both standards give an estimate for the annual $CO_{2(eq)}$ emissions and the average performance of the building stock as a whole.

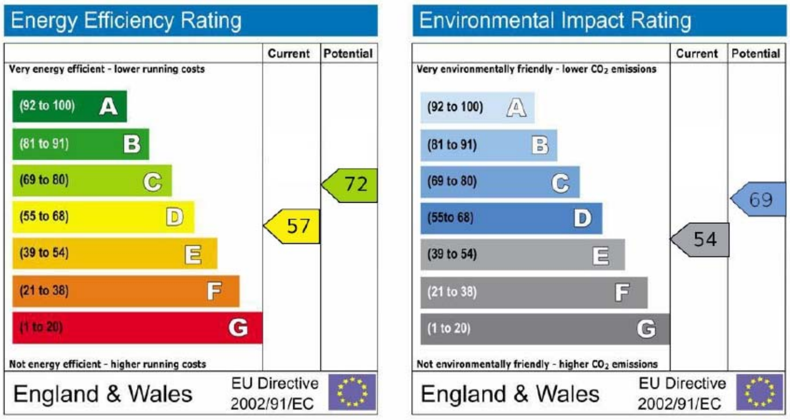

Figure 4.7: SAP and EI rating for Energy Performance Certificates (EPC) in England and Wales

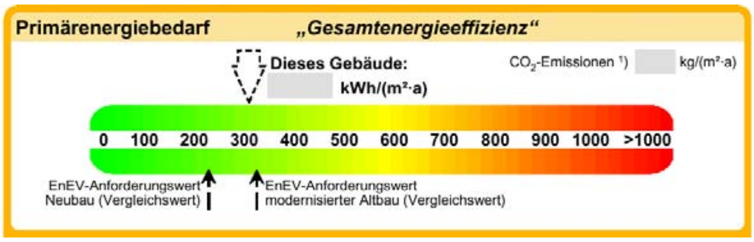

Figure 4.8: German Energy Performance Certificates

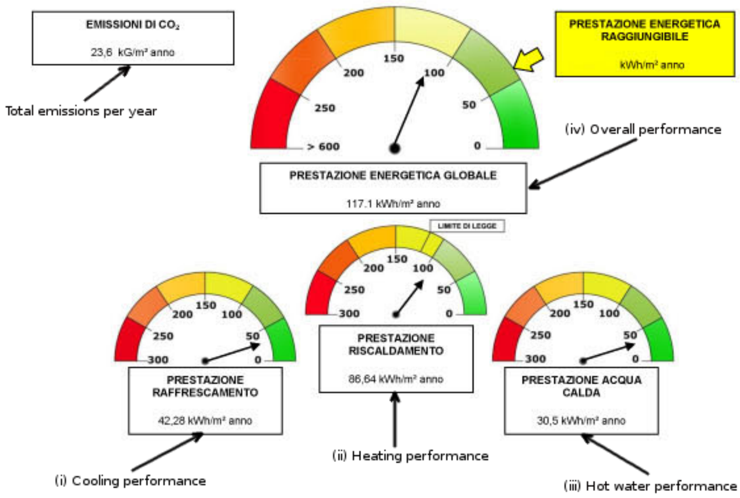

Figure 4.9: Italian Energy Performance Certificate showing a range of different measurements

In the UK, EPC's have been mandatory since October 2007, and provide important information to purchasers and renters about the performance of a building from which informed choices can be made. In essence, an EPC overcomes information asymmetry between the seller (who generally has good information about a building) and the buyer (who has limited information). Thus, EPCs act to facilitate the exchange of information between the buyer and the seller reducing the disparity between the market price and the fair value paid for a property (Sandmo, 1999). This is a significant point considering research by Wolseley (UK) has shown over two-thirds of respondents would pay more for an energy-efficient home (Wolseley, 2006). Even in cases where the seller may not have a good grasp of the energy performance of the property, an EPC may encourage the seller to improve the building performance in the hope it might increase the attractiveness of the property to buyers or renters who do place value on these qualities.

The process of delivery and the information contained on the EPCs has important ramifications for its success as a policy instrument if the proposed measures recommended on the certificate are eventually adopted. The perception of the EPC is as important to its effectiveness as the accuracy of information it contains. Banks (2008) found the majority of sellers had a negative attitude towards EPCs. The common attitude was resigned acceptance, with misgivings about the whole process and speculation that EPCs were just another stealth tax applied by the government. Banks (2008) found that estate agents had a similar view, speculating that the process was just a "big con" where they were left wondering what was gained from the process. As this type of attitude is so widespread, it may have an overall detrimental effect on the scheme. For example, homeowners are less likely to improve the performance of their home if they place no value on the results of the EPC and buyers will be less likely to consider EPC ratings when purchasing a home. User buy-in is thus essential for achieving market transformation, which in turn means a clearly established relationship between the numerical value on the EPC and actual energy savings.

Banks (2008) argues the costs associated with carrying out the assessments are one of the root causes of dissatisfaction. Banks (2008) suggests that reducing the VAT rate from the full rate of 20% may go some way to reducing such apprehension. Somewhat perversely, the VAT on energy consumed for home heating in the UK, is set at 5%, while costs associated with improving building efficiency (like EPC evaluations) are taxed at the full rate. This is a simple example where government policy is clearly sending the wrong message to consumers. Similarly, if building performance was linked to council tax rebates, the attitudes of buyers and sellers would likely favour improved energy efficiency.

In the UK, the full EPC contains more information than just the categorical A-G SAP scale. The certificate also includes an EI rating and information on the estimated running costs of the building broken down by service type. Average building performance of all UK dwellings is also included (grade E), but such information is only vaguely helpful. If the average performance of a building in the same building category (i.e. same building type, age and construction material) were given instead (similar to the German standard), it would give a better indication of the relative performance of a building within particular building category. Such an addition might stimulate an increase in energy efficiency, as new occupiers tend to make comparisons within a category of buildings rather than across them.

As stipulated in the EPBD, EPCs are required to include recommendations for cost-effective building improvements. This is probably the most valuable information contained on the EPC. These are separated into ‘lower cost measures’, ‘higher cost measures’ and ‘other solutions’. Lower cost measures typically cost less than £500 while higher cost measures typically cost more than £500. The ‘potential’ column in the EPC certificate only includes improvements from lower cost measures. The category ‘other solutions’ generally includes more expensive options which have much longer payback periods. The cost-effectiveness of options is estimated using a simple payback calculation. Although this is the easiest approach, it does have several drawbacks. Simple Payback is sensitive to changes in costs and is a poor estimate for costs that arise in the present and savings that accrue in the future. A more accurate method would use net present value (NPV) or internal rate of return (IRR) calculations to allow for the time value of money. In addition, the anticipated future price of fuels also needs to be included in calculations, as the effect of changing (rising) energy prices has a significant effect on the cost-effectiveness of different energy efficiency measures. A government certified annual forecast of future energy prices could be used to improve the cost estimates of different efficiency measures. Simply assuming existing energy prices continue at current prices is an incorrect assumption and leads to erroneous results that underestimate the cost effectiveness of building improvements.

An important component of the EPC is the list of cost-effective improvements listed on the certificate. Research by Oxera has shown that most residents have little or no knowledge about the characteristics of energy efficiency, including costs (Oxera, 2006). For example Oxera showed that only 8% of respondents were aware of accreditation schemes for existing domestic insulation installers and significantly over estimated both the time and cost of installations. Information concerning actual building running costs is also salient to new building occupiers. This highlights the importance of providing an indication for the true costs and savings to a dwelling. Unfortunately, only the estimated running costs are provided for a dwelling on the present EPC. Providing new occupiers with information on the actual energy consumption from metered energy consumption readings will give new occupiers a much better picture of the real energy consumption of the dwelling. With information about a dwelling's actual energy consumption, improved estimates about anticipated savings can be made and therefore more accurate recommendations for the most cost-effective energy efficiency measurements given.

If the EPC is to work effectively it must be made available to the new tenants as early as possible in the decision making process. Because many responsibilities for carrying out EPC duties fall on estate agents, solicitors and private landlords, the success or failure of the scheme lies with these professionals. Banks (2008) found that many professionals were not fully adhering to the scheme guidelines or simply doing the bare minimum to meet regulatory compliance. Banks (*Ibid*) also found statutory regulations were too relaxed, reducing the potential effectiveness of the scheme. One prime example is the absence of any requirement to show the EPC until right before a new contract is signed, at which point the decision to purchase or lease the property has already been made. This reduces the power of the market to discriminate between homes with different energy performance characteristics. One way to overcome this shortcoming is for the energy performance rating to be included with any advertisement, or marketing material aimed at selling or leasing a property. With the introduction of the Recast of the EPBD (European Parliament, 2010b) due to be enforced by all MS by January 2013, building performance ratings will be mandatory on all property advertisements. This will likely lead to greater awareness and use of EPC ratings for comparing building performance values, and increasing demand for energy efficient properties (Amecke, 2011).

The evidence presented suggests that actual energy consumption and calculated energy consumption are very different and sometimes differ by as much as twice to three times what appears on an EPC. Although much of this variance can be explained by missing variables (such as behaviour) this may be having a damaging effect on the credibility of BPEC which give the misconception that certificate estimates are accurately estimating energy consumption, energy efficiency and environmental impact. Providing sufficient detail on the certificate for what the indicators are actually measuring will go some way to alleviating this situation.

4.9 A critique of SAP

In the previous sections, the evolution of building simulation models were discussed in relation to how they have been used in the development of summary measures like SAP to estimate building performance. The role of EPBD to drive the transformation of buildings across Europe was then investigated. Attention then focused on the importance of EPC certificates and the differences in standards between European MS. Next, the strengths and weaknesses of SAP will be highlighted showing how BPEC procedures might be improved so that evaluated performance will better reflect actual performance and hence be used to identify the most cost-effective solutions and improve user confidence.

SAP ratings measure the annual unit cost of space and water heating from notional assumptions about heating patterns and internal temperatures. Fuel prices used by the present RdSAP model are averaged over three years and across regions in the UK. Because SAP represents an index calculated using many different building elements it allows developers to mix and match different building components to meet SAP requirements, often resulting in sub-optimal outcomes. For example, improvement to the building fabric might be sacrificed for an improved heating system, such as a condensing boiler. Although, in theory, this leads to cost-optimal solutions at the time the new technology is installed, it may result in sub-optimal solutions for building performance over the life of the building. For example the additional cost of a condensing boiler when replaced is negligible, making it an obvious choice for anybody wishing to meet minimum SAP requirements. If on the other hand, the lifetime emissions from competing energy efficiency measures are compared, cavity wall insulation and roof insulation tend to offer the most cost-effective $CO_{2(eq)}$ savings over the life of the measure. Nevertheless, a building owner trying to minimise costs whilst meeting minimum SAP compliance, will always choose the option that has the least capital cost to meet compliance. Alternatively the Net Annual Cost (NAC) method compares technologies over the entire life of the technology. It therefore becomes possible to compare the most cost-effective and most carbon efficient technologies for the duration the technology is installed and not just the most cost-effective technology at the time of installation.

The Energy Saving Trust (2006b) show that it is more cost-effective to install efficiency measures during construction or refurbishment than doing so haphazardly over the life of the building. This is due to the added costs of time and labour owed to piecemeal improvements. If the additional savings made by installing efficiency measures at one time – as opposed to haphazardly – then the overall economic performance of carbon saving measures will improve and reduce the total cost of the investment. Such benefits need to be included in estimates about the cost effectiveness when implementing energy saving technologies.

In Figure 4.10, three dwellings are chosen to represent the building stock in England. Dwelling 1 represents a typical home at the 25th percentile of energy consumption, Dwelling 2 is from the 50th percentile and Dwelling 3 from the highest 75th percentile. The SAP value for each home is calculated using the SAP2009 methodology with a standard typical floor area of 90m^2 for each dwelling. It is assumed one-third of each dwelling's total energy consumption is met by electricity with the remainder being supplied by coal, natural gas, wood, community waste (i.e. waste-to-energy) or bio diesel (Figure 4.10). The only exception is for homes using electricity for heating, where it is assumed electrical resistance heaters supply all the heat in the dwelling. When estimating the SAP rate for each dwelling, the only variable that is changed in the SAP calculation procedure is the fuel type used for space heating.

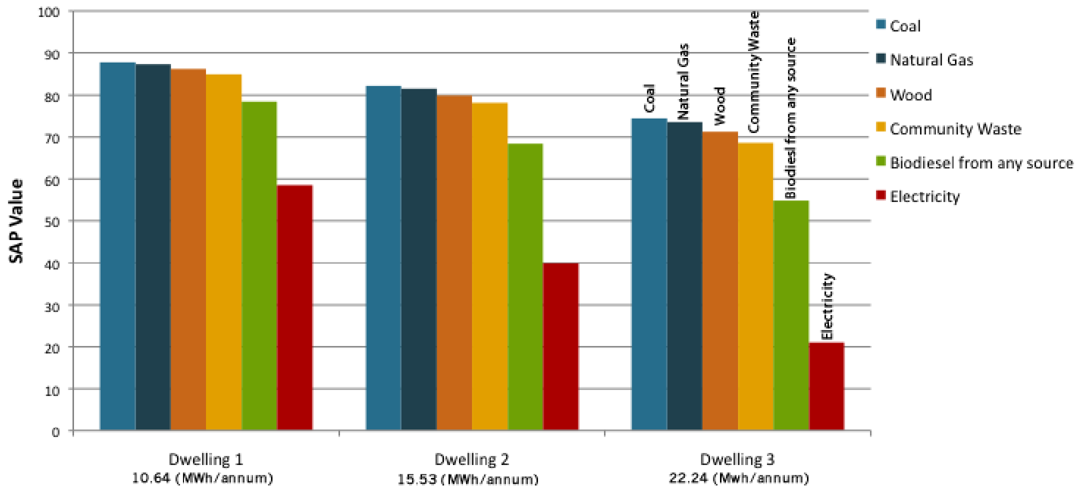

Figure 4.10: Effect of fuel type on SAP

The main conclusion from Figure 4.10 is that fuel type plays a very important role in determining a building's overall SAP rate. Strikingly, fuel type appears to make even more difference to SAP than improving building energy efficiency (e.g. a reduction in final energy demand is represented by a shift in demand from dwelling 2 to dwelling 1 but keeping fuel type constant). Surprisingly it shows that more carbon intensive fuels result in higher SAP values (i.e. an improvement) in large part because the more carbon intensive fuels tend to be less expensive per unit energy delivered. Unfortunately, this situation may lead to perverse incentives where it is possible to improve a building's SAP value by switching to coal from a less carbon intensive fuel such as wood or bio diesel. In this example, Dwelling 3 can jump from having an SAP rating of F to C simply by switching from electricity to coal for use in heating. In fact, because coal is one of the cheapest fuels used for heating it gives the highest SAP rate when compared with all non-renewable fuel types. This occurs because SAP is a measure of the economic performance of a building and not a direct measure of energy efficiency. It uses energy cost as a surrogate for energy consumption and/or carbon emissions, making it better suited to policies aimed at reducing fuel poverty than at reducing energy or carbon. Within SAP, energy consumption is estimated from space heating, water heating and electrical lights and appliances. The annual fuel bill is then estimated using standard prices (Table 7.21). It is from the predicted annual fuel bill that the Energy Cost Factor (ECF) is calculated using Equation (4.0) from the standard SAP procedures.

$$ECF = \frac{C.\mu}{45 + A_f} \tag{4.0}$$

$$\begin{aligned} ECF \geq 3.5: \quad & SAP2009 = 117 - 121 \times LOG_{10}\left(ECF\right) \\ ECF < 3.5: \quad & SAP2009 = 100 - 13.95 \times ECF \end{aligned} \tag{4.1}$$

In Equation (4.0) ECF is the Energy Cost Factor; C is the estimated annual energy bill for a property, μ is the GDP deflator that allows SAP values to be compared across different years, and A is the total floor area for the dwelling. Thus, the ECF is proportional to the anticipated annual fuel bill on a per m^2 basis. A log transformation is then applied to the ECF to convert it into a SAP rate and put it on a scale from 0-100 (Equation (4.1)).

The effect of including prices in the calculation of SAP distorts the overall assessment of building efficiency, and may undermine legitimate intentions to make buildings more energy efficient. Another unintended consequence of using energy prices to estimate building performance is that energy prices fluctuate, sometimes dramatically. Although changes to energy prices, within a basket of different fuel-types are captured by the GDP deflator, the relative price difference between different fuels is not captured until the model is next updated. For example, if the price difference between electricity and other fuels changes, the relative difference in

SAP rates will also change[15]. The result implies that SAP values will fluctuate between successive SAP models, not because of changes to building performance but simply because of differences in the market price of fuels. Another downside of the present SAP methodology is that it fails to consider the relative $CO_{2(eq)}$ emissions from different fuels. From Figure 4.10 it is clear that renewable fuels such as wood and bio diesel only contribute to SAP values through price; thus, if the price of renewable fuel resources increases, the effect will be a subsequent decrease in the SAP score for dwellings that use these renewable heating fuels. Absent a significant tax on carbon emissions (increasing the cost of fossil fuels) this problem with SAP will persist.

Thus far, it has been shown that SAP is actually a measure of the economic efficiency of a building and not energy efficiency per se. Now it will be shown that SAP is also a poor measure of economic efficiency. Recent changes introduced into SAP2009 allow dwellings to offset their energy consumption through the generation of electricity through micro-generation technologies. If electricity produced on-site exceeds the energy requirements of the dwelling it will receive an SAP rating over 100 as energy produced is deducted from energy consumed. Therefore, it is possible for a dwelling with very low building performance to get a high SAP rating if electricity is produced on-site from the installation of PV, micro wind or micro-CHP. The marginal abatement cost for the generation of electricity from these technologies is known to be much higher than that of energy saving measures (Scarpa and Willis, 2010). Because the cost of electricity produced by micro-generation technologies is not included in SAP calculations, SAP does not accurately estimate the cost of energy coming from micro-generation. By allowing such technologies to contribute to the overall SAP rating without considering the cost of these technologies, SAP rates fail to give a fair indication of the economic efficiency of a dwelling. Allowing SAP rates to change from onsite renewables also undermines the purpose of the EI rating which was precisely established to give feedback on $CO_{2(eq)}$ emissions. Furthermore, as SAP is inherently designed to be independent of both geographic location and human behaviour estimated SAP costs will be very different to actual costs (as shown in Figure 4.4).

15. Presently fuel prices are updated in the SAP calculation procedure every six months.

At present, SAP is not set up to handle costs and savings that result from micro-generation technologies installed because of FIT's or the RHI. Incorporating the financial benefits of FIT and the RHI into SAP will require significant changes to the way SAP is presently calculated. Cost rebates for different technologies vary, complicating energy cost estimates, and therefore complicating the estimated SAP rating. Moreover, most technologies qualified to receive a financial rebate under FIT and the RHI are subject to degression rates[16] thus changing the level of subsidy available depending on the year the technology was first installed. This unnecessarily adds several layers of avoidable complication to SAP calculations. A simple solution would be for SAP estimates to remove energy prices from the calculation procedure altogether (like most other European countries). SAP would then represent a much better estimate of a building's energy efficiency rate (kWh/m^2) and would be a better means for identifying strategies for reducing energy use and carbon emissions.

The SAP calculation procedure also assumes that electricity generated from PV is co-incident with average demand, therefore reducing net electricity consumption. This is not always true, as solar energy occurs during the day when occupants are typically at work requiring electricity to be exported to the grid. Simply assuming average solar capacity factors across the country also leads to erroneous results, as different parts of the country receive different amounts of sunshine. Another peculiarity of allowing on-site electricity production to contribute to SAP is that there is no allowance for on-site heat production, aside from energy produced through CHP district heating schemes (Kelly and Pollitt, 2010). The effect of recognising onsite electricity production but not heat is that it benefits expensive electricity technologies and therefore benefits wealthy households that can afford to invest in micro-generation technologies. In addition, no account is given to dwellings that may be on renewable electricity tariffs. If SAP aimed to be internally consistent, it would be possible to offset energy consumption using other forms of renewable heat such as homes heated by wood stoves, biomass or community heating supplied by renewable sources. At present, the use of these fuels for home heating contributes to energy consumption and therefore has a negative effect on the SAP rates. The opposite is true for micro-generation technologies where energy generated is deducted from final consumption thus improving final SAP rates.

16. Degression is the rate at which the levels of a tariff reduce over time allowing for the cost reductions of a technology as volumes build over time.

The present SAP calculation procedure does not allow solar hot water heating systems (SHWS) to be used within central heating systems, only in hot water systems. This is despite the significant potential for central heating to benefit from solar hot water during autumn and spring. Because of this, any additional solar hot water produced over and above the hot water demand requirements of a dwelling does not contribute beneficially to SAP rates. Unlike PV, SHWS have the advantage of storing heat in hot water cylinders until heating is required. Banks (2008) revealed that SAP calculations were only capturing 25% of the potential energy savings from SHWS. SAP procedures would therefore benefit from improved handling of renewable hot water heating systems.

The Environmental Impact Rating (EI) was developed to overcome the limitations of SAP on the EPC. Instead of using energy prices (like in SAP) the EI rating uses emissions factors from different fuel types. Using the same dwellings as were used in Figure 4.10, the EI rating[17] was estimated. An advantage of EI ratings over SAP ratings is that they include $CO_{2(eq)}$ emissions factors, but a disadvantage is that they fail to give an accurate measure of building efficiency. For example, in Figure 4.11 homes that use renewable fuels such as wood, will receive a high EI rating despite how much energy is consumed overall. For homes that use electricity from the grid, the EI rate is even more problematic as it completely depends on the carbon intensity of the national grid presently estimated at 0.517 $kgCO_{2(eq)}/kWh$[18]. Finally, having two different indicators on the EPC creates confusion about what the indicators actually measure. It is therefore not clear what indicators should be used as a measure of energy efficiency, energy use, reducing carbon emissions or lowering energy costs all of which are distinct policy aims.

17. For ease of comparison similar assumptions are made in this figure as the SAP figure (e.g. one-third of total energy is consumed as electricity and the floor area of each of the dwellings is $90m^2$)
18. This is predicted to change markedly over the coming several decades as the grid is decarbonised

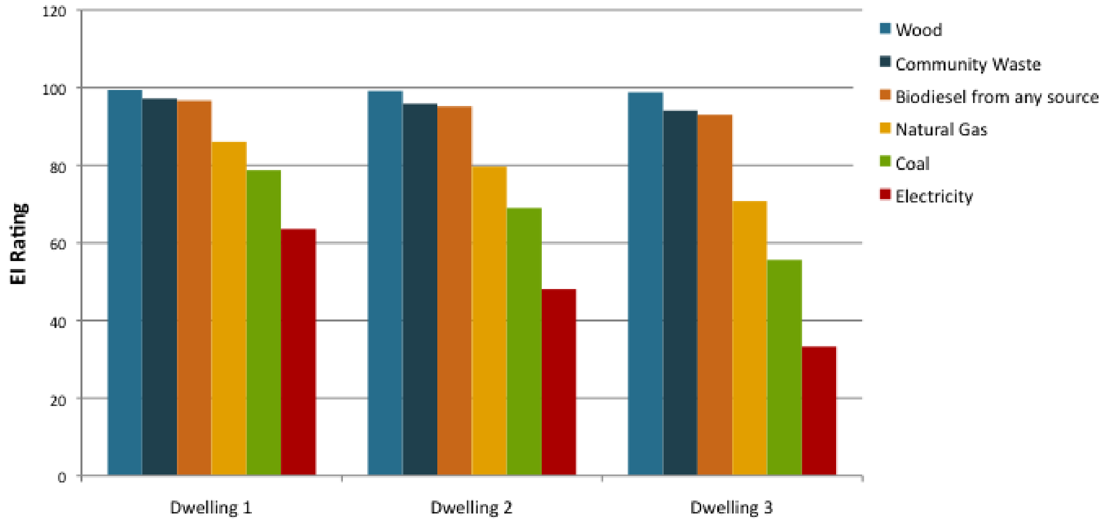

Figure 4.11: EI ratings for different fuel types

The effect of human behaviour on household energy consumption is known to be significant (G.Y. Yun and K. Steemers 2011; Kelly 2011a; K. J. Lomas 2010) and estimated to account for 51% of the variance in heat demand and 37% of the variance electricity demand for different energy users (Gill et al., 2010). Behaviour is also one of the biggest uncertainties in estimating household energy consumption. Even so, most building performance models do not incorporate human behaviour in their analysis. With the rollout of smart-meters and other technologies that integrate with human behaviour, it will be increasingly important to allow for the effects of these new technologies when estimating building performance. The time of day when energy is consumed is also an important factor (Lowe, 2007). For example, electricity consumed during peak periods will have different carbon emissions factors as the electricity generation mix fluctuates. As new demand is placed on the electricity system, the electricity mix changes as does the marginal generating plant. The more demand from the grid fluctuates the more important it will be to allow for this effect in calculating the emissions from discrete homes, each having varying energy demand profiles. The incorporation of emission factors for different demand profiles into building calculation procedures could incentivise people to shift their demand and therefore reduce overall emissions (James, 2011).

4.10 A critique of RdSAP

While SAP is primarily designed for assessing the performance of newly constructed buildings, RdSAP is designed for assessing the performance of existing buildings. RdSAP uses the same underlying algorithms as SAP, and therefore suffers many of the same criticisms. Unlike SAP where energy prices are updated every six months, energy prices in RdSAP are updated every three years. What makes RdSAP significantly different from SAP is that it is designed for people with very limited knowledge about building energy analysis and with limited information about the actual physical properties of the building. This means RdSAP requires assumptions to be made about energy consumption, based on the type and age of the building. Hence, it is an indication of energy consumption across large populations of buildings with similar general characteristics, rather than about the specific characteristics of a particular building. All buildings assessed in RdSAP are assumed to be located in middle England and have typical occupancy rates calculated as a function of floor area. There are also assumptions about heating requirements, where all rooms are heated to a comfortable level (21° in living areas and 18° elsewhere) with a high standard of hot-water heating. Thus, a trade-off between model simplicity, accuracy and comparability with other dwellings may lead to confusion and produce anomalous estimates about building performance for specific buildings (see Figure 4.4). Given the assumptions made by RdSAP and the large variance between different householders' actual energy use even within a building energy category, errors can be introduced for specific buildings even when estimates of means across categories are correct. For example, dwellings in colder parts of the country should expect their heating bills to be higher than that predicted by RdSAP.

This use of stock averages limits the potential of RdSAP to make sound recommendations for improvements. For example, within RdSAP, all homes constructed after 1983 are assumed to have cavity wall insulation; if a DEA learns this is not the case, there is no opportunity for including this as a recommendation for improvement within the analysis. Allowing assessors to enter known information about a dwelling will give better insights into recommendations for improvements. Allowing full SAP assessments to be carried out on existing dwellings will provide a more accurate measure of a buildings performance. Additionally, some of the default assumptions in RdSAP assume high-energy performance, thus when lower performance characteristics are present within a dwelling, the assessor has no motivation to enter the correct energy characteristics which will lead to worse results then default values. Defaults should therefore be set to be the poorest alternative; thus rewarding occupiers and developers for making the extra effort to calculate the true performance of the property. This principle is used by the PHPP standard (pasivhaus) in Germany (Reason and Clarke, 2008) and rewards occupiers for their time and effort when they complete an accurate assessment.

4.11 Discussion

It is argued that SAP and RdSAP confound cost-effectiveness, energy efficiency, environmental performance and GHG emissions adding unnecessary complexity and confusion to the SAP calculation procedure. As a result, it is not clear which of the many national policy aims – reducing fuel poverty, increasing energy efficiency, decreasing overall energy use, or reducing carbon emissions – is being captured by the various performance measures. This then leads to confusion and disconnect between policy targets and policy instruments leading to inadequate performance over all. Inconsistency across different approaches then leads to perverse incentives. For example, dwellings that switch to low cost fuels such as coal are rewarded with higher SAP rates despite the serious implications for increased carbon emissions.

As clearly shown in Table 4.1, there are large differences across policy instruments for the effects they have on policy objectives. As it stands, policy instruments are used haphazardly to meet multiple policy objectives. Unfortunately, this approach leads to unpredictable and possibly ineffectual outcomes. Redesigning BPEC tools so that they target specific policy objectives may lead to more cohesive and productive outcomes. For example, an EPC could contain separate indicators for energy consumption (kWh/m^2), $CO_{2(eq)}$ emissions ($kgCO_{2(eq)}/m^2$), and energy costs (£/dwelling). Matching measurements with policy objectives reduces confusion and may improve the effectiveness of policy instruments.

Table 4.1: Effect of policy instrument on policy objective

Policy instrument	Lower CO_2 Emissions	Improve fabric efficiency	Lower energy consumption	Reduce fuel poverty	Increase renewables	Improve security of energy supply
EPC	Medium	Medium	Low	Medium	Low	Low
SAP	Low	Medium	Low	Medium	Medium	Low
RdSAP	Low	Medium	Low	Medium	Medium	Low
EI	High	Medium	Low	Low	Medium	Medium
FIT	High	Low	Low	Low	High	High
RHI	High	Low	Low	Low	High	High
GreenDeal	High	High	High	High	Low	Low

In addition to targeting policy instruments to match policy objectives there is also a clear need for more detailed information about the building stock to be made publicly available for research purposes. This is particularly true for data at the dwelling level representing actual energy consumption data along with physical, technical, social and behavioural factors. These data will allow comparison of estimated and actual performance of buildings, enhancing confidence that such performance measures are useful in identifying the most cost-effective strategies for energy and $CO_{2(eq)}$ reduction. Such a statistical database will allow a set of criteria to be established so that buildings can be benchmarked against buildings of the same type. It will also allow researchers to monitor the progress being made in the transformation of residential dwellings.

4.11.1 Chapter conclusion

Despite the widespread use of SAP and BREDEM calculation procedures, they have never been subject to statistical validation tests that compare model outputs with actual measurements from a robust sample of dwellings representing the UK residential building stock. The few studies that have been completed use a small homogenous sample of dwellings from a confined geographic-climatic area. It is therefore not surprising to learn that SAP estimated energy costs only explain a small proportion of actual energy costs. Although some of the variance between SAP and actual energy costs can be explained by differences in behaviour and geographic location, the unexplained variance remains substantial.

Learning from European examples several improvements to UK standards were identified. In the UK, both SAP and EI scales are represented by a discrete range from 0-100 with no evident link to physical measures of performance. In addition, there is no relevant feedback to the user about what this means to their relative energy consumption or emissions and how this may compare to other dwellings of a similar building type. Many MS in Europe have opted to retain the original energy units on EPCs (e.g. in kWh/m^2 see Figure 4.8) so that occupiers of dwellings are encouraged to think about energy consumption in original units, therefore increasing awareness and perhaps changing energy practices. The EI rating on the other hand only considers the emissions factors of different fuel types, and provides these as an areal density (emissions per square metre) that is of limited use in assessing movement towards national emissions reduction targets. EI rates therefore allow profligate energy consumption as long as it is low carbon, ignoring issues of resource conservation and fuel poverty.

Building EPCs are a critical component of the BPEC system. New occupiers value knowledge about building energy performance, if informed decisions are to be made then EPCs need to be made explicit to all agents at the earliest stages of the transaction. Certificates need to be clear and well trusted by the new occupants or their effectiveness as a policy instrument is reduced. Recommendations presently contained on an EPC for improving building performance are based on estimated energy consumption and crude assumptions about the future price of different fuels. Including actual energy consumption data on the EPC will act as a reality check against which calculated energy performance could be compared. Using metered energy consumption data, for cost-effective efficiency recommendations (instead of estimated performance) will improve the accuracy of estimating the cost of energy saving technologies. Building performance recommendations can also be improved by using government approved energy price forecasts and the lifetime cost effectiveness calculations using the Net Annual Cost method rather than simple payback.

In conclusion, SAP, RdSAP and EPCs are critical for the transformation to a zero-carbon building stock. It is important that they accurately reflect building performance, and that these measurements directly relate to policy objectives. This requires calculation procedures that are robustly validated; standards that measure and compare the right factors; EPCs that are understandable and reliable and able to drive decision-making; and finally, a system of data gathering and research methods that improve knowledge of the building stock ultimately informing and improving policy design. The next chapter will develop a model for explaining what factors are important for explaining dwelling level energy demand. Special emphasis will be placed on the structure of relationships between different variables.

5

Explaining domestic energy consumption using Structural Equation Modelling

5.1 Chapter summary

Do homes that are more energy efficient consume less energy? This chapter will attempt to answer this question with the use of a SEM. Energy consumption from the residential sector is a complex socio-technical and economic problem driven by many explanatory factors. Using structural equation modelling it is possible to calculate the strength of causal relationships and their effect on dwelling level energy costs as a proxy for residential energy consumption. In addition, this method allows the calculation of direct, indirect and total effects relating to energy demand. Using the 1996 English House Condition Survey (EHCS) consisting of 2531 unique cases, the main drivers of residential energy consumption are found to be the number of occupants living in the dwelling; household income; household heating patterns; living room temperature; floor area; and finally, dwelling efficiency (SAP). In the multivariate case, SAP explains very little of the variance of residential energy consumption. Moreover, simultaneity bias between energy consumption and SAP is not taken into account. Using SEM it is shown that dwelling energy efficiency

(SAP), has reciprocal causality with dwelling energy consumption and the magnitude of these two effects are calculable. When nonrecursivity between SAP and energy consumption is allowed for, SAP is shown to have a negative effect on energy consumption but conversely, homes with a propensity to consume more energy have a positive effect on SAP rates.

5.2 Introduction

The residential sector has been repeatedly identified as having one of the lowest costs and largest impacts for reducing $CO_{2(eq)}$ emissions (Boardman et al., 2005; Communities and Local Government, 2006; WWF, 2007; Levine and Urge-Vorsatz, 2008; McKinsey, 2008; McKinsey, 2009; DECC, 2009a; World Business Council for Sustainable Development, 2009). Yet there remains significant debate about the best approach for reaching the $CO_{2(eq)}$ reductions imminently required. Moreover, there is insufficient empirical research quantifying the complex relationship between major driving forces purporting to explain residential energy consumption and in particular, the contribution improved building efficiency will have on final end-use energy demand.

5.2.1 Contribution of chapter

This paper presents the first known application of structural equation modelling (SEM) explaining residential energy consumption in England. This powerful statistical technique allows for the calculation of both direct and indirect effects that explain energy consumption in the residential sector. Using SEM it is possible to decompose the relative magnitude of these effects and therefore gain deeper understanding for what variables best explain residential energy consumption and therefore $CO_{2(eq)}$ emissions. With this technique, it is also possible to show the relative sensitivities of different explanatory variables on residential energy consumption. Sensitivity analysis is important for identifying leverage points within the system. This research therefore presents new evidence to quantify the extent that improved SAP rates will have on reducing residential energy consumption. More importantly, evidence is provided showing a reciprocal relationship between SAP and energy consumption and that, ceteris paribus, dwellings with a propensity to consume more energy will on average, have higher SAP ratings. However, the reverse is also true and dwellings with a high SAP will have reduced energy consumption owing to increased energy efficiency, ceteris paribus. Finally, these two effects are empirically calculated.

5.2.2 Structure of chapter

The first section of this chapter presents important recent developments in the state-of-the-art of residential energy modelling. A thorough literature review (Chapter 3) has shown a serious lack in recent years in the development of bottom-up statistical models helping to explain the driving forces behind residential energy consumption and particularly the measured benefits of energy efficiency upgrades. The basic principles of structural equation models are therefore discussed with an emphasis on how this relatively recent statistical technique can be applied and used to provide deeper insight into residential energy consumption. This is followed by a discussion on the application of structural equation models, a description of the dataset and the variables chosen, and finally, how these were prepared prior to modelling. This section includes a description for how missing values were treated and how grossing weights were dealt with. The importance of using more sophisticated methods like SEM on these types of analyses are highlighted by the results obtained from the simple bivariate regression; a technique unable to measure non-recursivity or separate between direct and indirect effects. Statistical results are presented before the main findings and implications for policy makers are discussed.

5.2.3 Background to Structural Equation Modelling (SEM)

Structural equation modelling otherwise known as simultaneous equation modelling with latent variables owes its origins to both exploratory factor analysis (EFA) (Spearman, 1904) and path analysis (PA) (Wright, 1921). Wright's major contribution was to show that correlations among variables could be related to the parameters of a model represented by a pictorial path diagram with a capacity to indicate both correlated and causal relationships (Kaplan, 2009, p.3). He also showed how such a representation could be used to estimate direct, indirect and total effects through intermediary or mediating variables. Since its early beginnings, SEM has seen remarkable advances in statistical development, particularly with modern computers and software packages. It is now possible to use SEM for the analysis of non-normal distributions including dichotomous, ordered categorical and continuous variables as well as for the analysis of longitudinal data and for the estimation of models that contain missing data. With a strong demand for models to represent and explain the complex problems of the real world, structural equation models have evolved as a tool to handle a large number of problems from many disciplines. Such advances include the development of nonlinear models, multi-level models, multi-sample models, mixture models and models with variables from the exponential family of distributions (Lee, 2007, p.15). Structural equation models are therefore able to provide new levels of insight previously unachieved with other more common techniques.

SEM subsumes both exploratory factor analysis and path analysis. In addition, SEM subsumes analysis of variance methods (ANOVA), multiple linear regression (MLR) and canonical analysis (CA). In fact, it can be shown that all of these well-developed statistical techniques are merely special cases of the standard structural equation model. Given the scope of problems that can be solved using SEM, its power as a statistical tool for solving complex real world problems is obvious. The mathematical foundations of SEM rely largely on the principles developed for typical regressions and therefore many problems can also be solved using common methods such as ANOVA or MLR, however, the process becomes overly complicated rather quickly using these more primitive techniques. With SEM this difficulty is obviated, where the natural focus is not on direct effects, as it is in MLR, but on indirect and total effects, where total effects are the sum of direct effects and indirect effects (Keith, 2006, p.213). As argued by several authors (Keith, 2006; Kline, 1998) structural equation modelling is a better choice for explanatory analysis of non experimental data and provides a clearer representation of the relationships between variables through a pictorial diagram. At the most basic level SEM's are a type of factor analysis and can therefore be viewed as a form of exploratory data analysis (EDA) where the number of factors, factor loadings and rotation of the factor loading matrix are determined through exploratory analysis (Lee, 2007). Nowadays however SEM is more commonly viewed as confirmatory data analysis where the researcher builds a substantive model based on existing theory, experience, logic and previous exploratory studies. That is, the researcher aims to confirm the theory using the underlying data.

As noted, it is possible to solve SEM's using standard MLR but as models become increasingly complicated, they become increasingly difficult and more tedious to solve using traditional methods. Therefore, it is common practice to enlist the power of specialised computer software (Keith, 2006, p.212). Today, there are many computer programs specifically developed to solve SEM's including AMOS, Mplus, EQS, Mx Graph, RAMONA and SEPATH. The analysis presented in this paper was completed using AMOS (Analysis of Moment Structures) (Blunch, 2008) which is a supplementary program bundled with PASW statistics.

Structural equation models allow both confirmatory and exploratory modelling, meaning that such models can be used for both theory testing and theory development. In this chapter, a more confirmatory approach is adopted to substantiate the explanatory power of different variables and their effect on household energy consumption. From here it is possible to test the hypothesis that SAP and household energy consumption have reciprocal causality, or nonrecursivity.

Structural equation models are typically solved using analysis of covariance structures utilising the maximum likelihood (ML) estimator. Although other methods such as generalised least squares (GLS), unweighted least squares (ULS), scale free least squares (SLS) and asymptotically distribution free (ADF) methods are increasingly being used in many SEM software packages, ML methods still dominate (Keith, 2006). The Bayesian approach is also growing in popularity with its own set of advantages and disadvantages over the covariance structure approach (Lee, 2007). In essence, SEM is a method for solving several simultaneous regression equations at once. In addition, SEM procedures allow for complicated interactions between variables, for example in one equation a single variable can be predicted and in another equation it may be a predictor. As SEM uses the same basic principles of regression, many of the fundamental assumptions that underpin MLR techniques also apply to structural equation models. For detailed mathematical derivation of SEM see the following textbooks (Kaplan, 2009; Blunch, 2008; Kline, 1998; Tabachnick, 2007).

5.3 Methodology

5.3.1 The dataset

The model is based solely on publicly available data and is comprised of information available from two principle datasets. These are The 1996 English House Condition Survey (EHCS) and the 1996 Fuel and Energy Survey (FES). The EHCS is conducted every five years and is the only survey to provide thorough data on the condition of the national housing stock (DETR, 1996). The 1996 EHCS consists of 12,131 real cases, and the sample is selected to represent the dwelling stock in

England. Usually the EHCS focuses primarily on the physical condition of dwellings and other building characteristics with limited scope for other demographic and economic information. In 1996 however, a supplemental FES was carried out on a subsample of 2,531 cases of the original EHCS. Importantly, the FES subsample includes metered electricity and gas consumption data, information on energy usage as well as data on energy expenditure. The interviews were conducted from January to May 1996, with the fuel survey collecting actual energy and fuel usage over eight consecutive quarters. Thus information on a dwelling's physical condition, the economic status of its inhabitants as well as demographic and behavioural information can all be used in an analysis to determine what factors may explain residential energy consumption. A similar survey of this scale and type has not been completed in England since 1996 but one is planned to be completed by the end of 2011 and available sometime towards the end of 2012 (Communities and Local Government, 2010). Although the 1996 EHCS is the most appropriate survey to use in this instance there are obvious issues with using old data. Over this period different government policies have been introduced, energy prices have shifted and demographic and behavioural factors may now have different influences over household energy demand. This analysis is therefore provided on the caveat that it can only be used to determine what factors explain energy demand in 1996 and therefore can only be cautiously extrapolated to explain present day energy demand. The relevance of using SEM to solve this problem is emphasised in several respects. One strength of structural equation models is their capacity to test the statistical significance of structural relationships between model variables. For energy consumption in the residential sector, such relationships are grounded in physical laws, defined by economic relationships and manifest as behaviour. For example, homes with a large floor area will take more energy to heat and homes having higher incomes will be more likely to spend more money on heating. For this reason, structural relationships estimated from historical data are still relevant for understanding energy consumption today and in the future. This is because, although the values of these variables may change substantially over time, the structural relationship between the variables will remain relatively stable. An unfortunate symptom of the residential sector is the large inertia of the system and therefore the significant time required for transition. For example, the average SAP value of dwellings surveyed in the EHCS went from 44 in 1996 to just 51 in 2007.

5.3.2 Explanatory variables

The EHCS and FES are two large datasets that when combined consist of hundreds of variables measuring almost every aspect of the physical dwelling and the occupants living there. Armed with such information it is possible to develop a model consisting of an enormous number of variables pertaining to explain energy consumption. However, in SEM, as it is in science more generally, parsimony is highly valued (as discussed in Section 1.5.6). If two explanations for a phenomenon are equally good, then the more parsimonious explanation is preferred. With this in mind, variables were chosen on the premise that they were likely to explain a large proportion of the variance in energy consumption. If the addition of a variable to the model performed just as well as the simpler, more parsimonious model, the new variable was discarded in favour of the more parsimonious model. The following variables were chosen for their capacity to explain residential energy consumption.

Number of occupants is the number of people living at the dwelling at the time the survey was conducted.

Household income is the annual net income for the household after tax and national insurance contributions have been deducted.

Floor area is the internal useful floor area for the dwelling.

SAP is the UK Governments standard assessment procedure for measuring the energy efficiency of dwellings. The values in this dataset were calculated using the 1996 SAP calculation procedure and were derived by the Building Research Establishment (BRE)[19.]

Dwelling temperature difference is the difference between the internal living room temperature and the outside temperature at the time the survey was conducted.

Energy patterns is on a scale from 0-5 and describes how frequently the occupants heat their home (0 being none 5 being all the time). Each respondent was asked to rank their home heating requirements for each of the following times and places:

19. BRE is the organisation responsible for managing SAP for the UK Government.

i) is the bedroom heated on the weekend?

ii) is the bedroom heated during the week?

iii) is the living room heated on the weekend?

iv) is the living room heated during week?

v) is the home heated during the week and throughout the day?

Dwelling Energy Expenditure	was collected over eight consecutive quarters and taken with permission from the energy supplier of the dwelling. Average annual energy expenditure is then calculated and used by the model.
The age of the head of the household	is a categorical indicator representing six age groups from 16 to 65 and over.
Degree days	is a measure of the temperature difference between the outside temperature and a base temperature of 18.5° Celsius and the length of time this temperature persists over one year
Urban dummy	is a binary indicator representing whether the dwelling is located in a city as opposed to the country
Owner dummy	is a binary number indicating whether the occupier owns the dwelling.
Economic status dummy	is a binary indicator for the employment status for the head of the household.

Energy prices were also considered as an important driver for explaining residential energy consumption. As this study used a cross-sectional analysis, it was not possible to control for the effect of energy prices on energy demand. As shown by Summerfield (Summerfield et al., 2010a), energy prices in the UK are relatively inelastic with an estimated elasticity of demand around -0.20. This means a 50% increase in energy price will lead to an approximate 10% decline in energy demand. Similar results were found by others (Hunt et al., 2003; Micklewright, 1989) with most studies finding elasticities in the range -0.05 to -0.50 (Boonekamp, 2007; Lijesen, 2007; Fouquet, 1995).

5.3.3 Preparing the data for analysis

The final dataset was created by combining the 1996 EHCS with the 1996 FES subsample using a field code common to both datasets. After the datasets were combined, the final sample contained 2,531 cases. The sum of grossing weights therefore equates to 19.265 million and represents the number of residential dwellings in England in 1996.

5.3.4 Dealing with outliers

Outliers are either extreme values within a single variable (univariate outliers) or values that represent a strange combination of values across two or more variables (multivariate outliers). Datasets containing outliers have the potential to distort model statistics. Histograms and box and whisker plots facilitated the detection and deletion of a very small number of univariate outliers, defined as singular isolated values well outside the majority of other values. Three continuous variables (HHLD Income, Floor Area and Energy Expenditure) had long right-hand tails that could adversely affect model results. The distributions of these variables were therefore truncated to five standard deviations from the mean. Multivariate outliers were found using Cook's distance and the Centred Leverage statistic but were found not to be problem once the univariate outliers had been removed.

5.3.5 Missing data

Missing data in substantive research is common (Lee, 2007, p.355) and can be problematic for structural equation modelling if not handled correctly (Tabachnick, 2007, p.61). It is common in multivariate methods, and particularly when using SEM that data is complete (i.e. no missing values) and therefore several well established methods have been developed to overcome this problem. The sample used in this analysis contains a small number of missing values with each covariate having less than 5% missing data[20] (Kline, 1998; Rubin, 1976). This was confirmed using a simple test created to examine the assumption that missingness would have no effect on results. In this test, three separate samples were created each using a different method for dealing with missing data. The first sample used listwise deletion and reduced the final sample size from 2,531 independent cases to 2,372. The second used expectation-maximisation (EM) and the third sample used regression

20. 5% is a standard benchmark typically shown not to cause substantive problems to statistical model results.

imputation (RI). The model was then used to generate sample statistics using the three different samples. Outputs from the three samples were compared using the following fit-statistics: Chi-Square Statistic (χ^2); Root Mean Square Error (RMSEA); Generalised Fit Index (GFI) and the Tucker Lewis Index (TLI). The fit-statistics remained comparable across the samples with only negligible differences for each of the three samples. For the purposes of this analysis, missingness was therefore shown to have a limited non-substantive effect on model results and showed that any of the three data replacement methods were equally effective at producing robust results. As found by Arbuckle (Schumacker and Marcoulides, 1996) maximum likelihood methods such as expectation maximisation (EM) generally outperform most other traditional methods and was therefore the method chosen to replace missing values in this dataset.

5.3.6 Applying sample grossing weights

Sample weights are defined as the application of a constant multiplying factor to the data provided by a respondent to vary the contribution each respondent's results make to the overall estimates. As shown by Dorofeev (2006, p.45) little has been published on the subject of weighting and is generally ignored in texts on statistics and survey research. Dorofeev (2006, p.45) shows that statistical procedures conducted on a sample without applying the grossing weights prior to the analysis may lead to incorrect inferences about the population including underestimation of standard errors of estimators leading to inflated Type I and Type II errors as well as erroneous model diagnostics. Grossing weights as they are used in the EHCS also incorporate expansion factors so the sum of the weights represents the size of the population.

The EHCS and FES are large complex stratified surveys designed with a priori weighting to represent the dwelling stock in England. Each case in the sample is associated with a grossing weight derived from a stratified multi-stage cluster sampling process and calibrated to auxiliary variables subject to survey non-response adjustments. This is to allow for accurate analyses of particular groups of dwellings. For example, the sample size for particular groups of dwellings such as local authority dwellings, unfit dwellings and RSL dwellings need to be sufficiently large to provide a statistically significant sample. Maximising the efficiency of data gathering while still achieving statistical significance was achieved using survey stratification. This technique requires over representation of small groups of dwellings and under representation of common groups of dwellings within the sample. Grossing weights are then applied to the final dataset to undo the effects of stratification so the dataset can accurately represent the population. After adjustments are made for non-response and response bias, the post-weighted dataset should be an accurate reflection of the population. If grossing factors are not taken into account, the results will not be accurate or meaningful at the national level and bias towards groups unequally sampled.

The overall effect after applying weights is increased accuracy (reduced bias) of the results, but this comes at the expense of precision. This is because weighting involves a substantive increase in the standard error of estimates, thus introducing wider confidence intervals and a loss of discrimination in significance testing. The loss in precision is directly proportional to the range of weights being applied, the greater the range in weights the greater the loss in precision. For any weighted sample, the overall loss in precision can be obtained by calculating the "effective sample size" given by n_c in Equation (5.1). The ratio of actual sample size to effective sample size is known as the design effect (DE) and is typically greater than 1.0 for weighted samples. Therefore the actual standard error (or confidence interval) of an estimate like the mean, $\bar{x}$, can be calculated by multiplying the actual estimate by the design effect and therefore the standard error of an estimate can be expressed by Eq (5.3).

$$n_c = \frac{\left(\sum_{i=1}^{n} w_i\right)^2}{\sum_{i=1}^{n} w_i^2} = 1,025 \tag{5.1}$$

Hence,

$$WE = \frac{n}{n_c} = \frac{2,531}{1,025} = 2.47 \tag{5.2}$$

$$s.e(\bar{x}) = \sqrt{WE}\,\frac{S}{\sqrt{n}} = \frac{S}{\sqrt{n/WE}} = \frac{S}{\sqrt{n_c}} \tag{5.3}$$

Where, n_c, is the calibrated sample size, S, is the standard deviation of the original variable x from the post weighted calibrated sample, and n is the original un-weighted sample size. The result of using the calibrated sample size, n_c has the same effect of reducing the sample size by $1/WE$ and therefore has the overall effect of increasing standard errors. Not applying the weighted sample correction factor will lead to incorrect computation of variance and incorrect margin of error calculations of the model estimates.

5.4 Testing for normality

A further complication arising from the sample relates to the normality of some of the variables. One of the many assumptions of multiple linear regression, and subsequently SEM, is the assumption that variables used in the model are normally distributed. As a matter of course, skewness and kurtosis were calculated for all model variables. Unfortunately the Kolmogorov-Smirnov and Shapiro-Wilk tests of normality are not recommended for sample sizes over 100 (Elliott, 2007, p.22). Therefore, in addition to skewness and kurtosis, frequency histograms were created for each variable and checked against the normal distribution for critical deviation. The variables representing Occupancy rates, Floor Area, HHLD Income and Energy Expenditure showed the largest deviations from normality and therefore appropriate normality transformations were chosen and applied to these variables. As shown by Tabachnick (2007, p.73) the severity of non-normality to distort regression results diminishes as sample size is increased. Thus, the effect of non-normality on model results from the SEM can only be determined by comparing model outputs from the two datasets i.e. the raw dataset and the dataset containing the transformed variables. Both the transformed and non-transformed datasets were applied to the SEM model and their results were compared. Differences in the output of the two datasets were considered to be insignificant and within standard error of each other. In conclusion, model variables were shown to be robust to deviations from normality. The non-transformed data was therefore chosen for the analysis.

5.4.1 Importing the dataset into AMOS 18.0

A major benefit of using AMOS 18.0 is the ability to import the correlation matrix of the dataset as opposed to the entire sample for solving the model. As AMOS 18.0 does not allow unequal weights to be used during model estimation, it was necessary to import a post-weighted correlation matrix into AMOS 18.0. The benefit of using this approach is that grossing weights could be correctly applied to represent the calibrated sample size, n_c, before being used to produce the correlation matrix

(Table 5.3), thus ensuring that variance and standard error estimates are correctly calculated for the sample being used.

5.5 Model development

Based on substantive prior research a structural equation model was developed to represent the expected underlying causal relationships likely to explain domestic energy consumption in England. This can be represented in pictorial form as a path diagram. The model developed is based on the premise that domestic energy consumption can be explained by several manifest variables. Using such a model it is possible to test a number of hypotheses about the explanatory power and statistical significance between model variables and what their relative effect on residential energy consumption might be.

Before presenting analysis that is more detailed, it is prudent to explain the different components that constitute path diagrams. Rectangles represent measured variables also known as manifest or indicator variables, while circles or ellipses represent unmeasured or latent variables. Single headed arrows in SEM show direct causation in the direction of the arrow between two model variables. Importantly, the underlying data used by the model is not used in any way to make inferences about the direction of causality. A researcher armed with such prior knowledge about the variables under question is thus only able to infer weak causal ordering to the underlying structural relationship between variables (Keith, 2006, p.215). For example, in Figure 5.1 when an arrow is drawn from Floor Area to Energy Expenditure it does not show that Floor Area causes higher energy consumption it says that if Floor Area and Energy Consumption are causally related it is likely to be in the direction of the arrow and not the reverse. The explanatory power of the causal relationship is provided by the regression weight and is usually drawn on the line between the two variables. Double-headed arrows represent correlations between variables and do not imply causality. Endogenous variables are variables that are defined by other variables in the model and are therefore identified as having at least one single headed arrow feeding into them (e.g. Floor Area, Temperature Difference, HHLD Income and Annual Energy Expenditure). Exogenous variables are only used to define other variables in the model and therefore only have arrows that lead to other variables (e.g. Number of occupants and Energy Pattern). All endogenous variables must have a disturbance or error term that represents the unexplained variation in the variable not accounted for by other variables, this also includes measurement error. Exogenous variables may also include a disturbance term but this is not a necessary component. It is therefore possible to represent the model originally derived as a system of simultaneous regression equations as a path diagram.

5.6 Model identification and non-recursivity

Ensuring the dof within the model are equal to or larger than the number of parameters to be estimated is a necessary but insufficient condition for identification. In SEM over-identification is preferred as they allow for the evaluation of the overall quality or fit of the model. The second condition that must be met is empirical identification and requires the data being used on the model to produce semi-positive definite matrices.

The addition of feedback loops in SEM automatically introduces non-recursivity thus making the model more difficult to solve due to the added restrictions placed on the model. One assumption for non-recursive models is the assumption of stationarity, requiring the causal structure of the model not to change over time. For cross-sectional data, like the one being used for this analysis, there is a further assumption of equilibrium. This means that any changes in the system underlying the feedback relationship have already manifested and the system has reached a steady state (Kline, 1998, p.239). The structural equation model developed here satisfies both of these conditions. Firstly, the stationarity assumption is satisfied because the causal effects of residential energy consumption do not substantially change over time. Secondly, the variables identified are long lasting and slow to change (number of occupants, floor area, income etc) and therefore the effects of these indicators are assumed to manifest on energy consumption over many years prior to the survey being taken. For example, people living in homes with a high household income have a degree of familiarity with receiving a high income and therefore income effects on energy consumption would have already manifested in the home prior to the survey being taken and therefore assumed to have reached equilibrium.

5.7 Weighted random sampling with replacement

Previously, the estimation of the model was achieved by directly importing the correlation matrix from the post-weighted sample into AMOS 18.0. However, there are several alternatives for estimation using a weighted dataset in AMOS 18.0. One such method is to use well-understood sampling procedures to create a new subsample from the original dataset. This method is known as weighted random sampling with replacement (WRSWR). It is a probabilistic sampling method where the grossing weights for each case represent the probability a case is selected and added to the subsample. Suppose that w_i are the grossing weights produced by the complex sample design, the probability that case i is selected from the sample is then given by $P\left(X_i = x\right) = w_i / \sum w_i$. Each time a case is selected it is replaced back into the sample at which point a new case is selected and saved in the new sample. Repeating this process N times creates a new sub-sample representative of a post-weighted sample. Similar to bootstrapping, the new sample will contain some cases repeated multiple times while other cases will not be represented at all. Because case selection is based on weighted probability, it simulates the effect of selecting a case at random from the population and therefore the subsample represents a post-weighted sample of the population. Importing a representative dataset into AMOS 18.0 rather than the correlation matrix allows for deeper statistical analysis such as bootstrapping.

5.8 Bootstrapping

Estimating model parameters is only part of the solution. Checking the precision and accuracy of the model is necessary if one is to have any confidence in the results. This requires the calculation of standard errors and confidence intervals for each model parameter. Bootstrapping was therefore completed to assess the precision that can be obtained from the model and the underlying data to test if model results are representative of the population within predefined confidence intervals. With bootstrapping it is possible to determine empirical estimates of standard errors for any parameter, even standard errors of standard errors (Keith, 2006, p.258). In addition, with nonparametric bootstrapping it is not necessary to have data that fits to a normal distribution, thus prior transformation of the data is not necessary. In fact, the only requirement is for the distribution of the sample to be the same basic shape as the distribution of the population. Confidence intervals for each of the model parameters are therefore calculable.

5.9 Results

5.9.1 Limitations of multiple linear regression for understanding energy consumption

Before any structural equation model was developed a standard multiple linear regression model was created to understand how much of the variance in energy consumption could be explained using standard regression methods. Many national level domestic energy models rely on household efficiency indicators such as SAP to predict future domestic energy consumption. It therefore follows that SAP should have strong predictive power when estimating domestic energy consumption. Testing this hypothesis was achieved using Equation (5.4).

$$\mathbf{y} = A + B_1\mathbf{x}_1 + B_2\mathbf{x}_2 + B_3\mathbf{x}_3 + B_4\mathbf{x}_4 + B_5\mathbf{x}_5 + \boldsymbol{\varepsilon} \tag{5.4}$$

Equation (5.4) measures the predictive power and statistical significance of SAP on energy consumption while controlling for several other important factors known to influence energy consumption. The results of this analysis are shown in Table 5.1.

Table 5.1: Mutiple Linear Regression diagnostics

	Unstandardised Coefficients		Standardised Coefficients	t-statisic	95% Confidence Interval for B	
	B	Std. Error	β		Lower Bound	Upper Bound
Intercept (A)	163.6**	0.262		624.9	163.0	164.1
SAP (β_1)	-0.971**	0.003	-0.053**	-280.6	-0.987	-0.964
Number in household (β_2)	62.67**	0.043	0.297**	1447.4	62.6	62.8
Floor Area (m2) (β_3)	2.380**	0.002	0.262**	1214.5	2.4	2.4
HHLD Income (000's £) (β_4)	3.944**	0.006	0.140**	644.6	3.9	4.0
Temperature Difference (C) (β5)	2.390**	0.011	0.042**	221.5	2.4	2.4
Energy Pattern (categorical) (β6)	25.76**	0.044	0.112**	585.4	25.7	25.8

1. $R^2 = 0.314$, Adj $R^2 = 0.314$, Std. Error of Estimate = 235.1
2. * p<0.05, ** p<0.010.

The null hypothesis for this experiment was that SAP is both statistically significant ($p < 0.01$) and correlated with energy consumption ($R^2 > 0.1$) after controlling for other covariates. As shown in Table 5.1, the model is reasonably well specified (Adj.$R^2 = 0.314$) and SAP is shown to be a statistically significant variable ($p< 0.01$). However, although SAP has the correct sign (increasing SAP reduces the expected level of energy consumption) the power for SAP to predict energy consumption is lower than expected as shown by the small standardised regression weight, β (-0.053), indicating that only a small proportion of the variance in energy consumption can be explained by SAP. The result of this simple analysis brings into question the basic premise of many domestic energy models, which rely on SAP measurements to predict household energy consumption.

5.9.2 Results of the structural equation model

Descriptive statistics for the variables used in this model are given in Table 5.2. The correlation matrix in Table 5.3, was created using the post-weighted sample and the calibrated sample size, n_c.

Table 5.2: Descriptive statistics for model variables

Variable name	Minimum	Maximum	Mean	Std. Error1	Std. deviation[1]
Number in household	1.00	10.00	2.51	0.04	1.35
Floor Area (m^2)	20.0	252.4	81.3	0.97	31.2
HHLD Income (£)	2,340	103,825	15,317	315	10,072
SAP Rating	0	109	44.4	0.49	15.6
Annual Energy Expenditure (£)	74.2	3332	642	8.87	284
Living room temperature (°C)	0.3	36.9	19.0	0.09	2.79
Outside temperature (°C)	-9.2	39.1	6.90	0.15	4.75
Temperature Difference (°C)	-20.0	27.1	12.1	0.16	5.02
Energy Pattern (categorical)	1.0	5.0	3.15	0.04	1.24
Degree Days (categorical)	1749	2367	2089	6.25	200
Urban_Recode (dummy)	0	1	0.81	0.01	0.39
Owner of house (dummy)	0	1	0.69	0.02	0.46
Economic Status (dummy)	0	1	0.57	0.02	0.45
Age of head of household (categorical)	1	6	3.95	0.05	1.57

1. Std.Error and Std.Deviation calculations were calculated from the re-calibrated effective sample size of (n_c = 1025).

Table 5.3: Correlation matrix of significant explanatory variables

Pearson Correlation	Energy expenditure	HHLD income	Floor area	No. of occupants	Temperature Difference	SAP	Energy pattern	Degree days
Energy expenditure	1	-	-	-	-	-	-	-
HHLD Income	0.375**	1		-	-	-	-	-
Floor area	0.420**	0.436**	1		-	-	-	-
Number of occupants	0.452**	0.475**	0.352**	1	-	-	-	-
Temperature difference	0.085**	0.104**	0.021	0.053	1	-	-	-
SAP	0.031	0.110**	0.106**	0.104**	0.034	1	-	-
Energy pattern	0.188**	0.100**	0.109**	0.131**	0.093**	0.084**	1	-
Degree days	0.012	0.013	-0.004	0.004	0.123**	0.012	0.04	1

** Correlation is significant at the 0.01 level (2-tailed) * Correlation is significant at the 0.05 level (2-tailed)

As the results from the multiple linear regression show, SAP performs less than expected as a predictor for HHLD energy consumption. This process however does not allow for reciprocal causality between energy consumption and SAP. A basic assumption of multiple linear regressions is that the independent variables have a direct effect on the dependent variable but also, the dependent variable does not have any effect on the independent variables. When both variables are thought to have an effect each other, the relationship is described as non-recursive or cyclical. Separating and quantifying two bi-directional effects is difficult but made possible utilising the properties of an over-identified non-recursive structural equation model.

The results of the structural equation model are presented in Figure 5.1. Standardised regression weights are shown on each of the arrows connecting two indicator variables and represent the direct effect that one variable has on another variable. The standardised and unstandardised regression coefficients for direct effects are shown in Table 5.4 alongside the respective statistical tests for significance. A key advantage of using standardised regression coefficients is the ability to compare the relative magnitude of effects across variables. Table 5.5 presents the standardised indirect effects each variable has on each related variable, and measures the effect of one variable on another variable through an intermediary variable i.e. HHLD Income effects Annual Energy Expenditure through the mediating variable of Floor Area. Total effects are the sum of direct effects and indirect effects of the variables shown to statistically explain the variation within that variable. The results for total effects are shown in Table 5.6. When reviewing Table 5.5 and Table 5.6 it should be read as the column variable affecting the row variable.

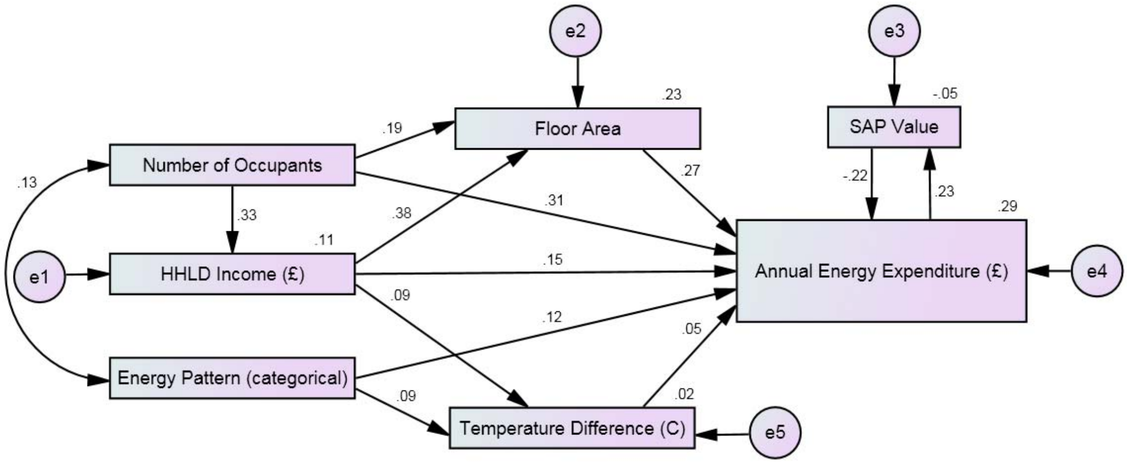

Figure 5.1: Path diagram of the structural equation model

Once the causal relationships between model variables have been determined, it is possible to represent the model as a set of simulataneous linear equations these are shown in Equation (5.4).

$$\begin{aligned}
&HHLDINCOME = w_1 NUMBEROCCUPANTS + \varepsilon_1 \\
&FLOORAREA = w_2 NUMBEROCCUPANTS + w_4 HHLDINCOME + \varepsilon_2 \\
&SAP = w_{12} ENERGYEXP + \varepsilon_3 \\
&ENERGYEXP = w_9 FLOOAREA + w_3 NUMBEROCCUPANTS + \\
&w_5 HHLDINCOME + w_7 ENERGYPATTERN + w_{10} TEMPDIFF + w_{11} SAP + \varepsilon_4 \\
&TEMPDIFF = w_6 HHLDINCOME + w_8 ENERGYPATTERN + \varepsilon_5
\end{aligned} \tag{5.4}$$

The EHCS does not contain longitudinal internal temperature measurements. Therefore, internal and external temperature readings taken on the day of the survey were used as proxies for average internal temperature readings. Because temperature readings were only recorded on the day of the survey, it is sensible to treat any relationships related to Temperature Difference with caution as results may lead to spurious conclusions. Large measurement error and therefore weak statistical significance between Temperature Difference and annual Energy Expenditure (P = 0.088) was therefore expected, and if more robust data on temperatures were available, the significance of this variable would no doubt improve. For completeness, the temperature variable was included in the final model as it does lead to an improvement in the overall model fit statistics. Removing temperature from the analysis was shown to have very little effect on other variables in the model.

Table 5.4: Coefficient estimates of model parameters using correlation matrix method

			Standardised Coefficients	Unstandardised Coefficients		Significance		
			β	B	Std.Err	C.R.[1]	P(sig.)	Label
HHLD Income	**<---**	**Occupants**	0.329	2463	(221.8)	11.1	***	W1
Floor Area	**<---**	**Occupants**	0.188	4.362	(0.677)	6.44	***	W2
Temperature	**<---**	**Energy Pattern**	0.087	0.354	(0.126)	2.80	0.005	W8
Floor Area	**<---**	**HHLD Income**	0.381	0.001	(0.000)	13.0	***	W4
Temperature	**<---**	**HHLD Income**	0.092	0.000	(0.000)	2.95	0.003	W6
Annual Energy Expenditure	**<---**	**Occupants**	0.306	64.52	(6.094)	10.5	***	W3
Annual Energy Expenditure	**<---**	**HHLD Income**	0.145	0.004	(0.001)	4.76	***	W5
Annual Energy Expenditure	**<---**	**Energy Pattern**	0.123	28.27	(6.205)	4.56	***	W7
Annual Energy Expenditure	**<---**	**Floor Area**	0.271	2.464	(0.276)	8.93	***	W9
Annual Energy Expenditure	**<---**	**Temperature**	0.046	2.584	(1.514)	1.71	0.088	W10
Annual Energy Expenditure	**<---**	**SAP Value**	-0.216	-3.924	(0.869)	-4.52	***	W11
SAP Value	**<---**	**Annual Energy Expenditure**	0.235	0.013	(0.003)	4.08	***	W12
Occupants	**<-->**	**Energy Pattern**	0.128	0.213	(0.053)	4.05	***	C1

1. C.R is the critical ratio (B / Std.Err) and is also known as the t-statistic.
2. Estimates are based on the calibrated effective sample size (1025)

Table 5.5: Standardised indirect effects

	Energy Pattern	Occupants	HHLD Income	Temperature	Floor Area	SAP Value	Annual Energy Expenditure
HHLD Income	0	0	0	0	0	0	0
Temperature	0	0.030	0	0	0	0	0
Floor Area	0	0.126	0	0	0	0	0
SAP Value	0.029	0.099	0.057	0.010	0.061	-0.048	-0.011
Annual Energy Expenditure	-0.002	0.113	0.095	-0.002	-0.013	0.010	-0.048

Table 5.6: Standardised total effects

	Energy Pattern	Occupants	HHLD Income	Temperature	Floor Area	SAP Value	Annual Energy Expenditure
HHLD Income	0	0.329	0	0	0	0	0
Temperature	0.087	0.030	0.092	0	0	0	0
Floor Area	0	0.314	0.381	0	0	0	0
SAP Value	0.029	0.099	0.057	0.010	0.061	-0.048	0.224
Annual Energy Expenditure	0.121	0.419	0.241	0.044	0.258	-0.206	-0.048

5.10 Other paths tested

A large number of other causal relationships between different variables were tested before arriving at the final solution as shown in Figure 5.1. These are referred to as nested models and defined as any model that can be derived from the initial model by deleting paths between model variables. Each path was systematically tested for significance and power. Paths not shown in Figure 2 were found to be statistically insignificant and therefore fixed to zero as they were found to have no significant causal effect within the model.

5.11 Testing for non-recursivity

Testing for non-recursivity between SAP and Energy Expenditure was accomplished using a Chai-squared test for two competing, but nested, models. Analysing the change in χ^2 between the two models makes it is possible to test whether a non-recursive model is able to improve model fit. The model with one or more paths deleted is more constrained, has higher dof, is more parsimonious and is therefore described as a nested model. To test whether the non-recursive, less parsimonious model is a statistically better fit, it is necessary to calculate $\Delta\chi^2$ and Δ dof between the two models, this is shown in Table 5.7. Looking up $\Delta\chi^2$ and Δ dof in probability tables shows a related probability ($p<0.01$); indicating that having two paths between Energy Expenditure and SAP resulted in a statistically significant increase in $\Delta\chi^2$. Not only does the simple model (with only one path between SAP and energy consumption) fit worse than the non-recursive model but also fits statistically significantly worse. Even though the recursive model is more parsimonious, it comes at too great a cost of model fit. In conclusion, non-recursivity between SAP and Energy Expenditure is shown to be an important parameter in explaining residential energy consumption.

Table 5.7: Test for nonrecursivity in the model

	χ^2	*dof*
Recursive model	25	9
Non recursive model	7.3	8
Difference	$\Delta\chi^2 = 17.7$	$\Delta dof = 1$

5.12 Variables analysed but not used within the final Structural Equation Model (SEM)

Table 5.8 shows the statistical results corresponding to the variables that were shown not to explain Energy Expenditure or contribute to the statistical fit of the model. In turn, each of the variables were added to the model and compared with the best fitting model. The only variable shown to be statistically significant was the variable indicating if the dwelling was built in a city (Urban Dummy). Unfortunately, with the addition of this variable the overall model fit statistics declined from (χ^2 = 7.3, RMSEA = 0.000, TLI = 1.00, AIC= 47.3) to (χ^2= 52.9, RMSEA = 0.052, TLI = 0.909, AIC = 96.9) and therefore this variable was also dropped from the final model as it lowered overall model fit.

Table 5.8: Unused variables

			Standardised Coefficients	Unstandardised Coefficients		Significance		
			β	B	Std.Err	C.R.	P(sig.)	Label
Annual Energy Expenditure	<---	**Age of Head Occupant**	0.026	4.7	5.4	0.86	.39	-
Annual Energy Expenditure	<---	**Economic Status (dummy)**	-0.015	-8.8	17.9	-0.50	.62	-
Annual Energy Expenditure	<---	**Owner Occupier (dummy)**	0.030	18.3	18.2	1.00	.32	-
Annual Energy Expenditure	<---	**Urban (dummy)**	0.093	67.2	19.6	3.4	***	-
Annual Energy Expenditure	<---	**Degree Days**	0.004	.0054	.038	0.14	.89	-

5.13 Model diagnostics and bootstrapping

Bootstrapping allows the calculation of standard errors and therefore confidence limits of the statistics of interest. Table 5.9 shows the upper and lower bounds for both the standardised and unstandardised direct effects in the model. A key benefit of bootstrapping is that it provides lower and upper confidence bounds for how well model results estimated from the sample compare with the population. The small difference between lower and upper confidence bounds indicate the sample represents the population very well. Note also the similarity in regression weights when comparing the bootstrap results to those regression weights obtained from the method where the correlation matrix was used for the analysis (Table 5.4). This shows the correlation matrix method and the post-weighted subsample selection method compare well with one another. However, as the correlation matrix method uses the entire post weighted dataset for creating the correlation matrix prior to importation, the correlation method is more accurate, but does not allow bootstrapping tests to be completed.

Table 5.9: Upper and lower bounds calculating from bootstrap estimates

			Standardised Coefficients			Unstandardised Coefficients		
			β	Lower	Upper	B	Lower	Upper
HHLD Income	**<---**	**Occupants**	0.335	0.320	0.356	2538	2402	2692
Floor Area	**<---**	**Occupants**	0.193	0.174	0.213	4.52	4.09	5.02
Temperature	**<---**	**Energy Pattern**	0.107	0.090	0.129	0.425	0.357	0.512
Floor Area	**<---**	**HHLD Income (000's)**	0.387	0.369	0.402	1.199	1.141	1.253
Temperature	**<---**	**HHLD Income (000's)**	0.095	0.078	0.116	0.046	0.037	0.056
Annual Energy Expenditure	**<---**	**Occupants**	0.302	0.284	0.320	64.071	60.0	68.2
Annual Energy Expenditure	**<---**	**HHLD Income (000's)**	0.130	0.114	0.151	3.655	3.222	4.272
Annual Energy Expenditure	**<---**	**Energy Pattern**	0.120	0.107	0.140	27.680	24.5	32.3
Annual Energy Expenditure	**<---**	**Floor Area**	0.297	0.275	0.314	2.692	2.51	2.86
Annual Energy Expenditure	**<---**	**Temperature**	0.039	0.0211	0.0553	2.264	1.23	3.21
Annual Energy Expenditure	**<---**	**SAP Value**	-0.212	-0.249	-0.184	-3.899	-4.55	-3.38
SAP Value	**<---**	**Annual Energy Expenditure**	0.227	0.197	0.262	0.012	0.011	0.014
Occupants[4]	**<-->**	**Energy Pattern**	0.231	0.199	0.261	0.139	0.120	0.156

1. Bootstrap confidence intervals are based on the bias-corrected percentile method.
2. Estimates are based on the bootstrap sample size (10,000 cases)
3. Confidence intervals are calculated at the 95% level
4. Covariances are listed under standardised estimates while correlations are listed under unstandardised estimates

5.13.1 Model fit statistics

Identifying and using model fit indices in SEM's remains, to this day, a greatly debated subject with no general agreement on the form or type of fit indices that should be used to measure model integrity. The development of different indices has been motivated, in part, by the known sensitivity of the χ^2 statistic to large sample sizes. Consequently, most literature on this subject suggests that a selection of indices need to be presented alongside model results. The most recent and comprehensive review on the subject of fit indices is found in a special edition of "personality and individual differences" (Vernon, 2007) where a number of papers debate the appropriateness and weaknesses of different fit-indices. The main conclusion from this collection of papers is a general agreement that χ^2 and p-value should always be reported. For this analysis, a selection of the most widely used fit indices is presented. As shown in Table 5.10, all indices show an extremely good fit of the model to the data providing evidence the model itself could have produced the underlying data.

Table 5.10: Model fit indices

	N	dof	χ^2	P-value	GFI	PGFI	TLI	CFI	RMSEA	SRMR	Stability Index
Correlation	1025	8	7.30	0.504	0.998	0.285	1.00	1.00	0.001	0.016	0.048

The degrees of freedom parameter (dof) is calculated as the number of distinct sample moments (28) minus the number of distinct sample parameters to be calculated (20) and therefore measures the degree to which the model is over identified. In SEM the null hypothesis (H_0) is that the model to be tested is unlikely to be due to chance and the alternative (H_a) is that it is not. The χ^2 statistic and its p-value therefore measure the probability that the model fits perfectly to the population. Therefore, if χ^2 is not statistically significant (p-value > 0.05) then it is not possible to reject the null-hypothesis that the model is accurate suggesting the model may explain reality.

The Goodness of Fit Index (GFI) is analogous to R^2 in multiple linear regressions and provides an estimate for the amount of covariance accounted for by the model. PGFI is simply a parsimony-adjusted value for GFI. Two similar indices are also listed, the comparative fit index (CFI) and the Tucker-Lewis Index (TLI) and they compare the fit of the existing model with the null-model. TLI makes a slight adjustment for parsimony but all four indexes, and particularly PGFI, are adversely effected by sample size, though much less than χ^2. For all three, values over 0.95 suggest very good fit of the model to the data while values over 0.9 suggest an adequate fit. The Root Mean Square Error of Approximation (RMSEA) is a measure of the error of approximation, with values below 0.05 suggesting close fit and values under 0.08 suggesting a reasonable fit (Keith, 2006, p.269). The standardised root mean square residual (SRMR) is among the best fit indexes and is a measure of the mean absolute value of the covariance residuals (Kline, 1998, p.141). Perfect model fit is indicated by SRMR = 0 and values under 0.1 are generally considered to be favourable. In addition, non-recursive models have a further statistic that measures the stability of the model. This is known as the stability index and is used only after equilibrium has been shown to exist on rational grounds. Values below 1.0 are thought to indicate a stable model. In summary, all model fit indices indicate that the model under analysis may be used to approximate reality and that the model and data are consistent with one another.

5.13.2 Model validation

Due to the paucity of disaggregated residential data within the UK and a serious lack of bottom up statistical residential building stock models, strong validation of this model against previous studies is difficult. Nevertheless, validation of model parameters (over and above statistical significance tests and bootstrapping exercises presented earlier) can be accomplished by comparing these results with other bottom up energy demand models. Using path analysis on the US residential sector, Steemers and Yun (2009) have showed the importance of floor area $(\beta = 0.255)$, household income $(\beta = 0.166)$, occupancy levels $(\beta = 0.109)$ and behaviour $(\beta = 0.124)$ for explaining residential heating demand. In a similar fashion with a limited number of variables Baker and Rylatt (2008) performed clustering and regression techniques on a small sample of homes in Leicester in the UK and confirmed the importance of floor area for explaining energy consumption $(r^2 = 0.272)$. Given the results presented using the novel structural equation modelling approach are of similar magnitude, scale and type to other published models, there is no reason to question the robustness of these results.

5.14 Discussion

Many of the conclusions drawn from this research can be identified through careful observation of the path diagram and from Table 5.3 - Table 5.6. Household Occupancy is shown to have a direct positive effect on dwelling Floor Area (β =

0.19**) and HHLD Income (β=0.33**). Household Occupancy has a direct and positive effect on Annual Energy Expenditure (β=0.31**). Total effects are the combined direct effects and indirect effects of one variable on another variable. For example, for each extra person living in a dwelling, the expected mean floor area will increase by 7.27m^2 (β=0.31**), the mean annual household income will increase by £2,463 (β=0.33**), and the mean energy bill will increase by £88/year (β=0.42**) ceteris paribus. Moreover, by considering the standardised regression weights of total effects it is possible to compare the relative magnitude of effects across different variables. Here, it is shown that Household Occupancy has the largest overall effect on energy consumption (β= 0.419**) followed by Floor Area (β= 0.258**) and then Household Income (β = 0.241**). It is important to note however, that Household Occupancy is strongly mediated by both Household Income (β=0.33**) and Floor Area (β=0.19**). Where, β-values can be interpreted as a change of one standard deviation in the independent variable corresponds β-std.deviations change in the dependent variable.

Because the units of β are standardised to z-scores, it is possible to derive the relative impact of each independent variable on the dependent variable. For example, it is shown that Household Income has a larger relative effect on Floor Area (β =0.38) then it does on Energy Expenditure (β=0.15). In fact, for each additional £1,000 in annual Household Income the mean Floor Area increases on average by 1.18m^2. However because Floor Area and Temperature Difference are both mediating variables between Household Income and Energy Expenditure it is necessary to use total effects (Table 5.6) to calculate the overall effect that Household Income will have on Energy Expenditure. For instance, using total effects, a £10,000 increase in annual Household Income will lead to an expected average increase in Energy Expenditure of £68/year. On the other hand, if only the direct effects of Household Income on Energy Expenditure are considered the average increase in Energy Expenditure is only £41/year. The remaining £27/year difference comes from the mediating effect that HHLD Income has on Energy Expenditure through an increase in Floor Area and an increase in the internal Temperature Difference.

An increase in Energy Pattern, as expected, increases both Temperature Difference and Energy Expenditure. Energy Pattern is an ordered categorical variable ranging between 1 and 5 where 1 represents someone who is never at home and rarely uses their heating compared to 5, representing a dwelling where heating is on all the time. The difference in annual Energy Expenditure between these two types of users is, on average £139/year. A correlation between Energy Pattern and Occupancy was identified by the modification indices and found to be significant. Such a correlation indicates the possibility of a shared common variable that explains both Energy Pattern and Occupancy. A logical choice for such a shared common variable is the relationship between occupants living in the dwelling. In one example, we have a large family consisting of several children where one partner stays at home during the week. In this example, household composition will have a positive effect on both Occupancy and Energy Pattern. In a second example, we have a household consisting of just one person who lives alone with a full time job. In this example, household composition will have a much smaller effect on both Occupancy and Energy Pattern. The addition of a new variable to represent household composition was excluded from the model, as it would not add any further insight. A summary of real effects on annual energy expenditure are shown in Table 5.11.

Table 5.11: Real total effects on annual energy expenditure

Variable	Effect	Annual HHLD Energy Expenditure
HHLD income	Increase £10,000	£67.80
Number of occupants	each extra person	£88.32
Floor area	Each extra 10m^2	£23.44
Temperature	Each 1°C increase	£2.50
Energy pattern	Living room heated week	£27.70
Energy pattern	Bedroom heated week	£27.70
SAP	30 -> 80 SAP	**-£185.00**

One of the most important findings of this research was the discovery and estimation of a non-recursive relationship between Energy Expenditure and SAP. Standard multiple linear regression methods do not allow the calculation of reciprocal relationships between variables, and therefore it is necessary to use SEM to solve such problems. Only after the non-recursive relationship between SAP and Energy Consumption has been allowed for, can the true effect of SAP on energy consumption be demonstrated. Here, it is shown the effect of SAP on Energy Expenditure has a moderate but statistically significant effect (β = -0.22**), while

Energy Expenditure is also shown to effect SAP (β = 0.23**). That is, for each standardised unit increase in the SAP rating there will be a subsequent decrease in Energy Expenditure of β = -0.22** as would be expected from existing theory. Similarly and to put this in context, it is necessary to examine the unstandardised regression weights. Remembering that SAP ranges in scale between 0 and 100, it is shown that one unit increase in SAP would give an average saving in annual Energy Expenditure of £3.73. For example, if a dwelling with a poor energy efficiency rating with SAP of 30, is renovated to have a SAP rate of 90 the expected annual average saving in energy expenditure will roughly be £222 per annum (£UK1996) ceteris paribus.

Perhaps what is more interesting is the finding that dwellings with a propensity to consume more energy due to higher occupancy rates, higher household incomes, larger floor areas, increased energy patterns and warmer internal temperatures are also more likely to have higher SAP ratings. This therefore suggests that homes with a propensity to consume more energy would in fact consume comparatively more energy if it were not for the fact that these homes were already relatively more efficient when compared to the rest of the building stock.

5.15 Chapter conclusions

In this chapter a structural equation model was used to determine the explanatory power and significance of multiple covariates on residential energy consumption. Using SEM it was possible to test the structure of relationships and therefore show how direct, indirect and total effects interact and explain residential energy consumption. It was shown the largest determinants for explaining residential energy consumption are the number of occupants living at the dwelling, household income, floor area, household energy patterns, temperature effects, and the SAP rating. While the number of occupants living in a dwelling was shown to have the largest magnitude of effect, floor area and household income are also substantial drivers. In addition, there is strong mediation between causal variables. For instance, household income and the number of occupants living in a dwelling are both strongly mediated by dwelling floor area. In other words, households occupied by more people or have higher incomes live in larger houses and therefore consume more energy.

Possibly the most important discovery of this research is the finding of a statistically significant reciprocal relationship between SAP and residential energy consumption.

This confirms earlier findings from Chapter 4 about the adequacy of SAP as a measure of household efficiency. This is the first time such a relationship has been empirically identified and may have important consequences for the development of new policy aiming to dramatically reduce emissions from the residential sector. This finding shows that homes with a propensity to consume more energy already have relatively higher SAP rates when compared to the rest of the building stock and therefore suggests the scope for further savings through the implementation of energy efficiency technologies may be limited. What is more, this finding implies that homes with a propensity to consume more energy are already relatively more efficient and therefore will be more expensive to decarbonise due to the law of diminishing returns. On the other hand, if policy were to focus on homes with a propensity to consume less energy, it can be shown that these homes have relatively lower SAP rates and are therefore in general less efficient. However, these homes tend to be more poorly heated with lower overall internal temperatures. Thus improving the efficiency of these homes through the implementation of energy efficiency technologies may contribute to the rebound effect (take back) acting to increase the average internal temperature rather than decrease energy consumption. This suggests there may be a residential energy efficiency barrier that must first be overcome before any real savings from the residential sector can start to accrue. This result may explain why several government-supported projects in the UK aimed at reducing residential energy consumption have not had the impact anticipated. With this purpose in mind, a dual policy approach may be more effective. Homes with a propensity to consume more energy should be targeted for changing user behaviour combined with economic penalties and incentives to reduce energy consumption. On the other hand, homes with a propensity to consume less energy should be targeted for whole home efficiency upgrades and break through the energy efficiency barrier.

6

A panel model for predicting the diversity of internal temperatures from heterogeneous dwellings

6.1 Chapter summary

In the previous chapter, direct, indirect and total effects for explaining residential energy demand were empirically estimated. A weakness of the previous analysis was its inability to accurately model the effects of internal and external temperatures as they change over time. In this chapter, a novel panel regression method is applied capable of modelling (predicting) internal temperatures from a heterogeneous building stock over time. The model therefore provides an important link connecting physically derived building stock models with human behaviour. A method for connecting human behaviour with the physical characteristics of buildings is absent from all existing stock models claiming to estimate energy demand. This model therefore represents the first time a panel model has been used to estimate the dynamics of internal temperature demand owing to the natural daily fluctuations of external temperature combined with important behavioural, socio-demographic and building efficiency variables. The model is able to predict internal temperatures across the building stock to within ~0.71°C at 95% confidence and explain 45% of the variance of internal temperature between heterogeneous dwellings. The model confirms hypothesis from sociology and psychology that habitual behaviours are important drivers of home energy consumption. In addition, the model offers the possibility to quantify take-back (direct rebound effect) owing to increased internal temperatures from the installation of energy efficiency measures. The presence of thermostats or thermostatic radiator valves (TRV) are shown to reduce average internal temperatures, however, the use of an automatic timer is shown to be statistically insignificant. Occupancy, household income, the elderly and the young all lead to a statistically significant increase in mean daily internal temperature. As expected, building typology, building age, roof insulation thickness, wall U-value and the proportion of double-glazing within a dwelling all have statistically significant effects increasing daily mean internal temperature. In summary, the model can be used as a tool to predict internal temperatures or for making statistical inferences. However, its primary contribution offers the ability to calibrate existing building stock models to account for behaviour and socio-demographic effects making it more accurate for predicting domestic energy demand.

6.2 Background

In 2011 almost 90% of all UK dwellings used central heating systems as a primary heat source. Thus, a transition from individual room fires and heaters to more modern, controllable central heating systems has dramatically changed the way in which people use energy in their homes. Although modern gas central heating systems are arguably much more energy efficient than traditional solid fuel stoves, they also provide users with instantaneous heating[21] and thus create opportunities for increased energy consumption. This is for several reasons. First, gas central heating systems benefit from advanced controls and automation giving them functionality and flexibility not available with more traditional heating methods. Secondly, little effort is required to increase consumption, unlike traditional wood and coal fired heating systems. Finally, central heating has afforded users the capability to heat every room in the house through dedicated radiators. As will be discussed, the repercussions of modern heating systems and controls on internal temperature profiles are still widely disputed. For example, Shipworth (2011) provides no evidence that thermostat settings have changed between 1984 and 2007. Shipworth

21. “Instantaneous heating” refers to the activation of the system. Central heating systems typically take approximately 30-90 mins for the dwelling to reach its set-point temperature.

suggests that despite overall efficiency gains, the absence of a reduction in energy consumption may be explained by an increase in the total area of the dwelling now being heated, an increase in heating duration and an increase in the frequency of window openings to control temperature.

Because home heating contributes towards a significant component of total residential energy consumption, it is worthwhile scrutinizing the driving forces behind demand for home heating. A growing body of literature suggests that home heating is just as much due to the behavioural and social characteristics of people and how they interact with energy technology as it is to do with the physical properties and efficiency of the building (Royal Commission, 2007; Crosbie and Baker, 2010; Lomas, 2010; Wall and Crosbie, 2009). The idea that people matter as much as buildings was pioneered by Lutzenhiser (1992) where he argued that psychological, social, economic and behavioural aspects must be considered alongside the physical properties of the building. In his seminal paper, Lutzenhiser coined this as the ‘cultural model’ of energy use. Following Lutzenhiser, Hitchcock (1993) argued the need for a systems based framework, able to integrate the social and technical aspects of energy demand into a single model. In his analysis Hitchcock asserts, “energy consumption patterns are a complex technical and social phenomenon – page 1” and thus to be fully understood must be “viewed from both engineering and social science perspectives concurrently – page 1”. Although both authors made the intellectual leap to bring two very distinct research approaches together, many of the building stock models developed over the following several decades have never managed to fully incorporate these early ideas (Emery and Kippenhan, 2006; DECC, 2008b).

Since these early pioneers, most research has attempted to model and understand home energy demand through a deeper understanding of society (sociology) and human behaviour (psychology) (Stevenson and Leaman, 2010; van Dam et al., 2010; Crosbie and Baker, 2010; Gill et al., 2010). Alternatively engineering models have attempted to build more accurate instrumentation and calculation algorithms to improve the accuracy of modelling heating systems and heat loss through building envelopes (Feist and Schnieders, 2009; Wright, 2008). Investigations in each research discipline have therefore grown in both scope and scale for the type of problems that can be considered, but neither has fully incorporated the beneficial advances made by the other discipline. Some authors, however, have started to develop bottom-up engineering models that utilise proxy variables to represent human behaviour. For example, Brown et al (2010) has developed a model utilising water consumption as a proxy for occupancy patterns and although this does not represent behaviour exactly, it is able to provide rough estimates for different for when people are likely to be home. Inroads have also been laid by Richardson et al. (2008) where time of use surveys have been used to estimate occupancy patterns and domestic energy demand profiles of dwelling inhabitants. Although such studies provide a glimpse of what energy profiles might look like at the individual building level, such information has never been integrated within a national building stock model. At the time of writing, there is still not a well-defined approach for incorporating the vagaries of human behaviour in bottom-up engineering building stock models. This is supported by Audenaert (2011) arguing that a clear gap exists in understanding the different behavioural factors that lead to an occupant's demand for heating, and calls for more research that identifies these driving factors.

The importance of behavioural and social factors is highlighted in a study by Gill and Tierney (2010) where it is found that behaviour (i.e. the decision to turn on heating in the home) accounts for 51%, 37% and 11% of the variance in heat, electricity and water consumption respectively across different dwellings. Implicitly this suggests that models neglecting human behaviour in the estimation of home energy consumption can be out by as much as ±50 percent. However, the majority of residential stock models do not take social and behavioural factors into consideration thus giving erroneous results. Top-down models neglect behavioural factors, simply because it is not possible to aggregate dwelling level behaviour into any meaningful aggregate statistic of the entire building stock. On the other hand, bottom-up models are dominated by engineering building physics models that only consider the physical properties of the building envelope and the efficiency of the heating system. In both modelling approaches, generalisations are made about the internal temperatures of dwellings. In top-down methods, internal temperatures are used to calibrate model estimates and adjust estimated energy consumption to match aggregate demand (Shorrock, 2000). In bottom-up methods internal temperature is generally assumed constant across multiple dwellings or similarly adjusted as a function of the physical properties of the building, ignoring completely the effect different behaviours may have on energy use (BRE, 2002)). Both approaches therefore miss an important opportunity to capture human behaviour through the decisions of individuals known to affect heating profiles and mean internal temperatures of dwellings.

There have been several other important contributions that add to our knowledge of how people interact with home energy systems. Contrary to popular belief, Shipworth et al. (2010) show heating controls may not reduce average living room temperatures or the duration of operation. Regulations, policies and programmes that assume the addition of controls will reduce energy consumption may therefore need to be revised. The impact that smart meters will have on reducing energy and emissions is also controversial. Darby (2010) maintains there is little evidence to suggest that smart meters will automatically lead to a dramatic reduction in energy demand. Instead she calls for increased focus on overall demand reduction (rather than peak electricity demand reduction), improvements to the ergonomic design of customer interfaces and on guiding occupants towards appropriate action through feedback, narrative and support for providing the best opportunities to reduce demand.

6.3 The problem with existing building stock models

Top-down models assume a single mean internal temperature for all dwellings in the building stock (Summerfield et al., 2010a; Utley and Shorrock, 2007; Shorrock, 2003) while the remaining models (including BREDEM) attempt to exogenously calculate internal temperature as a function of occupancy, building fabric and technology (Cheng and Steemers, 2011; BRE, 2002; DEFRA, 2005). Surprisingly, none of the building stock models developed for use in the UK include internal temperature estimates for temporal resolutions of less than one month. As a result, internal temperature is averaged over long periods losing important information about different heating profiles. Without detailed information on the day-to-day temperature differences from a heterogeneous building stock it is difficult to set targeted energy policy correctly accounting for the influence of behaviour. For example, the temperature profile of dwellings occupied by retirees will have very different energy and temperature requirements than a working couple or a busy family.

As smart grid technologies become increasingly prevalent, modelling the peaks and troughs will become important for managing the dynamic loads across the gas and electricity networks. Modelling peak demands in electricity requires demand profiles to be predicted in seconds, minutes and hours while for gas demand it is usually sufficient to model demand in hours, days and weeks. Incorporating the time dimension into building stock models at much finer granularity will allow the peaks and troughs in demand to be accurately modelled. Furthermore, improved understanding of such dynamics will help develop new strategies for reducing $CO_{2(eq)}$ emissions. Building stock models that utilise temperature data at finer temporal resolutions will be much more adept at predicting energy demand and therefore will be able to provide better insight in the development of future policy.

It is now well recognised that internal temperature remains a key determinant for explaining overall home heating energy demand (Firth et al., 2010). It is therefore of some concern that internal temperatures are one of the least understood (Natarajan and Levermore, 2007) and most generalised variables within domestic energy models. All other factors being equal, home heating energy demand is shown to be most effected by changes to internal temperature (Firth et al. 2009; Cheng and Koen Steemers 2011). A study by Cheng and Steemers (2011) showed that $CO_{2(eq)}$ emissions are most highly sensitive to internal temperature ($\sigma_{ij} = 1.55$)[22] meaning that a 1% rise in mean internal temperature set point leads to a 1.55% increase in $CO_{2(eq)}$ emissions. The same result was found by Firth et al (2010) where the length of the daily heating period had the second highest sensitivity ($\sigma_{ij} = 0.62$) and external temperatures the third highest sensitivity ($\sigma_{ij} = -0.58$). Although such models are useful as they provide additional insight into domestic energy demand, a shortcoming is that they do not use empirical data and instead estimate internal temperatures using thermodynamic heat balance equations similar to those employed within BREDEM. Energy demand estimations made with such models are known to have significant discordance with actual energy consumption (Kelly 2011a).

Firth et al. (2010) estimate internal temperatures using the standard BREDEM steady-state physical equation. In this method, an algorithm is employed to estimate monthly internal temperature using an iterative feedback process. Basing internal temperatures purely on the physical properties of a building is defective in several important respects. First, it ignores human behaviour and thus temperature fluctuations caused by people do not feature at all in the estimation. Secondly, the

22 . σ_{ij} is a sensitivity coefficient measuring the rate of change of CO_2 as a function of change in temperature.

temperature estimates are not based on empirical temperature readings from the dwelling; rather, they are estimated theoretically from a set of thermodynamic equations. Thirdly, there is no re-evaluation or verification that the temperature estimates used and predicted by the engineering model are representative of the characteristics for the dwelling. Finally, important information about the daily fluctuations to internal and external temperatures are neglected and replaced with monthly averages. Such fluctuations and extremes of external temperature readings are important because they act as triggers to occupants who may change their behaviour due to cold and hot weather events. For example, an early winter cold snap may cause occupants to switch on heating systems much earlier in the heating season than expected, putting increased load on energy networks. Predicting the magnitude and duration of such events is extremely valuable for predicting loads on national electricity and gas networks and for meeting peak demands.

Aside from engineering based approaches statistical or regression based methods can also be used to model energy consumption. For example, Summerfield et al (2007) carried out a follow-up study on the 1990 Milton Keynes Energy Performance Dataset (MKEP). In this study, 14 of the original 29 dwellings agreed to participate and all dwellings were centrally heated with gas. A regression model was developed that used mean daily external temperature as a predictor of mean internal temperature as well as daily gas and electricity consumption. The results focused on a longitudinal analysis of dwellings between 1990 and 2005. From this small sample, a simple bivariate regression model was developed. Due to the small sample size, the model prohibits the prediction of internal temperatures for the building stock more generally, but does provide guidance for conducting similar types of analysis. Several other studies have used regression methods to analyse buildings (Yun and Steemers, 2011; Summerfield et al., 2010a). However, none of these earlier studies managed to extend analysis to utilise the much more powerful statistical properties of panel based methods as they are used in this paper.

Three prominent UK physically based building stock models use BREDEM as the core calculation procedure (Shipworth et al., 2010). These are the UK Domestic Carbon Model (UKDCM) (Boardman et al., 2005); Johnston's model (Johnston, 2003); and the DeCarb model (Natarajan and Levermore, 2007). All models are based on standard BREDEM assumptions for estimating internal temperature and heating season duration. All models that adopt standard BREDEM assumptions ignore the effects of human behaviour on energy consumption. Disturbingly these models are still actively used in the development of national policy to curb emissions, improve fuel poverty and predict future trends in domestic energy demand. If emissions reductions are going to be taken seriously, then these models need to actively include the behaviour of individuals as a central component of the energy demand equation.

6.4 Contribution

A dwelling level temperature model that is capable of predicting internal temperature including the influence of human behaviour will be a useful tool and benefit many existing building stock models. This chapter research will therefore quantify the behavioural, social and demographic properties associated with a building and its occupants and determine the influence these factors may have on internal temperature. Benefiting this model is the capability to predict internal temperature at much higher temporal resolution than what is presently used by other building stock models. It is therefore able to predict the variability of internal temperatures as external temperatures fluctuate on a daily basis.

This chapter therefore offers several important contributions:

i) It represents the first known time that a panel regression methods have been used to predict mean internal temperatures from a large sample of heterogeneous dwellings.

ii) It presents a novel method for including social and behavioural variables and how these factors may influence internal temperature within a heterogeneous building stock.

iii) It offers a practical solution for energy demand modellers wishing to incorporate improved estimates of mean daily internal temperatures into bottom-up building stock models.

iv) It allows statistical inferences to be made about different physical, behavioural, socio-demographic and technical factors from a heterogeneous building stock and the proportion of variance that these different factors contribute towards explaining internal temperature.

6.5 Comparison of relevant data sources

With approximately 22 million heterogeneous dwellings spread across the UK, each dwelling has a unique energy profile due to its own set of physical properties, climatic conditions and behavioural characteristics of occupants. Built form may vary by date of construction, building typology, floor area, type of construction material and quality of workmanship. Energy systems within dwellings also vary markedly with differences between heating systems, fuel types and efficiency levels. The behavioural qualities of occupants range by socio-demographics, income levels, age and family type (Firth et al., 2010). Although dwelling set point temperatures maybe similar amongst a cohort of dwellings (e.g. 21°C) there may be important differences in the length of heating duration resulting in large differences in mean daily internal temperatures. Capturing the complexities inherent within the residential building stock thus requires a dataset that contains as much information on as many factors as possible that are also known to explain energy demand.

Concerning internal temperatures, National surveys such as the 1996 English House Condition Survey (EHCS) (DETR, 1996) contain spot temperature readings taken on the day of the survey and therefore, cannot be used for any meaningful temporal analysis. Smaller studies have focused on specific socio-demographic groups within society or specific geographic areas thus limiting the applicability of temperature readings to be used for representing internal temperatures across the national building stock (Hutchinson et al., 2006; Heyman et al., 2005; Summerfield et al., 2010b). Thermal comfort models such as PMV (British Standards, 1995) and adaptive models (De Dear and Schiller Brager, 2001) are developed for engineers and architects for the design of buildings and therefore do not generally consider the temperature requirements and profiles of different occupants.

Aside from the dataset used in this study, the most recent geographically and nationally representative survey of internal temperature measurements was completed by Hunt and Gidman (1982) between February and March in 1978. A total of 1000 households participated in the survey with spot temperature measurements recorded in all rooms of the dwelling. As only spot measurements were taken at the time of the survey, it is not possible to know the specific temperature profiles in each dwelling, but the large sample of homes does provide some indication for mean internal temperatures across England. From this study the mean internal temperature in the living room was 18.3°C ($p<0.001$) and for the main bedroom it was 15.2°C ($p<0.001$). Hunt and Gidman showed that the mean of all dwelling temperatures was most correlated with the landing or stairwell temperature ($r=0.96$), followed closely by the bedrooms ($r=0.94$).

The use of bottom-up building physics models to estimate internal temperatures and energy consumption stems from a paucity of empirical data, and in particular, inadequate samples of high resolution internal temperature readings. In light of these shortcomings McMichael (2011) completed a comprehensive review to catalogue all the relevant data sources and their potential for being used in understanding the relationship between energy consumption, buildings and behaviour. McMichael's (2011) literature search involved consulting numerous experts in the field, literature reviews of other grants and publications as well as searching through online data archives hosted by the UK government such as the UK Data Archive. Some forty-four different data-sources were consulted, with each dataset containing unique information applicable to modelling and understanding building energy consumption. The overall conclusion of this data survey was that the CARB-HES dataset was the most comprehensive and representative source of data for UK residential sector.

6.6 Data collection

Crucial to estimating and modelling the role of human behaviour as it pertains to residential energy consumption is having sufficient data about the social and behavioural characteristics of the sample being studied. Parameters need to be measureable and quantifiable and relate the socio-demographic and behavioural properties of people to the energy consumption of the dwelling being studied. One method to couple the latent property of 'human behaviour' to dwelling energy consumption is through the intermediary variable of internal temperature. Defining internal temperature in this way introduces several problems. If daily internal temperatures are to reflect human behaviour accurately, they must be of sufficiently high temporal resolution so that important distinctions across multiple dwellings will not be averaged out over long time periods. Moreover, internal temperature is both a function of human behaviour and the physical properties of the building. It is therefore important to include controls for as many relevant variables as possible in the analysis.

The model developed uses the CARB-HES dataset collected between July 2007 and February 2008. Households who participated in the survey were randomly selected from a stratified sample drawn from a postcode address file for England. To ensure a good geographic and socio-demographic spread, postcodes were stratified by Government office region and socio-economic class. From the total sample of 1134 eligible addresses, a total of 427 households opted to participate in the study. Of those households 390 agreed to house at least one temperature sensor, but some households returned their sensors early, withdrew from the study, or moved house; some sensors were faulty or could not be linked to a household, or the data could not be retrieved from them. Data was retrieved from sensors provided by 280 households, 266 of which had both bedroom and living room data. Occupants from each household were asked to give face-face interviews and answered structured questions about their homes' built-form, heating system, heating practices and socio-demographics. During the interview occupants were asked if they would be willing to accommodate temperature sensors in their living room and master bedroom (Shipworth et al., 2010). Having two temperature loggers for each dwelling was useful as it allowed suspected temperature logger errors (due to incorrect placement or hardware error) to be checked and verified against the second temperature logger. This also allowed for the examination of zoning within a dwelling and to test the accuracy of standard BREDEM assumptions.

The survey was designed for the CaRB consortium by M. Shipworth with sampling and face-to-face interviews conducted by the National Centre for Social Research (NatCen). A wide range of physical characteristics for each building was collected as well as many socio-demographic and behavioural attributes of the occupants. Internal temperatures were recorded using HOBO UA 001-08[23] temperature sensors in 266 dwellings. They are small, unobtrusive and silent. Participants were instructed to place the sensor on a shelf or other surface between knee and head height away from any heat sources (such as radiators) and away from direct sunlight.

The sensors are self-contained data loggers and the information was only retrieved once the study had been completed. Temperature recordings were taken at 45-minute intervals between 22 July 2007 and 3 February 2008. This period was chosen as it spreads across different heating seasons and allows for a sufficiently long monitoring period whilst still capturing short-term variations in temperature. The mean temperature over each 45-minute period was recorded at a resolution of 0.1°C. The

23. www.tempcon.co.uk/

HOBO temperature sensors had a reported accuracy of ±0.47°C at 25°C. Calibration measurements were taken on each sensor before they were installed in the home and used to correct the readings once the measurements had been downloaded. The calibration error from all sensors was found to be minimal $\left(\bar{x}=0.19,\sigma=0.11\right)$. The survey represents the first nationally representative sample to combine high temporal resolution temperature readings with both physical and socio-demographic characteristics of the dwelling.

A dataset containing several hundred dwellings each with temperature readings taken at 45-minute intervals over a period of 6 months generates a very large dataset with approximately 1.5 million temperature spot measurements. Datasets this large require specialist software packages for data handling and post-processing. In this study, MS Access, SPSS, STATA and MatLab were all used in the management of data. Dataset files were imported as MDB files into Microsoft Access and then converted to DBF files before they could be imported and processed in SPSS, STATA and Matlab for further statistical analysis.

Although the CARB-HES dataset covers a comprehensive array of social, behavioural and physical characteristics, external temperatures over the period of the study were not included in the original survey. This deficiency was overcome using average external daily temperature readings for each of the nine government office regions in England. Finer geographic-spatial resolution down to the local authority level was not necessary, as doing so did not add significantly more variation than what was already captured at the regional level. The dataset was downloaded and created with permission from the British Atmospheric Data centre (BADC) (UK Meteorological Office, 2011). The regional external temperature dataset is available for public use with appropriate recognition and permission from BADC (Kelly, 2011b). Figure 6.1 shows the mean daily external temperatures for each Government Office region in England from 1st August 2007 to the 31st January 2008.

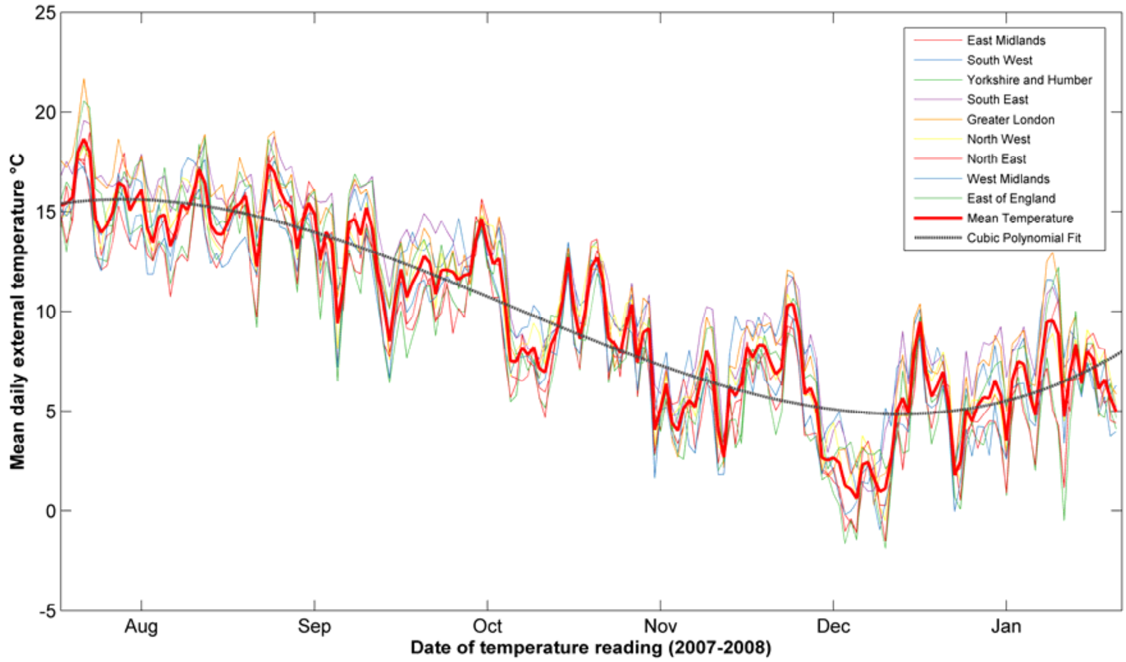

Figure 6.1: Mean external temperatures by Government office region (Aug 2007- Jan 2008)

6.7 Development of the statistical model

Several statistical procedures were reviewed for their appropriateness in modelling time-series data. Well developed panel data methods allow cross-sectional and time-series data to be modelled without incurring data reduction penalties due to averaging of the temperature readings over time or across dwellings. Panel data methods thus have several important benefits over other statistical methods because:

i) they produce more informative results because they contain more degrees of freedom and thus estimates are generally more efficient than standard cross-sectional methods;

ii) they allow the study of subject level dynamics by separating or controlling for different cohort effects over time;

iii) they provide additional information on the time ordering of events;

iv) they make it possible to capture variation occurring over time or space and how these two effects vary simultaneously;

v) they allow for the control of individual unobserved heterogeneity and contemporaneous correlation across a sample.

Given these advantages, it is no surprise that panel methods have become widely used in many quantitative research disciplines. Although panel-data approaches provide many benefits for substantive research, the method does introduce several complications that must be overcome before robust statistical inferences can be made or the model used to make credible predictions. A typical problem arising from the use of panel data methods is that they often violate standard OLS assumptions about the error process[24] (see Equations (6.1) - (6.3)) (Janoski, 1994). In typical regression methods, it is frequently assumed that errors are either normal or independently identically distributed (IID). In panel data this assumption is often violated due to the longitudinal nature of recordings, (i.e. measurements over time are correlated). Although it is common to assume that errors are not correlated with regressors over a cross-section of records, it is almost never the case that errors are uncorrelated within an entity over time, thus giving way to serial correlation. In addition, errors in panel data tend to be heteroskedastic such that they have changing variances over time and over panels. Panel data methods thus require the use of much more sophisticated estimation methods than typical cross-sectional or time-series dependent analyses to allow for the additional complications that arise.

Because panel methods are an extension of standard regression techniques, they are still dependent on many of the same assumptions:

i) $$E(\varepsilon_i \mid x_i) = 0 \quad \text{(exogeneity of regressors)} \tag{6.1}$$

ii) $$E\left(\varepsilon_i^2 \mid x_i\right) = \sigma^2 \quad \text{(conditional homoskedasticity)} \tag{6.2}$$

iii) $$E\left(\varepsilon_i \varepsilon_j \mid x_i x_j\right) = 0,\ i \neq j \quad \text{(conditionally uncorrelated correlations)} \tag{6.3}$$

Assumption 1 is essential for consistent estimation of β coefficients and implies that the conditional mean is linear and all relevant variables have been included in the regression. It is however possible to relax this assumption in some specific circumstances (Cameron and Trivedi, 2009, p.81). If all three assumptions are met then the OLS estimator is fully efficient. If in addition the errors are normally distributed then t-statistics are also exactly t-distributed. If Assumptions ii) and iii) cannot be met then OLS is no longer efficient and estimation using other methods is possible and generally more efficient.

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24. For OLS to be optimal it is necessary that all errors have the same variance (homoskedasticity) and that all the errors are independent.

Specially developed statistical techniques capture the variations across individuals whilst also allowing for variations that occur over time. Several practical considerations arise when conducting panel data analysis. Estimator consistency requires that the sample-selection process does not lead to errors being correlated with the regressors. However, when using panel-data, it is very likely that model standard errors are correlated with regressors over time. It is also plausible that error correlation exists between cross-sections of the sample. Special statistical techniques have been devised to ameliorate both of these situations. Regardless of the assumptions being made, it is typically necessary to make corrections to OLS estimations for panel data (e.g. PCSE). In addition, it is sometimes possible to improve the efficiency of the model by using other estimators such as generalised leased squares (GLS).

When performing panel analysis, regression coefficient identification depends on the type of regressors being specified. For example, some regressors are time-invariant and thus affect decisions about the type of model that can be used. Moreover, it is also possible that some regressors covary over time and also by cross-section. Many econometric techniques therefore recommend the use of either fixed effects models or random effects models for conducting panel data analysis; the method finally chosen ultimately depends on the structure of variables included in the model.

First, lets consider Pooled Regression (PR), also known as the population averaged model and is also the simplest approach for modelling panel datasets. If standard OLS assumptions are met (i.e. zero conditional mean of errors, homoskedasticity, independence across observations and strict exogeneity of covariates) then OLS techniques are efficient and can reliably be used to estimate parameters (Greene, 2012, p.349). However, because data are longitudinal, it is unreasonable to assume that errors are not correlated over time, thus ruling out pooled regression as an estimation technique in this circumstance.

Second, now consider the Fixed Effects (FE) model. Like first differencing methods, FE methods use a transformation to remove any unobserved effects prior to estimation. In this method time invariant explanatory variables are removed (Wooldridge, 2003, chap.13). In FE models it is not possible to draw inferences or predictions from time-invariant effects as such effects are averaged out and controlled for as part of the transformation process (Baltagi, 2005, p.12). In FE models, the researcher is primarily concerned with understanding the effect of different covariates as they vary with time. Any time-invariant cross-sectional heterogeneity (and unobserved time-invariant heterogeneity) therefore drops out during the differencing transformation. The result is a model with different estimates for model intercepts, v_i across the panel but with each panel having the same slope. Time-invariant effects are of acute interest for this model[25]. For the simple reason that FE models cannot estimate time-invariant effects, the FE method was rejected for use in this model. For completeness, the FE estimator is typically given by Equation (6.4).

$$y_{it} = \beta_1 x_{it} + v_i + \varepsilon_{it} \tag{6.4}$$

In Equation (6.4) for FE estimation, y_{it} is the predicted variable for entity *i*, at time *t*, β_1 is the common slope parameter, x_{it} is the covariate, v_i is the subject specific error and ε_{it} is the idiosyncratic error.

Similar to FE analysis the Least Squares Dummy Variable (LSDV) method includes dummy variables for every dwelling in the dataset. The LSDV method is generally not advised for long datasets when the number of cross-sectional variables in the data is close to the number of time-periods as this substantially reduces the degrees of freedom available to the model. This method was therefore also rejected on the basis that it would require 184 additional dummy variables representing each time period in the dataset.

For Random Effects (RE) models using standard OLS assumptions, it is possible to include time invariant covariates. In RE models, a constant intercept is added to Equation (6.4). The individual specific error, v_i, is assumed IID and assumes any unobserved effects are uncorrelated with all explanatory variables [i.e. $\mathrm{Cov}(x_{itj},a_i) = 0$]. In addition, $v_i \sim IID(0,\sigma_\mu^2)$, $\varepsilon_{it} \sim IID(0,\sigma_\mu^2)$ and v_i are independent of ε_{it}. The random effects model is an appropriate specification if the number of observations (dwellings), N, is large (Baltagi, 2009, p.14). Also, as the number of time periods, $X \to \infty$, the differences between FE and RE disappear. Thus for a RE model Equation (6.4) becomes:

25. Time invariant effects are factors that do not change over time, such as the number of occupants living in a household or whether a dwelling has temperature control.

$$y_{it} = \alpha + \beta_1 x_{it} + \nu_i + \varepsilon_{it} \tag{6.5}$$

When data are longitudinal, positive serial correlation in the error term can be substantial, and because OLS standard errors ignore such correlations the estimators predicted by OLS will be incorrect (Wooldridge, 2005, chap.14). Both RE and FE models that use OLS are best suited for short panels where N is large and X is small and errors are random. For a longer panel where N is large and the number of time periods: $X \to \infty$, much richer models can be specified using the more efficient General Least Squares (GLS) or Panel Corrected Standard Errors (PCSE) methods. These estimators are also able to control for serial correlation (Cameron and Trivedi, 2009, p.265).

After ruling out the OLS estimator, FE, LSDV and PR methods, the model was developed using RE and tested using a number of different estimators that allow for longitudinal serial correlation when errors are assumed not to be IID. The GLS estimator, PCSE estimator and XTSCC [26] estimation methods allow the errors $(\nu_i, \varepsilon_{it})$ to be correlated over *i,* allow autoregressive correlation of ε_{it} over *t,* and allow ε_{it} to be heteroskedastic (Parks, 1967; Kmenta, 1971). The GLS estimator as originally proposed by Parks and Kmenta involves complex matrix algebra to be solved (1967; 1971). However, modern econometric software packages now allow this step to be completed automatically. For a discussion on the benefits and disadvantages of GLS over other procedures please refer to the following text books (Baltagi, 2005, p.18; Wooldridge, 2002, chap.7)

The PCSE estimator uses OLS and by default assumes contemporaneous correlation between panels. Beck and Katz (1995; 1996) show that the overconfidence in standard errors makes the Parks-Kmenta method unusable in situations when $N < X$ and therefore they propose a new method. As already stated, if errors do not meet the standard OLS assumptions, the OLS estimates of parameter coefficients will be consistent but inefficient. Beck and Katz thus propose to retain the OLS parameter estimates but replace the OLS standard errors with Panel Corrected Standard Errors (PCSE) that take into account the heteroskedasticity and contemporaneous correlation between errors. As already noted the GLS and PCSE estimators offer some unique features, including flexibility to control for different assumptions

26 XTSCC estimates pooled OLS using fixed effects (within) with Driscoll and Kraay standard errors.

concerning the distribution of standard errors (StataCorp, 2009a, p.155). However, if the model is correctly specified then the GLS estimator is generally more efficient than PCSE (Cameron and Trivedi, 2009, p.268). Thus, to summarise, the error structure within panels for both GLS and PCSE estimators may be specified as having:

i) no autocorrelation within panels; or

ii) AR1 autocorrelation within panels where the coefficient of autocorrelation is constant across all panels, or,

iii) AR1 autocorrelation within panels where the coefficient of autocorrelation is panel-specific.

The errors structure between panels is specified slightly differently for GLS and PCSE models. For GLS models, between panel error correlations can be specified as:

i) homoskedastic with no contemporaneous correlation, otherwise known as IID,

ii) heteroskedastic with no contemporaneous correlation, or,

iii) heteroskedastic with contemporaneous correlation when $T > N$

For PCSE estimation, the structure of errors between panels is specified as being:

i) heteroskesdatic with contemporaneous correlation between panels (default)

ii) heteroskesdastic with no contemporaneous correlation between panels or,

iii) independent errors between panels with a single disturbance variance common to all panels.

When the error, ε_{it}, between panels are assumed to be IID using the GLS estimator, the pooled OLS estimator is obtained. When panels are assumed heteroskesdastic ε_{it}^2 is specified as independent with variance $E(\varepsilon_{it}^2) = \sigma_i^2$ and can be different for each dwelling. Because there are many measurements for each dwelling over time, σ_i^2 can be consistently estimated (Cameron and Trivedi, 2009, p.268). When, $X > N$, correlation across panels can be allowed for.

A third procedure developed by Driscoll and Kraay (1998) generalises the PCSE method. This was implemented in STATA by Hoechle (2007) to obtain Newey-West (1987) standard errors. Correlation of errors between panels (spatial correlation) is assumed while auto-correlation within panels can be assumed to be of the general-form rather than AR1. The general procedure determines the most efficient number of lags, m, for the model being estimated.

Several restrictions are placed on estimating these different models. If the GLS estimator is used with autocorrelation then time-series data must be equally spaced in time. If cross-sectional correlation is also assumed then the panel must be balanced. A model that assumes a common autocorrelation value across panels is only reasonable when the individual panel level correlations are almost equal and the time-series is short (StataCorp, 2009a). As the time series used in this analysis is represented by 184 unique days, the panel is considered too long to make this assumption and thus it is assumed that each panel has unique autoregressive properties.

6.8 Description of dataset

In Figure 6.2 the mean daily internal temperature distributions[27] for the living room and bedroom can be compared with the distribution for mean daily external temperature[28]. Figure 6.3 represents a binned scatter plot of mean daily internal temperature vs. mean daily external temperature by dwelling and by day. The large hollow circles represent a concentration of observations. The plot shows large variation between dwelling internal and external temperatures. The scatter plot also shows bimodality in external temperatures as also shown in the histogram plot (Figure 6.2).

27. Mean internal temperatures are estimated as the arithmetic mean of the bedroom and living room temperatures for each dwelling over 24 hours.
28. Mean external temperature is calculated for each government office region in England and is the arithmetic mean daily external temperature for all available weather station data within the government office region over 24 hours.

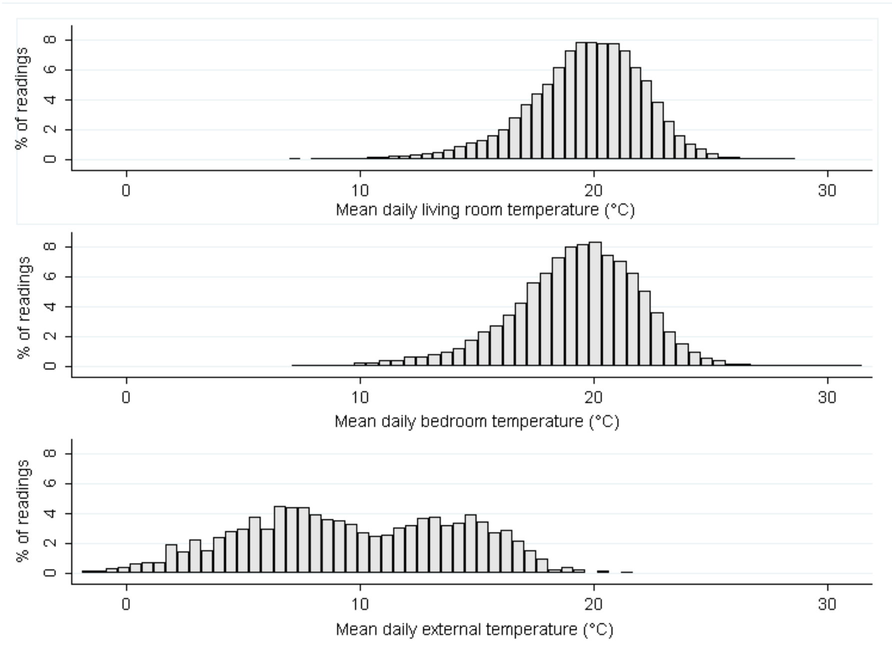

Figure 6.2: Internal and external temperature distributions

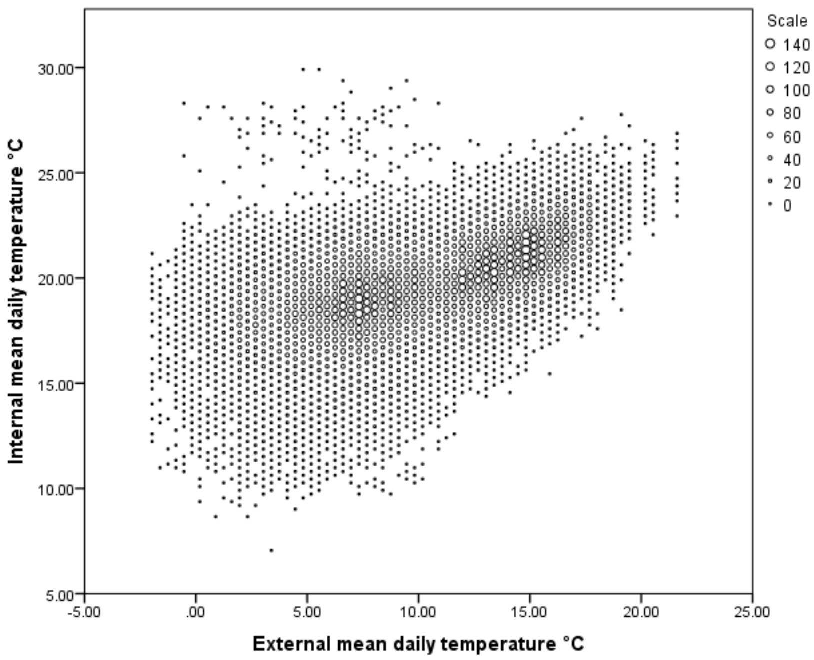

Figure 6.3: Internal temperature plotted against external temperature

A binned scatter plot of mean internal daily temperature readings for each dwelling is given in Figure 6.4. Several observations can be made from this plot. First, as external temperatures drop, so do mean internal temperatures. Second, internal temperatures are widely dispersed around the mean with dispersal increasing in the heating season. Interestingly, it appears several households heat their homes to much higher temperatures in winter than in summer. At the colder end of the spectrum, some homes do not even appear to be heated, with temperatures logged at well below 10°C. This might suggest these homes are either unheated or unoccupied. All observations were retained in the dataset for subsequent analyses.

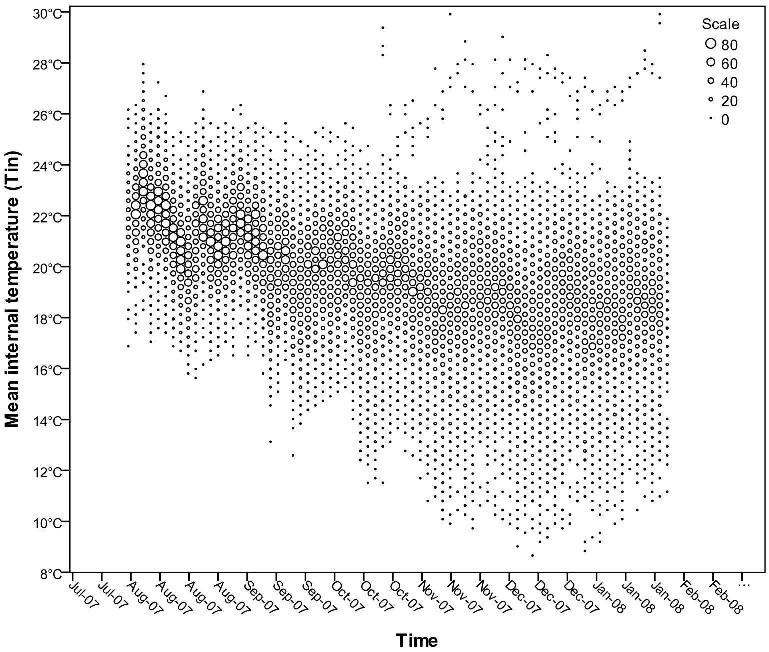

Figure 6.4: Temperature recordings

Comparison of the CARB-HES dataset with the English House Condition Survey (EHCS 2007) shows the CARB-HES dataset represents the English housing stock relatively well.

Table 6.1: Comparing the CARB-HES dataset with national estimates

Variable name	CARB-HES Survey (%)	EHCS 2007 (%)[1]
Tenure type		
Owner occupied	303 (71%)	7710 (71%)
Privately rented	46 (11%)	2,161 (12%)
Local Authority	39 (9%)	3,501 (9%)
Housing Association	38 (9%)	2,232 (8%)
Dwelling type		
Terraced	97 (23%)	4,775 (28%)
Semi-detached	125 (29%)	4,183 (28%)
Bungalow or detached	123 (29%)	3,661 (27%)
Flats	82 (19%)	3,598 (17%)
Dwelling Age		
Pre 1919	62 (15%)	3014 (21%)
1919 – 1944	79 (18%)	2,755 (17%)
1945 – 1964	98 (23%)	3,868 (20%)
1965 – 1980	96 (22%)	3,855 (22%)
Post 1980	90 (21%)	2,725 (20%)
Total number of households in survey	427	15,604

1. Weighted sample taken from the English House Condition Survey 2007 (Communities and Local Government, 2009)

6.9 The model

The aim of the model is two-fold. First, it can be used in the development of hypothesis and for making statistical inferences about the relationships between different variables and internal temperature. Second, the model can be used as a predictive tool to model internal temperatures. As it predicts temperature at the dwelling level, it is therefore implementable by any bottom-up engineering or statistical building stock model. Most building stock models would benefit greatly from robust estimates of internal dwelling temperature. Thus, the model is able to provide, within known uncertainty bounds, an estimate of the internal temperature for any typical dwelling in England for any given day of the year based on the dataset described. The variables used in the model were specifically selected for their known effect on mean internal temperatures from previous research and theory. The variables used by the model are separated into three distinct groupings:

i) intransmutable variables (variables that cannot be influenced or changed to reduce energy consumption) such as external temperatures and geographic location;

ii) behavioural and socio-demographic variables such as occupancy rates, thermostat settings and heating duration hours; and,

iii) engineering based variables that represent the physical and efficiency characteristics of the building.

The general form of the temperature model can therefore be given by Equation (6.6).

$$Tin_{it} = \alpha + \mathbf{\Gamma}_{it}\boldsymbol{\beta}_1 + \mathbf{\Psi}_i\boldsymbol{\beta}_2 + \mathbf{\Theta}_i\boldsymbol{\beta}_3 + \left(\nu_i + \varepsilon_{it}\right); \qquad \begin{matrix} i = 1,\dots,N \\ t = 1,\dots,X \end{matrix} \tag{6.6}$$

In Equation (6.6) Tin_{it} is the mean internal daily temperature associated with dwelling, i, at time period t and is the mean of the main bedroom and living room temperature over 24 hours; $\mathbf{\Gamma}_{it}$ represents a matrix of intransmutable variables with a complementary array of parameter coefficients, $\boldsymbol{\beta}_1$; $\mathbf{\Psi}_{it}$, represents a matrix of behavioural and socio-demographic variables and $\boldsymbol{\beta}_2$ is the corresponding array of parameter coefficients for each behavioural characteristic; $\mathbf{\Theta}_{it}$, is a matrix of physical building characteristics with a corresponding array, $\boldsymbol{\beta}_3$, of coefficient estimates; α is a constant intercept term; ν_i , is the between entity error; ε_{it} , is the idiosyncratic error term that varies for each dwelling and each time period. Table 6.2 gives important descriptive statistics for the data.

Although the model was generated using mean daily temperature data, it is still possible to predict average monthly or weekly internal temperatures using the corresponding monthly or weekly external temperatures. If mean monthly external temperatures are used instead of mean daily temperatures, then the model will predict the mean internal monthly temperature for the dwelling. However, the advantage of this model is its capability to model temperatures at much finer temporal resolution then has bee accomplished in the past.

6.10 Description of model

This dataset is unbalanced and contains 42,723 data-points from 266 separate panels (dwellings) over 184 time periods (days). Relative to other panel models, the data used for this analysis is described as both long and wide as it has both large N and large X. This is beneficial when conducting panel data analyses because the total number of data-points is very large and therefore the restrictions usually placed on models to maintain large degrees of freedom (dof) is not a limiting factor. Description of model variables

Dichotomous or dummy variables were created to represent nominal unordered categorical variables. Many of the response variables also contain multiple unordered categories. The dummy variable trap was avoided by creating dummy variables for each response category with the exception of the comparison category (Kremelberg, 2011, p.210). The comparison category is the category that all other dummy variables are compared against and occurs when all dummy variables from that category are equal to zero. Therefore, if a response variable has four categories then three dummy variables are chosen for three of the categories and the fourth category is assigned as the comparison category. In this model there are four response categories that represent Geographic Region, Age of Occupants, Ownership type and House typology.

Average daily internal temperature, $T\,in_{it}$, is the mean daily internal temperature and is calculated as the average of the bedroom and living room temperature over 24 hours. The mean daily temperature is calculated from 64 temperature readings taken at 45 minute intervals from each dwelling, i, for each day, t, from the 1st August

2007 to the 31st January 2008. Average daily external temperature, $Text_{it}$, is the regional external temperature on day, t, for the government office region where the dwelling is located. Regional dummies are included for each of the nine government office regions to control for any unobserved heterogeneity at the regional level that may affect internal temperatures.

Table 6.2: Descriptive statistics used in the analysis of the model [1,2]

Variable description	name	type	mean (%)[3]	median	std.dev	min	max
Mean internal daily temp	*$Tint_{it}$*	Scale	19.61	19.64	2.47	7.05	29.92
Intransmutable Variables, Γ_{it}							
Mean external daily temp	*Text*	Scale	9.71	9.43	4.59	-1.89	21.68
Geographic location							
(A) London	*LON*	Dummy	(8%)	-	-	0	1
(A) North East	*NE*	Dummy	(6%)	-	-	0	1
(A) Yorkshire and Humberside	*YORK*	Dummy	(9%)	-	-	0	1
(A) North West	*NW*	Dummy	(15%)	-	-	0	1
(A) East Midlands	*EM*	Dummy	(7%)	-	-	0	1
(A) West Midlands	*WM*	Dummy	(16%)	-	-	0	1
(A) South West	*SW*	Dummy	(15%)	-	-	0	1
(A) East of England	*EE*	Dummy	(13%)	-	-	0	1
(A) South East	*SE*	Dummy	(10%)	-	-	0	1
Behavioural and socio-demographic variables, Ψ_{it}							
Room thermostat exists	*T_Stat*	Dummy	(49%)	-	-	0	1
Thermostat setting	*T_Set*	Scale	19.19	19.4	3.40	0	32
Thermostatic radiator valve (TRV)	*TRV*	Dummy	(22%)	-	-	0	1
Central heating hours reported	*CH_Hours*	Scale	9.84	9	5.30	1	24
Regular heating pattern	*Reg_Pat*	Dummy	(88%)	-	-	0	1
Automatic timer	*Auto_Timer*	Dummy	(60%)	-	-	0	1
Household size	*HH_Size*	Categorical	2.3	2	1.15	1	7
Household income	*HH_Income*	Scale	31,570	23,833	24,191	1,940	137,500
Age of occupants							
Child aged < 5	*Child<5*	Dummy	(8%)	-	-	0	1
Number of children < 18	*Children<18*	Categorical	0.41	0	0.81	0	4
(B) All occupants aged under 60	*Age<60*	Dummy	(53%)	-	-	0	1
(B) Oldest occupant aged 60-64	*Age60-64*	Dummy	(14%)	-	-	0	1
(B) Oldest occupant 65-74	*Age64-74*	Dummy	(20%)	-	-	0	1
(B) Oldest occupant > 74	*Age>74*	Dummy	(13%)	-	-	0	1
Tenure type							
(C) Owner occupier	*Owner*	Dummy	(82%)	-	-	0	1
(C) Privately rented	*Rented*	Dummy	(5%)	-	-	0	1
(C) Council tenant	*Council*	Dummy	(8%)	-	-	0	1
(C) Housing association or RSL	*H_Assoc*	Dummy	(5%)	-	-	0	1
Weekend Properties							
Weekend heat same as weekday	*WE_Same*	Dummy	(77%)	-	-	0	1
Weekend temperature reading	*WE_Temp*	Dummy	(28%)	-	-	0	1
Building efficiency and heating system variables, Θ_{it}							
(D) Detached house	*Detached*	Dummy	(34%)	-	-	0	1
(D) Semi-detached house	*SemiDet*	Dummy	(29%)	-	-	0	1
(D) Terraced house	*Terraced*	Dummy	(23%)	-	-	0	1
(D) Not a house	*NotHouse*	Dummy	(14%)	-	-	0	1
Heating systems							
Gas central heating	*Gas_CH*	Dummy	(84%)	-	-	0	1
Non central heating is used	*Non_CH*	Dummy	(64%)	-	-	0	1
Electricity is main fuel	*Elec_Main*	Dummy	(7%)	-	-	0	1
Gas additional heat in living area	*Gas_OH*	Dummy	(33%)	-	-	0	1
Elec additional heat in living area	*Elec_OH*	Dummy	(13%)	-	-	0	1
Other additional heat in living area	*Other_OH*	Dummy	(13%0	-	-	0	1
Building efficiency							
Year of building construction	*Build_Age*	Categorical	5.45	5	2.18	1	10
Roof insulation thickness	*Roof_Ins*	Categorical	3.0	4	2.1	0	7
Extent of double glazing	*Dbl_Glz*	Categorical	4.32	5	1.32	1	3
Wall U-value	*Wall_U*	Scale	1.19	1.18	0.68	0	1

1. Response categories belonging to a group are given a letter so that is clear that these variables are part of the same group.
2. Variables in bold represent the comparison category and are excluded from the panel model (i.e. all dummy variables in the category are calculated relative to this variable)
3. For dummy variables the mean represents the proportion of the population (in percent) that are represented by that indicator

The following section describes each of the variables selected for the analysis starting with a description of the heating control options.

Room Thermostat	is a dichotomous variable that indicates if a room thermostat is present in the dwelling.
Thermostat setting	is the respondent's declared thermostat setting for the dwelling in degrees Celsius and has been grouped into four categories (Table 6.3).
Thermostatic Radiator Valve (TRV)	is a dichotomous variable indicating if the only type of temperature control is with thermostatic radiator valves.
Central heating hours reported	is a continuous scale variable indicating the average number of central heating hours reported per day over the week including weekends.
Regular heating pattern	is a dichotomous variable indicating if the home is heated to regular heating patterns during the winter.
Automatic timer	is a dichotomous variable indicating that the home uses an automatic timer to control heating.

There are several socio-demographic factors included in the model that contribute to internal temperature. These are Household size, Household income and the Age of occupants. A response category of dichotomous variables is used to describe differences amongst the older population.

Household size	is the number of occupants living in the dwelling at the time of the survey;
Household income	is the gross take-home income for the whole household and is categorised into seven income bands (Table 6.3);
Child<5	is a dichotomous variable indicating if any infants under the age of five are present in the dwelling;

Children<18 is a discrete scale variable indicating the number of children under the age of 18 living in the dwelling;

Table 6.3: Ordered categorical variables for socio-demographic and behavioural properties

Response category	Thermostat setting		Household size		Income groups	
	°C	Freq (%)	Occupants	Freq (%)	Income	Freq (%)
0	<18	12.77	-	-	<£5,199	2.58
1	18-20	64.85	1	25.72	£5,200 - £10,399	13.65
2	20-22	13.34	2	41.70	£10,400 - £20,799	26.62
3	>22	9.04	3	15.39	£20,800 - £36,399	26.99
4			4	12.88	£36,400 - £51,999	16.78
5			5	3.45	£52,000 - £94,999	12.49
6			6	0.43	> £95,000	3.88
7			7	0.43		

(A) Age<59 is a dichotomous variable indicating if the oldest person living in the dwelling is less than 59 years of age. For this analysis, this will also be the comparison category that other ages are compared against;

(A) ***Age59-64*** is a dichotomous variable that represents if the oldest person living in the dwelling is aged between 59 and 64;

(A) ***Age64-74*** is a dichotomous variable that represents if the oldest person living in the dwelling is aged between 64 and 74;

(A) ***Age>74*** is a dichotomous variable that represents if the oldest person in the dwelling is over 74;

The second response category captures the tenure of the property. Tenure type is represented by an exhaustive list of dichotomous variables with owner-occupiers selected as the comparison category.

(B) Owner occupier is a dichotomous variable and indicates the dwelling is owned by the occupants;

(B) ***Privately rented*** is a dichotomous variable and indicates the dwelling is privately rented by the occupants;

(B) ***Council tenant*** is a dichotomous variable and indicates if the dwelling is leased from the council;

(B) ***Housing*** is a dichotomous variable and indicates if the occupants

association	rent the property from a housing association or registered social landlord (RSL);

The effect of changes to internal temperatures due to weekends was also controlled.

Weekend heat same as weekday	is a dichotomous variable and indicates a positive response to the question: "Do you heat your home the same on the weekend as during the week?";
Weekend temperature reading	is a dichotomous variable indicating if the temperature reading was recorded during the weekend;

Although the primary interest in this study is the effect of behavioural and socio-demographic variables, it is necessary to include all factors known to influence the dependent variable (internal temperature). Therefore several building physics and energy efficiency variables unique to each dwelling were included in this analysis. House typology is the fourth and final exhaustive comparison category of dichotomous variables. A detached house was used as the comparison category.

(C) Detached House	is a dichotomous variable and indicates the dwelling is detached;
(C) ***Semi-Detached***	is a dichotomous variable indicating a semi-detached dwelling;
(C) ***Terraced house***	is a dichotomous variable indicating a terraced house;
(C) ***Not a house***	is a dichotomous variable used to represent flats and apartments or any other building not considered as a stand-alone house.

Several variables were included to represent the type of heating system present in the dwelling, as these may also affect the internal temperature.

Gas Central heating	is a dichotomous variable used to represent if the dwelling has gas central heating;
Non central heating	is a dichotomous variable used to represent dwellings with non-central heating systems (i.e. wood stove, electric

	fan heaters etc);
Electricity is main fuel	is a dichotomous variable that represents if electricity is the main type of heating fuel;
Additional gas heating in living room	is a dichotomous variable used to represent the presence of gas heating in the living room in addition to central heating.
Additional electrical heating in living room	is a dichotomous variable used to represent the presence of electric heating in the living room in addition to central heating;
Additional other heating in living room	is a dichotomous variable used to represent if the presence of additional other forms of heating in the living room.

Several variables were chosen to represent the overall efficiency of the building fabric. These variables were transformed into ordered categorical variables to capture the large variety of different efficiency levels within the building stock. The different categories chosen for these variables are included in Table 6.4. Categories were chosen to achieve a good spread of the distribution in different categories.

Year of construction	is an ordered categorical variable specifying the year the building was constructed.
Roof insulation thickness	is an ordered categorical variable representing the thickness of the roof insulation.
Extent of double glazing	is an ordered categorical variable indicating the proportion of double-glazing in the dwelling.
Wall U-value	is an ordered categorical variable and represents the average U-value of external walls.

Table 6.4: Ordered categorical variables used in model to describe building fabric

Response categories	Year of construction		Roof insulation thickness		Extent of double glazing		Wall U-value	
	Age band	Freq (%)	(mm)	Freq (%)	Fraction	Freq (%)	$W/m^2.K$	Freq (%)
0	pre 1850	5.6	None	24.46	None	9.76	>1.6	7.32
1	1850-1899	4.73	0-25	2.58	less than half	5.17%	0.6-1.6	32.74
2	1900-1918	4.31	25-50	8.15	about half	2.56%	0.4-0.6	28.66
3	1919-1944	16.73	50-75	14.57	more than half	7.72%	≤0.4	31.28
4	1945-1964	23.65	75-100	27.42	all windows	74.79		
5	1965-1974	15.83	100-150	13.78				
6	1975-1980	9.37	150-200	3.44				
7	1981-1990	10.73	>200	5.59				
8	1991-2001	4.74						
9	2002-2006	4.31						

6.10.1 Missing values, nonlinearities and variable transformations

Missing values can be problematic if not dealt with correctly. Although it is relatively straightforward to use panel methods when datasets are unbalanced (i.e. some values over time are missing) the problem becomes more serious when cross-sectional, time-invariant variables are missing for some of the panels (dwellings). One standard approach in econometrics is to use listwise deletion of the observation containing the missing variable. This has the negative effect of throwing away valuable information and reducing the size of the dataset, leading to less precise estimation and inference. Importantly, it may even lead to sample selection bias for the values retained. This was resolved for dummy variables by giving positive responses a value of one, and all negative or missing values a value of zero. Defining dummy variables in this way allows the retention of missing values in the dataset. The widely recognised mean substitution method was applied to scale variables (Beasley, 1998). When mean substitution is used to replace values missing completely at random (MCAR) the resulting parameter estimates are unbiased (Olinsky et al., 2003). In a comparative analysis, Donner (1982) showed that mean substitution is relatively effective even when the proportion of missing cases is fairly high and correlations between variables are low. The main criticism of mean substitution is that it gives no leverage to the replaced values; and when there are substantial missing values it reduces the Pearson correlation coefficient (R^2). The approach therefore implies that the mean substitution does not influence the predicted response (Beasley, 1998). Given the aforementioned problems of missingness as well as the extent and randomness of missingness within the original dataset, mean substitution was employed to replace the missing scale variables before they were categorised.

When using least squares estimates, the Gauss-Markov theorem does not require variables to exhibit univariate normality for the parameter coefficients to be meaningful. However, confidence levels and hypothesis tests will have better statistical properties if the variables do exhibit multivariate normality. It is typical for some distributions, such as Household Income, to have non-normal properties. This is shown in Table 6.2**,** where it is clear that the median of Household Income is very different to the mean suggesting deviation from the normal. Thus to counteract this effect, Household Income was categorised into a discrete number of bins (Table 6.3). This has the effect of grouping extreme values situated in the tail ends of the distribution into the final bin category therefore improving standard assumptions about the normality of distributions of covariates. The benefit of using this method over log-transformations is that the final output is directly interpretable and requires no post-transformation of model variables.

A further assumption of regression-based estimates is that a linear relationship exists between dependent and independent variables. It is incorrect to simply assume a direct linear relationship between external and internal temperature. One hypothesis is that internal temperatures exhibit a non-linear relationship with external temperatures. This is because as external temperatures increase, the power of external temperature to explain internal temperature increasingly dominates the equation. Said differently, as external temperatures rise, the need for central heating decreases nonlinearly, until internal temperature at least[29] reaches equilibrium with external temperature at which point there is no need for any space heating. This non-linear relationship was allowed for by the inclusion of a non-linear term ($Text^2$) within the regression equation.

6.10.2 Testing procedures

The temperature model described above was estimated using STATA11. Several statistical tests were conducted on the panel data before any substantive statistical modelling was undertaken. First the Breusch-Pagan Lagrange Multiplier (LM) test was used to decide if random effects regression was more appropriate than ordinary least squares (OLS) linear regression. The null hypothesis for the LM test is that the variance across dwellings is zero (i.e. no panel effect). The test rejected the null hypothesis that a random effects model was not appropriate. Evidence now suggests

29. Internal temperatures may exceed external temperatures due to internal heat gains (i.e. solar gains) even after heating systems have been switched off.

that a RE panel model will produce more efficient results than standard regression using OLS.

Panel level auto-correlation was tested using Druckers (2003) test procedure within STATA11. The theory behind this test is explained by Wooldridge (2002) and is able to identify serial correlation in panel data of the idiosyncratic error term. All non-time invariant variables were tested for serial correlation. The null for this test procedure was rejected (p<0.001), suggesting that the panel data structure may contain serial correlation. This result was expected as external temperatures are of course correlated over short periods of time (i.e. $corr(Text_n, Text_{n-1}) \neq 0$). Serial correlation in longitudinal panels is not uncommon and can be correctly handled using appropriate statistical techniques.

A Fisher-type test and Levin-Lin-Chu test were completed to test for stationarity within the panels. The Fisher-type test allows hypothesis testing in unbalanced panels while the Levin-Lin-Chu test requires strongly balanced panels (Baltagi, 2009). Both tests rejected the null hypothesis that at least one of the panels had a unit root leading to the conclusion that the panels satisfy the condition of non-stationarity implying it is possible to proceed with the panel analysis.

Two further tests were completed to check for heteroskedasticity amongst residuals. The assumption of homoskedasticity across residuals when heteroskedasticity is present results in consistent but inefficient parameter estimates (Baltagi, 2009, p.79). In addition, the standard errors of the estimates may be biased. A modified Wald statistic was used to test groupwise heteroskedasticity in the residuals. The null hypothesis ($H_0 : \sigma_i^2 = \sigma^2$) was rejected, suggesting deviation of the residuals from homoskedasticity. A likelihood ratio test also confirmed this conclusion. The likelihood ratio test requires the model to be tested while assuming homoskedastic residuals. Results are then compared to a second model that assumes heteroskedastic residuals. The test rejected the null hypothesis that there was no heteroskedasticity in the residuals $\left(P > \chi^2 = 0\right)$ (StataCorp, 2011). When studying the change in scale variance across many cross-sectional datasets it is not uncommon to find heteroskedasticity (StataCorp, 2010, p.157). This is not surprising considering the increasing variance of internal temperature as shown in Figure 6.4. As with serial correlation, once heteroskedasticity is shown to be present, it is relatively straightforward to implement appropriate statistical techniques capable of overcoming these issues.

6.10.3 Choice of estimators

The tests identified above narrow the scope of possible statistical analyses possible. Heteroskedasticity, intragroup correlations and serial correlations all adversely affect parameter estimates and standard errors. Given the variables in the dataset have both heteroskedasticity and serial correlation it is important to use the correct estimators with correct assumptions. The model was estimated using several different estimation techniques. The three estimators chosen for this analysis were GLS, PCSE and XTSCC. All estimators are invoked using STATA11.

6.10.4 Model Diagnostics

Post panel regression diagnostics were completed on all models. Residual plots remain the best check against violation of standard regression assumptions. The creation of several different residual plots confirmed that key model assumptions were upheld. Multicollinearity between model variables was tested post estimation using Variance Inflation Factors (VIFs). VIFs are a measure of how much the variance of an estimated coefficient increases if the explanatory variables are correlated. Values greater than 10 suggest substantial collinearity amongst predictors and may lead to inflated parameter coefficients (O'brien, 2007). The explanatory variables used in this model had a combined VIF of 2.71 suggesting multicollinearity was not a problem during estimation. Residual plots and histograms showed that errors were centred about the mean with properties closely matching a normal distribution.Robustness and validation checks

The benefit of using a large random sample is that it allows a sub-sample to be withheld prior to estimation for post estimation and cross-validation tests. Before any model estimation was completed, a random sample consisting of 10% of the original sample was withheld (27 observations). shows the predicted versus actual temperature readings for dwellings that were withheld from the estimation procedure. As shown, the predictability of the model remains strong and follows the peaks and troughs of the recorded internal temperature readings relatively accurately. Given the volatility of recordings the model predicts mean internal temperature particularly well.

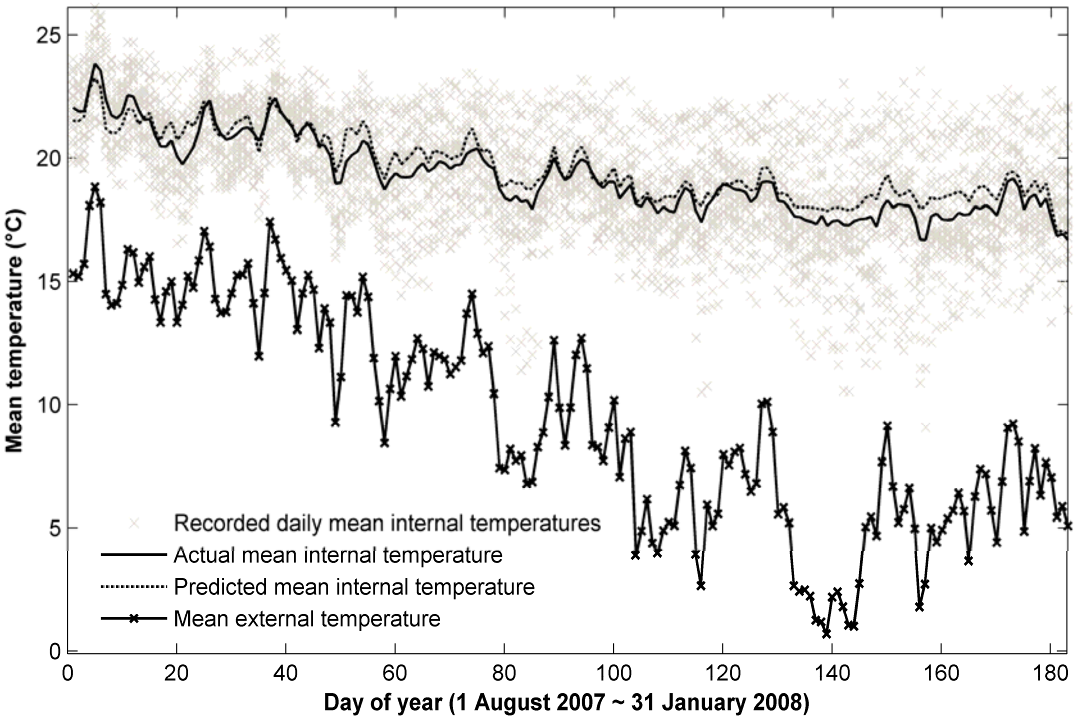

Figure 6.5: Validation sample compared with actual mean internal temperature

Figure 6.5 shows a plot of predicted versus actual temperature readings for one of the dwellings belonging to the subsample withheld from the original estimation. Once again, the relationship between predicted and actual internal temperature remain strong. The temperature profile of this particular dwelling was chosen because it shows two distinct periods where temperatures have dropped markedly due to insufficient heating. The cause of this is most likely due to the building being unoccupied over a weekend. The graph shows two periods of inactive heating that were not predicted by the model.

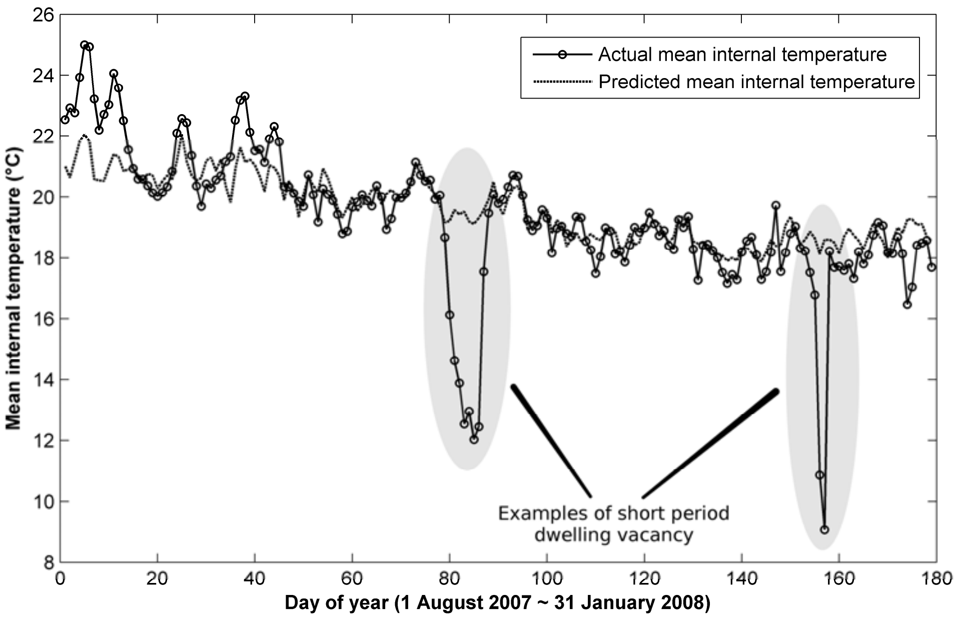

Figure 6.6: Predicted and actual internal daily temperature measurements for one dwelling

The model diagnostics presented thus far show the model performs well and is thus relatively accurate at making predictions. An important next step is to show the width of precision of model estimates (i.e. the width of the 95% confidence intervals). There are two choices for forming confidence intervals around $\hat{y}$:

i) predict a single observation (e.g. a single dwelling) that is yet to be observed and the range of values the internal temperature will most likely fall between (prediction interval);

ii) predict the average temperature over a group of dwellings and predict the range of values the average will most likely fall between (confidence interval).

The bands around the prediction interval are generally much wider than the bands around the confidence interval. This is because confidence intervals average out extreme values, and therefore the requirement is that the average value is within the specified confidence interval. It is possible to calculate the standard error of the prediction interval (in percent) using Equation (Rowntree, 1928).

$$S.E = 100\sqrt{\frac{\sum\left(\frac{y-\hat{y}}{y}\right)^2}{N-2}} \tag{6.6}$$

Using this formula it is concluded that a future prediction for a single dwelling will deviate from the actual value by an average of 11.14%. Alternatively, standard errors can be calculated and used to represent prediction intervals. Using a 95% confidence prediction interval, the predicted value for a random dwelling will be within ±3.66°C of the internal temperature for that dwelling on that day. Alternatively, it can be shown the confidence interval for the mean of internal temperature across all dwellings is on average 1.74%. Thus the predicted mean internal temperature across all dwellings is within ±0.71°C of the actual mean internal temperature for the entire building stock with 95% confidence.

6.11 Results

Results were compared using five different models. The five different models are (1) GLS with heteroskedastic errors only; (2) GLS with heteroskedastic errors and serial correlation; (3) XTPCSE with default assumptions; (4) XTPCSE with default assumptions absent of panel serial correlation; (5) XTSCC with the assumption that the error structure is heteroskedastic and auto correlated up to some lag as well as being correlated between panels. The results of these estimations are presented in Table 6.5. Further details on each of these estimation techniques can be found in STATA11 documentation (StataCorp, 2009b).

Table 6.5: Comparison of different estimation methods

Number Obs: 42,723 Groups: 233 Time periods: 184	Models				
	1	2	3	4	5
Model Assumptions					
Type of estimator	GLS	GLS	PCSE/OLS	PCSE/OLS	XTSCC
Heteroskedastic errors	yes	yes	yes	yes	yes
Contemporaneous corr.	no	no	yes	no	yes
Serial correlation	no	yes	yes	no	yes
Model Variables					
Text	0.034 (5.41)***	0.09 (21.52)***	0.052 (2.26)*	0.107 (6.34)***	0.052 (2.23)*
Text^2	0.013 (40.51)***	0.005 (23.64)***	0.012 (10.75)***	0.005 (5.67)***	0.012 (7.97)***
(A) London	- -	- -	- -	- -	- -
(A) North East	-1.303 (-30.20)***	-1.525 (-11.18)***	-1.392 (-25.06)***	-1.43 (-8.48)***	-1.392 (-11.34)***
(A) Yorkshire	-0.637 (-15.31)***	-0.989 (-7.53)***	-0.629 (-9.38)***	-0.966 (-6.09)***	-0.629 (-4.50)***
(A) North West	-0.916 (-24.38)***	-1.072 (-9.12)***	-1.031 (-20.57)***	-0.945 (-5.88)***	-1.031 (-11.98)***
(A) East Midlands	-0.501 (-11.62)***	-0.847 (-6.37)***	-0.458 (-10.53)***	-0.779 (-4.93)***	-0.458 (-6.09)***
(A) West Midlands	-0.597 (-15.76)***	-0.927 (-7.74)***	-0.828 (-13.17)***	-0.926 (-6.05)***	-0.828 (-6.69)***
(A) South West	-0.569 (-15.99)***	-0.757 (-6.68)***	-0.765 (-16.40)***	-0.729 (-5.35)***	-0.765 (-8.74)***
(A) East of England	-0.730 (-19.09)***	-0.852 (-6.92)***	-0.667 (-18.52)***	-0.681 (-4.50)***	-0.667 (-10.70)***
(A) South East	-1.332 (-34.18)***	-1.352 (-10.47)***	-1.464 (-35.00)***	-1.361 (-9.82)***	-1.464 (-18.44)***
T_Stat	-0.277 (-12.83)***	-0.338 (-5.20)***	-0.236 (-15.05)***	-0.319 (-4.42)***	-0.236 (-8.73)***
T_SettingResp	-0.078 (-7.38)***	-0.095 (-2.81)**	0.035 (4.18)***	-0.077 (-2.33)*	0.035 (2.02)*
TRV	-0.091 (-3.62)***	-0.077 (-0.96)	-0.169 (-7.76)***	-0.225 (-2.39)*	-0.169 (-4.40)***
CH_Hours	0.055 (34.70)***	0.055 (10.87)***	0.069 (25.96)***	0.055 (9.38)***	0.069 (11.79)***
Reg_Pat	0.882 (19.90)***	0.602 (3.76)***	1.189 (23.72)***	0.683 (4.19)***	1.189 (11.14)***
Auto_Timer	-0.079 (-4.53)***	-0.097 (-1.76)	-0.031 (-2.53)*	-0.069 (-1.34)	-0.031 (-1.27)
HH_Size	0.200 (16.72)***	0.213 (5.21)***	0.25 (20.07)***	0.217 (5.65)***	0.25 (9.19)***
HH_Income	0.125 (18.44)***	0.126 (5.58)***	0.084 (8.73)***	0.118 (5.06)***	0.084 (4.05)***
Child<5	0.752 (23.17)***	0.829 (8.84)***	0.495 (19.67)***	0.765 (7.76)***	0.495 (10.32)***
Children<18	0.157 (9.55)***	0.051 (-0.95)	0.219 (26.48)***	0.029 (-0.59)	0.219 (9.12)***
(B) Age<60	- -	- -	- -	- -	- -
(B) Age60-64	0.148 (6.47)***	0.066 (-0.85)	0.051 (2.19)*	-0.033 (-0.45)	0.051 (-1.04)
(B) Age64-74	0.486 (20.49)***	0.406 (5.31)***	0.37 (14.65)***	0.409 (4.49)***	0.37 (7.45)***
(B) Age>74	0.660 (23.18)***	0.775 (7.62)***	0.585 (22.03)***	0.829 (7.27)***	0.585 (11.12)***
(C) Owner	- -	- -	- -	- -	- -
(C) Renter	0.757 (21.16)***	0.811 (7.09)***	0.94 (32.59)***	0.895 (7.73)***	0.94 (14.75)***
(C) Council	1.263 (41.03)***	1.288 (13.40)***	1.374 (35.27)***	1.303 (14.18)***	1.374 (17.90)***
(C) H_Assoc	0.667 (15.87)***	0.873 (6.09)***	0.448 (15.10)***	0.867 (6.90)***	0.448 (8.27)***
WE_Same	-0.572 (-22.78)***	-0.515 (-6.24)***	-0.438 (-26.95)***	-0.56 (-6.79)***	-0.438 (-12.85)***
WE_Temp	0.049 (3.20)**	0.083 (13.64)***	-0.038 (-0.59)	0.088 (2.82)**	0.038 (-0.68)
(D) Detached	- -	- -	- -	- -	- -
(D) SemiDet	0.740 (34.13)***	0.623 (8.93)***	0.694 (29.90)***	0.683 (8.98)***	0.694 (13.38)***
(D) Terraced	0.664 (27.67)***	0.671 (8.54)***	0.607 (33.31)***	0.69 (9.61)***	0.607 (17.36)***
(D) NotHouse	0.621 (18.44)***	0.428 (4.07)***	0.541 (21.42)***	0.327 (3.28)**	0.541 (11.93)***
Gas_CH	-0.691 (-19.57)***	-0.566 (-5.03)***	-0.564 (-24.93)***	-0.57 (-4.71)***	-0.564 (-11.88)***
Non_CH	0.179 (6.58)***	0.071 (-0.78)	0.058 (4.60)***	-0.054 (-0.63)	0.058 (2.33)*
Elec_Main	0.140 (-1.95)	-0.103 (-0.42)	1.008 (13.20)***	-0.07 (-0.29)	1.008 (6.46)***
Gas_OH	-0.094 (-3.45)***	0.007 (-0.07)	-0.071 (-4.77)***	-0.007 (-0.08)	-0.071 (-2.17)*
Elec_OH	0.081 (2.60)**	0.245 (2.51)*	-0.195 (-8.14)***	0.285 (3.09)**	-0.195 (-4.32)***
Other_OH	-1.091 (-32.00)***	-0.951 (-8.36)***	-1.016 (-32.29)***	-0.88 (-7.55)***	-1.016 (-17.69)***
Build_Age	0.054 (12.59)***	0.058 (4.16)***	0.042 (8.07)***	0.039 (2.59)**	0.042 (4.12)***
Roof_Ins	0.081 (18.85)***	0.07 (5.10)***	0.125 (32.72)***	0.07 (4.88)***	0.125 (15.06)***
Dbl_Glz	0.190 (27.31)***	0.206 (9.17)***	0.188 (25.44)***	0.225 (10.39)***	0.188 (12.44)***
Wall_U	0.072 (8.48)***	0.067 (2.88)**	0.076 (9.18)***	0.086 (3.69)***	0.076 (4.54)***
Alpha (constant)	15.080 (170.88)***	15.819 (58.35)***	14.224 (79.91)***	15.599 (44.58)***	14.224 (46.27)***
Summary Statistics					
χ^2	51,201***	14,292***	50,398***	3,250***	-
Log Likelihood	-77,840	-	-	-	-
RMSE	1.87	1.95	1.84	1.93	1.84
R^2	-	-	0.45	0.88	0.45

* p<0.05, ** p<0.01, *** p<0.001, t-statistics are in parenthesis

It is worth noting that several other estimation techniques were also tested but not included in the table above. The PCSE estimator was tested with and without the assumption of heteroskedastic errors and within panel serial correlation. These produced very similar estimates as Model (4), with differences in standard errors. The GLS estimator was also tested with the assumption that standard errors were IID and had no within panel serial correlation. These parameter estimates were the same as in Model (1), with differences only in standard errors. The robust estimator was tested and is capable of giving estimates robust to autocorrelation and heteroskedasticity. It calculates the parameter estimates and standard errors using a linearised variance estimator instead of finding the minimum sum of squared errors. Results from robust regression produced the same parameter estimates as both PCSE and XTSCC with differences once again in the structure of standard errors.

Due to the way these different estimation methods work they do not all report similar summary statistics. This makes it difficult to compare these models against each other. For example, when estimating a model using generalised least squares (GLS) estimation it is not possible to calculate an R^2 statistic. Similarly, it is not possible to calculate the log-likelihood when OLS estimation is used. One summary statistic that is calculable by all estimation techniques is the root mean square error (RMSE). The root mean square error can be calculated using Equation (6.7). It represents the squared sum of differences between actual measurements, y, and predicted measurements, $\hat{y}$. The sum of squared differences is then divided by the number of degrees of freedom in the model, where N is the total number of observations and k is the number of covariates used to estimate the model – thus it rewards parsimony. The smaller the RMSE value the better the model is able to predict the actual values.

$$RMSE = \sqrt{\frac{\sum (y - \hat{y})^2}{(N - k - 1)}} \tag{6.7}$$

When reviewing Table 6.5 it is immediately obvious that almost all parameters are statistically significant in at least one of the five models tested. This highlights the importance of using the correct estimation technique with good understanding of the assumptions being used for the distribution of standard errors. Given the difficulty in assessing the different models, Figure 6.7 was produced to compare how different estimation methods are able to predict mean internal temperatures. The graph on the top of Figure 6.7 contains a scatter plot of all mean daily internal temperatures and the line graphs represents the recorded mean internal daily temperature alongside the five different models used to predict mean internal temperature. Due to the long time scale used for this model, it is difficult to differentiate the predictability of the different models using a single line plot. Therefore three zoom plots representing shorter time periods (as indicated by the shaded areas in the main plot) are shown.

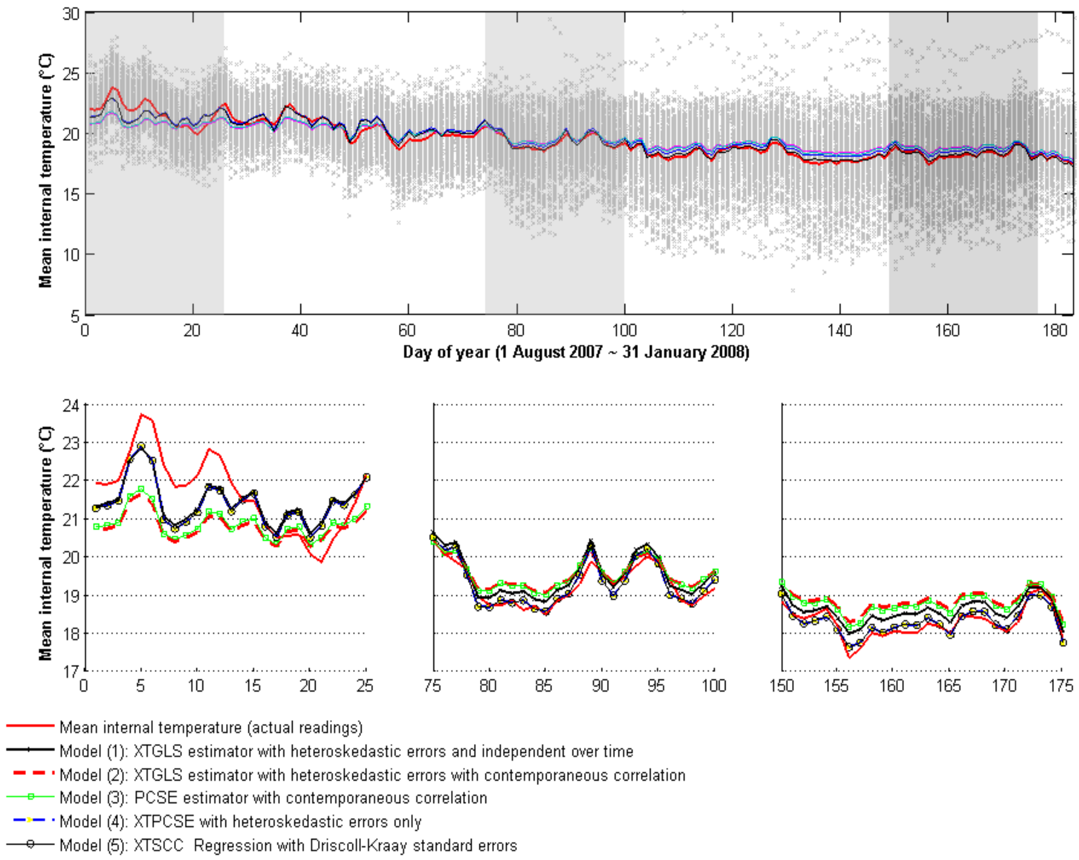

Figure 6.7: Comparison of different estimation techniques

Reviewing the three lower graphs of Figure 6.7 it is clear that the prediction accuracy of the model varies over time. Studying the graph on the lower left, Model (1), Model (4) and Model (5) give the closest predictions for mean internal temperature and essentially overlay each other on the same path. For the winter period, represented by the line graph on the lower right of Figure 6.7, Model (1) appears to have broken away from the original set leaving Model(4) and Model(5) to be the best predictors of mean internal temperature.

Another way to check how well the model is predicting actual measurements is to compare the distributions of the predicted values with the distributions of the recorded values. Table 6.6 gives these statistics for each of the different models. The distributions of all predictive models match fairly closely to the distribution of actual values. However, all modelled distributions predict under dispersion and have difficulty in matching minimum and maximum temperatures. This is not considered to be a significant problem as temperatures in the tail ends of distributions happen rarely, with very low temperatures most likely due to be periods of vacancy the model is not able to predict.

Table 6.6: Comparison of the distributions of predicted with actual temperature readings

Model	Variable	$\overline{X}$	Median	σ	Min	Max
Actual readings	y_{Tin}	19.46	19.64	2.47	7.05	29.92
Model (1)	$\hat{y}_1$	19.60	19.46	1.64	14.74	26.44
Model (2)	$\hat{y}_2$	19.62	19.58	1.32	15.17	24.57
Model (3)	$\hat{y}_3$	19.51	19.36	1.72	14.39	27.06
Model (4)	$\hat{y}_4$	19.61	19.57	1.37	14.81	24.80
Model (5)	$\hat{y}_5$	19.51	19.37	1.72	14.40	27.04

Given the evidence presented above, Model (5) (XTSCC) was chosen as the best model for predicting internal temperatures. Key statistics for this model are given in Table 6.7.

Each of the parameter coefficients, β, are subject to the same units as the underlying covariate. For example the β value for Text is measured in °C, implying that a 1°C change in external temperature will result in a change of ~0.052°C to the internal temperature. In this model an additional non-linear term, Text^2, is also included in the model. This term represents external temperature to the second power and therefore requires a non-linear response on internal temperature. For example, if external temperature was 10°C external temperature would be able explain (0.052x10°C + 0.012x10^2) 1.72°C of the internal temperature, where 0.52°C would be explained from the linear term and 1.2°C could be explained from the non-linear term. As external temperature increases, it explains a higher proportion of internal temperature (e.g. for an external temperature of 20°C, 1.04°C would be explained by the linear term and 4.8°C would be explained by the non-linear term. As different covariates are measured by different units, the magnitude of different coefficients cannot be used to compare the overall importance of different factors as they relate to internal temperature. In Table 6.7, a standardised parameter coefficient, Β, was included thus making it possible to compare the importance of all the covariates in the model. The higher the Βvalue, the more influence or effect that variable has on internal temperature. After standardisation, all covariates are comparable against the response variable. The Β-value therefore simply represents the number of standard deviations change from the mean that will occur in the response variable from one standard deviation change (positive or negative) in the predictor variable. In sum, the standardised coefficients can thus be used to compare the relative importance of different variables as they influence internal temperature.

Table 6.7: Key statistics for final panel Model (5)

Number Obs: 38,501 Groups: 210 Time periods: 183 Method: XTSCC Max Lag: 4	β	B	Driscoll Kraay Std. Errors	t-stats	95% confidence intervals	
Text	0.052	0.096	0.023	(2.23)*	0.006	0.098
Text²	0.012	0.455	0.002	(7.97)***	0.009	0.016
(A) London		-				
(A) North East	-1.392	-0.135	0.123	(-11.34)***	-1.634	-1.150
(A) Yorkshire	-0.629	-0.07	0.140	(-4.50)***	-0.904	-0.353
(A) North West	-1.031	-0.153	0.086	(-11.98)***	-1.201	-0.862
(A) East Midlands	-0.458	-0.049	0.075	(-6.09)***	-0.606	-0.309
(A) West Midlands	-0.828	-0.123	0.124	(-6.69)***	-1.072	-0.584
(A) South West	-0.765	-0.112	0.088	(-8.74)***	-0.938	-0.593
(A) East of England	-0.667	-0.089	0.062	(-10.70)***	-0.790	-0.544
(A) South East	-1.464	-0.172	0.079	(-18.44)***	-1.620	-1.307
T_Stat	-0.236	-0.047	0.027	(-8.73)***	-0.289	-0.183
T_SettingResp	0.035	0.011	0.017	(2.02)*	0.001	0.069
TRV	-0.169	-0.028	0.038	(-4.40)***	-0.244	-0.093
CH_Hours	0.069	0.143	0.006	(11.79)***	0.058	0.081
Reg_Pat	1.189	0.158	0.107	(11.14)***	0.978	1.399
Auto_Timer	-0.031	-0.006	0.025	(-1.27)	-0.080	0.018
HH_Size	0.250	0.114	0.027	(9.19)***	0.196	0.304
HH_Income	0.084	0.049	0.021	(4.05)***	0.043	0.124
Child<5	0.495	0.053	0.048	(10.32)***	0.401	0.590
Children<18	0.219	0.068	0.024	(9.12)***	0.171	0.266
(B) Age<60		-				
(B) Age60-64	0.051	0.007	0.049	(-1.04)	-0.046	0.148
(B) Age64-74	0.370	0.058	0.050	(7.45)***	0.272	0.468
(B) Age>74	0.585	0.083	0.053	(11.12)***	0.481	0.688
(C) Owner		-				
(C) Renter	0.940	0.088	0.064	(14.75)***	0.814	1.066
(C) Council	1.374	0.151	0.077	(17.90)***	1.222	1.525
(C) H_Assoc	0.448	0.038	0.054	(8.27)***	0.341	0.555
WE_Same	-0.438	-0.074	0.034	(-12.85)***	-0.505	-0.370
WE_Temp	0.038	0.007	0.056	(-0.68)	-0.072	0.149
(D) Detached		-				
(D) SemiDet	0.694	0.125	0.052	(13.38)***	0.591	0.796
(D) Terraced	0.607	0.103	0.035	(17.36)***	0.538	0.676
(D) NotHouse	0.541	0.075	0.045	(11.93)***	0.452	0.630
Gas_CH	-0.564	-0.083	0.047	(-11.88)***	-0.657	-0.470
Non_CH	0.058	0.011	0.025	(2.33)*	0.009	0.108
Elec_Main	1.008	0.108	0.156	(6.46)***	0.700	1.315
Gas_OH	-0.071	-0.014	0.033	(-2.17)*	-0.135	-0.006
Elec_OH	-0.195	-0.027	0.045	(-4.32)***	-0.284	-0.106
Other_OH	-1.016	-0.134	0.057	(-17.69)***	-1.129	-0.902
Build_Age	0.042	0.036	0.010	(4.12)***	0.022	0.062
Roof_Ins	0.125	0.106	0.008	(15.06)***	0.109	0.142
Dbl_Glz	0.188	0.102	0.015	(12.44)***	0.158	0.217
Wall_U	0.076	0.029	0.017	(4.54)***	0.043	0.108
Alpha (constant)	14.224	-	0.307	(48.53)***	13.618	14.830
R^2	0.45	*RMSE*	1.84	*Prob > F*		0

* p<0.05, ** p<0.01, *** p<0.001, t-statistics are in parenthesis

Benefiting the interpretation of results that many of the variables used in the analysis are dummy variables. Because all dummy variables have the same upper and lower bounds (and unit of measure), it is possible to directly compare parameter estimates using coefficients of dummy variables. Moreover, because dummy variables are a unit response they directly indicate the predicted change in degrees Celsius on the response variable. Any dummy variable that does not belong to a multicategory group represents the direct change this variable will have on internal temperature. For example if a child under five is present in the dwelling then the mean internal daily temperature is expected be ~0.5°C warmer when compared to a home without a child, ceteris paribus.

For dummy variables belonging to a multi-category group, the parameter coefficients represent the change to internal temperature with respect to that comparison category. For example, the regional β coefficients are all negative indicating that the mean internal temperature for London dwellings is higher than all other regions. This is due to a combination of factors, but most likely caused by high-density housing and smaller living spaces making homes in London easier to heat and thus leading to higher internal temperatures. The result may also suggest the presence of a heat island effect. Due to the complexity of this phenomenon more conclusive analysis is needed, and certainly beyond the scope of this study.

6.12 Discussion

The method developed above is the first time internal temperature has been predicted over a heterogeneous national building stock using panel methods. The benefit of this statistical method is that it allows us to retain valuable information about temperature as it varies over time and over the building stock. It thus allows the combination of a large number of different variables each known to individually effect internal temperature. Variables were chosen to represent the physical properties of the building, the external climate, behavioural and socio-demographic properties of occupants as well as the dwelling's geographic location. The model is able to predict daily mean building stock internal temperature to within ±0.71°C at 95% confidence.

Statistical inferences drawn from the magnitude of variables offer insight into what factors are important for explaining internal temperature demand. As shown in Table 6.5 most of the variables included in the model are highly statistically significant. Many of the variables also have a large magnitude and explain between 0.01 to 0.5 standard deviations of mean daily internal temperatures. Moreover, the model is shown to explain 45% of the variance (R^2 = 0.45) of internal temperature demand from dwellings in the English residential sector. This implies that 55% of the variance is explained by other factors not captured by the model. Such factors might include the differences in heating profiles between dwellings, other human behavioural factors, measurement error, observation error etcetra. It is impossible to try and guess all the factors that may explain the unexplained variance but it is a good exercise to go through to ensure as many factors as possible have been allowed for and captured by the model.

6.12.1 Intransmutable variable effect

Intransmutable variables are defined as variables that cannot be manipulated to have an effect on internal temperature. Examples include the external temperature and the geographic location of the dwelling. External temperatures are shown to be an important factor explaining the fluctuations of daily internal temperature. Moreover, it is shown that these effects are non-linear with higher external temperatures explaining a greater proportion of the variance of internal temperature. Geographic location was included to control for location specific unobserved heterogeneity between dwellings. London was shown to have higher mean internal temperatures than any other location in England. This is probably due to a number of factors such as high-density housing (e.g. smaller dwellings are easier to heat) and possibly the heat island effect (Mavrogianni et al., 2012). The regions having the lowest mean internal temperatures were the North East and South East. The combined effect of all intransmutable variables explains between ~0°C and ~6.8°C of the variance amongst dwellings for minimum and maximum external temperatures.

6.12.2 Heating control effect

Using the model it is possible to make inferences about the effect of different forms of heating controls. The effects of thermostat settings and heating controls has most thoroughly been looked at by Shipworth (2011; 2010). Comparing this research with earlier studies, five different forms of user control over internal temperature were analysed; these were:

i) the presence of a thermostat;

ii) the set point temperature of the thermostat;

iii) whether the only type of heating control in a dwelling was with a thermostatic radiator valve; and,

iv) the use of automatic timers as opposed manual operation.

The results suggest that the mere presence of a thermostat has the effect of reducing average internal temperature by ~0.24°C over the whole building stock. When thermostatic radiator valves are the only type of heating control, they again reduce internal temperature but only by ~0.17°C, compared to homes without any control at all. This result contrasts with Shipworth et al. (Shipworth et al., 2010) where they found no statistically significant difference in temperatures between homes with and without room thermostats. There are several important reasons for this discrepancy. Even though the dataset used in both analyses were the same, the periods over which the analysis was conducted was different[30]. In the analysis completed by Shipworth et al. (2010) maximum daily temperatures were averaged over the entire survey period to give a single maximum average daily temperature for each dwelling (i.e. a cross sectional study). In this analysis the mean daily temperature is used and it is not averaged over time thus giving a time-series model. The benefit of using panel methods is that the heterogeneity in daily temperature fluctuations is retained. Furthermore, maximum daily temperatures only capture the highest recorded temperature in a day; mean daily temperatures on the other hand capture the average of internal temperatures recorded over the whole day, thus giving a better picture of the relative heating profile of a dwelling. In Shipworth et al. an analysis of variance (ANOVA) is performed to determine the correlation between maximum internal temperature and the presence of a thermostat without controlling for other substantive factors. In this analysis, a large number of covariates known to effect internal temperature (like external temperature) are controlled for, and therefore a more accurate picture of the effect thermostats may have on internal temperatures is therefore achieved.

The respondent specified thermostat set point has the effect of increasing internal temperature as expected (e.g. higher thermostat set-points lead to higher internal temperatures). In this model, each household's thermostat setting was grouped into four discrete categories [<18, 18-20, 20-22, >22]. The analysis shows that each time a household increases its thermostat set-point category the mean daily internal temperature of the dwelling will increase by ~0.035°C. This implies that on average, the variation in temperature difference between a dwelling with a set-point

30. Shipworth et al. (Shipworth et al., 2010) used a three month period from 1st November 2007 – 31st January 2008. This study uses a six month period.

temperature below 18°C and a dwelling with a set-point temperature above 22°C will be ~0.14°C, ceteris paribus. This shows that thermostat settings have an important role to play in reducing overall household energy consumption. Although this conclusion supports earlier research completed by Shipworth (2010) more detailed analysis is recommended looking specifically at the effect of thermostat set-points and internal temperatures on energy demand over time.

Interestingly, the use of automatic timers does not lead to a statistically significant change to internal temperature when compared with a heating system that is controlled manually. In an analysis completed by Shipworth et al. (2010) the presence of an automatic timer was shown to have no statistically significant effect on the length of heating duration[31]. These results are most likely due to the way timers are used by occupants. Manual systems require occupants to interact with their heating system and physically turn it on. This requires the occupant to have a physiological response to the cold, psychological cognition and a decision to do something about it, and then physical effort to turn the heating system on. Thus the natural threshold or level of discomfort that must first be overcome before the occupant is bothered to alter their heating system is not insignificant. The corollary to this is also true. Central heating systems maybe switched on and then remain on long after heating is required. Automatic timers on the other hand are programmed to start and stop heating at predetermined periods. Some occupants may set their timers at the beginning of winter and leave them with the same settings for the duration of the heating season, regardless of occupancy or external temperatures. An early winter cold snap may precipitate the automatic timer being set early and therefore extend the length of the heating season. Furthermore, automatic timers do not require additional user interaction, and will automatically turn on whether heating is required by the occupant or not. This result suggests that it is not the presence of the automatic timer per se, but how people choose to interact with the technology that really matters. The final result implies there is no statistical difference in internal temperatures for homes that use automatic timers compared to homes that control heating manually. The combined effect of all different forms of heating controls is shown to explain up to ~0.38°C of the variance in mean internal temperatures.

31. In Shipworth et al (2010) the heating duration was estimated as the period of time when internal temperatures within a dwelling are increasing.

6.12.3 Human behaviour effects

In addition to the use of heating controls, behavioural variations across the building stock were captured using variables to measure the duration of heating periods and the regularity of heating patterns. Both variables were recorded from the occupants' responses to survey questions. This analysis shows that for each additional hour of heating duration, mean daily internal temperature increases by ~0.07°C. Thus a home that has its heating on for one hour per day, compared with home that has its heating on for four hours per day will have a difference in mean daily internal temperature of ~0.28°C. If a respondent answered positively to having a regular heating pattern, the mean internal temperature would also be ~1.19°C higher than a home without a regular heating pattern. This implies that occupant's with routine energy habits, consume more energy than those who do not have routines. This result presents strong quantitative evidence in support of more qualitative studies completed in the fields of psychology (Kahneman, 2003) and sociology (Olander and Thogersen, 1995) where it is believed that social norms and habitual behaviours are important for understanding energy consumption [see Triandis' Theory (Triandis, 1977)]. These qualitative studies hypothecate that a relationship exists between human behaviour and energy consumption. This analysis empirically proves that households who have routine energy behaviour have increased energy consumption compared to households with no fixed routines.

Internal temperatures over the weekend are also expected to be higher than average as people are more likely to be at home for the whole day. However, the final effect of weekends on internal temperature is shown to be statistically insignificant. As previously discussed, the model is not able to predict when a dwelling is unoccupied and in such circumstances this will lead to lower internal temperatures (assuming heating is switched off). The statistically insignificant result is most likely due to these two confounding effects. A second survey question asked if heating patterns over the weekend were typically the same as heating patterns during the week. If the respondent answered positively, this had a statistically significant negative effect, reducing internal temperature by an average of -0.44°C, ceteris paribus. This implies households who responded they had different heating patterns on the weekend, tend to heat their homes for longer and/or to higher temperatures. The corollary of this is that households with the same heating pattern all week (weekday and weekend) will have lower than average internal temperature on the weekend. In sum, the combined effect of heating duration and regularity of heating patterns may explain up to ~2.87°C of the variation in internal temperatures across all dwellings.

6.12.4 Socio-demographic and occupancy effects

Kelly (2011a) and Chapter 5 showed that the number of people living in a dwelling represents one of the most important determinants for explaining dwelling energy consumption. The results presented in this analysis support this finding. For each additional person living in a dwelling the mean daily internal temperature increases ~0.25°C on average. Thus a dwelling with a family of five would be ~1.25°C warmer than a single person household. Chapter 5 also showed that income has both a direct and indirect effect on final energy consumption. For this analysis net household income was separated into seven discrete income bands with the lowest band representing household incomes less than £5,199 and the highest band representing income greater than £95,000. The median income was ~£24,000/annum. For each jump in income bracket, the mean household temperature increases by ~0.085°C. Therefore the mean difference in temperature between a household in the lowest income bracket compared to a household in the highest income bracket is approximately ~0.59°C.

The age of different occupants is a significant driver of internal temperatures. The presence of a child under five years old increases the mean internal temperature by an average of ~0.5°C compared to a home where no child is present. The number of children under 18 also increases the internal temperature by ~0.22°C for each additional child. It is no surprise that dwellings with elderly occupants have higher internal temperatures as well. The internal temperature for a dwelling where the oldest person is aged 60-64 is not statistically different from a dwelling where the oldest person is under 60. However, a home where the oldest person is aged 64-74 will be ~0.37°C warmer than a home where the oldest occupant is under 60. Finally a home where the oldest person is over 74 will be ~0.59°C warmer. In sum, for occupants over the retirement age internal temperatures will increase with age. This clearly shows that older people have their heating on for longer and/or desire higher internal temperatures. In total, ~3.69°C of the variance in internal temperatures can be explained by socio-demographic factors alone.

6.12.5 Tenure effect

Four categories were chosen to model the effects of different tenure types on temperature. Owner-occupiers were chosen as the comparison category. Each of the three other categories (privately rented, council owned and housing association) had higher mean internal temperatures than owner-occupiers. Occupants living in a home belonging to a housing association will have mean internal temperatures which are on average ~0.49°C warmer than owner occupiers, while rented dwellings are on average ~0.94°C warmer and council tenants are ~1.37°C warmer. The cause of this seemingly surprising result may have something to do with the employment status of occupants. In England, 55% of owner-occupiers have a mortgage and 91% of these are employed full time. Employment rates reduce to 67% in the private rented sector, 30% for local authority tenants and 32% for RSL or housing association tenants[32]. Occupants in full-time employment spend less time at home and therefore require less heating, lowering the mean daily internal temperature. Employment status was not collected during the survey and was therefore not controlled for in this analysis. Owner-occupiers also live in larger dwellings and larger dwellings require more energy to heat. From the EHCS (2008) it can be shown that 29% of owner-occupiers live in homes that are larger than 110 m^2; compared to 13% of privately rented dwellings and less than 2.5% for local authority and housing association tenants. Another strong argument supporting the clear differences in temperatures between tenure, is the energy efficiency rating (EER) between different tenure types. The 2007 English House Condition Survey shows that 65% of owner occupiers live in dwellings with a building efficiency grade lower than “D”. When compared with other tenure types such as privately rented (60%), council owned (39%) and RSL (29%), owner-occupiers have the least efficient homes in the housing stock. This is most likely because of government-initiated programs supporting improved energy efficiency in social housing. Tenure effects can therefore explain up to ~1.37°C of the variance of internal temperatures between dwellings.

6.12.6 Heating system effects

A number of different physical characteristics were chosen to model the efficiency the building envelope and heating systems. If gas central heating is present in the dwelling mean internal temperature decreases by an average of ~0.56°C when

32. These statistics were calculated from the English House Condition Survey (Communities and Local Government, 2008).

compared to a house without gas central heating. Given that over 90% of dwellings in England have gas central heating, it is difficult to draw any more conclusive insight from this result. Households with other forms of heating systems (which may also include homes with central heating) have a marginal positive effect on internal temperature (~0.06°C), although the statistical significance of this result is not strong when compared with other results. Homes that use electricity as a primary heat source are on average ~1.0°C warmer than homes using other heat sources. This is most likely due to the effect of electric storage heaters that take advantage of off-peak electricity prices. These systems slowly release heating over long periods of time and maintain higher internal temperatures.

Many homes have additional heating systems in the main room of the house. The effect of additional heating systems on internal temperature was also studied. All fuel types used in additional heating systems (gas, electricity and other) have a negative effect and therefore reduce mean internal temperatures. Gas and electric main room heaters decrease internal temperatures by ~0.07°C and ~0.2°C respectively. The largest effect however comes from main room heaters fuelled by alternative fuels such as wood, coal or oil. The overall effect from these heaters reduces mean internal temperatures in the home by approximately ~1.0°C. The effect of main room heaters on internal temperature is therefore an important explanatory factor of internal temperature. This finding suggests homes with living room heaters provide occupants with the opportunity to use different heating sources and thus the ability to heat only the main room of the house, reducing the need for a central heating system that would otherwise heat the whole house. The combined effect of different heating systems may explain up to ~2.0°C of the variance of mean internal temperatures.

6.12.7 Building efficiency effects

Several variables were identified to control for the effects of building efficiency on internal temperature. The variable representing roof insulation contains eight categories, with each category representing an increase in insulation of 25mm (see Table 6.4) and thus increasing internal temperature by an average of ~0.13°C each time. Therefore, the temperature difference between a home with no roof insulation and a home with greater than 200mm of roof insulation is approximately ~1.0°C on average. The efficiency of walls as indicated by its U-value, also increase internal temperature. The average U-value for the exterior walls of each dwelling were categorised into four discrete bins [<0.4, 0.4-0.6, 0.6-1.6, >1.6]. For each improvement in the U-value category, the internal temperature increased by an average of ~0.08°C. Thus the difference in temperature between the best and worst performing categories explains ~0.32°C of the variation in temperature. The extent of double-glazing also contributes markedly to internal temperature. For each dwelling the extent of double-glazing was separated into five discrete bins [None, < ½, ~½, >½, All]. Improving the proportion of double-glazing in a dwelling by one category has the effect of increasing the mean internal temperature of that dwelling by an average of ~0.19°C. A dwelling that goes from having no double-glazing to having full double-glazing will increase the internal temperature by an average of ~0.94°C, ceteris paribus.

Building typology explains up to ~0.7°C of the variance of internal temperature between different dwellings. As expected, detached homes have the lowest internal temperature and are ~0.7°C colder than semi-detached dwellings; ~0.61°C colder than terraced dwellings and ~0.54°C colder than dwellings not considered houses (e.g. flat or apartment). The age of the dwelling was modelled using ten discrete categories ranging in construction period from prior to 1900 to post 2003. Each improvement in the age category of construction results in the mean internal temperature increasing by an average of ~0.04°C. Therefore, a building constructed after 2003 when compared to a building constructed prior to the 1900's will be ~0.42°C warmer, ceteris paribus. When all physical building effects are combined, it is possible to explain up to ~3.38°C of the variance of internal temperatures amongst heterogeneous dwellings.

6.12.8 Quantifying the rebound effect

The results of this analysis are consistent with both theory and previous empirical research. However, in this research these effects are quantified providing important information for policy-makers. In particular, this research may prove instrumental in helping to understand and quantify the rebound effect. It is now increasingly common for energy demand policy to allow a percentage of the anticipated energy savings to be lost due to the direct rebound effect[33] (usually estimated to be about 20% savings (Greening et al., 2000; Druckman et al., 2011)). This effect is not well understood and is usually arbitrarily applied consistently across all dwellings. This research provides researchers and policy makers with a simple tool to estimate the

33. The direct rebound effect is also known as take-back or comfort taking.

likely increase to internal temperature that will occur due to energy efficiency improvements across a heterogeneous building stock with each dwelling having a known set of socio-demographic, behavioural and physical parameters. Armed with improved understanding for how internal temperature may be affected by energy efficiency improvements, it is therefore possible to quantify the rebound effect owing to an increase in internal temperature. As this analysis allows for a diverse building stock with a wide range of different socio-demographic attributes, it is possible to model the effects that different policies will have on internal temperature and therefore quantify the level of direct rebound expected for different dwellings.

6.13 Chapter conclusion

In this chapter a panel model was developed for predicting and making inferences about the diversity of mean daily internal temperatures across the English domestic building stock. The model explains 45% of the variance of internal temperature and can predict the daily mean building stock internal temperature to within ±0.71°C of actual recorded temperature with 95% confidence. Daily fluctuations in external temperature are shown to impact internal temperatures non-linearly and to the second power. The mere presence of heating controls such as thermostats and thermostatic radiator valves lowers mean internal temperatures; however, the use of automatic timers is not a statistically significant factor. As expected a positive relationship exists between respondent specified thermostat set-point temperature and internal temperature, with higher thermostat set points leading to higher internal temperatures. The respondent specified average number of daily heating hours increases internal temperatures by an average of ~0.07°C for each additional hour of heating.

This research provides quantitative evidence supporting hypothesis from sociology (practice theory) and psychology (habitual behaviour) that routine behaviours are important drivers of home energy consumption. Households who responded with regular weekly heating patterns are on average ~1.19°C warmer than households claiming to have an irregular weekly heating pattern. Additionally, households who responded they had different heating patterns over the weekend compared to the working week were on average ~0.44°C warmer than homes who responded they kept the same heating pattern on the weekend as during the week.

As established by existing empirical research, both household income and household occupancy are important indicators that lead to an increase in household energy consumption. Households with annual incomes over £95,000 in 2007 are ~0.59°C warmer on average than households with annual incomes under £5,199, ceteris paribus. For each additional occupant, internal temperatures are shown to increase by ~0.25°C. Socio-demographic variables such as the age of occupants are also important drivers of internal temperature demand. The presence of a child under five, is shown to increase internal temperatures by an average of ~0.5°C while each child under the age of 18 increases mean internal temperature by ~0.22°C per child. The presence of an elderly person over the age of 75 increases internal temperature by ~0.56°C more than a home where the oldest person is under 64. On average, owner-occupiers live in the coldest homes and council tenants live in the warmest.

Heating systems also affect internal temperatures. Homes that use electricity as their primary heating fuel are on average ~1.0°C warmer than homes that use other fuels and this is most likely due to the presence of electric storage heaters. Homes that have secondary heating systems in the living room have lower internal temperatures when compared to homes that do not have secondary heating systems. This implies living room heaters give occupants the opportunity to just heat the main room in the dwelling, therefore lowering the mean temperature in the rest of the dwelling. Building efficiency measures such as cavity wall insulation, loft insulation and double-glazing all have the effect of increasing the mean internal temperature of the dwelling.

Looking at the combined effects of different variables it is possible to gain deeper insight into the most important factors that explain mean internal temperatures. Intransmutable variables (external temperature and geographic location) explain up to ~6.8°C of the variance of internal temperature from a heterogeneous building stock. Heating controls explain ~0.38°C of variance, behavioural variables explain ~2.87°C and socio-demographic factors explain up to ~3.69°C. Differences in tenure may explain up to ~1.37°C and different heating systems explain ~2.0°C. Capturing the wide range of different building efficiency measures may explain up to ~3.38°C of the variance with double glazing and roof insulation both explaining about ~1.0°C each. In sum, behavioural and socio-demographic factors explain up to ~6.56°C of the variance of internal temperatures. Therefore any analysis predicting energy demand must consider socio-demographics and behaviour appropriately.

In summary, this panel model presents a unique opportunity for future building stock models to incorporate the dynamics of internal temperature demand. Moreover, the model can be adapted to quantify the take-back effect (through the estimation of changes to internal temperatures) on discrete heterogeneous dwellings as combinations of different energy efficiency measures are applied. The model thus offers a unique method for predicting internal temperatures and making statistical inferences from environmental conditions, socio-demographics, behavioural factors and the physical properties of the dwelling.

7

A high temporal resolution model for predicting energy and emissions from the English residential sector

7.1 Chapter summary

The previous chapter estimated an equation to predict the expected daily internal temperature from a cross section of dwellings on any day of the year. This chapter will utilise this equation in the development of a bottom up physically based residential building stock model. Several new innovations are introduced greatly enhancing the estimation and prediction of energy and emissions from the residential sector. Using data from the English House Condition Survey (EHCS), energy demand is predicted independently for 16,216 dwellings for each day of the year[34]. For the first time behaviour and socio-demographic variables have been included within the building stock model to provide more realistic estimates of energy and emissions at the dwelling level. Predicted

34. Mean daily external temperatures are available for each day of the year over a thirty year period from which the average daily temperature is estimated.

daily internal temperature demand is first used to calculate dwelling specific heating degree-days that are then used to solve thermodynamic heat balance equations. Finally the model is validated using actual energy demand readings for different segments of the building stock (e.g. tenure, income, floor area etc). This model thus provides greater detail about the diversity within the building stock at much higher temporal resolution then any other building stock model developed to date.

7.2 Introduction

7.2.1 Contribution

There is a clear trend within the literature for increasingly detailed bottom-up building stock models. The first generation of engineering bottom-up models simulated demand from just two or three different dwelling archetypes (Hirst and O'Neal, 1981; Johnston, 2003). Simulating demand from a small number of archetypes greatly simplifies the process of simulation, but also greatly limits the capacity for these models to accurately represent a heterogeneous building stock. Older models such as BREHOMES (Shorrock and Dunster 1997b) and more recently the Great Britain Housing Energy Fact File (Palmer and Cooper 2011) recognise the benefits of representing the heterogeneity within the building stock to estimate energy demand. However, these methods still implement dubious energy demand estimation equations from SAP and BREDEM and fall short of robustly estimating behaviour. This model expands this frontier by increasing the number of dwellings being modelled, adding important detail to each dwelling and improving the temporal granularity over which the model is estimated.

A long recognised deficiency of engineering based methods is their inability to incorporate occupant behaviour (Aydinalp et al., 2003; Swan and Ugursal, 2009). Although several researchers have anticipated the need for such models (Micklewright, 1989; Hitchcock, 1993) there has not yet been a single building stock model that effectively includes the diversity of behaviour and demographic characteristics within a bottom-up engineering model to represent final domestic energy demand and emissions. This model overcomes this shortcoming by predicting daily mean internal temperature for each dwelling from the socio-demographic and behavioural characteristics of occupants; physical building attributes; efficiency of heating systems and external environmental conditions. This allows the distribution of internal temperatures as they vary over time and over the building stock to be captured by the building stock model.

Although heating degree days (HDD) have been used for detailed simulation models of energy demand from individual buildings (i.e. not building stocks) there are no building stock models to simulate energy demand using heating degree days on a daily basis for the building stock. This is a serious shortcoming of existing building stock models that only use mean seasonal or monthly internal and external temperatures that are kept constant over the entire building stock or over time. This model implements a dynamic internal and external temperature demand algorithm that estimates heating degree-days on a daily basis thus greatly improving the ability to estimate energy demand fluctuations across the building stock as external temperatures vary naturally over time.

7.2.2 Chapter overview

The chapter starts with an overview of the laws of thermodynamics before using them to construct energy and material flow analyses for thousands of typical dwellings. A substantive discussion about the modelling process is provided. End-use energy consumption is separated into five end-use energy service categories namely: lighting, appliances, cooking, hot water and space heating. Equations are derived to simulate energy demand for each energy service category. Space heating demand represents the largest of all five energy demand end-use categories and is also the most complicated energy demand category to estimate. This is because space heating depends on a large number of interdependent factors including: final energy demand from each of the other four energy service categories as well as the internal temperature requirements of occupants and external environmental conditions. For these reasons, the derivation of space heating is left until last and described in detail.

Information about the physical properties of each dwelling, the socio-demographic and behavioural characteristics of occupants and daily weather data are essential for estimating final dwelling energy demand. Thus the data requirements for this model are significant. The English House Condition Survey (EHCS) was identified as being the richest and most comprehensive source of data fulfilling many of the data requirements needed for this model. Regional weather data was downloaded from the UK Met Office while internal temperature data and socio-demographic variables were estimated using the CARB-HES dataset (Chapter 6).

7.2.3 Critique of literature

Bottom-up engineering building stock models have been used to estimate energy demand from the residential sector since the late 1970's (Hirst, 1978; Saha and Stephenson, 1980; Johnston et al., 2005; Boonekamp, 1997). The bottom-up approach encompasses all models which use input data from a hierarchical level less than that of the sector as a whole (Swan and Ugursal, 2009). These models therefore describe energy use at a disaggregated level and require detailed information about building efficiency and technologies. Data requirements vary by the level of disaggregation, the assumptions being applied, the degree to which occupant behaviour is taken into consideration and the level of detail used to describe energy consumption. Bottom-up models can therefore account for energy end-use service categories from individual houses or groups of houses and then can be scaled to represent aggregate consumption using the weights of each representative sample (Swan and Ugursal, 2009).

It is a feature of all bottom-up models that the efficiency of buildings and different technologies are accurately defined, because they determine the baseline scenario and therefore the potential for change and different paths for technological evolution (Jaccard and Bailie, 1996). Much of the research in bottom-up models must therefore be spent on data collection and the estimation methods used to explain existing efficiency levels as well as the types of technology employed to meet existing demand. In addition, bottom-up models tend to be driven by exogenous scenarios, based on a set of macro-economic assumptions (growth rates, structural change and energy prices) and therefore tend to lack the ability to explore feedback when prices affect the supply and demand for fuel. Nevertheless, the detail provided by bottom-up engineering models give them the capacity to model the effects of different technological options; a feature not afforded to other modelling approaches. The bottom-up engineering approach is therefore particularly useful for identifying areas of technological improvement. It is also possible to determine total aggregate energy consumption without relying on historical data (although historical data can be used for validation or calibration purpose as it is in this model).

As identified by Swan and Ugursal (2009) there are three main categories of bottom-up engineering based methods. The first approach utilises the distribution of appliance categories (A to E) to estimate final end-use energy demand. A weakness of this approach is that it does not allow for the interactions between different end use categories and does not give detailed information about the dynamics of energy use at the dwelling level. The second approach uses a small number of building archetypes to categorise building characteristics (age, typology, size etcetera). Most building stock models developed in the UK implement some variation on this method . For example, the most widely used model for setting government policy in the UK has been BREHOMES, and uses dwelling archetypes to estimate aggregate demand. Although the archetype method offers some potential for looking at disaggregated demand for each dwelling archetype, it is not possible to look at the distribution of demand across the population and therefore neglects the tail ends of distributions – where dwelling level energy demand is at its highest. The final method is known as the sample method and estimates energy demand for each ‘real’ dwelling within the sample. In order for the sample method to effectively estimate aggregate (or quasi-aggregate) demand, the sample must be large enough to represent the heterogeneity from the entire building stock. This method is considered to be the most accurate at representing the building stock but is also the most complicated due to the significant amount of detailed data necessary to estimate energy demand from all dwelling types (Swan and Ugursal, 2009). The most recent building stock model developed in the UK was created by Cambridge Architecture Research and was used to create the Housing Energy Fact File (HEFF). This model is based on an earlier version developed for Scotland (DEMSCOT) and uses an excel spreadsheet and a VBA script to estimate energy demand for each dwelling from the EHCS using RdSAP. Although it represents a significant step forward in the level of detail being modelled, it still only estimates energy demand on a monthly basis using mean internal and external temperatures and does not account for the behaviour of occupants. The model developed for this thesis solves many of these inadequacies by incorporating new and innovative methods to calculate individual demand across a large sample of dwellings.

7.2.4 Modelling approach

A standard thermodynamic heat balance equation is derived for a control volume drawn around the exterior envelope of a dwelling. The equation implicitly requires that while temperature and pressure difference over the control volume remain constant, all energy entering the control volume must equal the total energy leaving the control volume. Thus, it is possible to estimate the energy required to maintain internal temperature at a specified set point when both the external temperature and the rate of energy loss through the building envelope are both known. The rate of heat loss through the building envelope is given by the heat loss parameter (HLP) and is estimated for each dwelling and for each building element (roof, floor, external walls, windows and thermal bridges) and is purely a function of the area over which heat is being lost and the rate of heat loss for that building element. Losses due to ventilation and infiltration are also estimated. Incidental gains increase the internal temperature and therefore minimise the amount of additional heating required. Incidental gains from other energy services such as hot water, lighting and appliances are included in the model as well as gains from metabolic[35] activity. Gains from solar radiation are included in two different forms. Direct solar radiation acting on glazing traps long wave radiation thus increasing internal temperature. Insolation[36] on the façade of the building minimises heat loss through the building envelope. Irradiation acting on opaque building surfaces is rarely included in building stock models so the derivation of the sol-air[37] temperature for modelling insolation is described in detail.

Fuel share allocations for space heating are estimated from the primary fuel type and the heating system installed. Lights and appliances are powered entirely by electricity while the fuel used for cooking is allocated between electricity and natural gas depending on the primary fuel type of each dwelling. Allocating the fuel used for hot water heating, depends firstly on the hot water heating system installed and secondly, the presence of an electric immersion heater. Dwelling level emissions and energy costs are then estimated for each dwelling based on these fuel share allocations.

End-use energy demand service categories (excluding space heating) are calibrated to match aggregate DECC statistics for each energy demand category. The energy demand equations adapted from BREDEM and SAP methods are shown to over estimate energy demand from each of the energy service categories by between 5% and 15%. This has important implications in the future development of SAP and BREDEM as it implies these methods over-estimate demand. Finally, the model is validated against a number of different building stock segmentations (e.g. dwelling type, floor area, income band etc.) which are freely available from DECC energy statistics and are based on the NEED database. Given the inherent deficiencies of the NEED dataset (even though the data

35. Metabolic gain is the incidental internal heat gain that occurs during human and animal activity.
36. Insolation is a measure of the quantity of radiation energy received on a given surface over a period of time.
37. The sol-air temperature is the external air temperature adjusted for the effect of black-body radiation emitted from the façade of the building.

represents actual energy consumption) the domestic energy demand model appears to approximate energy demand relatively well over various building stock segments.

7.2.5 Modelling methodology

A high-temporal resolution bottom-up engineering and social-demographic energy and emissions domestic building stock model is developed for the English residential sector. The model has high-temporal resolution because it estimates energy demand for every day of the year. It is bottom-up because it independently estimates energy demand for each of the 16,216 dwellings from which aggregate demand can be estimated for the building stock (or any sub-group of dwellings within it) after the application of grossing weights. It is an engineering model because it applies thermodynamic equations to calculate the energy flows occurring over the building envelope. Using the basic laws of thermodynamics combined with information about the material properties of the building envelope, the addition of incidental gains and internal and external temperature profiles, it is possible to estimate energy demand so that dwelling specific temperatures are maintained. The model is socio-demographic because it uses the social, behavioural and demographic characteristics of occupants to estimate daily internal temperature (Chapter 6). It is an energy and emissions model because it estimates final energy demand and emissions using individual dwelling level data using the heating system type and primary fuel for each dwelling. Combining all of these characteristics into a single building stock model creates a powerful tool that is capable of answering a multitude of different questions about domestic energy demand and different decarbonisation strategies for England. It is particularly useful for drilling down into different sub-sectors of the building stock to understand the effect of different decarbonisation strategies for reducing emissions from different segments of society.

7.2.6 Material and energy flow analysis

The first law of thermodynamics – otherwise known as the law of conservation of energy – states that energy can be neither created nor destroyed but can change forms as it flows from one place to another. This law is helpful for understanding the persistence of energy but says nothing about the direction of flow between two bodies. The second law of thermodynamics states that the entropy within a closed system – that is also not in thermal equilibrium – must always increase. Said differently, energy will always flow from higher temperature bodies to lower temperature bodies. This will always increase the energy content (temperature) of the lower temperature body and lower the energy content (temperature) of the higher temperature body until the two bodies are in thermal equilibrium. The third law of thermodynamics states that the entropy of a system approaches zero as temperature approaches absolute zero. Finally the zeroth law of thermodynamics is simply a law of transitivity and states that if two separate bodies are independently in thermal equilibrium with a third body, then the first two bodies must also be in thermal equilibrium with each other.

Using these basic laws it is possible to construct a model that represents the typical energy flows that occur in a dwelling. In its most basic form the envelope of a building can be described as a control volume[38] where energy and material flows pass through the building envelope and therefore through the control volume (Vincenti, 1982). In the absence of work and heat transfer across the control volume the system is said to be adiabatic[39] and is therefore in a steady state where the temperature and pressure inside the control volume remain constant. In reality energy is constantly passing through the control volume and the energy contained within the control volume is constantly changing. Obeying the first law of thermodynamics (whilst keeping the temperature within the control volume constant) requires that all energy entering the control volume must equal the energy leaving the control volume. When the rate of energy flowing into the control volume is different to the rate of energy flowing out of the control volume, the energy content (or temperature) within the control volume will change.

This process can be shown diagrammatically in Figure 7.1, where $\dot{Q}_e$ and $\dot{Q}_g$ are the rate of energy flows for electricity and gas; $\dot{Q}_s$ is the rate of solar energy flow absorbed by the building; $\dot{Q}_m$ is the rate of metabolic energy transfer and $\dot{Q}_o$ is the rate of energy flow from other sources such as micro-renewable technologies. While $\dot{Q}_v$ and $\dot{Q}_f$ are the energy flow rates leaving the building due to ventilation and building fabric losses. In this model T_{int} and T_{ext} are the internal and external temperatures respectively.

38. A control volume is an engineering concept and represents a fictitious boundary around a volume for which material and energy is allowed to flow. Using the laws of energy and material conservation and assuming the volume is in equilibrium all material and energy flowing into the volume across the boundary must equal the material and energy leaving the control volume.
39 A system is said to be adiabatic if no energy is lost or gained by the system during the conversion process.

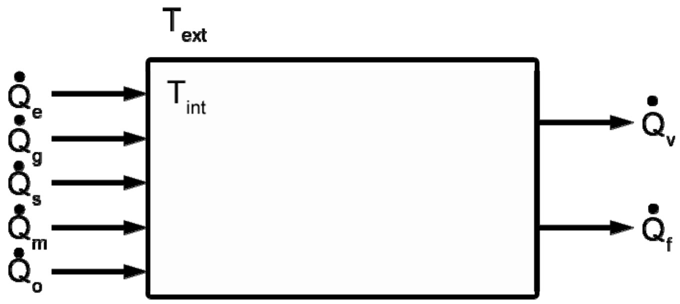

Figure 7.1: Diagrammatic representation of a building as a control volume

The second law of thermodynamics states that when two bodies are in thermal proximity to each other, energy must always flow from the high-energy medium to the lower energy medium and therefore generate entropy during this process. This requires that when $T_{ext} < T_{int}$ then the sum of $\dot{Q}_v$ and $\dot{Q}_f$ is positive (i.e. energy flows in the direction of the arrows shown in Figure 7.1) and when $T_{int} < T_{ext}$ the flow is negative (i.e. energy flows from the external environment to the internal environment contributing to an increase in T_{int}). Using these simple concepts it is possible to draw a control volume around a typical dwelling and study the energy and material flows occurring over the building envelope. In Figure 7.2 a dashed line represents the control volume and therefore all energy or material flows crossing this imaginary boundary are considered.

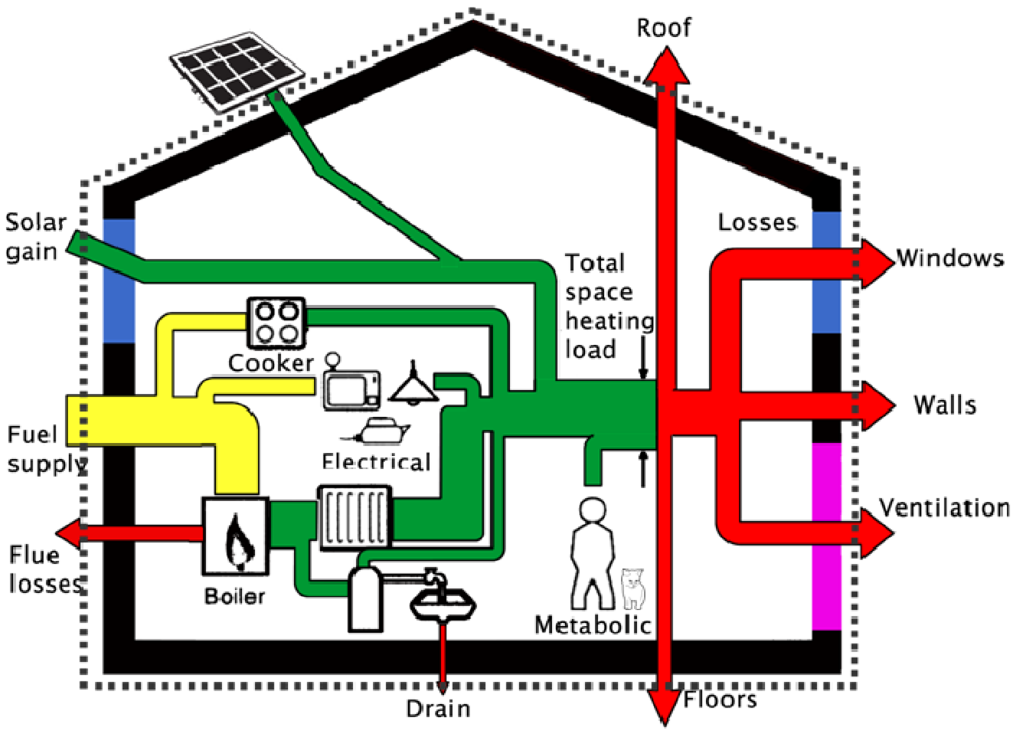

Figure 7.2: Energy flows in a typical dwelling[1]

1. Diagram recreated from BREDEM manual front cover

7.2.7 Structure of computer model

The engineering model was written in Matlab and developed to take advantage of the programming languages capacity to call user written functions. The model is structured so that one central Matlab routine sequentially calls a number of sub-routines (functions) that perform unique calculations necessary for the estimation of the model. Each sub-routine is called from the central program and passed the data required to perform the necessary calculations. Once each sub-routine has completed the calculation procedure, only the output that is relevant to other parts of the model are then passed back to the central program. Structuring the model in this way has several benefits. First Random Access Memory (RAM) is minimised because only variables central to the model are retained within the workspace. Second, it assists in the readability and transparency of the model and allows for easy model diagnostics. Finally, functions can be tested independently outside the modelling environment. The model consists of at least 22 different functions with each function serving a unique purpose, such as estimating energy losses from ventilation or calculating the number of heating degree-days for each dwelling to meet the required energy demand. A simple structure of the model is shown in Figure 7.3.

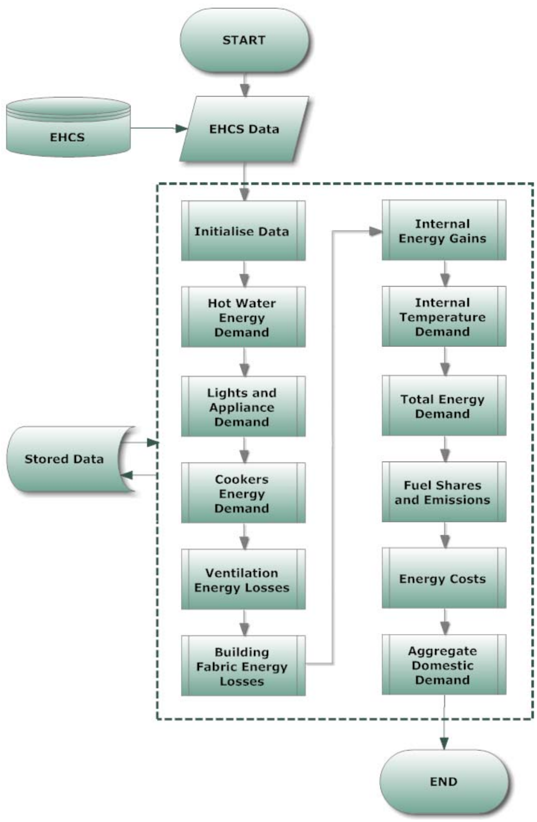

Figure 7.3: Flow chart for building stock model

7.3 Data management

7.3.1 Existing data sources

As discussed in the introduction, bottom-up energy demand models rely heavily on large disaggregated datasets. Where top-down models can be used to forecast trends in aggregate energy consumption across the entire building stock, bottom up models independently estimate demand for each dwelling and thus give the flexibility to aggregate demand in different ways (e.g. building type, heating type, efficiency levels, socio-demographic characteristics etc). The advantage of bottom-up methods is that known physical laws can be applied independently to each dwelling from which energy demand can be estimated at the dwelling level. Unfortunately this not only requires substantial information about each dwelling, but also that the sample of dwellings for which data is available is sufficiently large to be representative of the building stock. The most comprehensive dataset that fulfils these requirements is the English House Condition Survey (2008). One limitation of this dataset is that it only includes information on English dwellings. English dwellings account for 87.5% of dwellings in Great Britain and thus represent a significant proportion of national dwellings. Scaling factors are used to convert between UK, GB and English dwellings (Section 7.3.4) and requires the assumption that the distribution of dwelling characteristics in England the UK and Great Britain are similar.

Several government departments collect and manage a wide variety of data related to energy and emissions for the residential sector. Since 2005 DECC has started to release sub-national consumption statistics at the regional (NUTS1) and local authority level (LAU1) (DECC, 2012a). More recently, sub-national consumption statistics have been released for Middle Layer Super Output Area (MLSOA) and Lower Super Output Area (LSOA). Available within these datasets is the annual consumption of gas and electricity (GWh) and total number of customers within each of the areas being considered. This data will be used later in the validation of the model.

As well as looking more closely at geographic disaggregation, headway is also being made on accurately breaking down energy into different energy service categories. Between 2003 and 2008 BRE were commissioned to maintain and publish the Domestic

Energy Fact File (DEFF). The aim of DEFF was to report important statistics about trends in the national domestic building stock. DEFF therefore includes important indicators such as fuel prices, expenditure, population, condition and age of the building stock as well as important information on the condition of building fabric and heating systems. One weakness of this data source is that the data contained in DEFF is a mixture of both survey data and modelled data making it difficult to differentiate between actual and predicted values. In parallel, the Market Transformation Programme (MTP) was established in the year 2000 to record trends in lighting and appliances across the residential sector in the UK. It has now widened coverage to include general energy consumption from the residential sector and a significant part of the non-residential sector (MTP, 2011). Data from the MTP is available for download from DECC and separates national end use energy demand into different appliance sub-categories.

In 2011, Cambridge Architecture Research (CAR) were commissioned to produce the Housing Energy Fact File (HEFF) and similar to DEFF provides important statistics about trends in the national building stock over the last 40 years (Palmer and Cooper, 2011). Notably, the HEFF represents a major and important advance in the variety, availability and interpretability of data that is available describing the residential sector. Several important contributions have come out of this work. First, all the statistical data included in the final report is available for download in its original format from DECC. Second the data was then used to generate estimates for building energy efficiency and consumption using a bottom-up excel based building stock model. The model is primarily based on RdSAP but deviates from this standard procedure when more robust information and better methods are available. Third, a "Cambridge Housing Energy Tool" was developed so that users are able to interrogate the English Housing Survey and easily extract the information they require about the domestic building stock.

Research is now increasingly focused on understanding demand and efficiency at the individual dwelling level. This has led to the development of the Homes Energy Efficiency Database that aims to track efficiency improvements from UK dwellings. HEED was developed by the Energy Saving Trust (EST) and contains actual data on the efficiency characteristics of 50% of the UK housing stock from 1995 onwards. Unfortunately data is only publicly available at the LSOA level (Energy Saving Trust, 2012a). Similarly, the National Energy Efficiency Data-framework (NEED) is managed by DECC and is recognised as the most recent and nationally representative database on actual metered energy consumption. Metered energy readings at the dwelling level are important for understanding the 'real' effectiveness of energy efficiency improvements. Actual gas and electricity meter readings also provide a robust way to validate bottom-up building stock models. NEED was created by combining several large datasets through data matching at the address level. Detailed physical characteristics of dwellings are provided from the HEED dataset; metered energy consumption statistics are provided from xoserve and the independent gas transporters; modelled data about the occupants is provided by Experian; and finally, information about the value of properties is taken from the Valuation Office Agency (VOA). In addition to these data sources, DECC collects and makes available aggregate data on end-use energy demand from the residential sector. This information includes national statistics on the total consumption by fuel-type, energy intensity and end use category.

7.3.2 Conflicting data

Given the large variety of data-sources available and the assumptions underpinning how each source derives its information, it is not uncommon for two different datasets to contain conflicting information. For example, gas and electricity consumption statistics for the residential sector vary by as much as 5.1% between the NEED database and the statistics published by DECC (DECC, 2012b). Moreover, consumption by energy service (space heating, water heating, lighting etc) also vary markedly between the MTP figures and the DECC domestic data tables. These complications were overcome by checking each dataset for assumptions and different modelling criteria to create the most accurate energy demand estimates for each of the different building categories[40]. Given the large uncertainties between and within datasets, estimates produced by different datasets were shown to deviate by large margins. Therefore, any model output deviating by less than 5% from published statistics were considered as good approximations.

7.3.3 Grossing weights

Each of the 16,216 records within the EHCS records unique characteristics for every dwelling. It is not possible however to scale this data proportionally (1:1) to estimate aggregate consumption from the building stock. This is because the survey is stratified

40. Only aggregate national statistics are used for calibrating the engineering model to meet total demand.

and designed to be bias towards under-represented groups. Establishing estimates for the entire domestic building stock thus required grossing weights to be applied on each record to undo the effects of stratification and make the sample representative of the population. This was necessary as not applying the grossing weights would produce inaccurate estimates of the distribution of dwellings in the building stock and therefore incorrectly estimate final demand.

7.3.4 Scaling factors for converting between UK, GB and England

Although the EHCS only collects data on English dwellings, energy and emissions can be approximated for Great Britain and the United Kingdom using conversion factors calculated from the relative proportion of dwellings from the population. In 2008 the United Kingdom had 26.05 million residential dwellings; in Great Britain there were 25.36 million and in England there were 22.19 million. Using these values it is possible to calculate grossing weights that can be used on the dataset to estimate totals for the United Kingdom or Great Britain. This assumes that the distribution of dwellings in England is similar to the distribution of dwellings in Great Britain and the United Kingdom. Using this approximation it is possible to give rough estimates for total energy and emissions for different but related geographic regions. Table 7.1 shows the scaling factors used to convert between the UK, GB and England. For the remainder of this chapter England will be used as the representative geographic boundary as it represents the most accurate use of the data. Using the same method, aggregate consumption statistics can be converted effortlessly between different geographic boundaries for comparison purposes. This is necessary as DECC typically only provide data at the UK or GB level while other statistical databases only provide information for England.

Table 7.1: Scaling factors for GB, UK and England

	United Kingdom	Great Britain	England
Dwellings (000's)	26,048	25,359	22,189
United Kingdom	1	0.974	0.852
Great Britain	1.027	1	0.875
England	1.174	1.143	1

Table 7.2 gives final energy demand by end use service category for England, Great Britain and the United Kingdom. Statistics for England and the United Kingdom were derived from actual statistics from the Domestic Energy Fact File for Great Britain. This was achieved by scaling demand by end-use energy service category by the relative proportion of dwellings for that geographic region.

Table 7.2: DECC energy statistics showing energy demand for the UK, GB and England by end-use energy service category (2009)

Region	Number of Dwellings (thousands)	Total Energy (TWh/year)	Space Heating (TWh/year)	Water Heating (TWh/year)	Lighting (TWh/year)	Appliances (TWh/year)	Cooking (TWh/year)
England	22,189	441.7	290.2	73.3	14.4	51.1	12.4
GB	25,359	504.6	331.7	83.8	16.5	58.4	14.2
UK	26,048	518.3	340.7	86.1	16.9	60.0	14.6

7.3.5 Mapping, recoding and initialisation of data

Before any data from the EHCS was extracted for use in the engineering model, a large matrix of pre-selected data from the EHCS was imported directly into Matlab. Original variable names from the EHCS were preserved making it possible to refer back to the original data source for accessing more information about the derivation of any variable when required. An initialisation function was used to search and extract data from the main databank giving them unique handles. Matlab has the functionality to store structured arrays, giving users the ability to store common variables under the same structural definition. This is done to improve both the readability and transparency of the model. Any data required by the model is thus extracted from the main data matrix and saved as a named structured array before any substantive analysis is conducted.

Once all variables have been saved to the workspace it is necessary to initialise and recode the variables into useful values that can be used by the model. First, missing or unknown data are replaced by appropriate alternative values. This was not a huge concern as the EHCS has already undergone extensive cleaning and contains very little missing data. A second type of recoding was done to convert EHCS values into a format appropriate for conducting the calculations necessary to estimate energy demand. For example, the EHCS will provide categorical data on the boiler system installed in each dwelling but these need to be converted into boiler efficiency values as it is the efficiency of the boiler that matters for calculating energy consumption. Around thirty new variables were recoded from the original EHCS database. Often this required re-categorising variables in a way that could be matched and used based on the formats adopted within SAP and BREDEM.

7.3.6 Computing speed and hardware constraints

Due to the significant number of variables being used by the model, with each variable having a typical matrix size of 16216 x 365 (dwellings x days in year) it was infeasible (due to model run-time) to apply simple for-loops to perform the required calculations on each dwelling. An advantage of Matlab is that it implements a procedure known as logical indexing and therefore allows matrix operations to be performed in a fraction of the time typically necessary to complete a typical for-loop operation. This is particularly useful for repeated calculations on large matrices. Logical indexing was therefore implemented throughout the model saving significant computational time. Using this method the final run-time of the model was reduced to just 25 seconds from an original run-time lasting around 30 minutes.

Computer hardware, in particular, Random Access Memory (RAM), was also pushed to its limits. Workspace variables in Matlab are stored in RAM thus greatly enhancing the speed at which Matlab can retrieve and send data to perform the necessary calculations. When a significant number of sufficiently large matrices are being stored within the workspace Matlab runs into contiguous and absolute memory problems. Two solutions to this problem were implemented. First the amount of RAM allocated by MS Windows for use by third party applications was circumvented during start up and increased to 3GB (the maximum). Second, any data that was created and required by the rest of model was not returned back to its calling routine and therefore removed from the memory workspace. These strategies increased model efficiency and allowed the model to run without significant investment in new computer hardware.

7.3.7 A note about notation

The significant level of detail provided by this model requires extensive use of matrices. Variables used within the model can be matrices, vectors arrays or scalars. Matrices consist of 16216 rows and 365 columns where each row represents a separate dwelling each column represents a day of the year. Vector arrays can be either a single column array representing each dwelling or a single row array representing each day of the year. It is convention for matrices to be distinguished using bold type font (e.g. $\mathbf{H}_{id}$) and the dimensions of the matrix to be denoted by sub-scripts, where dwellings are represented by the symbol, *i,* and days are represented by the symbol, *d*. Variables that represent a rate of change are distinguished from standard variables using a single dot above the variable (e.g. $\dot{Q}$).

7.4 Description of the model

7.4.1 Dwelling dimensions

The EHCS includes a number of different dwelling dimensions. Details include dimensions for each surface in the dwelling (floors, walls and ceilings) requiring lengths, widths and ceiling heights. With this data the internal areas and volumes for each unique dwelling were calculated[41]. Other useful dimensions include exterior wall areas, total glazing area and various room dimensions. The slope area of roofs was not available and was therefore approximated using the area of the ground floor of each dwelling. Flats not on the top floor, are assumed to have no external roof and therefore do not have any heat loss through the roof. Throughout the model it is assumed that interior surfaces shared with adjacent heated spaces result in no net benefit to either dwelling (i.e. a net zero sum game). Thus only energy loss from external surfaces estimated. This approximation allows the model to be simplified without significant loss of important information.

7.4.2 Number of occupants

The number of occupants living in a dwelling has a significant effect on dwelling energy consumption (Kelly 2011a; Richardson et al. 2008) and is therefore an important parameter within building stock models. The EHCS contains detail on the number and type of occupants for each dwelling. SAP and BREDEM both estimate occupancy based on dwelling floor area, not actual occupancy. A simple correlation analysis using data from the EHCS shows no correlation between floor area and the number of occupants[42]. Thus, any model able to use actual occupancy instead of estimated occupancy will give a more accurate representation at estimating final energy demand. Actual occupancy was therefore used where ever possible but some dwellings still had missing information on the number of occupants, therefore rather than discarding the entire record, the missing

41. When the ceiling height is missing from the dataset (273 of 16216) a height of 2.4m is assumed.
42. The correlation between floor area and occupancy was found to be $r = 0.0077$

occupancy values were replaced by the SAP derived occupancy equations as shown in Equation (7.1) [43].

$$
\begin{aligned}
&A_{f,i} > 13.9 : N_i = \left\| 1 + 1.76\left(1 - e^{-0.000349(A_{f,i}-13.9)^2}\right) + 0.0013\left(A_{f,i} - 13.9\right) \right\| \\
&A_{f,i} \le 13.9 : N_i = 1
\end{aligned} \tag{7.1}
$$

In the above equation, $A_{f,i}$ is the total floor area and N_i is the number of occupants within each dwelling. Less than 4% of dwellings in this model have had occupancy estimated in this way[43]. It is important to note that behavioural aspects have only been modelled for heating energy demand.

7.4.3 Energy consumption from lighting

Almost one-fifth of total electricity consumption is consumed by lighting in the average home (DECC 2011). Lighting demand is complicated due to the behaviour of occupants, availability of natural light and occupancy patterns (Yao and Steemers, 2005; Christoph, 2004). Research is also hampered by the limited availability of empirical data which is both costly and time-consuming to collect (Stokes et al., 2004). Lighting demand is therefore problematic to simulate accurately. There are however several studies that have attempted to simulate lighting demand from dwellings (Richardson et al., 2009; Stokes et al., 2004; Paatero and Lund, 2006; Capasso et al., 1994). Such models typically aim to simulate lighting demand using half-hourly or minute-by-minute temporal resolutions. At present BREDEM and SAP estimate lighting demand on a monthly basis. The model used here estimates lighting demand on a daily basis and therefore bridges the gap between the high temporal resolution models developed in the literature and the BREDEM and SAP approach.

Energy consumed for lighting is a direct function of floor area, occupancy and any available natural daylight coming through windows and skylights. If no energy saving light bulbs are used in a dwelling the average annual energy consumption used for lighting in UK dwellings is approximately 9.3 kWh/m^2 (DECC, 2009b). This model adopts the lighting equations used in BREDEM and SAP to estimate the annual lighting energy requirements for a dwelling.

43. There are 613 dwellings from a total 16,216 recorded as having no occupants.

$$\mathbf{Q}_{L,i} = C_{1,d}\left[F_i \varepsilon \lambda_i + \left(F_i - 1\right)\lambda_i\right] \qquad \text{(MWh/year)} \qquad (7.2)$$

$$\lambda_i = 59.73 \times \left(A_{f,i} \times N_i\right)^{0.4714} \qquad \text{(MWh/year)} \qquad (7.3)$$

Equations (7.2) and (7.3) are used to estimate lighting demand where $\mathbf{Q}_{L,id}$ is the annual lighting requirement for a dwelling; $C_{1,d}$ is an adjustment factor that allows for the variability and availability of natural daylight over the year; F_i is the fraction of low energy lighting in the dwelling; ε is the efficiency of low energy lighting compared to incandescent light bulbs (IL); λ_i is the average annual lighting requirement for a dwelling without low energy lighting, where λ_i is a function of the area of the dwelling, $A_{f,i}$, and the number of occupants living in the dwelling, N_i. Low energy light bulbs are assumed to consume ~ 25%[44] of the energy as a normal IL for the same level of lighting. Light emitting diodes (LED) typically consume 50% compared to CF's (12.5% of an IL)[45].

The availability of natural daylight has a measurable effect on the demand for artificial lighting in dwellings (Steemers, 1994). A correction factor $C_{1,d}$ is therefore derived from Equations (7.4) and (7.5) that is a function of the relative fraction of glazing for each dwelling, $G_{L,i}$. The glazing fraction is simply the ratio of the proportion of natural light entering a dwelling and the floor area of the dwelling, $A_{f,i}$, as given by Equation (7.4)[46].

$$G_{L,i} = \frac{\sum 0.9 A_{g,i} \times g_{L,i} \times ff_i \times Z_i}{A_{f,i}} \qquad (7.4)$$

$$\begin{aligned} G_{L,i} \leq 0.095: \; & C_{1,i} = 52.2 G_{L,i}{}^2 - 9.94 G_{L,i} + 1.433 \\ G_{L,i} > 0.095: \; & C_{1,i} = 0.96 \end{aligned} \qquad (7.5)$$

In Equation (7.4) $A_{g,i}$ is the total area of glazing in the dwelling; g_L is the light transmittance factor[47]; ff_i is the frame factor (Table 7.9); Z_i is the light access factor and $A_{f,i}$ is the floor area of the dwelling. The EHCS does not include information on the relative shading factors for different dwellings. This is resolved by randomly taking values from a Gaussian distribution created from known information about shading

44. http://www.linanwindow.com/light/index.htm
45. See Figure 2.3 for existing penetration levels of different types of lighting.
46. These equations have been taken directly from the SAP energy calculation procedures.
47. Light transmittance factor for single glazing: $g_L = 0.9$; double glazing: $g_L = 0.8$.

factors for typical English dwellings. In England the mean light access factor, Z , is 0.75 and the standard deviation is 0.08 with limits that range from 0.5 to 1.0. Each dwelling is therefore assigned a light access factor that is drawn at random from this probability density function representing the range of light access factors for English dwellings. Demand for lighting also changes over the year. In winter it is generally darker and therefore people require more lighting. An example of this is shown in Figure 7.5. Simulating this effect requires the annual lighting demand profile to be mapped onto a sinusoid over 365 days. The function used to simulate this is derived and given by Equation (7.6)

$$\mathbf{Q}_{L,id} = Q_{L,i}\left(\frac{1+0.48\cos\left(2\pi.d/365\right)}{365}\right) \qquad \text{(kWh/day)} \qquad (7.6)$$

In Equation (7.6) $\mathbf{Q}_{L,id}$ is the daily lighting energy demand for dwelling *i* on day *d*. By summing over *d*, the annual energy lighting demand can be calculated for each dwelling and is given by $Q_{L,i}$. Energy consumed for lighting indirectly contributes to internal heat gains. It is possible to validate the approximation used in Equation (7.6) using Stoke's equation (Stokes et al., 2004) and Richardson's simulations (Richardson et al., 2009). Stoke's equation was developed from half-hourly recordings of electricity demand from 100 UK dwellings, and so is based on empirical data. Richardson's model is based purely on simulation results but was validated using Stoke's empirical data. When comparing the approximation presented in (7.6) lighting demand was calibrated for a typical dwelling using approximately ~709 kWh/year. As shown in Figure 7.4, the approximation given by Equation (7.6) performs well when estimating a typical dwelling's annual lighting requirement when compared with other models.

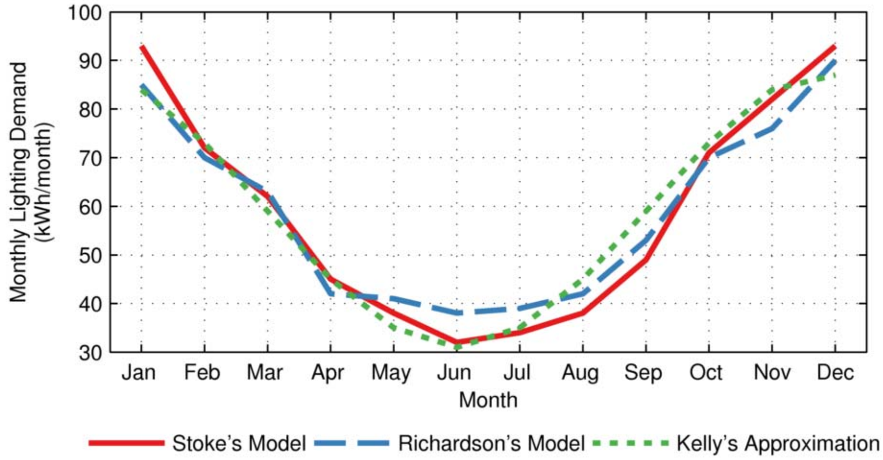

Figure 7.4: Validation of lighting energy demand equation

First, annual lighting energy demand is estimated using Equations (7.2) and (7.3) then daily lighting demand is estimated using Equation (7.6). The daily demand for electricity used for lighting can thus be estimated for each dwelling simply knowing the annual demand for lighting. Figure 7.5 gives a lighting energy demand density plot that shows how daily lighting energy demand changes over the year for the stock. The intensity of colour in Figure 7.5 represents the concentration of dwellings having similar daily lighting energy demands. As expected, lighting demand is lowest during the summer (~0.5 - 1.5 kWh/day) and highest during the winter (~1.8 - 4.0 kW/day). The variability in lighting demand across the building stock is maximal in winter. Figure 7.6 is a weighted histogram plot showing the distribution of annual lighting energy demand in the residential sector.

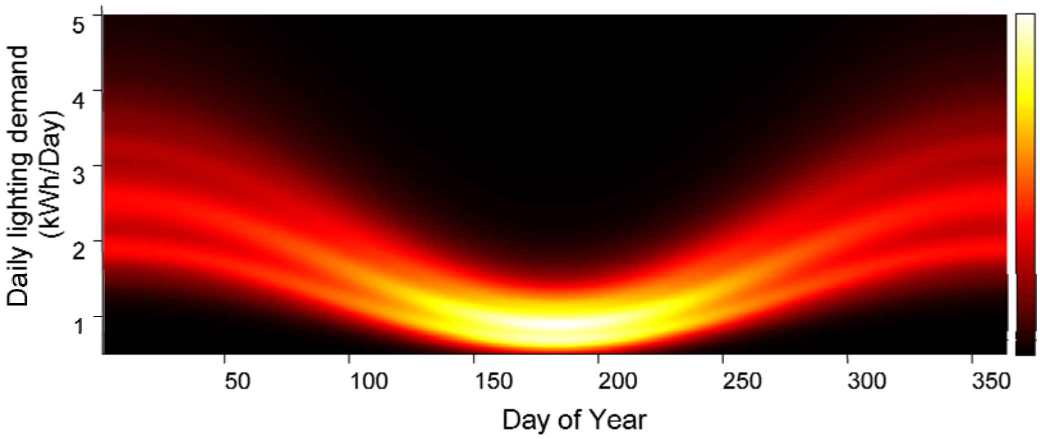

Figure 7.5: Lighting electricity demand density plot in the residential sector

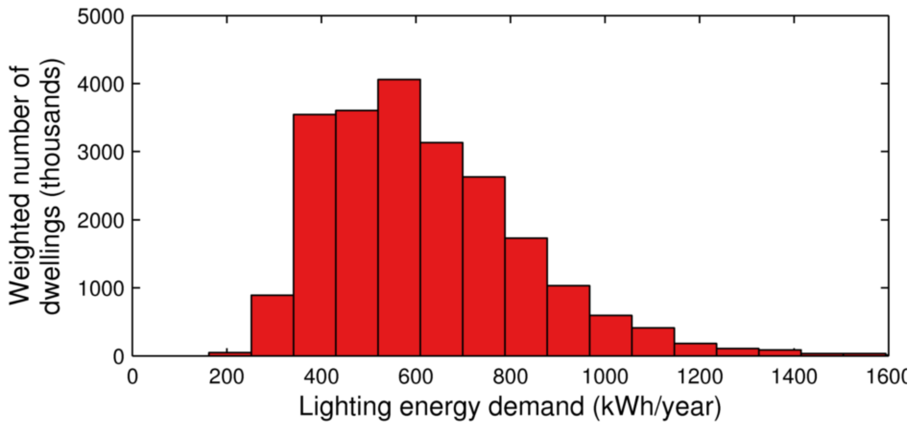

Figure 7.6: Weighted histogram of annual lighting energy demand in the residential sector

7.4.4 Energy demand from electrical appliances

Similar to lighting demand, the annual household demand for electricity from appliances $Q_{A,i}$ is modelled as a function of floor area, $A_{f,i}$ and the number of occupants living in the dwelling; N_i . Equation (7.7) is adapted from SAP methodology and gives the annual plug-load of a dwelling, *i,* for all electrical appliances.

$$Q_{A,i} = 207.8\left(A_{f,i}.N_i\right)^{0.4714} \qquad \text{(kWh/year)} \qquad (7.7)$$

Appliances include fridges, freezers, dishwashers, washing machines, consumer electronics and computing equipment. Similar to lighting demand, the overall efficiency of appliances and the saturation of different appliances over time leads to changes in demand for electricity. Demand for appliances also fluctuates throughout the year. An equation is therefore derived to estimate appliance plug load over the year. Given the demand for appliances does not experience as much seasonal fluctuation as lighting, the annual profile from appliance energy demand is less pronounced (Richardson et al., n.d.). Possible explanations for an increase in appliance plug load during winter months in UK could be due to the fact that people spend more time indoors therefore increasing the number of opportunities for appliances to be switched on such as television sets. Equation (7.8) estimates the sinusoidal annual appliance energy demand profile over a year. Figure 7.7 represents the plug-load dwelling density plot and shows how daily electricity demand from appliances varies over the year and over the residential sector. Figure 7.8 is a weighted histogram of annual appliance plug load for the building stock.

$$\mathbf{Q}_{A,id} = Q_{A,i}\left(\frac{1+0.1\cos\left(2\pi.days/365\right)}{365}\right) \qquad \text{(kWh/day)} \qquad (7.8)$$

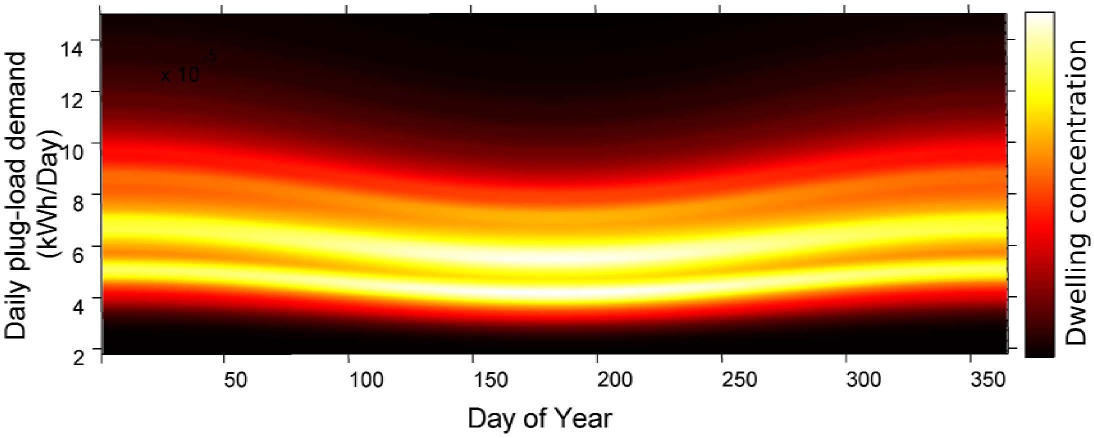

Figure 7.7: Electricity plug-load density plot for the residential sector

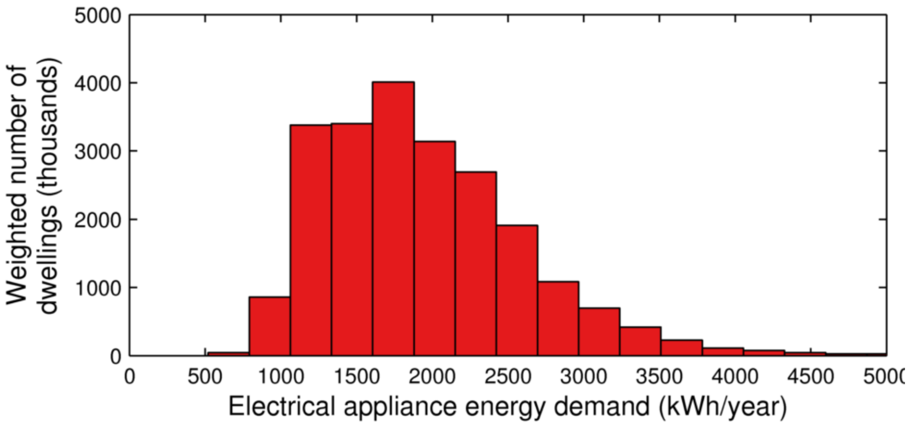

Figure 7.8: Weighted histogram of annual appliance plug load in the residential sector

7.4.5 Energy demand from cooking appliances

The SAP methodology does not allow for the calculation of energy consumed from cookers so the methodology used in BREDEM was adapted for this model. Two types of cookers are modelled: (i) gas hob and electric oven; (ii) electric hob and electric oven. Information on cooker type is not provided in the EHCS so the cooker type is derived using the main fuel category for each dwelling. The respective cooker fuel consumption for each dwelling is given by the following equations:

$$\begin{array}{ll} \text{Electric oven:} & \mathrm{Q}_{ce,i} = (0.473 + 0.094N_i) \\ \text{Gas oven:} & \mathrm{Q}_{cg,i} = (0.414 + 0.833N_i) \\ & \mathrm{Q}_{ce,i} = (0.236 + 0.047N_i) \end{array} \qquad \text{(MWh/year)} \qquad (7.9)$$

In Equation (7.9) $Q_{ce,i}$ and $Q_{cg,i}$ are the estimated annual energy consumption values for electricity and gas for each dwelling *i*; with N_i is the number of occupants. Total cooker energy demand is given by the histogram in Figure 7.9.

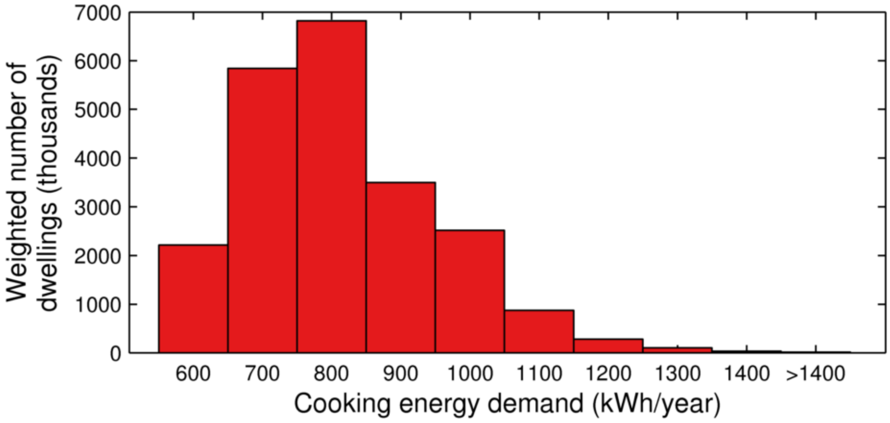

Figure 7.9: Weighted histogram of annual appliance cooking demand in the residential sector

7.4.6 Hot water demand

Hot water energy demand includes the energy and water consumed for domestic purposes other than for direct heating (e.g. showering, washing dishes etc). It is well recognised that hot water demand is largely a function of the number of people living in the dwelling and the personal preferences relating to the amount of time spent bathing (Wright, 2008). Parker (2003) shows that hot water energy demand is foremost a function of the number of occupants living in the dwelling with secondary factors including external temperature, seasonality and day of the week. The majority of building stock models use dwelling occupancy to derive hot water demand. This approach was identified as the most appropriate method. The amount of energy required to heat water from its inlet temperature is also allowed to vary over the year. The total energy required for hot water is therefore the energy required to heat water to the required temperature for a given number of people while taking into account losses in combustion, storage, heating and distribution. The annual hot water energy demand requirements for each dwelling can therefore be defined by Equation (7.10).

$$\mathbf{Q}_{hw,id} = \mathbf{Q}_{dl,id} + \mathbf{Q}_{pl,id} + \mathbf{Q}_{cyl,id} + \mathbf{Q}_{e,id} \qquad \text{(kWh/day)} \qquad (7.10)$$

In equation (7.10) $\mathbf{Q}_{hw,id}$ is the total hot water energy demand; $\mathbf{Q}_{dl,id}$, is the distribution losses associated with transporting hot water around the home; $\mathbf{Q}_{pl,id}$, is the primary network losses associated with the boiler; $\mathbf{Q}_{cyl,id}$ is the cylinder losses from hot water storage; and finally, $\mathbf{Q}_{e,id}$ is the hot water end-use demand requirements of users. Losses associated with distribution and storage of hot water, indirectly contribute to space heating and thus will be used to estimate space-heating requirements later in Section 7.5. Equation (7.11) was developed using a modified version of the SAP hot water demand equation and recent findings from Aguilar (2005) showing the relationship between hot water demand and occupants is monotonically increasing concave (Figure 7.10). A robust estimate for hot water demand is therefore given by the annual hot water demand equation, where, $\dot{m}_{u,i}$, is the flow rate of hot water per day per dwelling and N_i is the number of occupants.

$$\dot{m}_{u,i} = 50 + 35N_i - 2N_i^{1.9} \qquad \text{(litres/day)} \qquad (7.11)$$

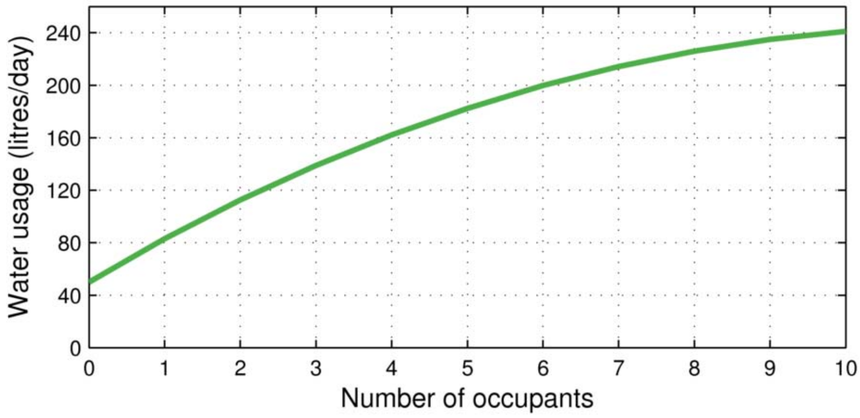

Figure 7.10: Hot water demand by occupancy

Once daily hot water demand has been estimated it is straightforward to calculate the energy required to heat water to its required temperature to meet this usage demand. Using the principles of thermodynamics and the known properties of water it is possible to calculate energy demand for each dwelling, *i,* on each day of the year, *d*, $\mathbf{Q}_{e,id}$ from Equation (7.12).

$$\mathbf{Q}_{e,id} = \rho \dot{m}_{u,id} C_p \Delta T_d \qquad \text{(kJ)}^{48} \qquad (7.12)$$

In Equation (7.12) ρ is the density of water (985 kg/m^3 @ 70°C), C_p is the specific heat of water (4.19 kJ/kg) and ΔT_d is the change in temperature required to heat the water on

48. To convert to kWh multiply by 2.78 x 10 $^{-4}$

each day of the year (Table 7.6). Distribution losses associated with the delivery of hot water around the dwelling are estimated to be fixed at 15% of total hot water energy demand. Primary losses $\mathbf{Q}_{pl,id}$ are the losses associated with the boiler and pipe work and are derived using temperature values from Table 7.6. Storage losses $\mathbf{Q}_{cyl,id}$, are those losses associated with storing water in the cylinder. Ideally the manufacturers' specifications are used, but as this information is not available for each of the 16,216 dwellings, it is necessary to derive the energy loss from cylinder size, type of insulation and thickness of insulation. Equation (7.13) gives the equation used to calculate the energy losses from storage cylinders. This is the same method used by SAP. Equations (7.13) to (7.16) give the analytical solution used by the model to estimate energy losses from cylinders.

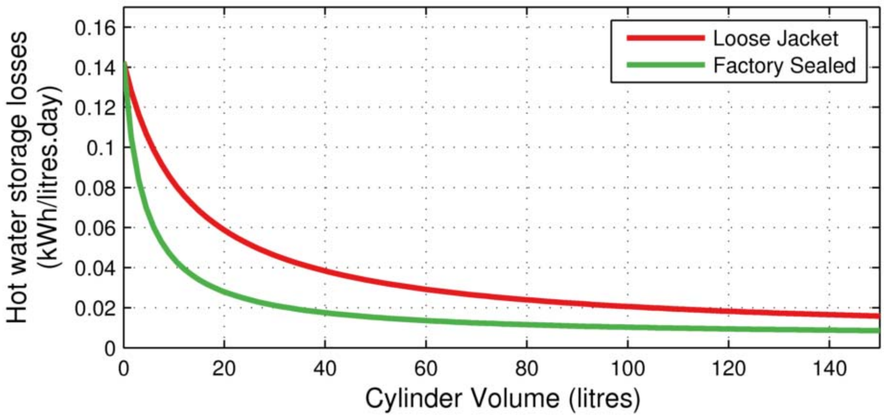

Figure 7.11: Hot water storage losses by cylinder volume

$$Q_{cyl,i} = V_i \alpha \beta \tau \quad \text{(kWh/year)} \tag{7.13}$$

$$\alpha_i = \begin{cases} 0.05 + 1.76(t_i + 12.8); & \textit{if loose cylinder jacket} \\ 0.05 + 0.55(t_i + 4.0); & \textit{if factory insulated cylinder} \end{cases} \tag{7.14}$$

$$\beta_i = (120 / V_i)^{1/3} \tag{7.15}$$

$$\tau = \phi_1 \phi_2 \phi_3 \tag{7.16}$$

In Equation (7.13), $Q_{cyl,i}$, is the energy lost from the cylinder; V_i is the volume of the cylinder (litres); α_i, is the cylinder loss factor derived from the thickness of insulation and cylinder insulation type (Figure 7.12), β_i, is the volume factor as given by Equation (7.15); and, τ, is the temperature factor[49] (BRE, 2005).

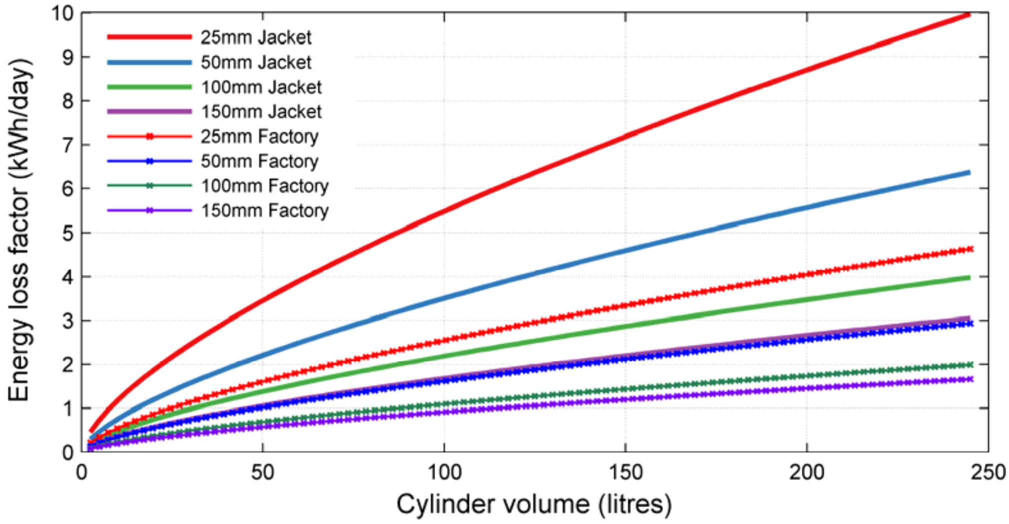

Figure 7.12: Energy loss factor for different cylinder insulation thicknesses

A distinction is made between instantaneous water heating, where water is heated when it is required, and hot water storage. When hot water is delivered instantaneously, there are no primary or cylinder losses. Distribution losses are still calculated for instantaneous heaters except for the case of single-point (as opposed to multi-point heating) where water is heated where it is used. A breakdown of modelled hot water energy demand for ten randomly selected homes is shown Figure 7.13. It shows the variation of hot water energy demand for different forms of losses over the building stock. Figure 7.14 is a weighted histogram showing the distribution of hot water demand for the residential sector as predicted by the model.

49. ϕ_1 = 0.6 if an electric immersion heater is present and ϕ_1 = 1.0 otherwise
ϕ_2 = 1.3 if the cylinder thermostat is absent and ϕ_2 = 1.0 otherwise
ϕ_3 = 0.81 if there is a separate timer on the cylinder ϕ_3 = 1.0 otherwise

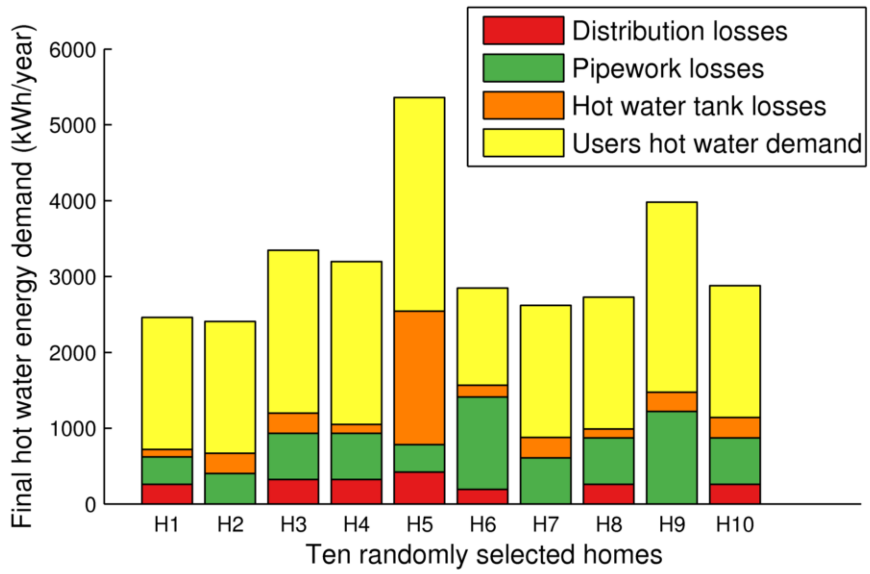

Figure 7.13: Hot water energy consumption from ten randomly selected homes

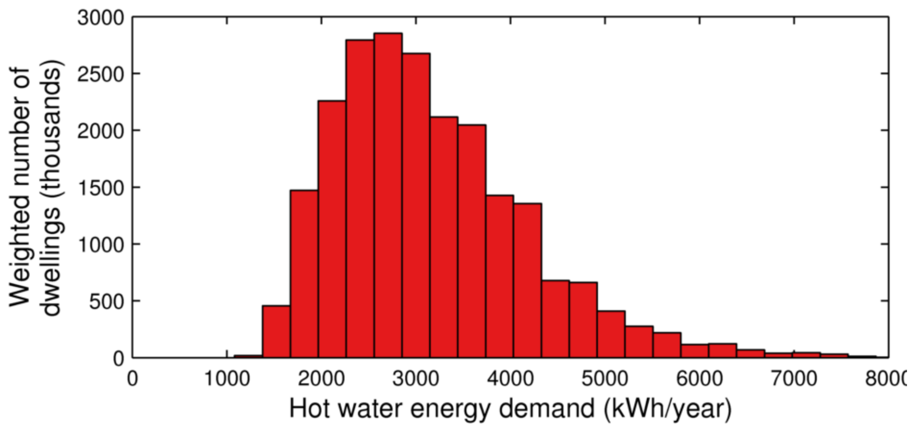

Figure 7.14: Weighted histogram of annual hot water demand in the residential sector

7.5 Space heating demand

Around 60% of the total energy consumed in English dwellings is for space heating (DECC 2011). Heat transmission through the building envelope is therefore one of the most important considerations when modelling dwelling energy consumption. Each dwelling in the model has a unique set of building envelope characteristics that combine to give the overall energy loss from the building. In this model every dwelling consists of five basic elements: (i) exposed roof; (ii) exposed walls; (iii) glazing; (iv) floors; (v) thermal bridges; and, (vi) infiltration and ventilation. The dimensions and materiality for each dwelling are available from the EHCS thus making it possible to estimate heat transmission through the building envelope. With information on the materials used for constructing the building fabric, it is possible to determine the material and thermal characteristics of these materials and then simulate energy loss. In this model it is assumed that non-exposed walls (internal walls) are shared with other heated spaces or dwellings. Thus all non-exterior walls are excluded from the analysis.

Using simple thermodynamic principles it can be shown that the heat transfer through any medium is a function of the material properties of the medium and the difference in temperature on either side of the medium. The U-value (or specific heat loss coefficient) represents the rate of heat transfer through the medium, over which there is a temperature difference (e.g. the internal and external temperatures of a dwelling). Once the material properties of the medium and the internal and external temperatures are known, it is possible to calculate the energy being dissipated through the building fabric. The standard thermodynamic equation used for calculating the thermal energy loss of any element, *j*, is thus given by Equation (7.17).

$$\dot{Q}_{T,\,i} = \sum_{j} A_{ij} U_{ij} \Delta T_i \qquad \text{(kW)} \qquad (7.17)$$

In Equation (7.17) *j* is the external element under consideration for dwelling, *i*; $\dot{Q}_{T,i}$, is the energy required to maintain the dwelling at the specific internal temperature T_{int}; A_{ij} is the area of element *j*; U_{ij} is the U-value and is a constant measuring the rate of heat transmission through element *j*; and, ΔT_i is the difference between internal and external temperatures $\left(\Delta T_i = T_{int,i} - T_{ext,i}\right)$. Therefore, Equation (7.17) gives the instantaneous rate of energy loss through element, *j*. If on the other hand the energy loss over a period of time is required, then Equation (7.17) needs to be integrated over time, *t*. Therefore, Equation (7.18) gives the energy required to maintain the internal temperature at a constant level over the specified time period.

$$Q_{t_1,i} - Q_{t_0,i} = \int_{t_0}^{t_1} \sum_{j} \mathbf{A}_{ij} \mathbf{U}_{ij} \Delta T_i \; dt \qquad \text{(kWh)} \qquad (7.18)$$

Both internal and external temperatures vary over time making it difficult to estimate heat loss directly without making assumptions about temperature profiles. Most models therefore assume constant temperatures. The most accurate method is to estimate Δt using very small time steps. However, this approach is infeasible due to the copious amount of temperature data – both internal and external – that would be required for each dwelling over the year. Here, an alternative method is proposed using heating degree-days

(HDD). The use of HDD in building energy models is not a new concept and a very simple application of HDD has already been adopted by the first versions of BREDEM. SAP on the other hand does not use HDD but instead calculates energy demand from average internal monthly temperatures and regional monthly external temperatures (one of the least accurate methods). In BREDEM, HDD are calculated on a monthly basis where the base temperature of a dwelling is estimated as an arbitrary function of heat gains and losses for each dwelling. This is a crude assumption that has led many building stock modellers to rightly question the robustness of the HDD method (Layberry, 2009). The innovation in this model is that HDD are estimated on a daily basis using an independently derived internal temperature equation. Thus the internal temperature for each dwelling for each day of the year is used to estimate a corresponding HDD value. All building stock models developed to date estimate HDD days on a monthly or seasonal basis limiting the true variability of temperature demand in the building stock. By letting $t_0 = 0$ and integrating over one day (24 hours) it is possible to derive HDD over one day and then estimate the total energy loss through the building fabric over that day. This is a significant improvement on other methods.

$$\Delta\mathbf{Q}_{h,id} = \sum \mathbf{A}_{ij}\mathbf{U}_{ij}.\mathbf{DD}_{id}.24 \qquad \text{(kWh/day)} \qquad (7.19)$$

In Equation (7.19) $\mathbf{Q}_{h,id}$ is the total energy loss for dwelling i from heat transmission through the building fabric over a periof of 24 hours and $\mathbf{DD}_{id}$ are the heating degree-days for each dwelling on each day of the year.

HDD are thus calculated as the integrated temperature difference for each day of the year. The model therefore considers both the extremes and the duration in temperature profiles. Providing independent degree-days for each dwelling for each day of the year allows more accurate estimation of energy demand. Each HDD is independently calculated using the daily internal temperature demand for each dwelling and the external temperature for each geographic region. This approach is unique because it estimates degree-days at the individual building level and calculates energy demand both temporally (over the year) and spatially (over the UK). Previous models assume constant average internal temperatures and therefore must make dubious assumptions about the length of the heating season. This is shown to be an erroneous approach and does not allow for the heterogeneity of energy demand from different dwellings. Because this approach estimates unique HDD for each dwelling for each day of the year it is not necessary to make assumptions about the length of the heating season. This is because HDD will approach zero as the external temperature approaches and exceeds the internal base temperature of each dwelling. Thus the length of the heating season for each individual dwelling is endogenously estimated.

7.5.1 Calculating losses from the dwelling

Estimating fabric losses requires each dwelling to be separated into six distinct building components. These are (i) exposed roof; (ii) exposed walls; (iii) windows; (iv) floors; (v) thermal bridges; and, (vi) ventilation and infiltration. The overall heat loss parameter H_i for each building element can therefore be defined using Equation (7.20).

$$\mathbf{H}_i = \sum_j \mathbf{A}_{ij}\mathbf{U}_{ij} \qquad \text{(W/K)} \qquad (7.20)$$

Summing the heat loss parameters (HLP) for each building element gives the total heat loss parameter for a building.

$$H_{T,i} = H_{r,i} + H_{w,i} + H_{g,i} + H_{gf,i} + H_{b,i} \qquad \text{(W/K)} \qquad (7.21)$$

Where, $H_{T,i}$ represents the HLP for the entire building; $H_{r,i}$ is the HLP for the roof; $H_{w,i}$ is the HLP for exposed external walls; $H_{g,i}$ is the HLP for glazing; $H_{gf,i}$ is the HLP for the ground floor; and, $H_{b,i}$ is the HLP for thermal bridges.

7.5.2 Heat loss parameter for the exposed roof

The equation for estimating the HLP from the dwelling roof is given by Equation (7.22). $H_{r,i}$ is the HLP for the roof on dwelling *i*; $A_{r,i}$ is the roof plan area and $U_{r,i}$ is the dwelling specific U-value for the roof.

$$H_{r,i} = A_{r,i}U_{r,i} \qquad \text{(W/K)} \qquad (7.22)$$

The heat loss parameter for exposed roofs $H_{r,id}$ includes the material properties for everything between the ceiling and the outer layer of the external roof. Because the U-value depends on a large number of different and very specific details about the roof covering, roof space and construction material, it is a very difficult to estimate the U-values for each dwelling accurately. An almost inexhaustible number of materials used in various combinations in the construction of the roof make this a difficult problem to solve. Other considerations such as converted loft spaces, the pitch angle of the roof and thermal bridges (created due to inadequate insulation between joists) all have measurable effects on the rate of heat loss through the roof of a dwelling. The methodology chosen utilises as much information as is available in the EHCS to construct best estimates about the materiality of the roof to calculate the HLP.

The calculation procedure first determines if the insulation thickness in the roof for each dwelling is known. If the insulation thickness is known and the roof is not flat then the U-value is estimated from the insulation thickness and roof covering type (slates and tiles or thatched roof) using (Table 7.10). Approximately 75% of all cases from the EHCS are therefore captured using this method. If roof insulation thickness is unknown then U-values are assigned based on six different roof construction types and eleven dwelling age brackets (Table 7.12). There are two options for pitched roofs that allow for differences in the amount of loft space available. Further options exist for buildings with flat roofs, rooms in the attic and buildings with thatched roofs[50]. The material properties such as U-values are adapted from SAP data tables. Figure 7.15 is a weighted histogram showing the distribution of roof insulation thicknesses in the residential sector in England.

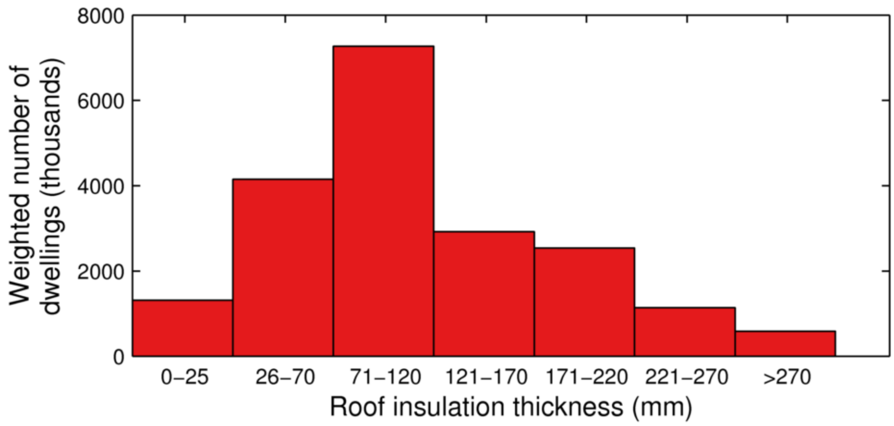

Figure 7.15: Weighted histogram of dwelling roof insulation thicknesses

7.5.3 Heat loss parameter of exposed walls

The HLP, $H_{w,i}$, for walls is calculated using Equation (7.23). The U-value is derived using SAP methodology and incorporates the wall construction type and the age of the

50. Thatched roofs have the best insulation properties when compared to other roof types.

dwelling. The EHCS includes information on dwelling age, wall construction type and the internal area of all external walls. The majority of building stock models assume energy loss is a function of building typology (e.g. detached, semi-detached, bungalow etc) rather than the construction material the building is made from (UKDCM, DECM etc). This model improves on these assumptions by using the physical properties of the construction material rather than building typology and therefore improves the accuracy of the model for calculating heat losses using thermodynamic equations rather than generalisations about energy losses based on building typology.

$$H_{w,i} = A_{w,i} U_{w,i} \qquad \text{(W/K)} \qquad (7.23)$$

7.5.4 Heat loss parameter for exposed glazing

The amount of glazing has several important effects on dwelling energy consumption. Windows typically have very high U-values and therefore a significant proportion of heat is usually lost through glazing. However, in warm sunny weather glazing allows for radiant energy from the sun to heat a dwelling and therefore increase internal temperature. Although at times this can be beneficial, if not managed correctly, it can also sometimes also lead to over-heating. Finally, light that is allowed to penetrate through a window has a measurable effect on the overall lighting requirements of a dwelling. This model captures the dynamics of each of these different effects from glazing. Here, the focus is on energy loss through glazing due to conductive heat transfer. Calculating the total conductive heat transfer from glazing requires information about the U-value and the area of exposed glazing. The U-value depends on the number of layers of glazing (i.e. single, double or triple glazing) and the window frame installed in the dwelling. Accurately estimating heat loss through windows requires information about the proportion of windows that are single, double and triple glazed and the predominant type of window frame in the dwelling. This data is all available within the EHCS. The glazing heat loss parameter $H_{g,i}$ can be calculated using Equation (7.24).

$$H_{g,i} = \sum U_{1g,i} A_{g,i} f_{1,i} + \sum U_{2g,i} A_{g,i} f_{2,i} + \sum U_{3g,i} A_{g,i} f_{3,i} \qquad \text{(W/K)} \qquad (7.24)$$

where, $$f_{s,i} + f_{d,i} + f_{t,i} = 1 \qquad (7.25)$$

Here, $U_{1g,i}, U_{2g,i}, U_{3g,i}$, are the U-values for single, double, and triple glazing respectively; $A_{g,i}$ is the total area of glazing; and f_i is the fraction of each glazing type in the dwelling which sums to unity. Although participants of the EHCS were not asked about how much triple glazing they had installed in their homes, only a very small proportion of homes in England have triple glazing. This, however, does not preclude the fact that occupants may wish to install triple glazing in their home in the future and so this was included in the model.

The EHCS gives four options for the overall proportion of double-glazing installed in a dwelling. These range from dwellings with none; one-third; two-thirds and full double-glazing. Table 7.11 gives the U-values for different levels of glazing and window frame characteristics. Figure 7.16 is a weighted histogram showing the distribution of dwelling glazing area in the English building stock.

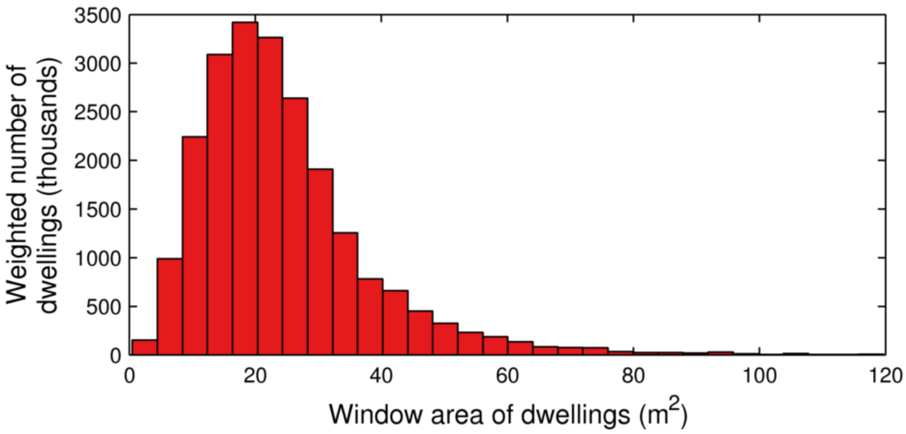

Figure 7.16: Weighted histogram of dwelling glazing area

7.5.5 Heat loss parameter for floors

The U-value for floors is calculated using the BS EN ISO 13370 methodology. The U-value for floors is a function of ground floor area, $A_{gf,i}$, the external perimeter of the building P_i, and the thermal conductivity of floor material including insulation. Two equations are defined one for solid ground floors and one for suspended floors. Factors, B_i and $d_{ins,\,i}$ are common to both floor types.

$$B_i = 2\frac{A_{gf,i}}{P_i} \tag{7.26}$$

$$R_{f,i} = \frac{0.001 d_{ins,i}}{0.035} \qquad (m^2K/W) \qquad (7.27)$$

Where: B_i represents the ground floor area to perimeter ratio;

$R_{f,i}$ is the thermal conductivity of a floor including any insulation; and,

d_{ins} is the thickness of insulation contained within the floor (mm).

Equations (7.28) and (7.29) are used for solid floors:

$$dt_i = w_i + \lambda_{gi}\left(R_{si,\,i} + R_{f,\,i} + R_{se,\,i}\right) \qquad (7.28)$$

$$\begin{aligned} &if \quad dt_i < B_i, \quad U_{f,i} = \frac{2\lambda_{g,i}\ln\left(B_i\pi / dt_i + 1\right)}{\left(B_i\pi + dt_i\right)} \\ &if \quad dt_i \ge B_i, \quad U_{f,i} = \frac{\lambda_{g,i}}{\left(0.457B_i + dt_i\right)} \end{aligned} \qquad (W/m^2K) \qquad (7.29)$$

Where: w is the thickness of the wall (Table 7.13);

λ_g is the thermal conductivity of clay (1.5 W/m.K);

R_{si} is the surface resistance downwards through the floor (0.17 m^2K/W);

R_{se} is the surface emissivity factor (0.04 m^2K/W);

dt_i is a decision parameter that determines which equation to use; and,

U_{gf} is the calculated U-value of the solid floor

For suspended floors Equations (7.31) and (7.32) are used:

$$d_{g,i} = w_i + \lambda_{g,i}(R_{si,i} + R_{se,i}) \qquad (7.30)$$

$$U_{x,i} = 2hU_w / B_i + \left(1450 \times \varepsilon \times v \times f_w / B_i\right) \qquad (W/m^2K) \qquad (7.31)$$

$$U_{S,i} = \frac{1}{2R_{si} + R_f + 0.2 + \frac{1}{U_{f,i} + U_{x,i}}} \qquad (W/m^2K) \qquad (7.32)$$

Where: $U_{x,i}$ is the composite U-value between the floor and the ground;

$U_{f,i}$ is calculated using Equation (7.29)

U_w is the U-value of walls to under floor space (1.5 W/m^2K)

h is the height above external ground (0.3 m);

υ is the average wind speed at 10 m height (5 m/s);

f_w is the wind shielding factor (0.05);

ε is the length of ventilation for the exposed perimeter (0.003 m^2/m);

R_f is the thermal resistance of the floor deck (0.2 m^2K/W); and,

d_{gi} is a decision parameter that determines the equation (Equation (7.30));

The wall thickness w_i, is a function of wall type and dwelling age as given by Table 7.13 When the floor insulation thickness d_{ins} is missing from the EHCS, it is determined from Table 7.14 and is purely a function of the age of the dwelling. Figure 7.17 gives a weighted histogram of floor areas from the English residential sector.

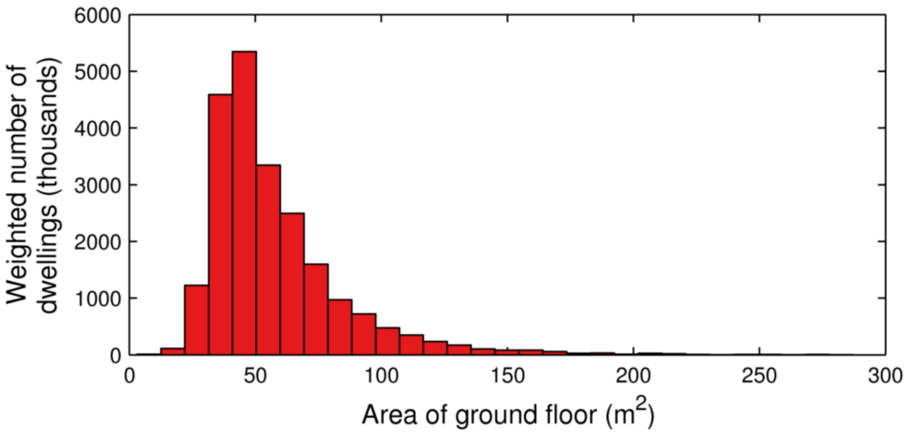

Figure 7.17: Weighted histogram of dwelling floor areas

7.5.6 Heat loss parameter for thermal bridging

Thermal bridges refer to specific areas of the dwelling envelope that allow energy conduction through paths of least resistance (Asdrubali et al., 2012). They are typically located around the joints of construction where insulation is both difficult and expensive to install. Thermal bridges can have a significant effect on the energy performance of a dwelling. They are considered to be a consequence of poor construction and are almost impossible to get rid of entirely – but good design, workmanship and good quality materials make a significant difference. For dwellings that have poor energy performance, the effect of thermal bridges is comparatively small compared with the dwellings total energy loss. However, as dwellings undertake significant energy efficiency improvements, whilst simultaneously not addressing thermal bridges, means the relative proportion of energy lost through thermal bridges increases significantly. If thermal bridges are not dealt with concurrently alongside other energy efficiency improvements, they may become one of the most significant energy loss factors within a dwelling. In the absence of better empirical data on thermal bridges from UK dwellings, the methodology from SAP is applied as given by Equation (7.33).

$$H_{b,i} = 0.15\Psi_i A_{w,i} \qquad \text{(W/K)} \qquad (7.33)$$

In Equation (7.33), $H_{b,i}$ is the thermal bridge HLP; Ψ_i is the thermal bridge U-value that depends on building age; and, $A_{w,i}$ is the total internal area of externally exposed walls. Table gives the U-values for different aged dwellings.

7.5.7 Heat loss parameter for ventilation and infiltration

Energy losses through ventilation and infiltration depend on a large number of factors many of which may not be known and are difficult to estimate. For example the permeability of different building materials, the quality of construction, the age of the building, old chimney flues, and any gaps around doors and windows all contribute to the permeability of a dwelling. Even though adequate ventilation is necessary for the health safety and comfort of occupants, many dwellings in the UK are excessively ventilated leading to wasted energy and occupant discomfort.

The importance of building permeability has been known for some time (DETR, 2000) but was only made official when Part L of the UK building codes for new dwellings were amended to include a maximum air leakage target of 10 $m^3/h.m^2$ @ 50 Pa[51] for both domestic and non-domestic buildings (Johnston et al., 2004). Research has now found that only 41% of existing UK dwellings meets the 10 $m^3/h.m^2$ @ 50 Pa standard. However, reasonable levels of air tightness below 10 $m^3/h.m^2$ @ 50 Pa can be achieved if careful consideration is given to the choice of materials, the design of the building and construction workmanship.

The mean leakage rate of UK dwellings is approximately 11.48 $m^3/h.m^2$ @ 50 Pa . This is extremely high compared to European equivalents where it can be shown that UK dwellings are 2-3 times as leaky as dwellings in Belgium, Norway, Switzerland and Sweden (Johnston et al., 2011). And when compared to the German pasivhaus standard which requires buildings to have a leakage rate less than 0.75 $m^3/h.m^2$ @ 50 Pa the UK average is more than a factor of ten higher (Passivhaus Institute, 2012). This suggests

51. This gives the flow of air in m^3 per hour per m^2 of building envelope area at 50 Pa pressure. The rule of thumb for converting this value into standard pressure is to simply divide by 20.

significant savings may be possible through more concentrated effort to draught proof existing UK dwellings. Johnston et al.(2004) analysed a BRE database containing the permeability results of some 471 UK dwellings ranging in construction period from pre 1900 to 1994. Results from this analysis suggest that new dwellings perform no better than older dwellings (Figure 7.18). Contrary to this conclusion is a more recent study from Pan (2010) where the permeability of dwellings constructed post 2006 were tested and found to have an average air tightness of 5.97 $m^3/h.m^2$ @ 50 Pa suggesting significant improvements have been made in the UK construction standards post 2006 to improve the air tightness of new dwellings.

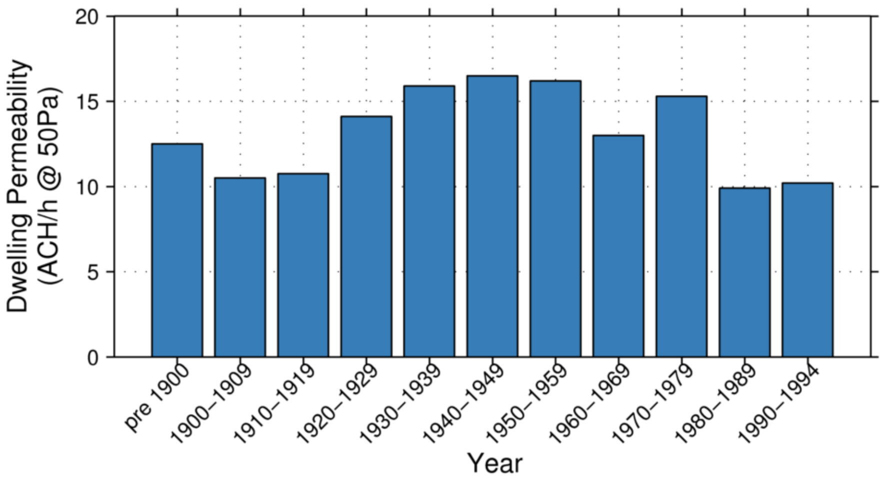

Figure 7.18: Air permeability by dwelling age
Data source: (Johnston et al., 2004)

The only accurate way to calculate the permeability and therefore the infiltration rate of dwellings is through a pressurisation test. Unfortunately this information is both expensive and time consuming to collect and was therefore not included in the EHCS. In the absence of more robust empirical evidence giving details about the permeability of different building classes, the methodology outlined in SAP was adopted. Calculating the infiltration rate for each dwelling requires information about the number of chimneys, fans, flues and passive vents as well as details about the leakiness through windows doors, building age and construction material. Building infiltration can therefore be defined using Equation (7.34).

$$\dot{\mathbf{V}}_{T,id} = \left(V_{m,i} + V_{st,i} + V_{a,i} + V_{c,i} + V_{f,i} + V_{seal}\right) E_f \,.\, W_{f,d} \qquad (\text{m}^3/\text{hour}) \qquad (7.34)$$

Where, $\dot{V}_{T,i}$ is the total ventilation rate for dwelling i; $V_{m,i}$ is the sum of ventilation rates from the number of toilet fans, F_{wc} ; bathroom fans, F_{br} ; kitchen fans, F_k ; and passive vents and chimneys, F_{Ch} (Table 7.18). While $V_{st,i}$ is the ventilation rate from the number of stories of the dwelling where: $V_{st,i} = 0.1 \times Stories$; V_a is ventilation rate given as a function of the age of the building (Table 7.16); $V_{c,i}$ is the ventilation rate due to the construction material of walls (Table 7.17); $V_{f,i}$ is the ventilation rate for the floor type (e.g. solid, suspended, sealed or unsealed); E_f is the exposure factor for the building to the environment and is a function of the number of exposed walls where N_e ranges from 1 to 4; and, W_f is a wind factor that varies over the year. Equations (7.34) to (7.36) can then be used to estimate the ventilation rate of each dwelling, i[52].

$$V_i = nF_{wc,i} + nF_{br,i} + nF_{k,i} + nCh_i \qquad (\text{m}^3/\text{hour}) \qquad (7.35)$$

$$E_f = 1 - (0.075(4 - N_e)) \qquad (7.36)$$

Once the infiltration rate of a dwelling has been estimated, it is possible to calculate the energy lost due to infiltration using Equation (7.37)[53].

$$\mathbf{H}_{V,id} = C_{p,air}\rho\dot{\mathbf{V}}_{T,id} \times \frac{1000}{3600} \qquad (\text{W/K}) \qquad (7.37)$$

Where, $\mathbf{H}_{V,id}$ is the heat loss parameter from ventilation; $C_{p,air}$ is the specific heat capacity of air (1.005 kJ/kg°C); ρ is the density of air (1.2 kg/m^3) and $\dot{\mathbf{V}}_{T,id}$ is the total infiltration loss (m^3/hour). Figure 7.19 is a weighted histogram showing the distribution of infiltration rates from the residential sector in England where the average infiltration rate is 1.44 m^3/h.m^2.

52. For values given in ACH/hour, these were converted into m^3/hour by multiplying by the volume of the dwelling.
53. SI units require the volume flow rate to be given in kg/s so Equation (7.37) is multiplied by 1000/3600.

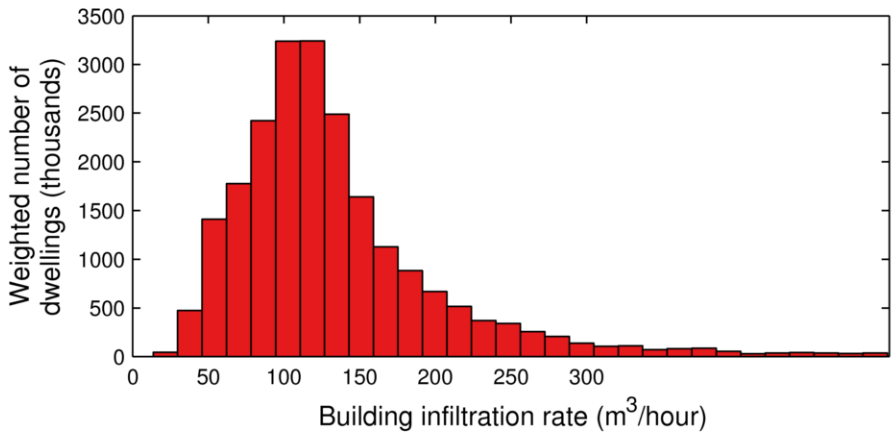

Figure 7.19: Weighted histogram of dwelling infiltration rates

7.5.8 Concluding remarks about the heat loss parameter

In sum, the heat loss parameter is a measure of the rate of heat loss from a dwelling and is a function of both the thermal characteristics and the area of the element where heat is being transmitted. Estimating the heat loss for each building element in each dwelling can then be calculated by multiplying the heat loss parameter by HDD. The heat loss parameter is therefore a good indicator for estimating the magnitude of heat losses from different building elements. This is shown for the residential sector in England in Figure 7.20. The largest range in values is from external walls; but energy loss through windows has the largest average loss. This analysis shows that infiltration and ventilation losses are a significant contributor to energy losses in the residential sector and must therefore be taken more seriously in future climate change mitigation policy.

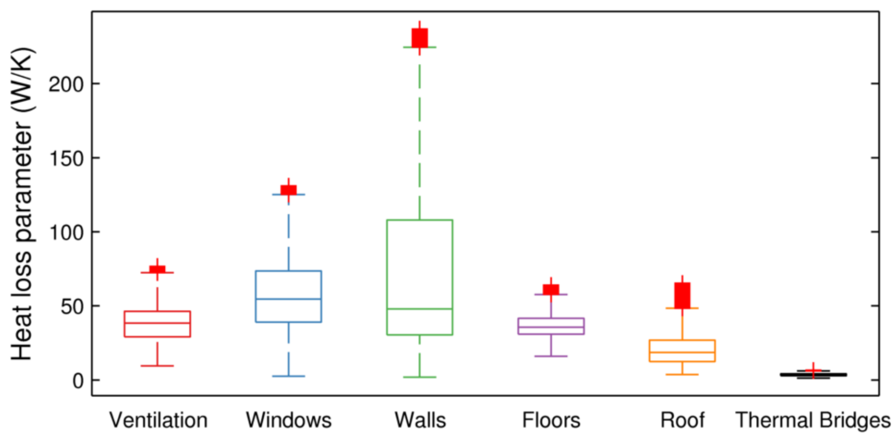

Figure 7.20: Box and whisker plots of the heat loss parameter for different building elements[1]

1. Outliers have been removed above twice the median value

7.5.9 Incidental gains

Estimating the amount of heating energy required to maintain the dwelling at a specific incidental temperature requires energy losses to be balanced against energy gains. There are many factors contributing to a dwellings incidental heat gains other than the heating system. These are identified in Equation (7.38).

$$\mathbf{Q}_{G,id} = \mathbf{G}_{l,id} + \mathbf{G}_{a,id} + \mathbf{G}_{hw,id} + \mathbf{G}_{c,id} + \mathbf{G}_{m,id} + \mathbf{G}_{s,id} + \mathbf{G}_{ht,id} \qquad \text{(kWh/day)} \qquad (7.38)$$

Where, $\mathbf{G}_{T,id}$ represents the total gain for dwelling i on day d; $\mathbf{G}_{l,id}$ represents the incidental gain from lighting; $\mathbf{G}_{a,id}$ represents the incidental gains from appliances; $\mathbf{G}_{hw,id}$ represents the incidental gains from hot water, $\mathbf{G}_{c,id}$ represents the incidental gains from cooking; $\mathbf{G}_{m,id}$ represents the metabolic gains from people, $\mathbf{G}_{s,id}$ represents the incidental gain from solar radiation through glazing, and $\mathbf{G}_{ht,id}$ is the solar gain due to insolation. Incidental gains from lighting and appliances are estimated using Equations (7.39) and (7.40).

$$\mathbf{G}_{l,id} = 0.9\mathbf{Q}_{l,id} \qquad \text{(kWh/day)} \qquad (7.39)$$

$$\mathbf{G}_{a,id} = 0.67\mathbf{Q}_{a,id} \qquad \text{(kWh/day)} \qquad (7.40)$$

Equation (7.39) represents the daily heat gain from lighting where it is assumed 90% of energy consumed by lighting is converted into heat contributing to a temperature rise inside the dwelling. This is true for all forms of lighting, however, more energy efficient lighting consume less energy and therefore a smaller overall quantity is converted to heat. Similarly, Equation (7.40) gives the heat gain that occurs due to the use of appliances, where it assumed that 67% of the energy consumed by appliances is converted to heat contributing to a rise in internal temperatures.

Incidental gains from hot water come from several sources (e.g. storage losses, primary network losses, distribution losses and heat loss from water at the point of end use). The energy consumed (lost) due to hot water storage, primary network utilisation and distribution are assumed to make a useful contribution to incidental gain, therefore any energy lost during the production and distribution of hot water (e.g. hot water pipes, storage etc) increases the temperature of the environment where the heating system is located. However, the majority of hot water that is consumed at the point of end use is lost down the drain. Therefore it is assumed that only 30% of end-use hot water consumption makes a meaningful contribution to internal heat gain the remainder is lost down the drain. Equation (7.41) defines the incidental gains attributable to hot water consumption.

$$\mathbf{G}_{hw,id} = \left(\mathbf{Q}_{dl,id} + \mathbf{Q}_{pl,id} + \mathbf{Q}_{cl,id}\right) + 0.30\left(\mathbf{Q}_{e,id}\right) \qquad \text{(kWh/day)} \qquad (7.41)$$

Similarly, the fuels used by ovens for cooking contribute to incidental gain. This is governed by Equation (7.42) where it assumed that 90% of energy used by cookers contributes to incidental gain. These equations have been adapted from standard SAP and BREDEM methodologies.

$$\text{Electric oven:} \quad \mathbf{G}_{c,id} = 0.9\mathbf{Q}_{C,id} \qquad \text{(kWh/day)} \qquad (7.42)$$

Metabolic heat gain is the energy that is released from human activity and is directly proportional to the number of people living in the dwelling. Rates vary depending on the size of the person and the level of activity. A typical metabolic rate for an adult male at rest is 100W. Allowing for different occupancy patterns, activity levels and different sized people, the average metabolic heat rate is assumed to be 80 W/person (Equation (7.43)). Figure 7.21 represents a box and whisker plot showing how incidental gains vary by different types of gains over the building stock.

$$\mathbf{G}_{m,i} = 80N_i \times \frac{24}{1000} \qquad \text{(kWh/day)} \qquad (7.43)$$

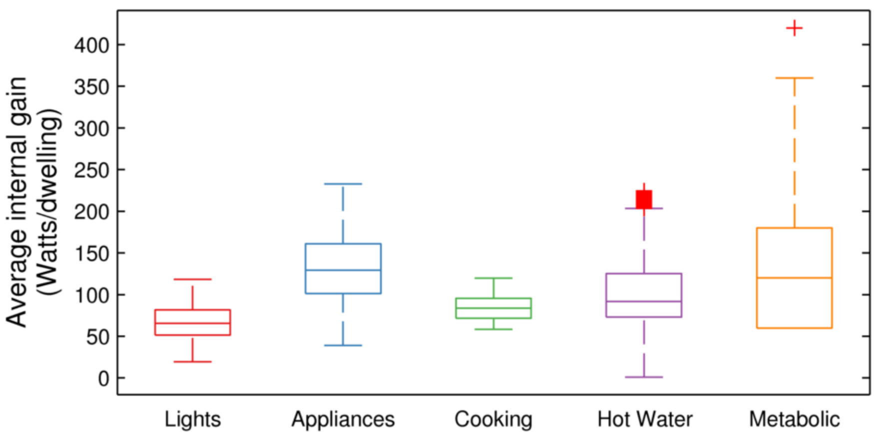

Figure 7.21: Box and whisker plot showing distribution of average incidental gains

1. Outliers have been removed above two times the median value0.

7.5.10 Solar gain

Insolation from solar radiation occurs throughout the year. However, solar irradiation that occurs during winter contributes much less to incidental gain, because the sky is generally more overcast, temperatures are much lower and the days are shorter. Nevertheless, solar gains are significant and must be included. This model allows for two forms of solar irradiation on dwellings. These are (i) solar gains that occur from direct solar radiation on glazing and (ii) solar irradiation being absorbed by opaque surfaces such as walls and roofs. The latter of these two forms of insolation are generally allowed for in detailed analysis of individual building energy simulations, but often neglected in building stock models. For example, none of the building stock models surveyed for this research incorporated the effect of insolation on opaque surfaces. This is most likely a limitation of these methods due to the way they handle temperatures. This is a significant oversight and may explain why many building stock models fail to estimate energy demand more accurately.

The periods most effected by insolation are the shoulder seasons (Autumn and Spring). This is because gains that occur in the summer do not contribute beneficially to heating (because heating is not required in summer) and solar gains occurring in winter are minimal compared gains that occur in spring and autumn. Because this model has been parameterised to solve energy consumption for each day the year, the effect of insolation on the building envelope is a significant factor and cannot be ignored. The model therefore represents the first time that insolation has been properly allowed for and included in a building stock model benefiting from daily estimations of energy demand.

The radiative energy absorbed by a dwelling requires accurate data on the amount of solar flux hitting a vertical surface. There are several factors that determine the magnitude of solar flux. These are the location of the dwelling; the time of the year; and the orientation of the building. CIBSE Guide J (CIBSE, 2002) provides mean irradiation data at different surface inclinations for each month of the year for three UK based locations. Direct beam radiation, diffuse radiation and reflected diffuse radiation on a vertical surface are used in this model for estimating the absorbed radiative energy on building façades. Summing all three forms of radiation gives the value for the global radiation on a vertically inclined surface (Table 7.20).

7.5.10.1 Insolation on the building façade

Solar radiation on exterior building surfaces has the effect of reducing heat loss through the building envelope (CIBSE, 1999). The majority of irradiation absorbed by the exterior of a building comes directly from the sun (beam radiation) but other indirect sources of radiation must also be considered such as diffuse radiation and reflected diffuse radiation (from the ground). Radiation is both absorbed and emitted from the building façade simultaneously. The net radiation energy balance is the difference between the radiation absorbed by the surface and the radiation emitted (CIBSE, 1999, sec.2 – 69). The exchange of irradiative energy is affected by the surface emissivity and absorptive properties of the façade material. On a clear, cloudless night the long-wave radiative flux coming from the external environment is low and the radiative flux emitted by a warm building is high, thus increasing the net radiative energy loss. On a sunny day, the net radiative energy loss from the building will be much less due to increased radiative energy being absorbed by the building façade from increased solar flux.

CIBSE Guide A estimates net radiative energy from a building façade as a function of the long-wave radiation absorbed by the facade from the sky and from the ground (W/m^2); the orientation of the surface; the external air temperature; cloud cover; and the Stefan-Boltzmann constant ($\sigma = 5.67 \times 10^{-8}$ W/m^{2}K^4). From these variables it is possible to estimate the sol-air temperature, $T_{sol-air}$, for different weather conditions at various times of the year and locations. In this model an analytical method is implemented that allows for both speed and flexibility, but also allows for different environmental and building characteristics to be incorporated. As the effect of external radiation on opaque external building structures have been neglected by existing building stock models, an analytical derivation of the sol-air temperature is presented.

Insolation on walls and roofs has the effect of warming the surface affecting the rate of conductive heat transfer (CIBSE, 1999). Consider the model presented in Figure 7.22 showing a cross section of the energy flows occurring across a typical building envelope due to incident solar radiation. In this figure solar flux transmitted through glazing is shown, but also how it is absorbed by opaque surfaces on the building façade including external walls and roofs, thus changing the thermodynamic properties of energy transfer.

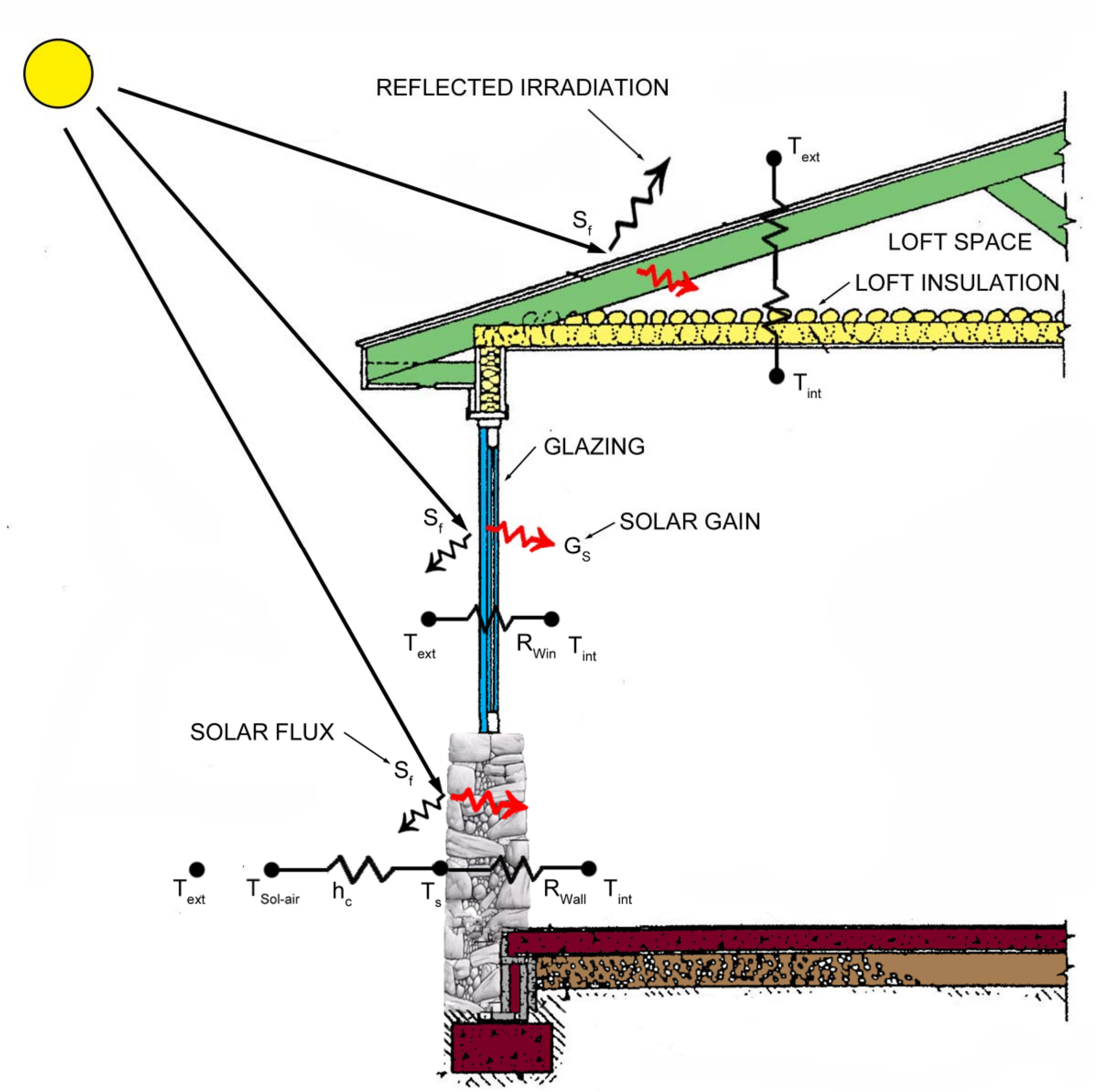

Figure 7.22: Cross section of building showing effect of insolation

In Figure 7.22; S_f is the daily solar heat flux which varies throughout the year; T_{ext} is mean daily external air temperature; $T_{sol-air}$ is the analytically calculated sol-air temperature; T_s is the surface temperature of the external wall; T_{int} is the mean daily internal temperature; h_c is the heat transfer convection coefficient (HTCC); R_{win} is the thermal resistance of glazing; R_{wall} is the thermal resistance of the wall[54]; and G_s is the solar gain directly caused by solar flux being transmitted through glazing. Energy loss through exterior walls is given by the following energy balance.

$$S_f \alpha + h_c \left(T_{ext} - T_s\right) = \left(T_{\text{int}} - T_s\right) U_{wall} \qquad \text{(kW)} \qquad (7.44)$$

54. The U-value is simply the reciprocal of resistance R

In Equation (7.44) α is the fraction of solar radiation absorbed by the wall and is a function of the absorptivity and emissivity of the wall[55]. The right hand side of this equation represents the heat transfer through the wall and the left side represents the energy gain from solar radiation and energy loss due to convective forces such as wind. It is now useful to reformulate the left side of this equation in terms of the effective outdoor sol-air temperature, $T_{sol-air}$. This is accomplished by defining;

$$S_f\alpha + h_c\left(T_{ext} - T_s\right) = h_c\left(T_{sol-air} - T_s\right) \qquad \text{(kW)} \qquad (7.45)$$

and then solving Equation (7.45) for $T_{sol-air}$ gives:

$$T_{sol-air} = T_{ext} + \frac{S_f\alpha}{h_c} \qquad \text{(K)} \qquad (7.46)$$

The sol-air temperature, $T_{sol-air}$, has now been defined as a function of the external temperature T_{ext}; the solar radiation S_f; the fraction of absorbed solar energy α; and the heat transfer convective coefficient (HTCC), h_c. As shown in Equation (7.46) solar radiation absorbed by exterior surfaces of buildings effectively increase the external air temperature by a fraction proportional to the solar flux, absorptivity of the wall and the HTCC. This can now be implemented by the standard thermodynamic equations already defined in Equation (7.19) but replacing the external temperature for the sol-air temperature (Figure 7.22). Thus energy lost from conduction through opaque external walls and roofs will use the daily mean sol-air temperature. Energy lost from conduction through glazing, thermal bridges and ventilation will use regular mean daily external temperatures, as these features have limited radiative absorptive capacity.

A substantial amount of research has been conducted to accurately estimate the HTCC and therefore experimentally estimate the thermal resistance between the exterior surface of the wall and the outside air under different environmental and physical conditions. One of the most comprehensive reviews bringing together these research findings was completed by Defraeye (2011) for his PhD thesis. CIBSE recommends estimating HTCC using Equation (7.47), however, for this model the method proposed by Emmel, Adabie and Mendes (2007) is adopted as they estimate different HTCC coefficients for leeward

55. The absorptivity and emissivity are assigned based on the construction materials of the wall: Solid concrete blocks α =0.8; cavity filled and masonry walls α =0.7; Timber walls α =0.3.

and windward surfaces. This is useful as information on the number of sheltered walls for each dwelling is available within the EHCS making it possible to incorporate the exposure of different building surfaces to provide better estimates of energy losses from convective heat transfer. The HTCC is thus purely a function of wind velocity and the extent of surface exposure. The equations governing HTCC are given by Equations (7.48) to (7.49) where $h_{c,d}$ is the HTCC and $v_{w,d}$ is the daily mean wind velocity for each dwelling on each day of the year. Figure 7.23 shows how the HTCC varies over the year for windward and leeward walls.

CIBSE Standard: $$h_{c,d} = 4 + 4v_{w,d} \quad (\mathrm{W/m^2K}) \qquad (7.47)$$

for windward wall: $$h_{c,d} = 5.15v_{w,d}^{0.81} \quad (\mathrm{W/m^2K}) \qquad (7.48)$$

for leeward wall: $$h_{c,d} = 3.54v_{w,d}^{0.76} \quad (\mathrm{W/m^2K}) \qquad (7.49)$$

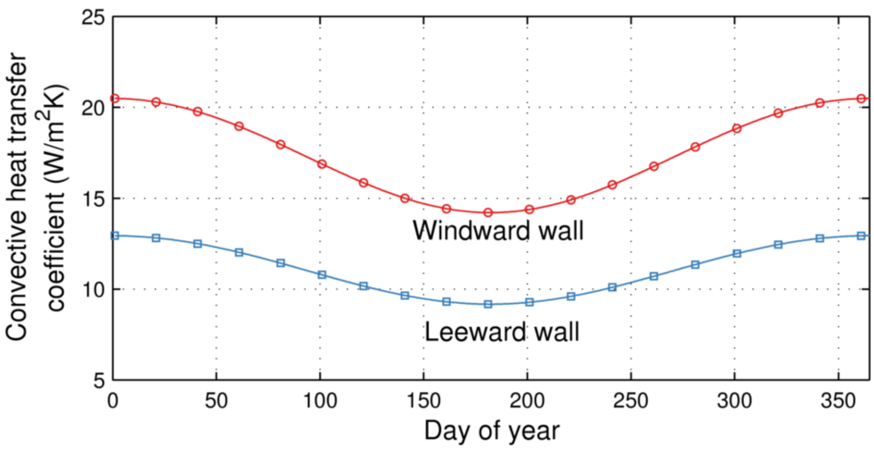

Figure 7.23: Convective heat transfer coefficient as a function of wind velocity

7.5.10.2 Solar gain from glazing

Solar gain through glazing is one of the most significant forms of heat gain for dwellings. The equation determining the amount of heat gain received by each dwelling is governed by Equation (7.50). The level of solar gain depends on several factors including: the total area of glazing[56] given by $0.9A_{g,i}$; the glazing transmittance factor $g_{\perp}$ (Table 7.8) the frame transmittance factor ff_i (Table 7.9); and the solar flux transmitted from the sun on a particular day of the year, $S_{flux,d}$. The solar flux on a vertical surface for any day of the

56. A_g represents total window area, this is therefore multiplied by the ratio of glazing area to total window area (e.g. ~0.9) to get total glazing area.

year can be described using Equation (7.50) and was derived by fitting a cosine function to the monthly solar flux values given in CIBSE Guide J.

$$\mathbf{G}_{s,id} = 0.9 A_{w,i} \cdot g_{\perp,i} \cdot ff_i \cdot S_{flux,d} \qquad \text{(W)} \qquad (7.50)$$

$$S_{flux} = 65\cos\left(\frac{d}{58} + \frac{365}{4}\right) + 90 \qquad \text{(W)} \qquad (7.50)$$

Solar gain is the largest form of incidental gain but varies markedly over the year, contributing marginally in winter – when heating is most required – and significantly in summer when heating is not required. A box and whisker plot is drawn in Figure 7.24 showing how solar gain through glazing and irradiation to the building fabric varies over the building stock over two seasons.

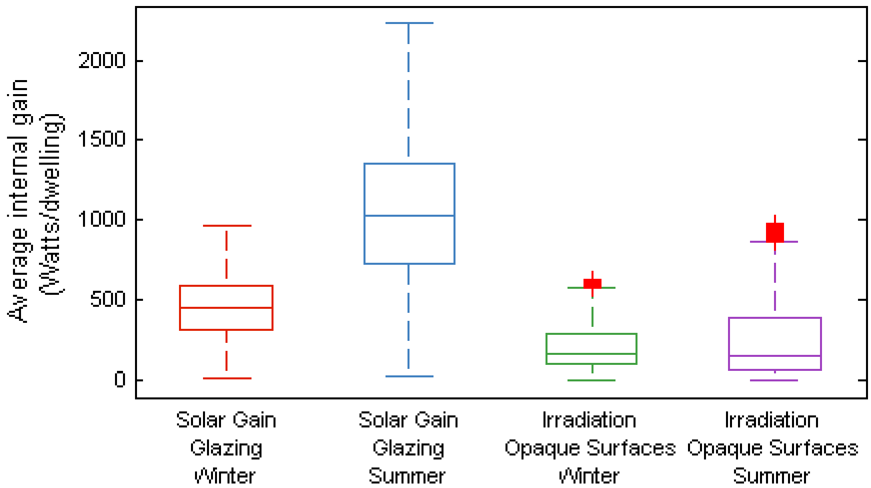

Figure 7.24: Beneficial insolation absorbed by dwellings in winter and in summer[57,58]

7.5.10.3 External temperature data

Time-series temperature data were downloaded from the UK Met Office for the period 1960-2006. Daily temperature data giving the average minimum and average maximum daily temperatures were downloaded as text files with each daily temperature record having a grid spatial resolution of 50×50 km^2. From this dataset the mean-maximum, mean-minimum and mean-mean temperatures for each day of the year were found for each region in England. A Matlab algorithm was therefore developed to process tens of thousands of temperature records that were collected from hundreds of different weather

57. Beneficial insolation refers to solar irradiation that usefully counts towards building heating requirements.
58. The winter period includes October – March; the summer period includes April – September.

stations geographically spaced over the country. Figure 7.25 shows the output of the daily temperature records for each region. Figure 7.26 shows a map where the external temperature measurements were taken to represent England.

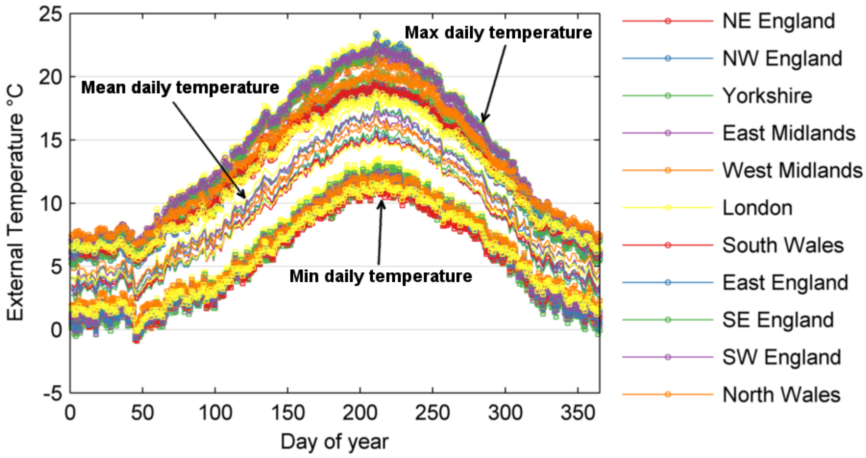

Figure 7.25: Minimum, maximum and mean daily temperatures for different regions in England

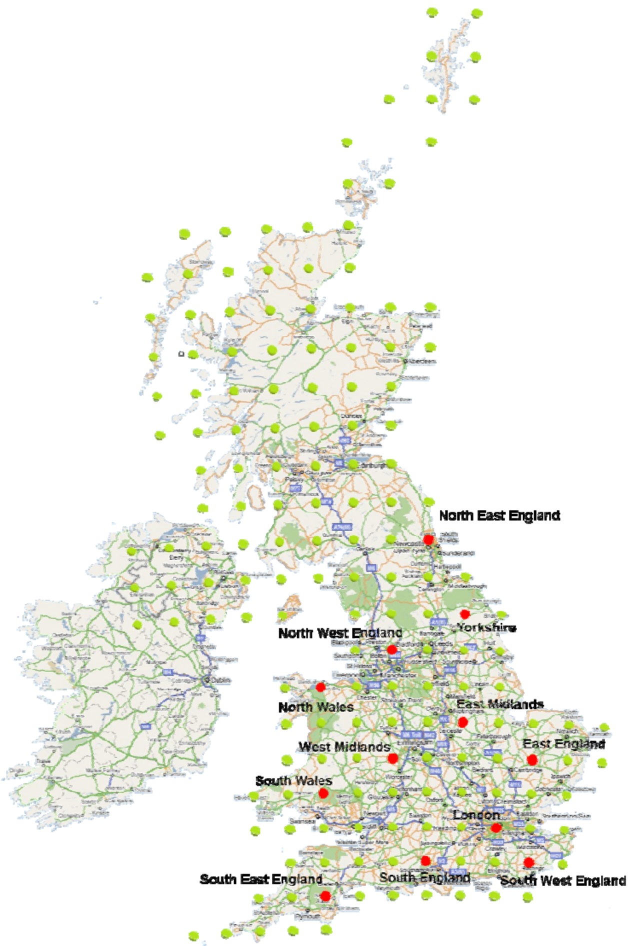

Figure 7.26: Map of England with external temperature measurement locations (1960-2006)

7.5.10.4 Predicting internal temperatures

As discussed in Chapter 6 daily internal temperature is one of the most important factors explaining dwelling level energy demand. It is therefore surprising that UK building stock models do not place more emphasis on collecting and estimating better estimates of internal temperature from heterogeneous dwellings. It has become generally accepted that building stock models either assume a constant internal temperature across the entire building stock, or alternatively estimate a constant internal temperature for the entire heating season for each dwelling. Until now, there has been no method proposed that is able to adequately estimate the diversity of internal temperatures from a heterogeneous building stock over time and over dwellings. Moreover, there is a serious lack of building stock models that adequately incorporate the behavioural and socio-demographic qualities of occupants in the estimation of internal temperatures and therefore energy demand.

Using the method described in Chapter 6 the internal temperatures were predicted for each day of a typical year for each of the 16,216 dwellings contained in the original 2008 EHCS. As the original internal temperature prediction model requires a large number of inputs, and several of these variables were not available within the EHCS, it was necessary to re-estimate the temperature prediction model using variables available common to the original CARB-HES dataset an the EHCS. The output for the new model predictions can be viewed in Table A-1. The outputs show that all coefficients remain statistically significant and the level of explained variance for the model remains high (R^2=0.423). Once the panel model coefficients had been re-estimated, Equation (7.51) was used to predict the daily mean internal temperatures for each dwelling on each day of the year.

$$\begin{aligned}\hat{T}_{int,id} = {} & 15.72 + 0.048 \cdot T_{ext,id} + 0.013 \cdot T_{ext,id}^2 - \beta_1 \cdot LOC + 0.149 \cdot TSTAT + 0.17 \cdot TIMER + \\ & 0.108 \cdot OCC + 0.165 \cdot INCOME + 0.241 \cdot BABY + 0.223 \cdot CHILDREN + \\ & 0.4 \cdot AGE64 + 0.506 \cdot AGE74 + 1.09 \cdot RENT + 1.455 \cdot COUNCIL + 0.306 \cdot HASSOC + \\ & 0.47 \cdot SEMIDET + 0.366 \cdot TERR + 0.26 \cdot NOHOUSE - 0.432 \cdot GASCH - 0.126 \cdot NONCH + \\ & 0.439 \cdot ELEC - 0.828 \cdot OHLIV + 0.077 \cdot BUILDAGE + 0.096 \cdot ROOFINS + \\ & 0.203 \cdot DBLGLZ + 0.028 \cdot WALLUVAL\end{aligned} \tag{7.51}$$

In Equation (7.51) T_{ext} represents the mean daily external temperature for each of the regions in England; LOC is a location dummy array and β_1 are the coefficients of this array given in Table 7.3; $TSTAT$ is a dummy variable indicating the existence of a thermostat in the dwelling; $TIMER$ is a dummy variable indicating if the heating system has an automatic timer; OCC is a variable for the number of occupants living in the dwelling; $INCOME$ is the annual household income bracket; $BABY$ is a dummy variable indicating if a child under five is living in the dwelling; $CHILDREN$ represents the number of children under 18 living in the dwelling; $AGE64$ is a dummy variable indicating if the oldest person living at the dwelling is aged between 64 and 74; $AGE74$ is a dummy variable indicating if the oldest person living at the dwelling is over 74 years old; $RENT$ is a dummy variable indicating if the property is rented; $COUNCIL$ is a dummy variable indicating if the property is owned by the council; $HASSOC$ is a dummy variable indicating if the property is owned by a registered social landlord or housing association; $SEMIDET$ is dummy variable indicating if the dwelling is semi-detached; $TERR$ is a dummy variable indicating if the dwelling is terraced; $NOHOUSE$ is a dummy variable used to indicate the dwelling is not a house; $GASCH$ is a dummy variable indicating if the main source of heating in the dwelling is gas central heating; $NONCH$ is a dummy variable indicating that the dwelling has no central heating; $ELEC$ is a dummy variable indicating the main type of heating in the dwelling is electric; $OHLIV$ is a dummy variable indicating if the dwelling has a secondary heating system in the living room; $BUILDAGE$ is an ordered categorical variable of building age; $ROOFINS$ is an ordered categorical variable of the thickness of roof insulation; $DBLGLZ$ is an ordered categorical variable for the extent of double glazing present in the property; $WALLUVAL$ is an ordered categorical variable for the buildings U-value. The reader is referred to Chapter 6 for more details about the derivation of this panel estimation.

Table 7.3: Location dummy array

Location	β
London	-
North East	-0.141
Yorkshire	-0.082
North West	-0.138
East Midlands	-0.038
West Midlands	-0.11
South West	-0.119
East of England	-0.079
South East	-0.162

Internal dwelling temperature predictions are given by the scatter bin plot in Figure 7.27 and show the distribution of internal temperatures across the building stock (y-axis) and over time (x-axis). Additionally, Figure 7.27 shows that during the winter period, temperatures vary across the building stock from a minimum of 15.5°C to a maximum of

22°C and in summer from a minimum of 19°C to a maximum of 25.5°C – this is a significant range in temperatures that is not being allowed for by existing building stock models. The figure also shows that the majority of dwellings have an internal temperature around 17.5°C in winter and 21.5°C in summer (by locating the position of the largest circles in Figure 7.27).

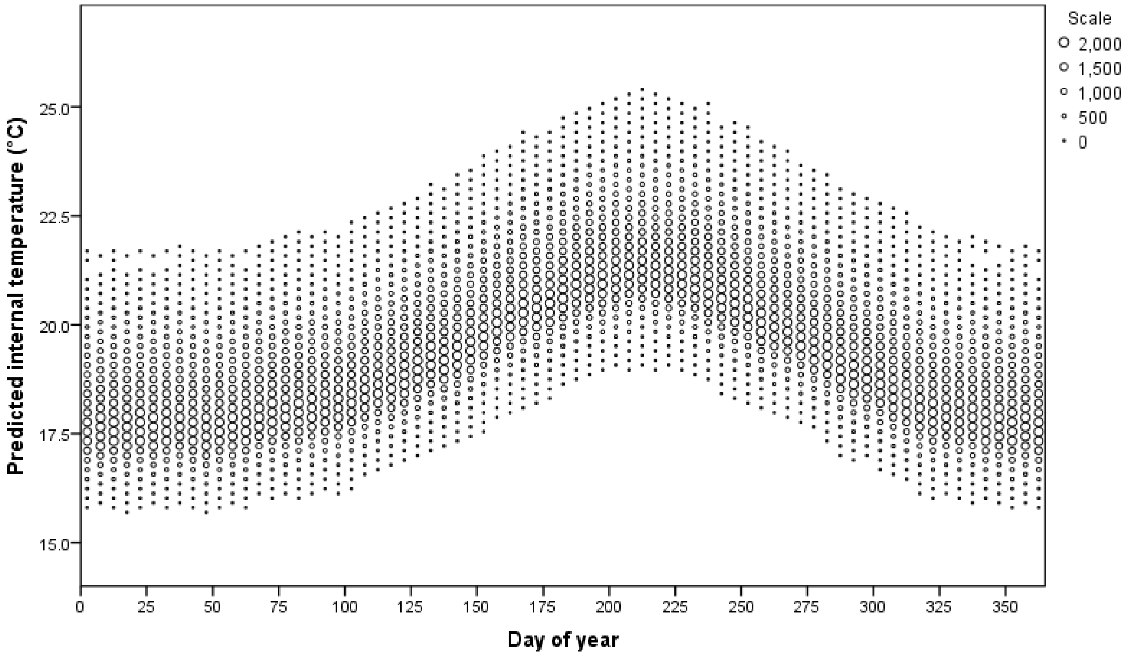

Figure 7.27: Predicted internal temperatures from a heterogeneous building stock

1. Bin size represents the number of dwellings in thousands

As clearly shown in Figure 7.27 internal temperatures across the building stock vary significantly both across dwellings and over time. Building stock models that fail to take into account this natural heterogeneity will fail to provide robust predictions about dwelling energy consumption. Unless internal temperatures are estimated from human behaviour and demographics, building stock models will fall short of accurately predicting energy consumption. The diversity of internal temperatures within the building stock is therefore important – if not more important – than the diversity of different building efficiency technologies.

7.5.10.5 Heating degree day algorithm

Heating degree-days (HDD) are widely used to estimate external weather conditions as they are able to measure both the duration and severity of temperature changes over time (Day et al., 2003; CIBSE, 2006). Heating degree-days can be described as a function of the temperature difference between the external temperature T_{ext} and the base temperature

T_b as well as the duration over which a temperature difference exists. The formulation of HDD can be traced back to 1878 when the original concept was developed for comparing crop-growing yields; a purpose for which HDD are still widely used today (Strachey, 1878). Using HDD for energy building models is not new either (Christenson et al., 2006; Haas et al., 1998; Layberry, 2008; Sarak and Satman, 2003). Historically, HDD have been used for the estimation of mean internal temperatures so that energy loss calculations can be completed (Day et al., 2003; Day and Karayiannis, 1999). It is shown here that the HDD method is more accurate at estimating energy losses than the mean temperature difference method because HDD can measure both the extremes and the duration of external temperature profiles. The main advantage of using HDD is that it performs an integration of external temperature against the base temperature over time. Therefore it calculates the area under the curve, not just the mean differences between the curves.

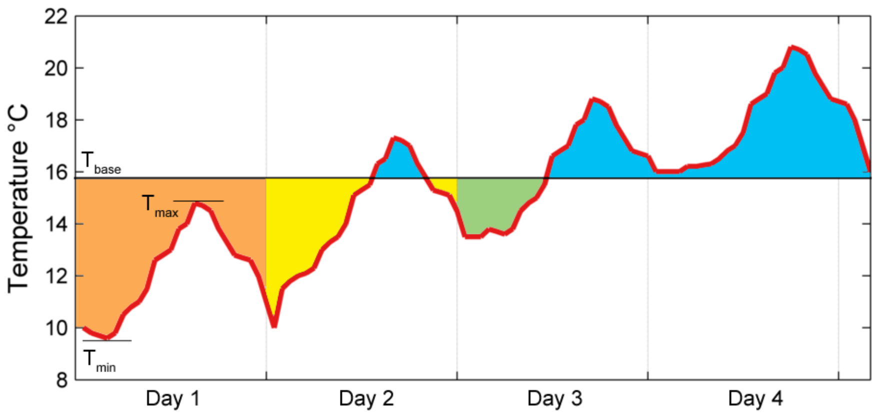

Figure 7.28: Hypothetical example of a daily temperature profile

Figure 7.28 plots a single hypothetical external temperature profile T_{ext} over four days. In this example the base temperature, T_{base}, is kept constant to make the explanation of HDD simpler. In the building stock model the base temperature (internal temperature) is also allowed to vary over dwellings and over time. On day one, both $T_{\max}$ and $T_{\min}$ are below T_{base} so the area (orange) between T_{ext} and T_{base} is used in the estimation of energy demand. On days 2 and 3 (yellow and green) the maximum temperature is above the base temperature for a portion of the day (the area is shaded blue when $T_{\max} > T_{base}$). When this occurs, only the area under T_{base} will be used in the estimation of heating degree-days. On day 4, T_{ext} is always above the base temperature so no heating is required. However, it will be demonstrated that when $T_{\max} > T_{base}$ energy is absorbed by the building (due to the second law of thermodynamics) and thus needs to be allowed for in the heat balance equation.

Building stock models that have used HDD in the past (like the early versions of BREDEM) generally calculate the number of HDD over long periods (months or seasons) to estimate total energy demand. These calculations usually implement a constant base temperature over the entire period (for the UK this is typically 18.5˚C) over which variations in external temperature are used to estimate the number of HDD. This approach severely limits one of the major advantages of using heating degree-days (i.e. that HDD can account for both the duration and severity in differences in temperature). Unfortunately all existing building stock models that adopt the HDD method estimate HDD over very long periods and use a constant base temperature for the dwelling over this period. This approach limits the true variability of internal temperatures that fluctuate naturally between dwellings and over time.

An alternative approach to the HDD method is the mean temperature difference method. This is the approach adopted by SAP and most other building stock models based on SAP. These models assume mean external temperatures and mean internal temperatures over some pre-specified period of time. Similar to HDD method, time periods are often long and range from one month to an entire heating season. Although this approach attractively simplifies the dynamics of heating energy demand analyses, it completely ignores the principle that energy losses are larger when the temperature differences are higher. Said differently, the rate of heat loss through the building envelope increases as the difference between external and internal temperatures diverge. When only mean temperatures are used, the severity of extreme temperatures and their duration are therefore not accounted for and energy demand estimates will be less accurate. This is because mean temperatures only find the average temperature between maximum and minimum values and the external temperature might rise above the internal temperature set point of the dwelling.

The novel method adopted in this building stock model allows the base temperature (internal temperature) to vary over time as well as across dwellings on a daily basis. As this model estimates degree-days on a daily basis the model is able to capture both the severity and duration of temperature differences for each day of the year. This approach is much more accurate than methods that use simple mean temperature differences or HDD that use a fixed base temperature over long periods of time for the entire building stock.

In this model the McVicker equations are used to estimate HDD, which adopt the same set of equations as used by the meteorological office (CIBSE, 2006). The HDD method as given by Equations (7.53) to (7.56) approximate the perfect integral in Equation (7.52) and have been shown to only generate a small margin of error compared to actual differences (CIBSE, 2006). Each equation is executed in the order given below. The calculation of HDD requires both the maximum temperature $T_{\max}$ and the minimum temperature $T_{\min}$ for the period of interest (i.e. over a 24-hour period).

$$HDD = \int (T_b - T_e)\,dt \qquad \text{(degree-days)} \qquad (7.52)$$

When, $T_{\min} \geq T_b$:

$$HDD = 0 \qquad \text{(degree-days)} \qquad (7.53)$$

$(T_{\max} + T_{\min})/2 > T_{base}$:

$$HDD = \frac{T_b - T_{\min}}{4} \qquad \text{(degree-days)} \qquad (7.54)$$

$T_{\max} \geq T_b$:

$$HDD = \frac{T_b - T_{\min}}{2} - \frac{T_{\max} - T_b}{4} \qquad \text{(degree-days)} \qquad (7.55)$$

$T_{\max} < T_b$:

$$HDD = T_b - \frac{T_{\max} + T_{\min}}{2} \qquad \text{(degree-days)} \qquad (7.56)$$

7.5.10.6 Incidental gains when external temperatures are above internal temperature

A unique feature of this building stock model is that it endogenously estimates required energy demand for each day of the year. This is very different from existing building stock models that only model energy demand over a user imposed heating season. In a typical building stock model it is assumed that minimum and maximum temperatures are always below the desired internal temperature and therefore heating is always required. When energy demand is being estimated for every day of the year there will be periods (especially in the shoulder months of autumn and spring) when $T_{\max}$ rises above T_{int} for short periods in the day (see Day 3 in Figure 7.28). Not only will no heating be required when T_{ext} rises above T_{int} but there will be a proportion of energy that is absorbed by the dwelling and then released by the building fabric as T_{ext} drops below T_{int} thus contributing to beneficial incidental gains.

In other building energy models (e.g. BREDEM) the energy required to heat the thermal mass is inadequately allowed for, and assumed to be a function of the thermal mass of the building and some time constant with no thermodynamic allowance for where the energy comes from that is absorbed by the thermal mass. For example in SAP2009 a time constant is estimated that is a function of the thermal mass and the heat loss parameter of the building multiplied by a constant (see SAP2009). In other words there is no variable to represent energy flows absorbed by the thermal mass. Energy absorbed by a buildings thermal mass will not only vary over the year depending on the amount of energy available from the sun, but will also vary over night and day. The energy absorbed by a dwelling will also be a function of the internal temperature of the dwelling and the temperature profiles kept by the occupants. The BREDEM models treat thermal mass as a form of energy supply that contributes to internal temperatures but with no empirical basis for where, when or how this energy is absorbed by the building and released over time. SAP or BREDEM methods therefore do not adequately account for the energy that is absorbed by the building when $T_{\max} > T_{\text{int}}$ and therefore they do not correctly attribute these thermal gains at the right time of the year or over the day. This is a significant oversight and given the relatively high thermal mass of UK dwellings, more research needs to be done to understand the role that thermal mass plays in energy and emissions from the UK building stock.

The occurrence of $T_{ext} > T_{\text{int}}$ rarely happens in winter, semi-frequently in the shoulder seasons of autumn and spring, and frequently over summer. The period over which this effect occurs is different between different regions and therefore has a significant effect on the amount of internal heating required by the dwelling. In Figure 7.29 the maximum daily energy available when $T_{ext} > T_{\text{int}}$ for each dwelling is plotted. It shows the energy gain across all dwellings vary but also that these gains start and end at different times of the year for different dwellings. This shows the heating season varies greatly from dwelling to dwelling, and cannot be exogenously imposed by the modeller. In this building stock model it is assumed that 50% of the energy is absorbed by the dwelling when $T_{ext,i} > T_{\text{int},i}$ and then released as useful gains when $T_{ext,i} < T_{int,i}$. The remaining 50% of available energy is deliberately vented by the occupants through opening windows doors and increasing natural ventilation to keep the internal environment cool during periods when the external temperature is higher than desired[59].

$$\mathbf{G}_{ht,id} = \delta\left(24.\mathbf{CDD}_{id}\left(\mathbf{H}_{w,id} + \mathbf{H}_{r,id}\right)\right)/2 \qquad (7.56)$$

In Equation (7.56) $\mathbf{G}_{ht,id}$ represents the gain absorbed by the dwelling when $T_{ext,i} > T_{\text{int},i}$ and released as useful heat when the external temperature drops below T_{int}; δ is fraction and represents the absorptive capacity of the exterior building[60]; $\mathbf{CDD}_{id}$ is the cooling degree-days for each dwelling for each day of the year and are calculated in similarly to heating degree-days but are a measure of the extent to which $T_{ext} > T_{\text{int}}$; $\mathbf{H}_{w,id}$ and $\mathbf{H}_{r,id}$ are the heat loss parameters for the walls and roof respectively (e.g. the two building elements exposed to thermal gain). This gain is added to the total gain, $G_{T,id}$ in Equation (7.38).

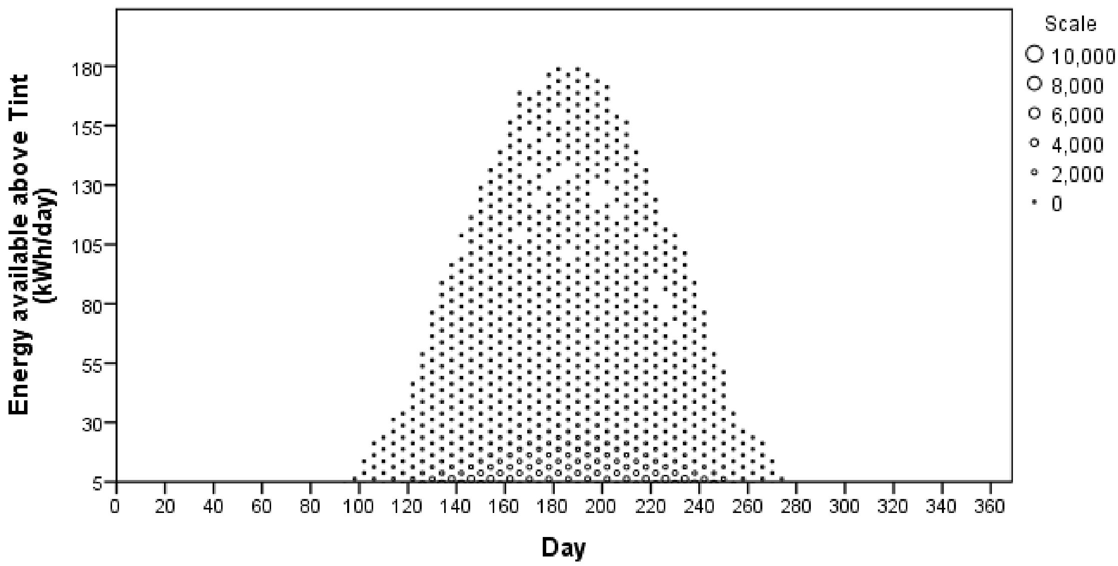

Figure 7.29: Scatter bin plot showing the total energy available for each dwelling for each day of the year for the period when external temperature is greater than internal temperature

7.5.11 Final dwelling space heating demand

All the required variables for calculating energy demand have now been defined. These factors include the physical and material characteristics of the building envelope; a collection of different incidental gains each contributing to a rise in internal temperature;

59. In this version of the model the effect of cooling energy demand is not modelled (i.e. fans or AC systems)
60. For buildings with high thermal mass (450 kJ/kg.m^2): solid walls, concrete block: $\delta = 1$; for cavity walls (250 kJ/kg.m^2): $\delta = 0.7$; for light construction buildings made of timber $\delta = 0.1$.

and the calculation of both internal and external temperatures for computation of HDD. It is therefore now possible to sum the energy flows over the control volume drawn around the building envelope (Figure 7.2) to determine the amount of energy required for each dwelling on each day of the year. This is achieved using Equation (7.57).

$$\mathbf{Q}_{T,id} + \mathbf{Q}_{G,id} = 24\left[\mathbf{DD}_{id}\left(\mathbf{H}_{f,id} + \mathbf{H}_{b,id} + \mathbf{H}_{g,id} + \mathbf{H}_{v,id}\right) + \mathbf{DD}_{sol,id}\left(\mathbf{H}_{r,id} + \mathbf{H}_{w,id}\right)\right] \text{(kWh/day)} \quad (7.57)$$

For each dwelling *i* and for each day of the year *d*; $\mathbf{Q}_{T,id}$ is the total energy demand (from fuel and electricity) to maintain the dwelling at its base temperature, $T_{\text{int},id}$; $\mathbf{Q}_{G,id}$ is the total gain for each dwelling on each day of the year; $\mathbf{DD}_{id}$ is the number of HDD's calculated for each dwelling on each day of the year; $\mathbf{DD}_{sol,id}$ are the degree days calculated for each dwelling using the sol-air temperature; $\mathbf{H}_{f,id};\mathbf{H}_{b,id};\mathbf{H}_{g,id};\mathbf{H}_{v,id}$ are the respective heat loss parameters from the floor, thermal bridges, glazing and ventilation respectively; and finally, $\mathbf{H}_{r,id} + \mathbf{H}_{w,id}$ represent the heat loss parameters from the roof and walls of the dwelling allowing for solar insolation. Figure 7.30 shows the distribution of predicted space heating demand requirements for the domestic building stock in England. The model estimates the annual space heating demand requirement for an average English dwelling as 13.34 MWh/year while the median space heating demand is 10.83 MWh/year.

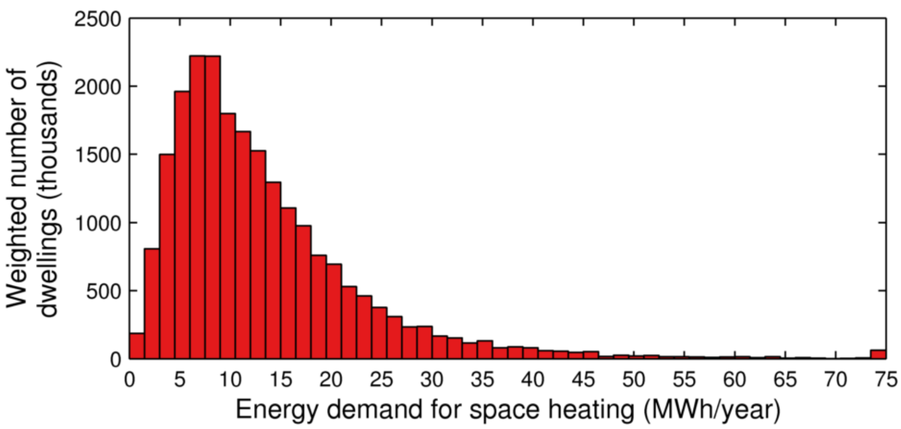

Figure 7.30: Weighted histogram for net annual space heating energy requirement

Figure 7.31 shows the space heating demand profiles for fifteen randomly selected dwellings from the 16,216 dwellings included in the stock model. As clearly shown the heating demand varies significantly over the building stock and over time. Figure 7.31 clearly shows that the heating season starts and finishes at different times of the year for different dwellings. It also shows the importance of modelling heating demand outside the heating season.

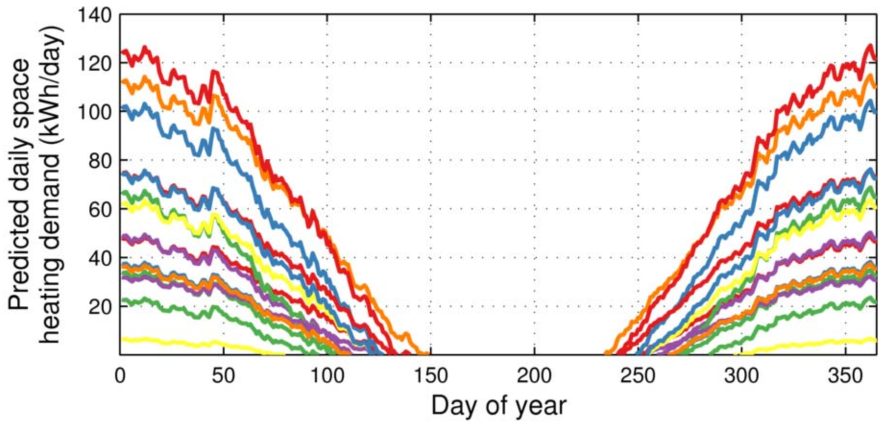

Figure 7.31: Annual space heating demand profiles for fifteen randomly selected dwellings

7.6 Model calibration

Because the systems being modelled are complex, real world calibration is almost always required to ensure estimated demand is able to predict final demand. The model estimates energy demand for each dwelling for five end-use energy service categories. By aggregating the energy services in each category for each dwelling it is possible to derive an estimate for national demand. Comparing the aggregates of each energy service category with actual demand it is possible to derive the calibration factor, κ, to scale each observation (dwelling) in the dataset so that estimated aggregate demand will match actual aggregate demand as provided by DECC. This can be achieved using Equation (7.58).

$$\kappa = \frac{\sum Q_{actual}}{\sum Q_{model}} \tag{7.58}$$

The reason calibration factors were chosen rather than altering various parameters within the model to meet demand was to retain model transparency. This means that all equations, coefficients and model parameters derived thus far have been adopted from published research or derived using raw data. (this links to earlier points made in the introduction about model integrity, honesty, transparency and the scientific method). Table 7.4 lists the calibration factors that were applied to the model so that final estimated aggregate demand would indeed match total actual aggregate demand. It is important that each of the energy service sub-categories given in Table 7.4 is correctly calibrated as they each have a substantive effect on space heating. A calibration factor was not created for space heating as final aggregate energy demand matched actual demand within 2%.

Table 7.4: Calibration factors for energy demand sub-categories

Energy Demand	Actual aggregate demand (TWh/year)	Model estimated aggregate demand (TWh/year)	Calibration Factor (κ)
Hot water	73.3	86.8	0.84
Lighting	14.4	16.0	0.90
Electrical appliances	51.1	56.7	0.90
Cooking	12.4	19.8	0.63
Space heating	290.2	296.1	-

As shown in each of the energy service sub-categories, the model over estimates energy demand. The differences between modelled and actual aggregate consumption has important implications and suggests the equations underlying SAP and BREDEM need to be re-estimated.

7.7 Total energy demand and fuel shares

The annual energy demand for each dwelling is the sum of demand from each energy service category (e.g. lighting, appliances, cooking, hot water and space heating). Figure 7.32 shows the distribution of energy demand across four energy demand categories as an output of the model.

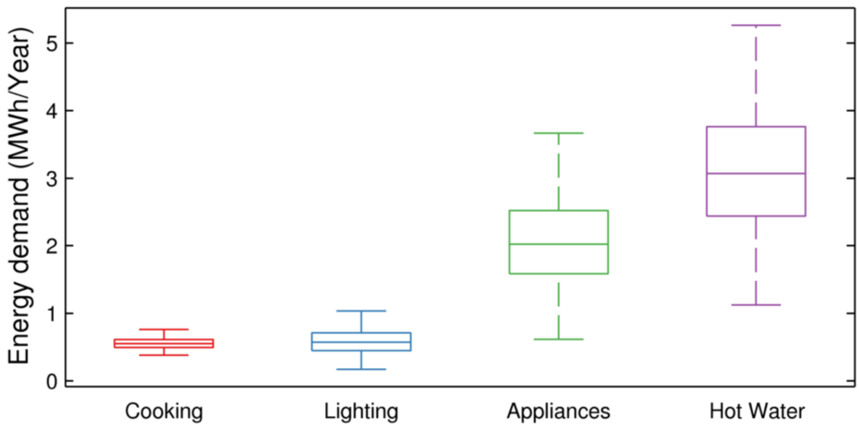

Figure 7.32: Box and whisker plot for dwelling energy demand for different end-use energy service categories

Knowing the energy demand for energy service category allows fuel shares to be estimated. In this model it is assumed that lights and appliances are powered completely by electricity. The fuels used for cooking, hot water and space heating are allocated based on the information available for each dwelling. For cooking appliances connected to gas mains supply it is assumed the hob will use gas and the oven will be electric. For dwellings that do not have gas mains supply, the oven and hob are both assumed to be electric.

Allocating fuel shares for hot water usage is more complicated. In dwellings where off-peak electricity is available it is important to estimate the fraction of on-peak usage as it has a significant effect on the overall running costs. It is also common for hot water cylinders in the UK to have electric immersion heaters designed take advantage of off-peak rates. Dual immersion hot water systems have two electric resistance heaters; one heats the whole cylinder overnight and another smaller heater is placed near the top and heats the water during the day - if and when required. Single immersion systems have one electric resistance heater that is connected to a time clock for controlling day and night-rate charging. Thus hot water systems can be heated by both gas and electricity. If a hot a hot water cylinder is classified as having an electric immersion heater the fraction of off-peak electricity consumed is calculated according Equation (7.59). The fraction below has been derived from field data collected by the electricity association (Anderson et al., 2001).

Fraction of off-peak: $$f_{,id} = 1 - \frac{1}{100}\left[\mathbf{N}_{id}\left(6.8 - 0.024\mathbf{V}_{cyl,id}\right) + \left(40 - 0.07\mathbf{V}_{cyl,id}\right)\right] \qquad (7.59)$$

In Equations (7.59), f_{id} , is the fraction of off-peak electricity consumed by cylinders with dual and single immersion heaters. The EHCS provides data on four different hot water heating systems. These are; hot water systems connected to central heating systems (86%); dedicated hot water boilers (1%); solely electric immersion water heaters (11%); and instantaneous hot water (2%). Approximately 48% of hot water heating systems have an electric immersion heater in England. Thus the fraction of electricity used within hot water systems from electric immersion heaters was first estimated. Any remaining hot water demand was allocated based on (i) the primary fuel type for each dwelling and (ii) the hot water heating system type for that dwelling (e.g. the primary fuel type might be gas but electric immersion heaters require fuel share allocations to be correctly allocated).

Allocating fuel for space heating was more straightforward and was assumed to come from the primary heating fuel for each dwelling. Table 7.5 shows how the building stock model predicts fuel share allocations when compared with DECC aggregate figures.

Table 7.5: Fuel share allocations of model and comparison with DECC aggregate statistics

Energy carrier	Space heating	Water heating	Cooking	Lights and Appliances	Model Totals	DECC Totals
Gas	245.4	46.9	7.9	-	300.2	300
Electricity	18.9	22.2	4.5	65.5	111.1	100
Other	31.8	3.54	-	-	35.3	41
Model Total	296.1	72.6	12.4	65.5	446.6	-
DECC Totals	290.2	73.0	12.4	65.5	-	441.0

1. All values are given in TWh/year
2. Data source for DECC data is the Great Britain Domestic Energy Fact File.
3. DECC statistics have been multiplied by a factor 0.875 to convert from Great Britain values into to totals for England.
4. Lights and appliances have been combined for brevity.
5. EHCS dwelling grossing weights have been applied to all model totals.

7.8 Carbon emissions

One of the fundamental purposes of this building stock model was to produce realistic estimates of carbon emissions from a heterogeneous building stock. From this base, the merits of different decarbonisation strategies were explored. It was possible to estimate the emissions being generated once energy demand had been allocated to different fuel types. The quantity of each fuel consumed by each dwelling was then multiplied by the carbon intensity of that fuel type.

The carbon intensity for electricity depends on a number of factors, namely: the carbon intensity of electricity generation, the efficiency of generators and the efficiency of transmission and distribution networks. The carbon intensity of electricity is dynamic and fluctuates in the short term as different power generation facilities come and go offline. In the long-term electricity generation is decarbonised due to the penetration of additional renewables. For home heating, the carbon intensity of natural gas is not expected to change dramatically over the short term and will most likely remain fairly constant over the long term – unless bio-gas is injected into the national gas grid therefore reducing the carbon intensity of gas (Kelly and Pollitt, 2011). Other fuels such as coal, heating oil and timber each have their own carbon emission intensity factors that were also included in the model. Table 7.21 gives the emissions factors, unit prices and primary energy factors for different fuel types considered in this model. Figure 7.33 gives an indication for the distribution of emissions from the building stock by fuel type. As shown in Figure 7.34 even though electricity consumption only accounts for 25% of aggregate energy consumption from the residential sector (as calculated by the model) it accounts for 45% of total emissions.

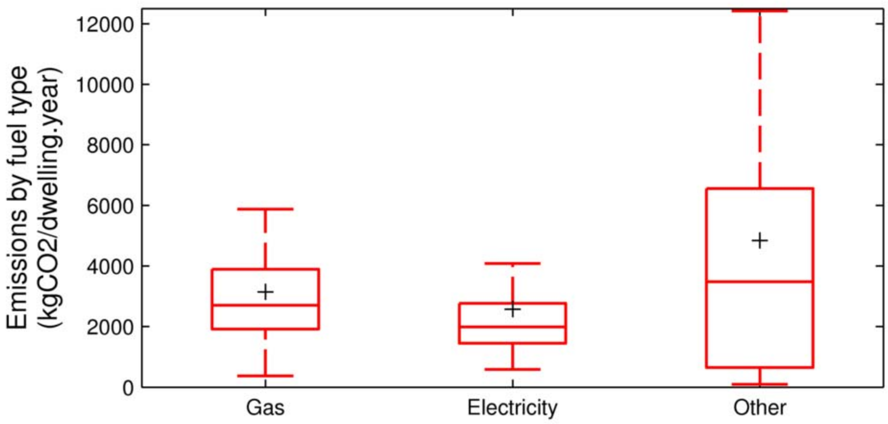

Figure 7.33: Box and whisker plot of annual carbon emissions by fuel type

1. Plus signs indicate the mean annual emissions per year
2. Only dwelling belonging to each fuel type are included in the box and whisker plot for that fuel type.

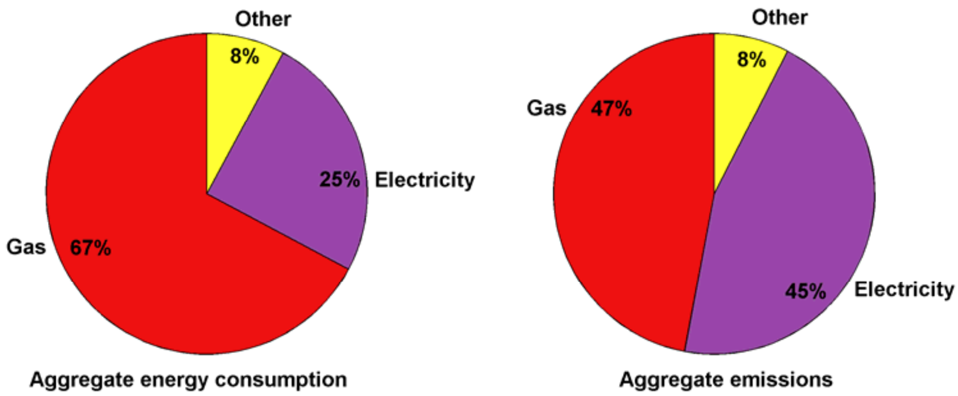

Figure 7.34: Two pie charts showing the post-weighted aggregate energy consumption and emissions for different fuel types as calculated by the model

Figure 7.35 is a box and whisker plot showing the distribution of emissions by end use service category. Figure 7.36 is a weighted histogram showing the distribution of emissions per dwelling over the building stock.

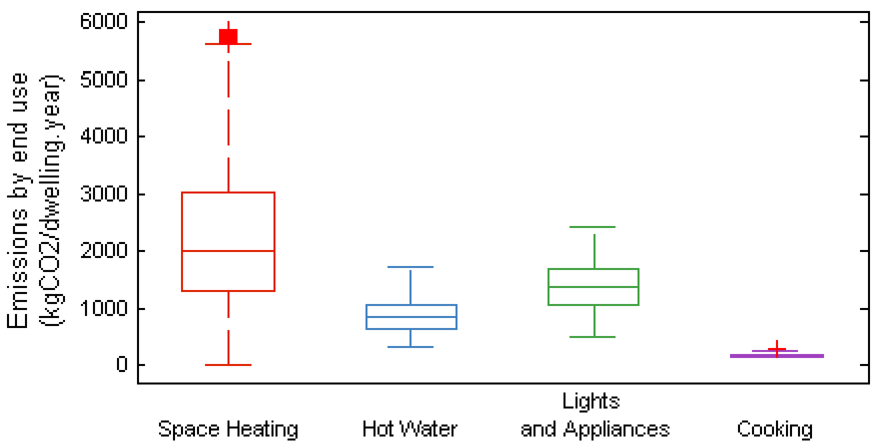

Figure 7.35: Box and whisker plot showing carbon emissions by end use category

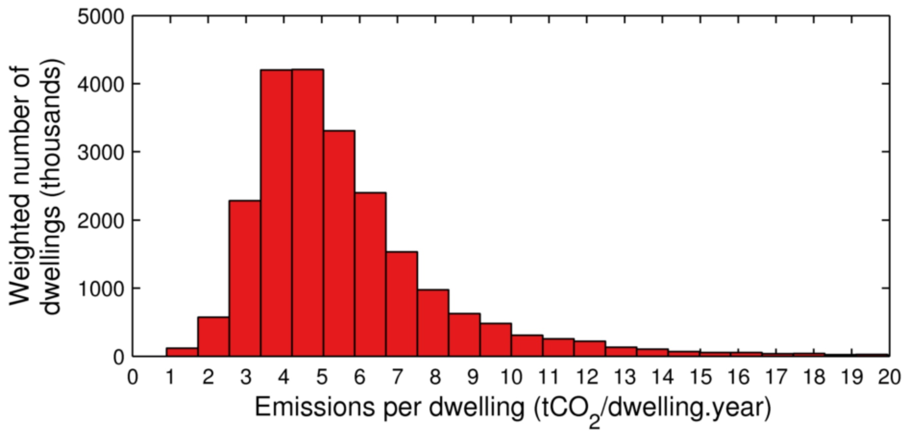

Figure 7.36: Weighted histogram of emissions per dwelling

7.9 Energy costs

Once fuel shares have been allocated it is possible to calculate the annual cost of energy for each dwelling. Two sets of different prices have been applied. The first set is taken from SAP2009 methodology and are based on average UK energy commodity prices for the preceding three years prior to 2009. Figure 7.37 is a box and whisker plot of average annual energy costs broken down by end use service category. The differences between SAP2009 and DECC 2011 prices is partly due to an increase in the real price of energy between 2009 and 2011 and partly due to the esoteric energy price calculation procedure implemented within SAP (e.g. SAP2009 does not impose standing charges for electricity but does for gas while DECC lists standing charges for both gas and electricity). Energy prices and standing charges for different fuels can be viewed in Table 7.21.

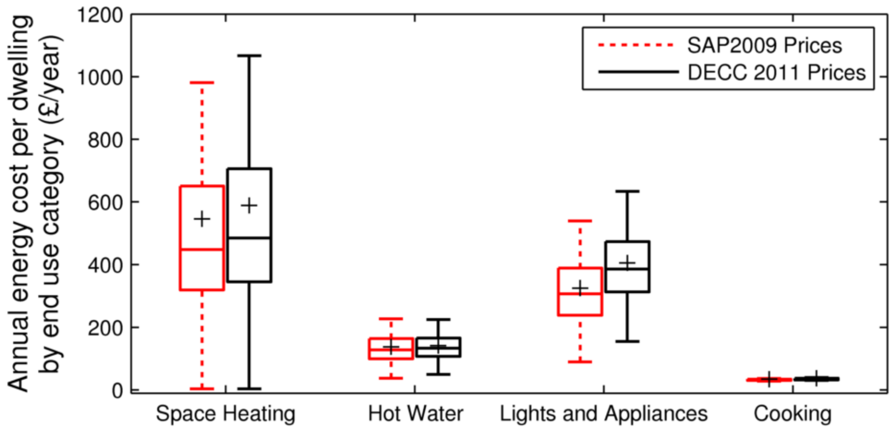

Figure 7.37: Box and whisker plot showing energy costs by end use category

1. Plus signs indicate the mean annual cost.
2. SAP2009 prices have been taken from SAP 2009 documentation
3. DECC 2011 prices have been taken from DECC energy price statistics online [http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/prices/prices.aspx]

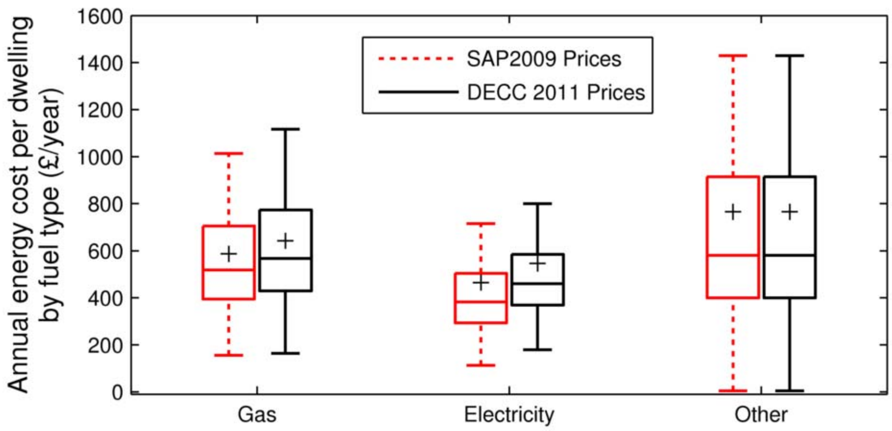

Figure 7.38: Box and whisker plot showing annual energy costs by fuel type

1. Plus signs indicate the mean annual cost.
2. Only the dwellings belonging to each fuel type are included in the box and whisker plots for that fuel.
3. SAP2009 prices have been taken from SAP 2009 documentation
4. DECC 2011 prices have been taken from DECC energy price statistics online [http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/prices/prices.aspx]

In Figure 7.38 'other' includes all forms of heating other than electricity and gas. Using this model it is possible to estimate energy and emissions from 17 different fuel types but as electricity and gas account for 92% of all energy consumed by English dwellings these 15 other fuel types were aggregated into one category represented by 'other'. As shown, the average fuel cost for homes that use 'other' fuel types (e.g. heating oil, wood or LPG etc.) have much higher average annual costs when compared against electricity and gas. This is most likely because 'other' fuels make up a niche market with high distribution costs and high unit marginal costs.

Average annual domestic gas and electricity bills for a typical UK consumer in 2009 was £683 for gas and £430 for electricity (DECC, 2012c). These compare relatively well with the model estimated results shown in Figure 7.38. Another way to compare model outputs with DECC results is to compare aggregate expenditure on energy. In 2009 household expenditure on fuel and power equated to £33.18 billion in the UK. Using the conversion factors described in Section 7.3.4 it is possible to convert UK consumption into English consumption thus giving a total expenditure of £29.03 billion. From the model, total expenditure for fuel and power in England is estimated at £27.5 billion. The reasons for the £1.5 billion discrepancy might be due to differences in the classification of residential dwellings by DECC. For example, in other energy consumption statistics produced by DECC the definition of 'residential' includes all dwellings with annual consumption less than 73,500 kWh, including commercial customers. The discrepancy may also be due to additional costs not picked up by the domestic building stock model. Finally it maybe because the model uses average UK bills and therefore does not appropriately weight different energy bills by geographic region thus introducing aggregation bias. Figure 7.39 shows the distribution of total annual energy costs for English dwellings estimated by the model.

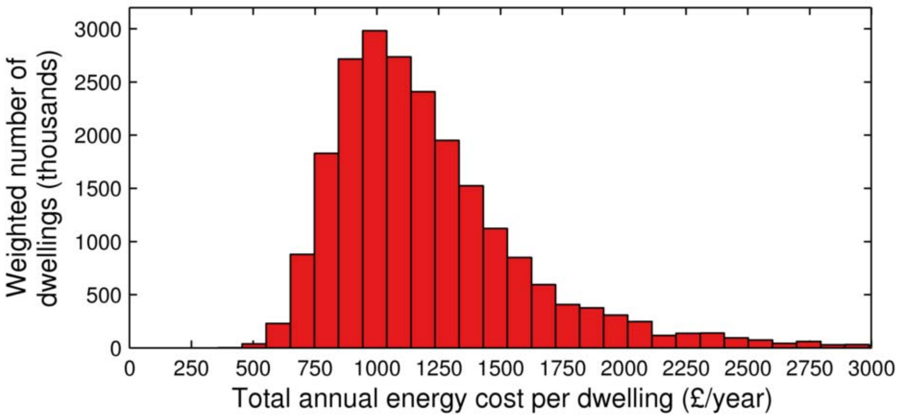

Figure 7.39: Weighted histogram of annual energy costs per dwelling as estimated by the model

1. This includes the costs of heating homes using ten different fuel types Table 7.21

7.10 Model validation

Validation of building stock models is problematic. The most appropriate way to validate a model is to compare model estimates with real data. Real data must be independently measured and unused during the development of the model. Unfortunately, nationally representative databases containing dwelling level metered energy consumption combined with information on physical building properties, social-demographics and behavioural characteristics of occupants are nonexistent. The most recent and most comprehensive national survey to include metered gas and electricity consumption data was last published in 1996. This is too long ago to use in the validation of this building stock model designed to use data from 2008 onwards.

It is only recently that government departments have recognised that a paucity of dwelling level empirical data is negatively impacting on building related research and therefore climate policy. A concerted effort is now underway to improve data availability. Collaboration between the Energy Saving Trust (EST) and other government departments such as DECC have resulted in the development of new datasets. These datasets combine several existing datasets containing energy efficiency and socio-demographic variables at the address level. This dataset is known as the National Energy Efficiency Data framework (NEED) and contains millions of records down to the address level.The

NEED database includes energy efficiency information from HEED. Unfortunately dwelling level information from these datasets is not made publicly available for data protection reasons and was therefore not available for this validation exercise.

Even though dwelling level information is not available from NEED, DECC does provide quasi-aggregate information by combining different sub groups of the building stock[61]. Quasi-aggregate data from this dataset is still valuable because it represents 'actual' energy consumption as opposed to estimated consumption for different building sub-categories. However, there are still many problems with the dataset and its limitations must be understood before it can be used for validation purposes. One issue with NEED is that it is a self-selected database and therefore only contains details from dwellings that have installed energy efficiency measures. Documentation from NEED also explains that the energy readings for flats are not accurate enough to produce robust statistical estimates about energy consumption. Meter readings have also been weather corrected by scaling energy demand by observed temperature data thus changing actual consumption readings. Finally, the dataset contains information from meter-points having an annual consumption less than 50,000 kWh/year for electricity and less than 73,500 kWh/year for gas. Problematically, this means this data-set includes all electricity and gas meters for small businesses (DECC, 2011d). This model was developed to estimate consumption from the residential dwellings only, thus making direct comparisons difficult.

The total affect of including small business meter-point readings in NEED can be estimated by finding the difference in aggregate DECC domestic consumption statistics and aggregate NEED consumption statistics for England. Aggregate gas consumption taken from NEED is 376.5 TWh/year and the annual electricity consumption is 97.9 TWh/year. Compared with DECC estimates for the residential sector the NEED data overestimates domestic gas consumption in England by 76.5 TWh/year while it predicts national electricity consumption almost exactly.

Because the total annual gas demand from the residential sector for England is known (from published DECC energy statistics) it is possible to calibrate NEED to make these datasets compatible. This is accomplished by scaling back the disaggregated NEED estimates by the amount that NEED overestimates domestic gas consumption. This is

61. http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/en_effic_stats/need/need.aspx

done for each subcategory of the six disaggregated summary consumption statistics provided by NEED[59]. These are dwelling type; floor area; dwelling age; tenure; region and household income. Each disaggregation type is broken down differently (e.g. floor area is broken down into seven categories) with summary statistics provided for each consumption category. A comparison between the model and NEED are given for gas and electricity demand in Figure 7.40 and Figure 7.41. Both gas and electricity demand approximate actual demand relatively well for each disaggregation type. Electricity demand appears to approximate actual demand much better than gas. This might indicate that anomalies from gas demand within the NEED dataset are still present, or that the model is not estimating demand as well as it could. For example, when compared to the NEED dataset the model seems to over-estimate gas consumption from older dwellings and under-estimate consumption from newer dwellings. Similarly the model also over estimates consumption from poorer households and under estimates consumption from wealthier households. Putting these differences aside the model is able to estimate different demand categories relatively accurately.

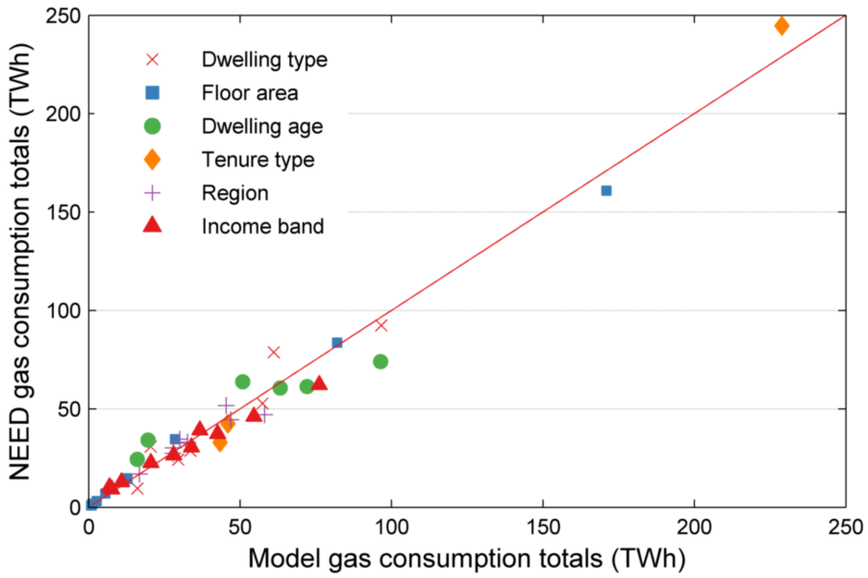

Figure 7.40: Comparison of aggregate model domestic gas consumption and actual gas consumption from the NEED dataset

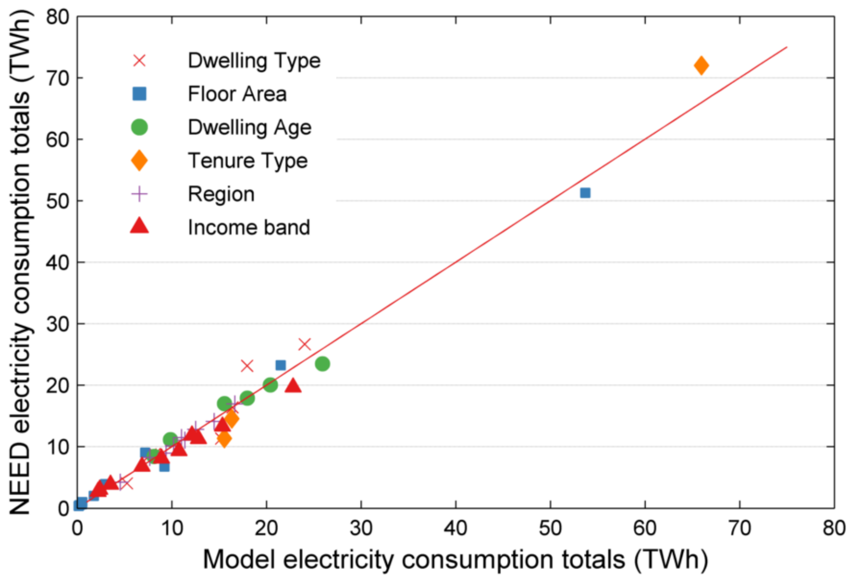

Figure 7.41: Comparison of aggregate model domestic electricity consumption and actual electricity consumption from the NEED dataset

7.11 Chapter conclusion

The first innovation of this building stock model is the high level of detail that is used to simulate energy demand for each dwelling across a large cross section of representative dwellings. Owing to the high granularity and large sample size it is possible to segment portions of the building stock for more detailed analysis. Modelling energy demand independently for each individual dwelling is a unique feature of this building stock model when compared to other building stock models that assign groupings of domestic buildings to a small number of different building 'archetype' categories. Archetype building stock models limit the true heterogeneity from within the building stock and therefore are only able to provide general approximations about differences in energy consumption between different 'archetype' categories. By modelling energy demand from each dwelling individually, it is possible to understand the true distribution of energy demand amongst heterogeneous dwellings not merely the average consumption from a particular dwelling archetype.

The second innovation of this model is that energy demand is estimated independently for every day of the year and for each dwelling. This is a significant improvement on existing building stock models that attempt to estimate energy demand on a month-by-month basis or over a pre-defined heating season. As shown the internal temperature requirements, physical building characteristics, dwelling specific incidental gains and external temperatures all combine to make the energy demand requirements of each dwelling unique. The end result is that the heating season for each dwelling is different and only calculable once the interaction of different variables is allowed for. This has important implications for gas and electricity network operators trying to predict national energy demand requirements on a daily basis. By implementing the heating degree-day method on a daily basis it becomes possible to estimate both the duration and extremes of external temperature profiles – not just mean differences.

The third innovation of this model is its ability to include human behaviour and endogenously allow for the rebound effect. Daily internal temperatures are predicted from daily external temperatures the physical properties of each dwelling and the socio-demographic and behavioural characteristics of occupants. This building stock model represents the first instance that internal temperatures have been predicted from occupant socio-demographic and behavioural characteristics and successfully incorporated in a bottom-up building stock model to estimate final energy demand for England, the UK and GB. Given the significant effect that internal temperature has on final dwelling energy demand, it is surprising that existing building stock models have not placed more emphasis on estimating internal temperatures more accurately. In this model internal temperatures are predicted as a function of income and building efficiency (among other factors) and therefore the model is able to endogenously model the rebound effect (take back). This is possible because daily internal temperature is estimated independently for each dwelling and therefore any building efficiency improvements (or increases to household income) will lead to higher internal temperatures increasing energy consumption.

In conclusion this model offers new opportunities for the development of future bottom-up building stock models using the engineering method. In this chapter a robust method is described showing how occupant behaviour can be used in the prediction of internal temperatures that are then used by the engineering model to estimate energy demand. The cross-sectional and inter-temporal detail provided by this new building stock model offers new insight and improved understanding for how people actually consume energy in the home. Using this model it is possible to develop and compare future scenarios for the residential sector from which robust decarbonisation strategies can be developed. This has important implications in the development of future energy policy, new building standards and carbon mitigation strategies.

7.12 Appendix to chapter 7

Table 7.6: Temperature increase required for heating hot water in different months

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Temperature ΔT (°C)	41.2	41.4	40.1	37.6	36.4	33.9	30.4	33.4	33.5	36.3	39.4	39.9

Table 7.7: Primary cylinder losses

Conditions	Losses (kWh/year)
Boiler with no controls and no cylinder thermostat	1220
Boiler with no controls and a working cylinder thermostat	610
Boiler with controls but no cylinder thermostat	610
Boiler with controls and with thermostat	360
Combination boiler	0

Table 7.8: Solar transmittance factor

Type of glazing	Glazing transmittance factor ($g_{\perp}$)
All windows single glazed	0.85
Some windows double glazed	0.76
Some windows are triple glazed	0.64

Table 7.9: Frame factors

Window type	Frame factor (ff)
Mixed types	0.7
Wooden frame	0.7
Metal frame	0.8
Ultra polyvinyl chloride (UPVC)	0.7

Table 7.10: U-values when roof type and insulation thickness is known

Insulation thickness at joists (mm)	Roof U-value (W/m2K)	
	Slates or tiles	Thatched roof
NONE	2.3	0.35
0-12	1.5	0.32
13-25	1	0.3
26-50	0.68	0.25
51-75	0.5	0.22
76-100	0.4	0.2
101-150	0.29	0.16
151-200	0.2	0.13
201-250	0.16	0.11
250-300	0.13	0.1
>300	0.1	0.6

Table 7.11: U-values for different types of windows

Type of Glazing	U-value
Single glazing, wood	4.8
Single glazing, metal	5.7
Double glazing, wood	2.6
Double glazing, metal	3.2
Triple glazing, wood	2.0
Triple glazing, metal	2.5

Table 7.12: U-values when roof insulation thickness is unknown

Category		Roof U-value (W/m^2K)					
Age of dwelling		Pitched roof no loft space	Pitched roof with loft space	Flat roof	Room in roof	Thatched roof	Thatched roof, room in roof
A	<1900	2.3	2.3	2.3	2.3	0.35	0.25
B	1900-1929	2.3	2.3	2.3	2.3	0.35	0.25
C	1930-1949	2.3	2.3	2.3	2.3	0.35	0.25
D	1950-1966	2.3	2.3	2.3	2.3	0.35	0.25
E	1967-1975	1.5	1.5	1.5	1.5	0.35	0.25
F	1976-1982	0.68	0.68	0.68	0.8	0.35	0.25
G	1983-1990	0.4	0.4	0.4	0.5	0.35	0.25
H	1991-1995	0.29	0.35	0.35	0.35	0.35	0.25
I	1996-2002	0.26	0.35	0.35	0.35	0.35	0.25
J	2003-2006	0.16	0.2	0.25	0.3	0.3	0.25
K	>2007	0.16	0.2	0.25	0.25	0.25	0.25

Table 7.13: U-values for walls when construction material and building age are known

Category		Wall U-value (W/m2K)					
Age of dwelling		Solid – no insulation	Solid – with insulation	Cavity wall (as built)	Filled Cavity	Timber Frame No Insulation	Timber Frame with Insulation
A	<1900	2.4	0.6	2.1	0.5	2.5	0.6
B	1900-1929	2.4	0.6	1.6	0.5	1.9	0.55
C	1930-1949	2.4	0.6	1.6	0.5	1.9	0.55
D	1950-1966	2.4	0.6	1.6	0.5	1	0.4
E	1967-1975	1.7	0.55	1.6	0.5	0.8	0.4
F	1976-1982	1	0.45	1	0.4	0.45	0.4
G	1983-1990	0.6	0.35	0.6	0.35	0.4	0.4
H	1991-1995	0.6	0.35	0.6	0.35	0.4	0.4
I	1996-2002	0.45	0.3	0.45	0.35	0.4	0.4
J	2003-2006	0.35	0.25	0.35	0.35	0.35	0.35
K	>2007	0.3	0.21	0.3	0.3	0.3	0.25

Table 7.14: Floor insulation thickness when data is missing

	Dwelling Age			
	1900- 1995	1996-2002	2003-2006	>2007
Thickness of floor insulation (mm)	0	25	75	100

Table 7.15: Thermal bridges for different age categories

Band	Age category	Thermal Bridge Ψ (U-value)
A	<1900	0.2000
B	1900-1929	0.2000
C	1930-1949	0.1800
D	1950-1966	0.1700
E	1967-1975	0.1600
F	1976-1982	0.1500
G	1983-1990	0.1500
H	1991-1995	0.1500
I	1996-2002	0.1500
J	2003-2006	0.1100
K	>2007	0.0800

Table 7.16: Ventilation rates by building age category

Band	Age category	Ventilation rate (ACH/hour)
A	<1900	0.35
B	1900-1929	0.35
C	1930-1949	0.28
D	1950-1966	0.25
E	1967-1975	0.20
F	1976-1982	0.20
G	1983-1990	0.15
H	1991-1995	0.10
I	1996-2002	0.05
J	2003-2006	0.05
K	>2007	0.05

Table 7.17: Ventilation rate by building structure

Building Structure	Ventilation rate (ACH/hour)
Solid Walls	0.30
Solid Wall with insulation	0.28
Cavity wall with no insulation	0.35
Cavity wall with cavity insulation	0.30
Timber wall with no insulation	0.40
Timber walls with insulation	0.30

Table 7.18: Ventilation rate by extraction fans

Fan type	Ventilation rate (m3/hour)
Chimney	40
Open flue	20
Intermittent extract fan	10
Passive vent	10
Flueless gas fire	40

Table 7.19: Wind factors

Month	Wind Factor
January	1.35
February	1.28
March	1.28
April	1.13
May	1.03
June	0.98
July	0.93
August	0.93
September	1.05
October	1.13
November	1.20
December	1.28

Table 7.20 Monthly mean daily vertical irradiation for three UK based locations

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Mean
London area (Bracknell) (1981 - 1992)													
Beam and diffuse (Wh/m^2)	808	1237	1724	2483	2795	2728	2817	2727	2195	1509	990	650	1889
Ground reflected (Wh/m^2)	70	130	220	365	462	481	482	419	288	165	89	54	269
Global radiation (Wh/m^2)	878	1367	1944	2848	3257	3209	3299	3146	2483	1674	1079	704	2158
Average irradiation (W/m^2)	37	57	81	119	136	134	137	131	103	70	45	29	90
Manchester (Aughton) (1981 - 1992)													
Beam and diffuse (Wh/m^2)	740	1205	1684	2496	2986	2841	2832	2499	2116	1357	799	509	1839
Ground reflected (Wh/m^2)	61	123	211	361	483	487	478	380	274	147	71	41	259
Global radiation (Wh/m^2)	801	1328	1895	2857	3469	3328	3310	2879	2390	1504	870	550	2098
Average irradiation (W/m^2)	33	55	79	119	145	139	138	120	100	63	36	23	87
Edinburgh (Mylenfield) (1981 - 1992)													
Beam and Diffuse (Wh/m^2)	635	1126	1812	2361	2837	2845	2795	2500	2015	1268	821	382	1783
Ground reflected (Wh/m^2)	48	103	208	330	447	474	455	369	248	128	62	31	242
Global radiation (Wh/m^2)	683	1229	2020	2691	3284	3319	3250	2869	2263	1396	883	413	2025
Average irradiation (W/m^2)	28	51	84	112	137	138	135	120	94	58	37	17	84

1. Data source: CIBSE Guide J (CIBSE, 2002 Appendix 6)

Table 7.21: Prices, emissions and standing charges for common fuels

Fuel Type	Standing charge	Unit price (p/kWh)	Emissions factor ($kgCO_{2(eq)}$/kWh)	Primary energy factor	Standing charge (£)	Unit price (p/kWh)
	SAP 2009				DECC 2011	
Mains gas (Natural gas)	106	3.1	0.198	1.02	109.3	3.44
Bulk LPG	70	5.73	0.245	1.06	~	~
Bottled LPG	0	8.34	0.245	1.06	~	~
Oil (heating oil)	0	4.06	0.274	1.06	~	~
Solid Fuel (coal)	0	2.97	0.301	1.02	~	~
Wood	0	3.42	0.008	1.05	~	~
Standard Tariff	0	11.46	0.517	2.92	58.6	12..21
Off Peak Tariff	18	6.17	0.517	2.92	72.73	5.78
Biodiesel (any)		5.7	0.047			
Community Waste	106	3.78	0.04	1.28	~	~

1. SAP 2009 figures taken directly from SAP 2009 methodology
2. Standard tariff electricity prices were estimated from DECC energy price statistics as the average of standard credit, direct debit and pre-payment charges for the UK. Standing charges were calculated similarly.
3. Off peak electricity prices were similarly estimated from Economy 7 tariffs where the average was taken from standard credit, direct debit and prepayment charges for the UK. Standing charges were calculated similarly.

Table 7.22: Panel model results for predicting internal temperatures

Number Obs: 42,723 Groups: 233 Time periods: 183 Method: XTSCC Maximum Lag: 4	β	B	Driscoll Kraay Std. Errors	t-stats	95% confidence intervals	
Text	0.048	0.093	0.022	(2.17)*	0.004	0.093
$Text^2$	0.013	0.458	0.002	(8.51)***	0.010	0.016
(A) London	-	-	-	-	-	-
(A) North East	-1.316	-0.141	0.106	(-12.37)***	-1.526	-1.106
(A) Yorkshire	-0.597	-0.082	0.123	(-4.86)***	-0.838	-0.355
(A) North West	-0.739	-0.138	0.073	(-10.16)***	-0.883	-0.596
(A) East Midlands	-0.347	-0.038	0.066	(-5.24)***	-0.477	-0.216
(A) West Midlands	-0.682	-0.11	0.104	(-6.58)***	-0.887	-0.478
(A) South West	-0.751	-0.119	0.076	(-9.91)***	-0.900	-0.602
(A) East of England	-0.558	-0.079	0.055	(-10.06)***	-0.667	-0.449
(A) South East	-1.397	-0.162	0.061	(-22.88)***	-1.518	-1.277
T_Stat	0.149	0.009	0.028	(5.36)***	0.094	0.204
Auto_Timer	0.170	0.108	0.026	(6.63)***	0.119	0.220
HH_Size	0.108	0.045	0.019	(5.80)***	0.071	0.145
HH_Income	-0.165	-0.02	0.017	(-9.80)***	-0.198	-0.132
Child<5	0.241	0.05	0.041	(5.82)***	0.160	0.323
Children<18	0.223	0.081	0.023	(9.61)***	0.177	0.268
(B) Age<64	-	-	-	-	-	-
(B) Age64-74	0.400	0.039	0.043	(9.36)***	0.316	0.484
(B) Age>74	0.506	0.076	0.037	(13.63)***	0.433	0.579
(C) Owner	-	-	-	-	-	-
(C) Renter	1.092	0.095	0.062	(17.60)***	0.970	1.214
(C) Council	1.455	0.181	0.090	(16.12)***	1.277	1.633
(C) H_Assoc	0.306	0.05	0.046	(6.60)***	0.214	0.397
(D) Detached	-	-	-	-	-	-
(D) SemiDet	0.470	0.105	0.032	(14.69)***	0.407	0.533
(D) Terraced	0.366	0.06	0.033	(10.95)***	0.300	0.431
(D) NotHouse	0.260	0.041	0.047	(5.55)***	0.168	0.352
Gas_CH	-0.432	-0.082	0.040	(-10.78)***	-0.511	-0.353
Non_CH	-0.126	-0.018	0.024	(-5.33)***	-0.173	-0.080
Elec_Main	0.439	0.024	0.080	(5.51)***	0.282	0.596
Other_OH	-0.828	-0.109	0.049	(-16.93)***	-0.924	-0.731
Build_Age	0.077	0.083	0.006	(13.26)***	0.066	0.089
Roof_Ins	0.096	0.041	0.015	(6.45)***	0.066	0.125
Dbl_Glz	0.203	0.11	0.014	(14.29)***	0.175	0.231
Wall_U	0.028	0.026	0.011	(2.52)*	0.006	0.050
Alpha (constant)	15.717	15.72	0.173	(90.82)***	15.376	16.058
R^2 = 0.423	RMSE= 1.88					

* p<0.05, ** p<0.01, *** p<0.001 t-statistics in parentheses

8

Modelling results

8.1 Chapter summary

Using the building stock model developed in Chapter 7 realistic decarbonisation pathways of the residential building stock are projected for the period 2010-2050. Demolition and construction rates for new buildings are applied to the building stock using historical trends. Logistic s-curves are used to model the penetration of ten different technology benchmarks within the building stock. Improving the U-value of exterior walls to 0.3 W/m^2 was shown to have the largest cumulative effect on aggregate $CO_{2(eq)}$ emissions for the period 2010-2050. This is closely followed by the combined effect of installing double and triple glazing in all dwellings and then reducing the air-permeability of all buildings to be below 1 m^3/h.m^2. The importance of using a portfolio approach for measuring the carbon mitigation potential of different technologies is paramount and has a large effect on final aggregate emissions. Importantly, retrofitting the existing building stock to the ambitious technology benchmarks identified is shown to be insufficient for meeting national carbon budgets. Therefore, decarbonisation of all energy sources used for space heating, water heating, cooking, lights and appliances will be paramount if future targets are to be met.

8.2 Newly constructed dwellings

8.2.1 Construction and demolition of buildings

Household projections for each region in Great Britain are available from the Communities and Local Government (CLG) website[62]. The net supply of new domestic housing is the sum of new constructions and conversions minus the number of demolitions. The average rate of additional new housing stock in England between 2006 and 2011 was 182,710 dwellings per year[63]. Over the same period the average rate of demolition was 18,120 dwellings per year (roughly 10% of the number of new dwellings). According to CLG projections, the number of dwellings in England will increase from 22.2 million in 2011 to 27.5 million in 2033. If this trend continues the number of households in England will reach 30.7 million in 2050 and represent a net increase of 8.3 million net additional dwellings between 2011 and 2050 (an increase of 38%). Meeting this demand will require an average annual net increase of 214,000 dwellings per year, or more accurately, a compounding natural rate of increase of 0.797% of the building stock each year. The total number of new dwellings constructed each year will be higher than the absolute growth in dwellings to account for the natural rate of demolition.

Projecting future demolition rates is problematic. Historical trends in demolition rates have fluctuated greatly, ranging from a minimum demolition rate of 9,000 dwellings in 1991 to a peak of 22,300 in 2006 dropping back to 14,900 dwellings in 2010[64]. Boardman et al. (2005) argue (in 40% House) it is necessary to demolish around 3.2 million dwellings by 2050 to meet stringent energy efficiency targets. Achieving this target requires 80,000 dwellings to be removed from the building stock each year until 2050. Since being published, '40% House' has received a great deal of criticism for not considering the lifecycle emissions embodied in construction materials as well as other factors affecting the environment such as land use change, infrastructure and area blighting (Power, 2008). Unfortunately the demolition rates used in other bottom-up building stock models including BREHOMES, Johnsons Model and DeCARB, remain illusive (Shorrock and Dunster, 1997; Johnston, 2003; Natarajan and Levermore, 2007). In the absence of any data predicting future

62. Communities and Local Government live tables on household projections (Table 104): http://www.communities.gov.uk/housing/housingresearch/housingstatistics/housingstatisticsby/householdestimates/livetables-households/
63. Communities and Local Government live tables on household projections (Table 120).
64. Communities and Local Government live tables on household projections (Table 111).

demolition rates as well as important considerations of embodied carbon in construction materials and the controversy surrounding the demolition of the building stock (due to the nature of historical buildings) a natural demolition rate was calculated based on historical demolition trends in the UK. The demolition rate is estimated to be 0.09% of the total building stock on average per year. Table 7.5 gives the projected new build and demolition rates for England used by the model.

Table 8.1: Dwelling projections for England - demolitions and new builds

	2010	2020	2030	2040	2050
Demolitions per year (000’s)	20.1	21.9	23.8	25.7	27.7
Net new dwellings per year (000’s)	176.8	193.9	210.9	228.0	245.1
Total new dwellings built per year (000’s)	196.9	215.8	234.7	253.7	272.8
Building Stock (000’s)	22,189	24,329	26,469	28,609	30,749

8.2.2 Performance of new buildings

There are several building standards aimed at improving the performance of newly constructed dwellings in the UK. These are Part L of the building regulations, the code for sustainable homes and BREEAM. Predicting energy consumption and emissions from newly constructed buildings is not straightforward due to frequently changing government policy. In 2006 Gordon Brown and Yvette Cooper announced that all new buildings constructed from 2016 would be zero carbon (Communities and Local Government, 2006). Arguments over the definition of zero carbon have persisted and the practical interpretation of zero carbon homes has consistently and repetitively been weakened (UK Green Building Council, 2008; Goodchild and Walshaw, 2011; Kennedy and Sgouridis, 2011). The zero carbon homes standard as it presently stands requires a 70% reduction of regulated energy use compared to 2006 building standards. The most recent changes – announced in the 2012 budget – allow emissions generated from cooking and appliances to be completely ignored. In practical terms this requires emissions from any typical new dwelling to be under 1 $tCO_{2(eq)}$/year[65] down from the existing building stock average emission rate of approximately 4.25 $tCO_{2(eq)}$ per dwelling per year (excluding cooking and appliances). Minimum carbon compliance for new build homes from 2016 will therefore be as follows[66]:

- low-rise apartment block: 14 $kgCO_{2(eq)}/m^2$.year

65. This is based on a mid or end terrace house with a floor area of 90 m^2.
66. Carbon Compliance addendum from the Zero Carbon Hub (Zero Carbon Hub, 2011)

- mid & end terrace house: 11 $kgCO_{2(eq)}/m^2.year$
- detached house: 10 $kgCO_{2(eq)}/m^2.year$

It is not possible to predict each of the technologies installed in new homes between now and 2050. However, it is safe to assume, the form, structure and material properties of future dwellings will be as diverse as the existing stock is today. Therefore, instead of ascribing a single dwelling type with a single set of properties (e.g. construction material, floor area or occupancy rates etc.) as has been done in other building stock models, a selection of top performing homes (e.g. less than 30 $kgCO_{2(eq)}/m^2.year$) are drawn at random from the existing building stock and retrofitted to have the best available technology to meet the zero carbon standard. These homes will then represent the base sample of dwellings from which the model will randomly select the construction of new dwellings. It is therefore an assumption of the model that buildings constructed between 2010 and 2016 will be constructed to meet the standards of the top performing 20% of existing dwellings. All buildings constructed after 2016 meet the Zero Carbon standard as it presently stands. These new buildings will therefore have a distribution of different floor areas, window areas, building typologies and building materials as they have been taken from a large sample of dwellings from the existing building stock. Meeting the new Zero Carbon building standard requires all new buildings (which were selected at random from the existing building stock) to be upgraded to have the following physical characteristics:

- Building construction year modified to post 2007;
- Roof insulation >300 mm;
- All exterior walls to have minimum U-value of 0.3 W/m^2;
- 100% double glazing throughout the dwelling;
- Air permeability improved to 0.3 $m^3/h.m^2$;
- Energy efficient condensing gas boilers (90% efficient)[67]
- Hot water cylinders installed with 150 mm full factory insulation;
- 100% energy efficient lighting used throughout the dwelling.

67. In this scenario we assume there is no transition to use heat pumps

A reduction in carbon emission can occur from either greater building energy efficiency or from low carbon onsite energy generation. It is assumed that in the first instance buildings are made more efficient at the construction phase (as this is shown to have the lowest overall cost) and for cases when the Zero Carbon standard is still not met, the remaining excess energy demand is met by low carbon onsite energy generation (e.g. solar or biomass). The distribution of energy consumption for newly constructed buildings compared to existing buildings for different end use categories is shown in Figure 8.1. The largest improvements to the building stock come from improvements to space heating while energy consumption from appliances leads to a slight increase due to an increase in the floor area of new dwellings, from which appliance energy consumption is derived. In addition, the energy consumed by appliances is subject to two counteracting factors. Although the total number of appliances per dwelling is increasing, the efficiency of appliances is also improving.

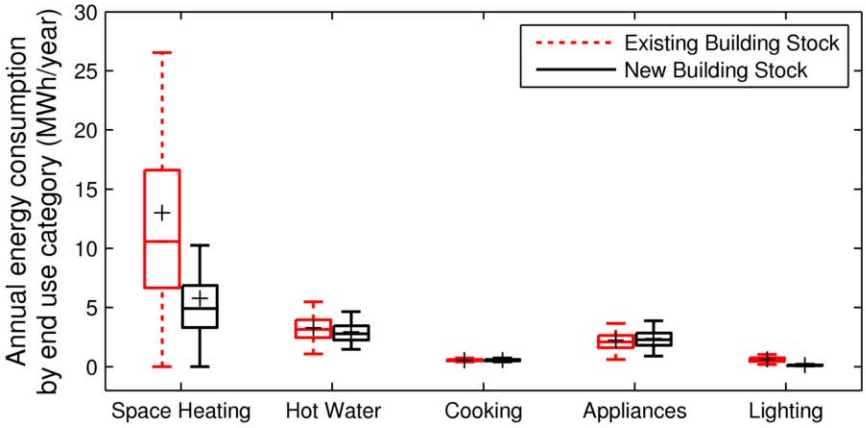

Figure 8.1: Comparison of energy consumption of old stock and new stock by end use category

Emissions factors for end-use electricity consumption will also change over time and this will need to be included in modelling estimates. Table 8.2 compares projected emissions factors used by different energy demand modelling groups. The MTP programme and the 40% house project use emissions factors in the development of decarbonisation scenarios. DECC does not publish emissions factors directly but using other published DECC statistics it is possible to estimate them indirectly. In Table 8.2 projected UK electricity grid emissions factors were estimated from DECC data by dividing total expected annual electricity generation for the period 2010-2050 by the estimated annual aggregate emissions from major power producers. The committee on climate change recommends that emissions factors from the power sector will need drop to at least 0.05 $kgCO_{2(eq)}$/kWh by 2030 with a further reduction to 0.01 $kgCO_{2(eq)}$/kWh by 2050 (CCC, 2010) in order to meet existing carbon budgets. These results do not concur with the emissions factors derived from DECC data. Final projected emissions factors used in the model therefore aim to strike a balance between the realism proposed by DECC and other building stock models and the ambitious emissions reductions proposed by the CCC.

Table 8.2: Projections for emissions factors from the power sector

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Projected electricity generation[1] (TWh)	352	373	399	417	435	-	-	-	-
Emissions from major power stations[1] ($MtCO_2$)	153	125	91	72	49	-	-	-	-
Emissions Factors (DECC)[2] ($kgCO_2/kWh$)	0.435	0.335	0.228	0.173	0.112	-	-	-	-
Emissions Factors CCC[3] ($kgCO_2/kWh$)	0.520	0.430	0.32	0.13	0.05	0.025	0.02	0.015	0.01
Emissions Factors MTP[4] ($kgCO_2/kWh$)	0.520	0.471	0.423	-	-	-	-	-	-
Emissions Factors 40% House[4] ($kgCO_2/kWh$)	0.510	0.403	0.393	0.367	0.367	0.367	0.367	0.367	0.367
Central scenario (business as usual) ($kgCO_2/kWh$)	0.517	0.430	0.350	0.250	0.200	0.150	0.10	0.05	0.02

1. Adopted from DECC energy and emissions projections for large power producers in the UK (DECC, 2012d)
2. These have been independently calculated from DECC statistics and only includes $CO_{2(eq)}$ emissions (i.e. not other GHG) (DECC, 2012d)
3. Taken from the Committee on Climate Change central scenario carbon budget from the power sector (taken from graph) (CCC, 2010)
4. Adopted from the Market Transformation Programme statistics (Market Transformation Programme, 2009)
5. Emissions factors used by the 40% House Project (Boardman et al., 2005).

Figure 8.2 compares emissions (excluding onsite energy generation) for newly constructed buildings in 2020 and 2050 within the existing stock. The rapid decarbonisation of the electricity sector reduces aggregate emissions from the built environment and thus helps to meet 2050 targets. Under these assumptions, many of the dwellings constructed post 2016 meet the Zero Carbon building standard using energy efficiency improvements alone, however, there are still some buildings that need to meet excess energy demand using low carbon onsite generation. As indicated in Figure 8.2 flats and apartments will achieve the largest reduction in $CO_{2(eq)}$ emissions from the decarbonisation of electricity generation. This is because a higher proportion of flats and apartments use electricity for space and water heating.

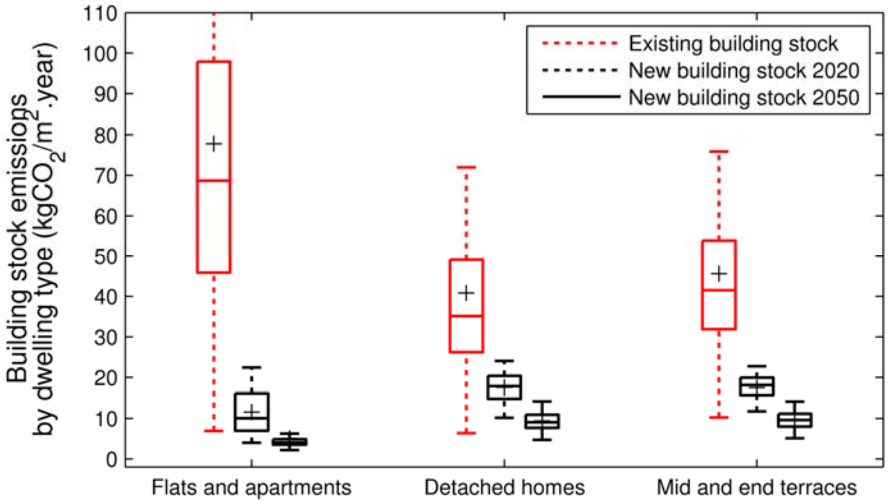

Figure 8.2: Emissions for new buildings by dwelling types in 2050

1. Emissions exclude emissions reductions from low carbon onsite energy generation.

8.2.3 Business as usual scenario

Figure 8.3 shows the evolution of aggregate total energy consumption from new and existing buildings until 2050. It clearly shows that despite the implementation of radical new efficiency standards for newly constructed buildings total energy demand from the residential sector still increases. Under business as usual (with no radical implementation plans to decarbonise the existing building stock) final energy demand is projected to increase from 447 TWh in 2010 to 533 TWh in 2050. Under the same scenario whilst assuming that all new buildings meet the Zero Carbon standard and that the power sector is decarbonised at the rate given in Table 8.2, annual aggregate emissions from the building stock will decrease from 126.4 $MtCO_{2(eq)}$ in 2010 to 86.5 $MtCO_{2(eq)}$ in 2050. To put this in perspective, the building stock will swell by 38% between 2010 and 2050 but overall emissions will decrease over the same period by 31.6%. Under the business as usual scenario, none of the existing stock has been decarbonised and therefore this saving is a direct result of decarbonising the power sector and improving the efficiency standards of all newly constructed dwellings. It also highlights that under a 'no-retrofit' business as usual scenario presented here, none of the government's decarbonisation targets will be met which require at least 80 $MtCO_{2(eq)}$ abated by 2030 and emissions eliminated almost entirely from the building stock by 2050 (CCC, 2010).

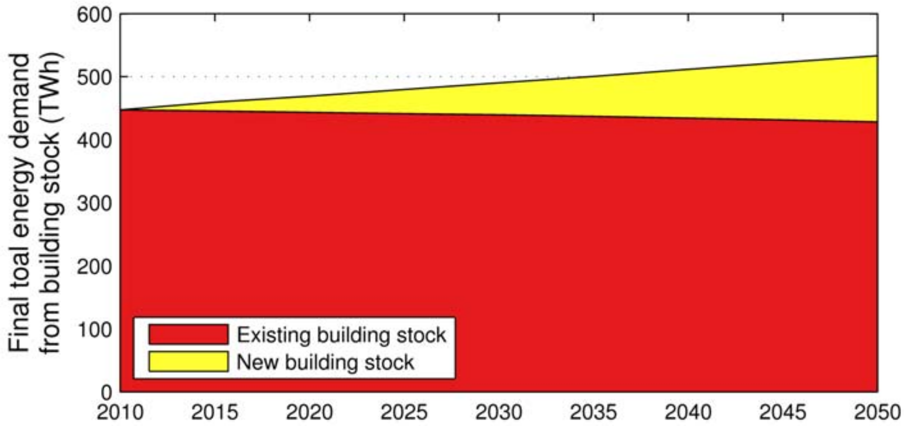

Figure 8.3: Aggregate final energy demand from new and existing buildings under business as usual

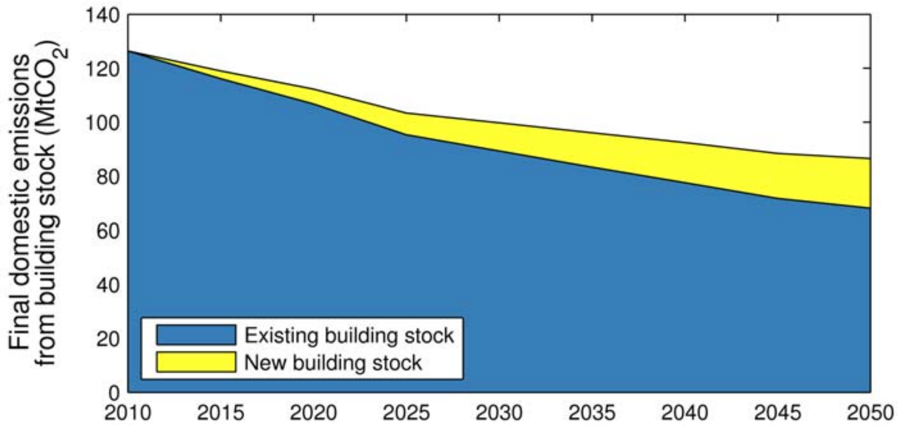

Figure 8.4: Aggregate final emissions from new and existing buildings under business as usual

1. Assumes that the Zero Carbon standard is met for new buildings from 2016 but emissions from cooking and appliances (presently excluded from zero carbon standard) are added back to final emissions.
2. Assumes that demand for electricity remains at the same proportion of overall emissions as in 2010, although total demand for electricity increases in absolute terms.
3. Assumes that the power sector is decarbonised at the rate given in Table 8.2.

With this model it is possible to project the aggregate effects of energy and emissions by end use energy service category. As shown in Figure 8.5, energy demand for each energy service increases steadily as the building stock expands. Over the period to 2050 emissions decline for all end-use categories which are reliant on electricity. Even though the model predicts that demand for electricity from appliances will increase by over 50% between 2010 and 2050, total emissions from appliances will decrease significantly due to the decarbonisation of the electricity production sector. Even with rapid decarbonisation of the power sector, aggregate emissions from the building stock (under a 'no retrofit scenario') remain high, only falling by approximately 25% over the period 2010 to 2050. This is largely because most emissions in the home are generated from gas heating and without retrofitting or changing to low carbon energy sources for heating, these homes emissions remain relatively unchanged.

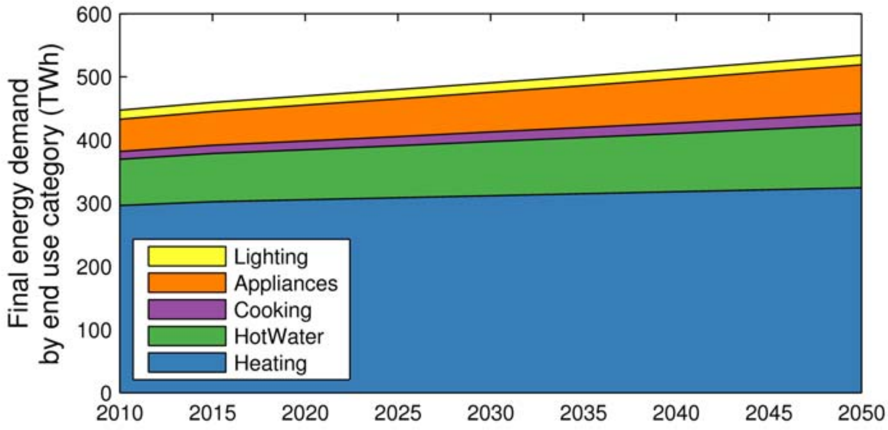

Figure 8.5: Aggregate energy demand by end use category under business as usual[68]

1. Assumes full decarbonisation of the power sector by 2050
2. Excludes retrofitting of the existing building stock
3. Assumes all newly constructed dwellings are zero carbon from 2016
4. Assumes the structure of energy demand will not change between now and 2050 (e.g. appliances use will remain a function of floor area).

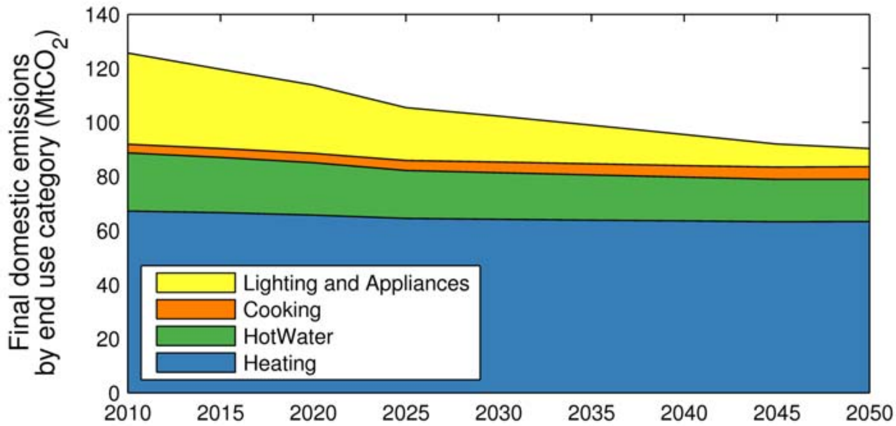

Figure 8.6: End use emissions by energy service category under business as usual

1. Assumes full decarbonisation of the power sector by 2050
2. Excludes retrofitting of the existing building stock
3. Assumes all newly constructed dwellings are zero carbon from 2016

8.3 Retrofitting the existing building stock

8.3.1 Assumptions for retrofitting

As discussed in the previous section, retrofitting the existing building stock is required if emissions reductions targets are going to be met. Accurately modelling and therefore predicting the diffusion of energy efficiency technologies into the existing building stock remains problematic. Not least because of the assumptions and approximations that need to be made about the diffusion of existing technologies, but also because it is impossible to predict how the innovation of new technologies may evolve and contribute to decarbonisation. In this analysis, the

68. This scenario ignores the effect of electric vehicles.

innovation and diffusion of unknown technologies is ignored. It is recognised however there are many promising technologies on the horizon that have the potential to contribute to decarbonisation targets within the built environment. Without robust data on the performance of these new technologies it is difficult to include them in any modelling exercise. Even though it is possible to incorporate such technologies in the existing model, this exercise is left for future research.

An assumption of the retrofit scenario is that fuel shares remain constant over the building stock between 2010 and 2050. Therefore, natural gas will remain the dominant fuel source for heating while the diffusion of solar photovoltaic's (or other renewable electricity technologies) will only produce sufficient electricity to meet lighting and appliance demand (this assumption is already covered by the renewable electricity supply targets covered in Section 8.2.2). This assumption is not unduly unrealistic. Under the central price scenario, DECC predicts the future price of electricity will grow three times as fast as the price of natural gas[69] (DECC, 2012e). This is largely because of the rising costs of electricity generation and recent discoveries of unconventional gas reserves predicted to expand twice as fast as conventional resources (BP, 2011). Although it is possible to analyse the effect of changing fuel shares within the residential sector, this is outside the scope of this thesis and will be left for future work.

Retrofitting the existing building stock is achieved using technology benchmarks. It is assumed that as each dwelling is upgraded to meet a new technology benchmark, it does this in one complete step. For example, if two dwellings have different levels of loft insulation (one has 200mm and the other has 50mm) it is assumed that as each dwelling is upgraded to meet the benchmark (300mm) this is achieved in one single step regardless of the initial conditions for that dwelling. Again, this is not an unrealistic assumption. Dwellings undergoing renovation will likely install the best available technology minimising future hassle and costs.

Temperature demand within dwellings is also assumed to remain stable over the foreseeable future. Historical trends indicate that mean internal temperatures in UK dwellings have been steadily rising since records began. However, concerns about climate change, improving home energy efficiency levels, and rising external

69. DECC projections for the central price scenario indicates residential electricity prices will increase by 66% between 2010 and 2030; while natural gas will only increase by 26% (DECC, 2012e).

temperatures due to the effects of climate change all interact in complex ways leading to uncertain outcomes. One major benefit of this model is its capability to model the effects of internal and external temperatures; however, this modelling effort is outside the scope of this thesis and will be left for future work. Therefore it is assumed external temperatures in Britain will remain relatively unchanged.

Smart grids and time of use pricing will also have important implications for energy demand in the residential sector. However, the scale of impact from these new innovations remains debated (Darby, 2010; Kilpatrick et al., 2011). Given the interdependent nature of these innovations and the uncertainty for how they may evolve over time, the overall impact of 'smart grids' will be left for future research.

8.3.2 Methodology

The principal question under consideration relates to the estimation and calculation of the decarbonisation potential for different energy efficiency technologies. The best way to answer this question is to estimate how energy and emissions change as new technologies are installed within a heterogeneous building stock. Reasonable assumptions about technology diffusion rates are therefore required. It is important to note that modelling the energy efficiency improvements for one technology on its own will give different results to modelling the effect of two or more technologies installed as a portfolio. This is because of complex interactions that occur between different technologies and between technologies and users. In other words, it is not possible to simply sum the expected energy savings of each individual technology to calculate the expected savings of installing all technologies in a particular dwelling. This is simply because of diminishing marginal returns for each subsequent technology. Technologies are thus non-linear in their return to carbon mitigation potential. In other words, the marginal rate of carbon saving decreases as the number of new technologies in the home increases. As this model is a bottom-up building stock model it is able to capture many of these complex interactions occurring at the dwelling level.

The diffusion of technology is widely recognised to follow typical logistic s-curves (Andersen, 1999). Logistic s-curves are therefore employed to model the diffusion of energy efficiency technologies in the existing building stock over time. At any point in time the logistic s-curve therefore represents the proportion of buildings in the building stock that meet a particular technology benchmark (e.g. the proportion of buildings that have 100% energy efficient lighting). In this model logistic s-curves were developed for each technology benchmark and used to predict the penetration of technologies that meet a particular 'technology benchmark'. The period of the study is between 2010 and 2050. The rate of diffusion for each 'technology benchmark' depends on the initial conditions for that technology (e.g. the number of homes that already meet that technology benchmark); the specific characteristics of the technology (e.g. can the technology be quickly and easily deployed) as well as other exogenously applied factors (e.g. whether it is possible for the technology to reach 100% diffusion within the existing building stock). The penetration of energy efficiency technologies in the existing building stock will therefore be a function of the properties of the technology and the initial conditions of the technology in the building stock. Ten different end use energy saving technology benchmarks were chosen to model the impact they may have on decarbonising the existing building stock (Table 8.3 and Figure 8.7). It should be noted that appliance efficiency improvement are excluded from these technology benchmarks. Although home appliances are expected to become more efficient, the overall demand from appliances is expected to increase. The overall effect is that electricity consumption from appliances decreases by only 6% between now and 2020 (Energy Saving Trust, 2011). In addition, the increased level of detail required for estimating appliance efficiency improvements for different appliance types and estimating trends for an increasing number of appliances and therefore final plug-load is outside the scope of this analysis. Final fuel-shares for each dwelling were assumed to remain constant over the modelling period, even though total final demand from each dwelling could change over time.

Table 8.3: Benchmarks and trajectories for retrofitting the existing building stock

	2010	2015	2020	2025	2030	2035	2040	2045	2050
100% Energy efficient lighting	12%	50%	88%	98%	100%	100%	100%	100%	100%
Loft insulation increased to >300mm	3%	13%	28%	52%	74%	89%	96%	98%	99%
Exterior walls improved to U-value 0.3 W/m^2	2%	6%	14%	31%	55%	77%	90%	96%	98%
Thermal bridge improved to U-value 0.05 W/m^2	2%	4%	11%	24%	45%	66%	79%	86%	88%
Floors improved to U-value of 0.5 W/m^2	9%	22%	45%	70%	87%	95%	98%	99%	100%
100% Double glazing	60%	84%	92%	87%	72%	50%	27%	12%	5%
10)% Triple glazing	0%	2%	5%	12%	27%	50%	73%	88%	95%
Energy efficient boilers (90% efficient)	16%	34%	59%	79%	91%	97%	99%	100%	100%
Factory hot water tank insulation 150mm	10%	30%	63%	87%	96%	99%	100%	100%	100%
Air leakage improved to 1 m^3/h.m^2	5%	11%	21%	36%	52%	66%	76%	80%	83%

Specific properties for each technology were used to derive logistic s-curves. Information such as the initial conditions, the angle of the slope and limiting values were all derived from known information about each technology. For example, energy efficiency lighting can be rolled out much more quickly across the building stock and therefore the gradient on the logistic s-curve is much steeper relative to other technologies. Similarly, around 60% of existing homes already have double-glazing installed and this has the effect of bringing the initial condition for double-glazing further along the logistic s-curve compared to other technologies (Figure 8.7). The penetration of triple glazing is installed at the expsense of double glazing until all homes have triple glazing by 2050. Additionally, the technology benchmark for thermal bridging and air permeability have much smaller initial conditions so they will take much longer to penetrate. It is also recognised that 100% penetration of thermal bridging or air permeability may not be possible due to technical difficulties and escalating marginal costs for unique or historic building types. Therefore the limiting values of these technology benchmarks are much lower than the limiting values for other technology benchmarks, typically set around 80%-90% (Figure 8.7). It should also be noted that improvements to appliance energy efficiency have not been included in this list of benchmarks (though it would be possible to add this as an additional benchmark).

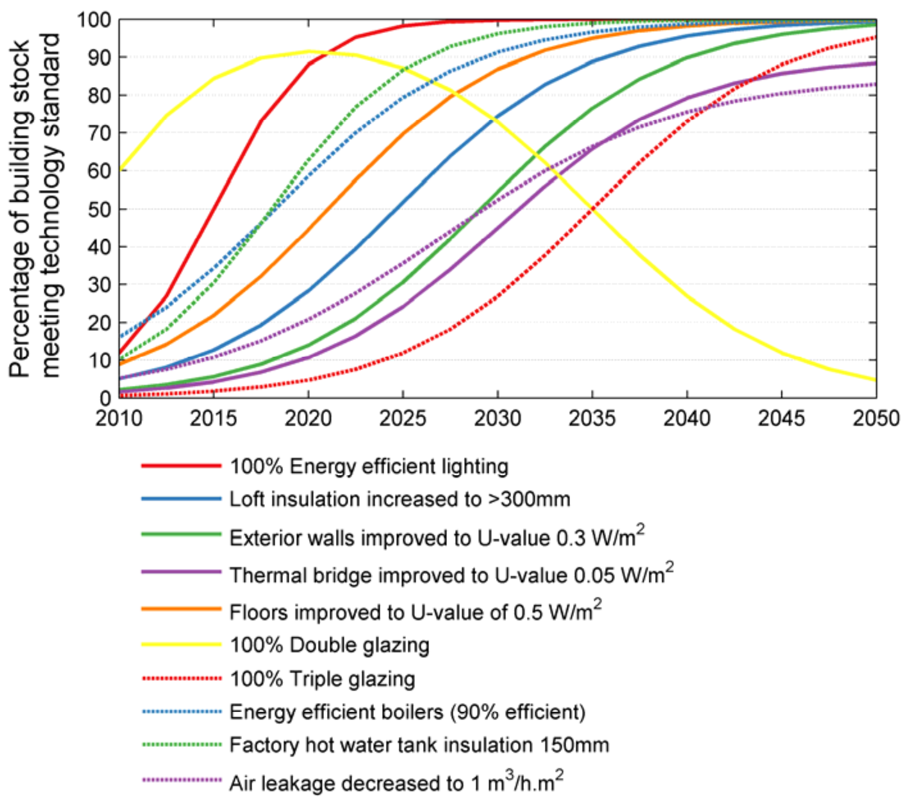

Figure 8.7: Logistic penetration s-curves for different technology benchmarks

8.3.3 Modelling procedure

Once the logistic s-curves were defined for each 'technology benchmark' an algorithm was developed to retrofit sufficient numbers of the existing building stock to meet the new technology benchmark in each period. As shown by the logistic s-curves in Figure 8.7, the proportion of homes meeting the technology benchmark varies over time. The model is therefore solved every five years between 2010 and 2050 to meet specific technology benchmarks (as shown in Figure 8.7). Dwellings chosen for retrofit are selected at random (using the dwelling grossing weights) from the sample of dwellings chosen to represent the building stock in each year. The number of dwellings randomly chosen from the sample must match the proportion of dwellings upgraded to that technology benchmark for that particular period. Energy and emissions distributions over the building stock are therefore simulated for the entire building stock for each period. The model can produce a number of outputs including energy and emissions by end-use category, by fuel-type or any other segmentation of interest, such as those homes that are in fuel-poverty, building type, floor area, income deciles etc. It is therefore not only possible to calculate the mean from any segment of interest but the distribution of values over different segments. The following principles were used to model the retrofitting process of the building stock.

i) All dwellings not meeting particular technology benchmarks are eligible to be selected at random from the sample representing the population of dwellings[70].

ii) Dwellings are chosen at random and retrofitted to meet the new technology benchmark.

iii) The random selection of dwellings from the building stock is repeated until the proportion of dwellings meeting the new technology benchmark meets the proportion of homes within the building stock to particular technology benchmarks.

Technology benchmarks and penetration rates are necessarily optimistic to meet government energy efficiency and climate change targets. However, they are also selected to be both physically and economically realistic given assumptions about

70. Dwellings are randomly selected using dwelling grossing weights.

future energy prices and government policy. The scenario presented represents just one possible future pathway from an infinite number of possibilities. It is not claimed that the analysis is able to predict the future in some probabilistic sense, nor is it claiming that this future will unfold in some positivist way if a particular set of policies and technologies were put in place. The benefit of conducting such an analysis is that it highlights the extent of change that is required and the relative magnitude of energy and emissions reductions necessary for different end-use technology service categories. Importantly, it allows specific carbon mitigation technology benchmarks to be targeted for maximum emissions reductions at lowest cost. Moreover it highlights the importance of understanding how the rate of change of decarbonisation is important for the overall magnitude of emissions reductions. This has important implications for the timing of policy implementation aiming to maximise carbon mitigation and meet future carbon budgets. It also highlights the need to appreciate how different policies (and technologies) will interact over time. Developing strategies that target these dynamics will be central to meeting future climate change targets and for defining critical decarbonisation pathways.

8.4 Results

Each technology benchmark was modelled independently on the building stock using the penetration rates given in Table 8.3. By summing the energy and emissions savings from each independent technology benchmark (neglecting the effects of other technologies) the expected energy and emissions savings for the building stock can be estimated for each unique technology benchmark. This approach is incorrect because it assumes savings from each unique technology benchmark are additive. Savings from each technology are not additive for two reasons. First, as new technology benchmarks reduce dwelling energy consumption, the next marginal technology installed must make savings from a lower absolute rate of energy consumption. Second, there are complex interactions that occur between technologies and between technologies and people. Accurately understanding these effects can only be understood when modelled together as a portfolio of technologies.

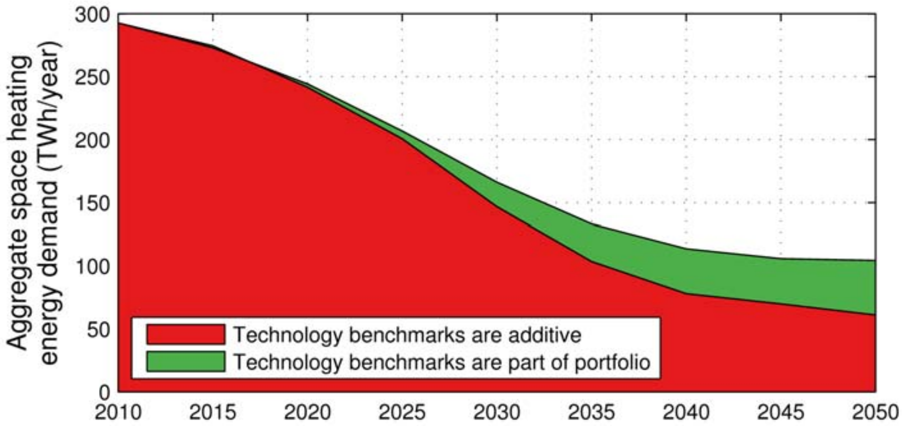

Figure 8.8: Comparison between technologies modelled independently or as part of a portfolio

As shown in Figure 8.8 substantive differences exist between these two modelling approaches. The effect of modelling each technology independently (not as part of a portfolio of technologies) has a substantive effect on the predicted final energy consumption. It is shown the effect of modelling technologies independently incorrectly reduces final total energy demand in 2050 by an additional 43TWh/year. This difference is around 42% of final energy demand by 2050 and signifies the importance of using the portfolio approach as opposed to calculating the efficiency gains made by each technology individually on each dwelling.

The correct procedure for modelling the effects of different technology benchmarks is to recognise that portfolios of technologies change the overall amount of energy and emissions reductions possible. The effects of individual technologies can still be estimated by cumulatively adding new technology benchmarks to the existing building stock and then taking the marginal rate of improvement as each new technology is applied. Using this procedure it is possible to determine the marginal savings that can be made from each successive technology benchmark. By its nature, this implies the order technologies are deployed will have an effect on the relative savings attributed to each specific technology. Because the order in which technologies are deployed is important, each technology benchmark was heuristically ranked from the simplest and cheapest to install to the most difficult and most expensive. This order is given below in Table 8.4:

Table 8.4: Order technology benchmarks are installed

Order	Technology Benchmark
1	100% Energy efficient lighting
2	Loft insulation increased to >300mm
3	100% Double glazing
4	Factory sealed hot water tank insulation >150mm
5	Energy efficient boilers (90% efficient)
6	Floors improved to U-value of 0.5 W/m^2
7	Thermal bridge improved to U-value 0.05 W/m^2
8	100% triple glazing
9	Air leakage improved to 1 m^3/h.m^2
10	Exterior walls improved to U-value 0.3 W/m^2

Figure 8.9 and Figure 8.10 give aggregate energy and emissions projections to 2050 using the portfolio approach. The order that each technology benchmark is applied is read from bottom to top of the legend in Figure 8.9. One of the most striking results from Figure 8.9 and Figure 8.10 is that even with aggressive investment in retrofit technologies, aggregate energy consumption from the residential sector only reduces by about one-third between 2010 and 2050. Although aggregate space heating demand is shown to decline from roughly 292 TWh/year in 2010 to 104 TWh/year in 2050 (a reduction of ~188 TWh/year) total aggregate energy demand for all energy services over the same period only reduces by 146 TWh/year. This is because energy consumed by cooking, hot water and appliances increase over the same period. This is mainly due to the expansion of the building stock and increasing demand for electricity.

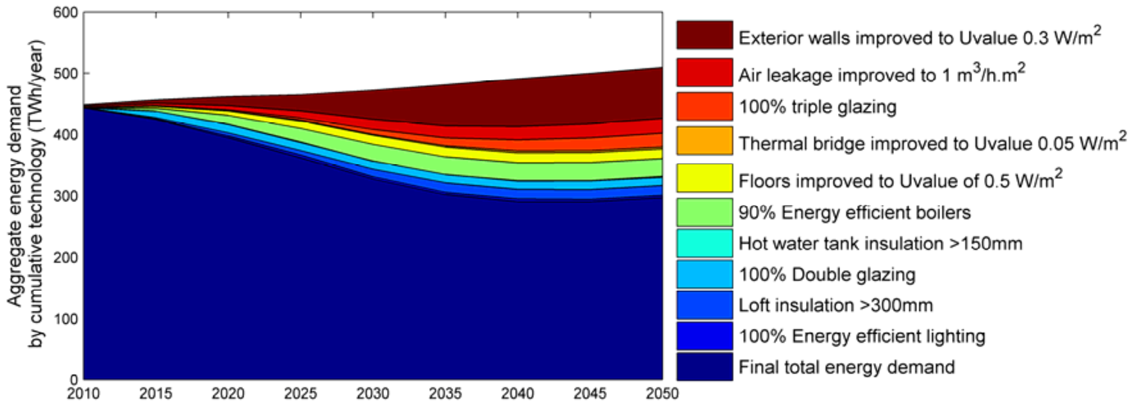

Figure 8.9: Aggregate energy consumption and savings by technology benchmark

Most technology benchmarks contribute an important and substantive reduction to energy demand. The most important of all technology benchmarks is to improve the U-value of exterior walls to 0.3 W/m^2. Unfortunately to meet this standard will require substantial investment in either internal or external solid wall insulation as simple cavity wall insulation is insufficient to meet the required U-value of

0.3 W/m^2. According to the energy saving trust (Energy Saving Trust, 2012b) solid wall insulation costs between £6,000 and £13,000 per dwelling to install, making it one of the most expensive retrofit technologies available.

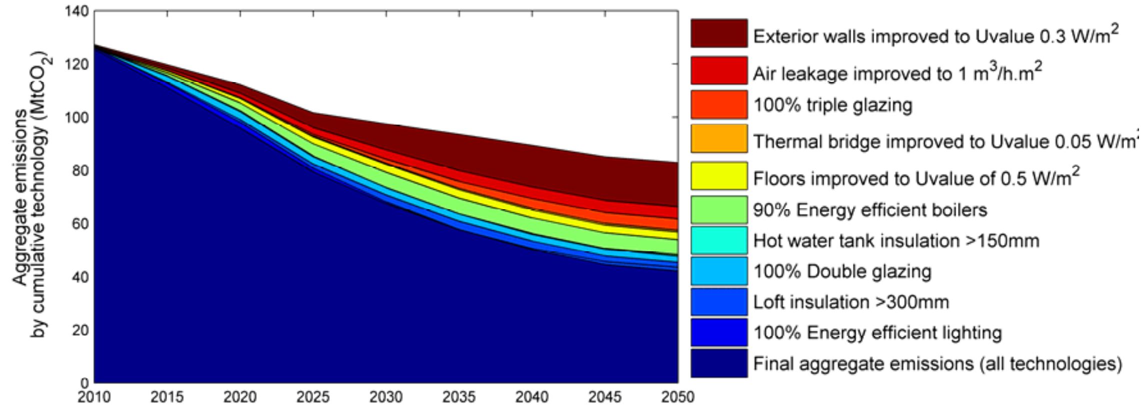

Figure 8.10: Aggregate emissions reductions from retrofitting the existing building stock

1. This assumes the power sector is essentially decarbonised by 2050 (~0.02 $kgCO_2$/kWh) and that all new buildings meet the existing zero carbon building standard.

Finding additional solutions to reduce energy and emissions must therefore also come from reducing demand from cooking, hot water and electrical appliances. However, reducing demand from these energy service categories remains problematic. For electrical appliances such as fridges and washing machines, the introduction of new government policies to improve energy efficiency standards is beginning to have a measureable effect, but any gains that are implemented are unfortunately far outweighed by the accumulation of additional electronic gadgets in the home. For cooking and hot water energy consumption, reducing energy consumption through efficiency alone is difficult. Thus lowering emissions from cooking and hot water consumption must rely on switching to low-carbon fuels such as solar thermal, CHP with district heating and renewable electricity rather than relying solely on improvements to energy efficiency. When comparing Figure 8.9 with Figure 8.10 it is clear that emissions decline far more rapidly than energy demand between 2010 and 2050 (due to the decarbonisation of the power sector). Even so, the reductions made in $CO_{2(eq)}$ emissions are still insufficient to meet government emissions reductions targets.

Figure 8.11 is an area plot showing aggregate energy-use by end use service category. It shows that although energy consumed for space heating continues to decline – due to ambitious retrofit technology benchmarks – the energy consumed for hot water and appliances continues to increase. It is predicted that the energy consumed by lighting, appliances, cooking and hot water will dominate domestic energy demand from around 2040 if radical retrofitting of the existing building stock is carried forward.

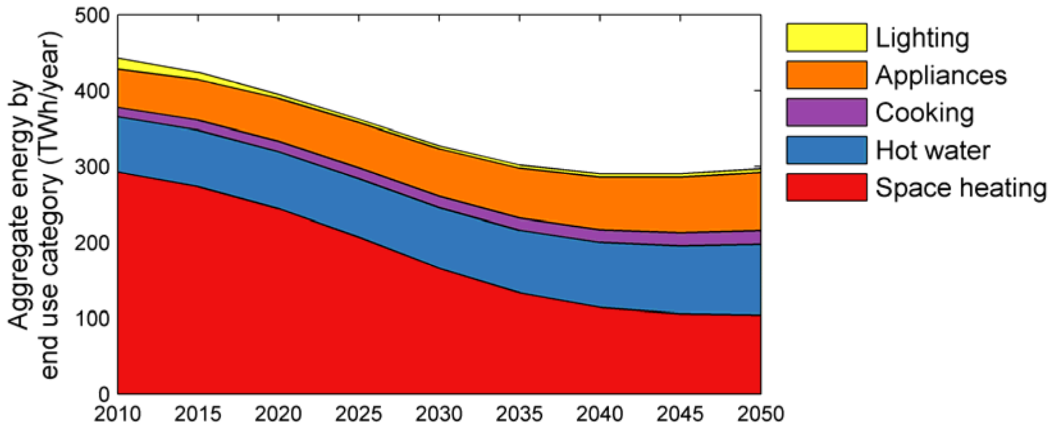

Figure 8.11: Aggregate energy demand by end use category

Emissions by end-use energy service category are given in Figure 8.12. The energy service categories with the most rapid decarbonisation pathways are those categories that use electricity as their main energy source (lighting and appliances). This is because the retrofit scenario assumes the power sector is essentially decarbonised by 2050 (~0.02 kg$CO_{2(eq)}$/kWh) and the fuel shares used in the residential sector remain constant between 2010 and 2050 (i.e. natural gas remains the dominant source of heating fuel). Although this latter assumption may seem unrealistic, there are presently no substantial government policies to decarbonise fuels used in dwellings. Using existing fuel shares also provides a realistic benchmark for comparing the potential for decarbonisation from energy efficiency improvements. Meeting future targets will also require new policies for reducing hot-water consumption (i.e. water used for bathing and for washing dishes) or the implementation of new technologies (such as heat exchangers) to re-capture energy which is lost down the drain.

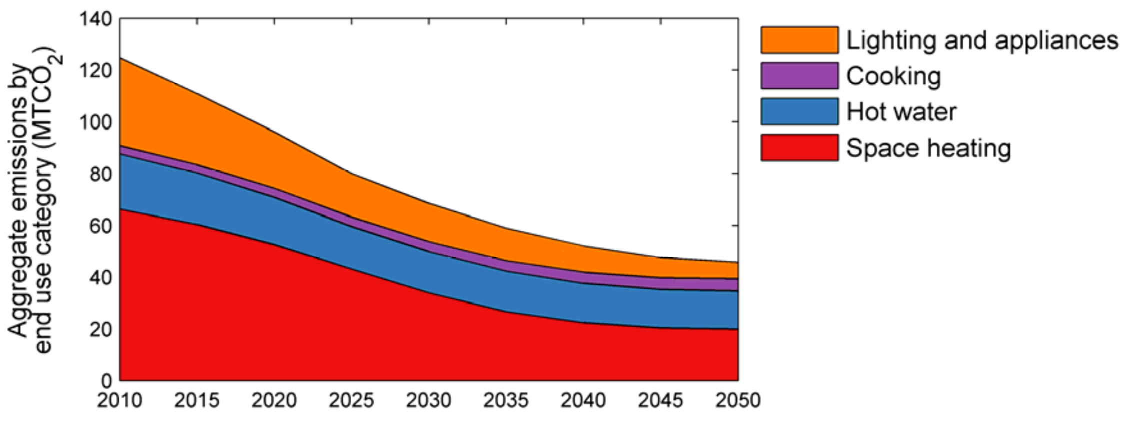

Figure 8.12: Aggregate emissions by end use category

1. This assumes the power sector is essentially decarbonised by 2050 (~0.02 kg$CO_{2(eq)}$/kWh) and that all new buildings meet the existing zero carbon building standard.

Even with a decarbonised power sector, zero carbon new buildings, and a building stock that has been retrofitted to very high standards, total emissions from the residential sector in England will still only drop by around two-thirds between 2010 and 2050. This is clearly insufficient for meeting future energy and emissions reductions targets. Decarbonising the remainder of the residential sector will require an additional ~200 TWh/year of low carbon energy supply. This is equivalent to roughly 50 new biomass power stations with a mean output capacity of 500 MW and a mean capacity factor of 90%.

8.4.1 Space heating

Reductions to energy and emissions in space heating benefit the most from the implementation of aggressive retrofit technology benchmarks. As shown in Figure 8.13 and Figure 8.14 all retrofit technologies are important for reducing overall energy and emissions from the built environment.

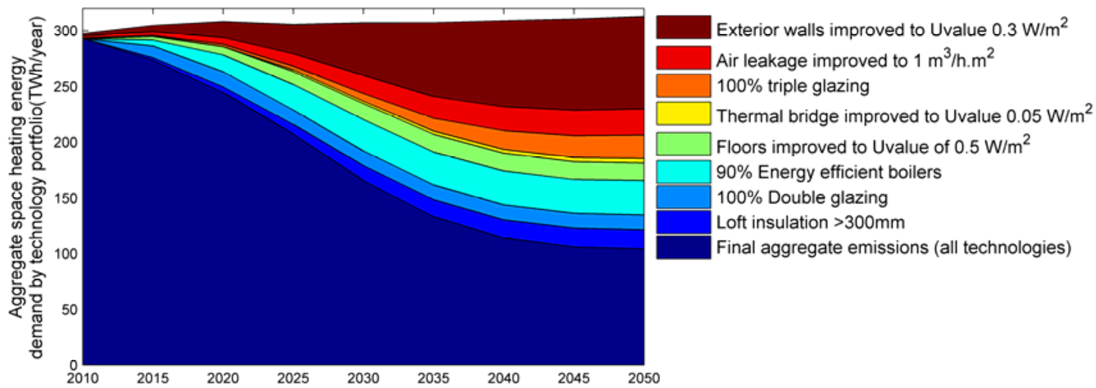

Figure 8.13: Space heating energy demand by technology portfolios

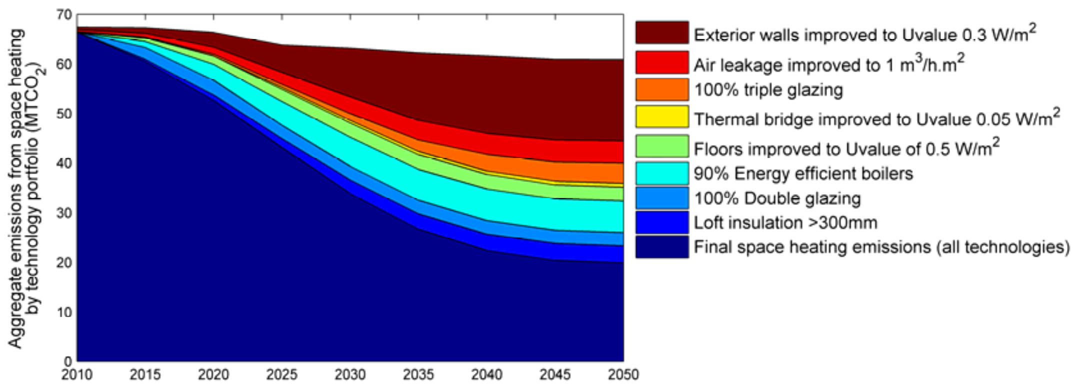

Figure 8.14: Emissions from space heating by technology portfolio

8.4.2 Cumulative emissions

Climate change is occurring because the global stock of $CO_{2(eq)}$ in the atmosphere is increasing. The sooner each technology benchmark meets full penetration the better the outcome for mitigating climate change will be. By adopting the same realistic penetration rates as discussed previously, it is possible to estimate the total cumulative emissions savings made from each technology benchmark. These are shown in Figure 8.15.

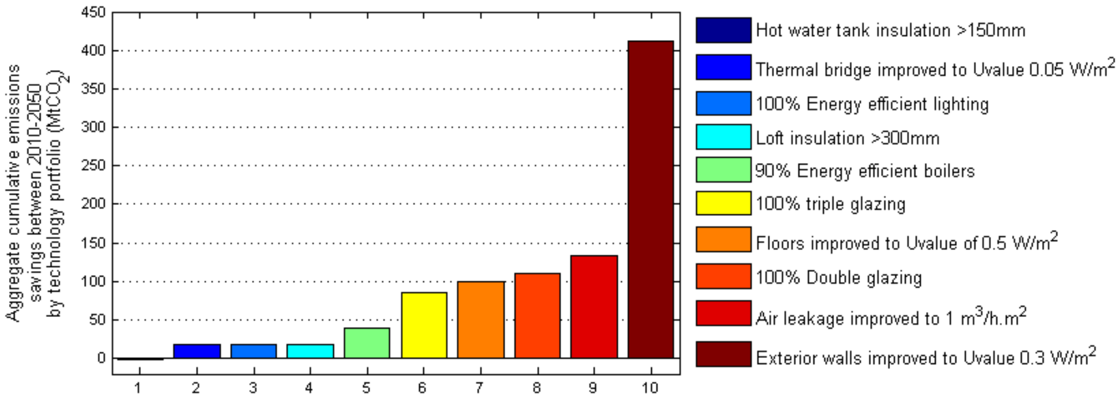

Figure 8.15: Cumulative emissions from different technology benchmarks

What is clear from Figure 8.15 is the overwhelming carbon mitigation potential that accrues from improving exterior walls to have a U-value of 0.3W/m^2. The second most important cumulative emissions reductions come from improving air leakage rates to be less than 1 m^3/h.m^2. Interestingly, improving the efficiency of floors will lead to larger cumulative emissions savings than the installation of loft insulation. This is mostly because most dwellings already have some form of loft insulation already installed, but floor insulation is problematic and is generally not considered for improving efficiency. Emissions savings made from both double and triple glazing offer an important emissions reduction strategy that cannot be ignored. The combined cumulative savings from triple and double-glazing would offer the second largest carbon saving potential saving roughly 200 MtCO$_{2(eq)}$ between now and 2050.

8.4.3 Technology benchmarks leading to increased emissions

Intriguingly the installation of hot water tank insulation results in a cumulative increase in CO$_{2(eq)}$ emissions and not CO$_{2(eq)}$ emissions reductions. This is also true for energy efficient lighting for the period after 2035. This implies that in the long run, energy efficient lighting and the installation of hot water tank insulation actually contribute to aggregate emissions rather than reducing emissions. This seemingly surprising outcome is a by-product of projecting existing government policy out to 2050. Such policies include the complete decarbonisation of electricity by 2050 and the installation of energy efficient lighting. Approximately 90% of the electricity consumed by traditional incandescent light bulbs is typically converted into heat.

Uninsulated hot water cylinders using either single or double electric immersion heaters are similar in that they also heat up the environment where they are located.

The relative carbon emissions shown in Figure 8.16 compare the difference in annual emissions between meeting the technology benchmark and the business as usual scenario when the technology benchmark is not implemented. As the power sector is slowly decarbonised the consequential heating that occurs due to the consumption of electricity in lights, appliances and hot water heating is increasingly carbon free. Thus when these technologies are replaced by more energy efficient technologies, any consequential heating that these technologies did provide will need to be met by traditional heating systems. As the final fuel shares for domestic heating are predicted to remain unchanged – and therefore natural gas remains the dominant fuel type – any consequential heating that occurred from carbon free electricity will need to be replaced by conventional heating systems. The end result is an increase in emissions. Figure 8.16 shows this trend very clearly where the annual emissions from lighting start to accumulate very rapidly from 2035 after the grid is almost completely decarbonised.

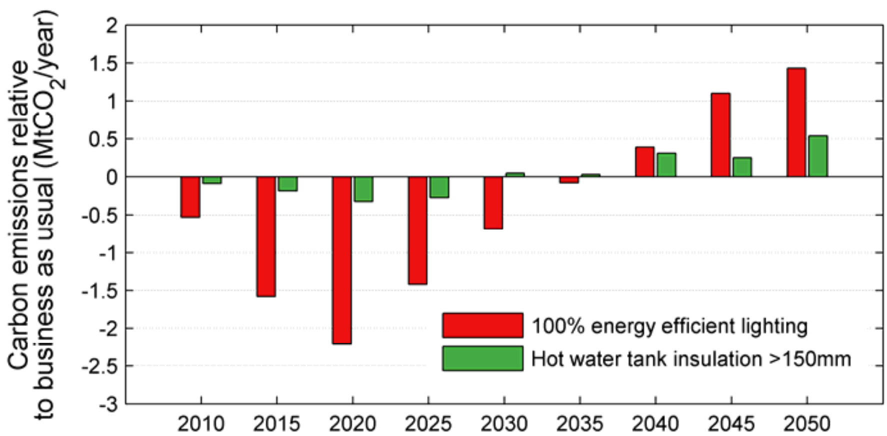

Figure 8.16: Average annual emissions from lighting and hot water tank insulation

8.5 Chapter conclusion

In this chapter several decarbonisation scenarios have been explored. Construction and demolition rates of the residential building stock were projected forward to 2050 using CLG live data tables. A model was developed to simulate the construction and diversity of new buildings to meet the Zero Carbon building standard. Emissions factors for electricity generation were heuristically projected to 2050 combining several different sources. Low carbon electricity is shown to have most effect on lighting and appliances and despite the residential sector expanding by over 38%

between 2010 and 2050 aggregate emissions over this same period decrease by 40 $MtCO_{2(eq)}$. Logistic s-curves were then derived for each of the ten ambitious technology benchmarks to model the diffusion of different retrofit technologies in the building stock. The importance of modelling technologies as part of a portfolio (as opposed to individually) was shown to be significant. Improving the U-value of exterior walls is shown to have the largest cumulative impact followed closely by the combined impact of double and triple glazing and then air-infiltration rates. Surprisingly, energy efficient lighting and hot water tank insulation both lead to an increase in carbon emissions in 2050 as the electricity grid is decarbonised.

This chapter has highlighted several important implications for the development of future policy. Firstly, the decarbonisation of electricity alone is insufficient for meeting national $CO_{2(eq)}$ mitigation targets. Secondly, even with aggressive retrofitting programmes aiming to install ambitious technology benchmarks in almost every existing home, future national decarbonisation targets will still fall short. Thirdly, if the stock is retrofitted to the standard suggested by 2050, hot water heating will become the dominant source of household carbon emissions. Decarbonising hot water will therefore require a major shift to new low carbon energy supply. Meeting future $CO_{2(eq)}$ mitigation targets will require an additional ~200 TWh/year of low carbon energy sources as well as the implementation of all 10 technology benchmarks. To put this figure in perspective in 2010 the UK generated a total of 384 TWh of electricity. This represents an additional 50% increase of present production.

Perhaps one of the least discussed but possibly most important implications for renovating the building stock relates to the timing of policy and the rate of diffusion of different decarbonisation technologies. More consideration needs to be made looking at the portfolio of technology options and their timing to achieve maximum cumulative $CO_{2(eq)}$ mitigation reduction. While previous government policy has appeared to focus on ‘low-hanging fruit’ such as roof insulation and low energy lighting, the final carbon reductions from these technologies are relatively small when compared to what is required to meet future targets. Timing is important because the faster new technologies diffuse into the building stock the larger the cumulative $CO_{2(eq)}$ savings will be. Moreover, if energy demand is not treated as a complex system of interconnected components unexpected outcomes that may lead to an increase in emissions may result. For example, it is shown that in 2050 under existing government policy, hot water tank insulation and energy efficient lighting will end up emitting more carbon then they will save. In conclusion more emphasises needs to be placed on properly coordinated government policy considering the interaction of energy policies and technologies over time.

9

Conclusion

9.1 Final remarks

In the opening paragraph of this thesis it was argued that energy and emissions reductions from the built environment have not materialised and the pathway towards decarbonisation are still openly disputed. This is true despite the residential sector having the largest $CO_{2(eq)}$ mitigation potential and some of the lowest costs when compared against all other sectors. Much of the lack in progress stems from poor understanding of highly complex socio-economic, socio-dynamic and technical physical systems that underpin energy use in dwellings. The overarching question of this thesis therefore seeks to understand what realistic carbon mitigation strategies might look like if an integrated complex systems perspective were applied with the objective of reducing emissions from the residential sector. The development of this methodology therefore required the application of innovative methods and the development of new models capable of representing the complex interactions that occur between people and the technical physical energy systems that underpin residential energy demand and emissions.

Given the importance of viewing the residential sector as a complex integrated system, the first substantive chapter of this thesis sought to untangle deficiencies from existing building energy simulation models; emphasise the limitations of existing building energy regulations; highlight the importance of public perception for communicating the benefits of building performance (e.g. EPCs); and underscore the inconsistencies with existing SAP standards that perversely incentivise increased $CO_{2(eq)}$ emissions from dwellings. Several important outcomes from this chapter are worth repeating. The SAP and RdSAP standards are still widely used for the rating of both new and existing dwellings and are based on BREDEM standard assumptions. However, none of these building energy models claiming to measure building performance has ever been statistically validated against a representative sample of dwellings. It is no surprise, therefore, that such a large variance exists between actual and estimated energy consumption. Models that do not estimate building performance correctly may impinge on the uptake of energy efficiency technologies more broadly. Moreover, many of the existing models were developed in the early eighties and now suffer from path-dependence and lock-in thus limiting the development of new innovative building models. Learning from international best practice, several improvements can be made to EPCs to improve their acceptability and impact. Changes include the display of actual energy consumption in original units, requirements to make energy rating publicly available, and improved design and communication of EPCs to reflect government policy objectives.

Despite popular belief, SAP and RdSAP do not estimate building energy efficiency but instead attempt to estimate the cost effectiveness of building performance and thus create perverse incentives that may lead to an overall increase in $CO_{2(eq)}$ emissions. In this regard, the SAP standard confounds cost-effectiveness, energy efficiency and environmental performance giving an inadequate estimate of all three policy objectives. Motivating individuals to invest in energy efficiency therefore requires a self-reinforcing system where building performance standards directly reflect policy targets and methods; energy models are estimated and statistically validated against empirical data; and policy objectives are communicated effectively through campaigns and certification programmes to industry and the public to build trust and engender further support. Finally, investment in research prioritising carbon mitigation opportunities within the built environment will lead to important discoveries and the opportunity to reduce emissions and close the loop leading to improved models, better policy and new innovations.

System wide factors such as trust in building rating systems and EPCs are necessary if long-term targets are going to be met. However, systemic change will also require a deep understanding of the complex web of interdependent factors and their relationship to energy demand. Acknowledging the complex interactions that occur between different explanatory factors therefore requires the implementation of new methods for understanding building energy demand. In Chapter 5 a Structural Equation Model was developed to calculate the strength of causal relationships giving their direct, indirect and total effects on dwelling level energy consumption. The main drivers of residential energy consumption in order of importance were found to be, the number of occupants living in a dwelling; dwelling floor area; household income; building energy efficiency (SAP); heating patterns; and, living room temperature. As expected, floor area mediates both household income and occupancy while internal temperature mediates energy patterns.

In the multivariate case, SAP explains very little of the variance of residential energy consumption. However, this procedure fails to account for simultaneity bias between energy consumption and SAP. Using SEM it is shown that dwelling energy efficiency (SAP) has reciprocal causality (non-recursivity) with dwelling energy consumption and the magnitude of these two effects are calculable. This finding shows that homes with a propensity to consume higher quantities of energy have relatively higher SAP rates when compared to the rest of the building stock. Due to the law of diminishing returns this implies that homes with a propensity to consume more energy will be more expensive to decarbonise because they are already relatively more efficient. On the other hand, homes with a lower overall SAP rate have a lower propensity to consume energy. However, these homes tend to be poorly heated with lower overall internal temperatures. Improving the efficiency of these homes through the implementation of energy efficiency technologies may contribute to the rebound effect (take back) acting to increase average internal temperatures rather than decrease energy consumption. This suggests the costs of decarbonising the built environment might be high at first, but will decline over time once the initial hurdles are overcome. This effect is coined as the residential energy efficiency barrier and represents the size of investment that must be made before substantial energy and carbon savings start to accrue.

The effects of socio-demographics and human behaviour on dwelling level energy consumption are known to be significant and researchers are increasingly demanding that such effects are included in bottom-up building stock models. Yet, until now, no method has been developed for how to include the capriciousness of human behaviour in bottom-up energy demand models. In Chapter 6 a model is developed to incorporate the effects of social demographics and human behaviour on energy demand. Using panel based methods it is possible to predict daily mean internal temperatures over a large cross-section of dwellings and over time. This model therefore represents the first time a panel model has been used to estimate the dynamics of internal temperature demand owing to the natural daily fluctuations of external temperature combined with important behavioural, socio-demographic and building efficiency variables. The model is able to predict internal temperatures across the building stock to within ~0.71°C at 95% confidence and is able to explain up to 45% of the variance of internal temperature between heterogeneous dwellings.

The internal temperature prediction model confirms hypothesis from sociology and psychology that habitual behaviours are important drivers of home energy consumption. In addition, the model offers the possibility to quantify take-back (direct rebound effect) owing to increased internal temperatures from the installation of energy efficiency measures. The presence of thermostats or thermostatic radiator valves (TRV) are shown to reduce average internal temperatures, however, the use of an automatic timer is shown to be statistically insignificant. Occupancy, household income, the elderly and the young all lead to a statistically significant increase in mean daily internal temperature. As expected, building typology, building age, roof insulation thickness, wall U-value and the proportion of double-glazing within a dwelling all have a positive and statistically significant effect on daily mean internal temperature. The major contribution of this model is that it puts forward a process for predicting internal daily temperatures over a large cross-section of dwellings thus making it possible to include human behaviour and socio-demographics within physically based building stock models.

Chapter 8 develops a bottom-up physically based building stock model of the English residential sector. Although there are many bottom-up building stock models that estimate energy and emissions from the residential sector, this model is unique in several important respects. Firstly, energy demand is estimated independently for each of the 16,216 dwellings taken from the English House Condition Survey (2008). This method represents a major improvement on the typical archetype method that estimates energy and emissions from a handful of different dwelling archetypes to represent the entire building stock. Because this model estimates energy and emissions independently for each unique dwelling, it is possible to create consistent distributions of model estimates that represent the actual building stock. Thus the heterogeneity from the building stock is preserved and conclusions can be made about energy consumed in the tail ends of distributions. Another major benefit of estimating energy demand from independent dwellings is that it becomes possible to scrutinise different segments from the building stock at much greater detail (such as income groups, building types etc).

A major innovation of this building stock model is the level of detail that is used to simulate energy demand for each dwelling across a large cross section of representative dwellings and over time. Most existing building stock models use standard RdSAP assumptions thus greatly simplifying the building stock into several distinct age category bands and building typologies. In this model every effort is made to accurately capture the true U-value for each element of the building envelope. Furthermore, most existing models estimate energy demand over a pre-defined heating season. As this model estimates energy demand on a daily basis for each day of the year, there are no assumptions made about the length of the heating season. This is achieved by integrating external temperature with respect to time making it possible to capture both the duration and extremes of daily external temperature. This is much more accurate than using mean monthly internal and external temperatures.

Internal temperature is known to be one of the most important drivers of dwelling energy consumption thus it warrants more detailed analysis. In Chapter 6 an equation was empirically derived to predict internal temperature from a number of explanatory factors. This equation was then applied to the physical building stock model to produce a distribution of internal temperatures that vary over the building stock and over the year. An analytical thermodynamic heat balance equation is then derived using the heating degree-day method to estimate the energy required to maintain internal temperatures at the predicted internal temperature set point. As internal temperature is derived from human behaviour (among other factors) the physically based bottom-up building stock model is able to incorporate socio-demographic and behavioural factors in a bottom-up physically based building stock model.

The model separates energy demand into five end-use service categories (space heating, water heating, cooking, appliances and lighting) and three main fuel types (gas, electricity and other). Each of the end-use service categories (except space heating) were calibrated using aggregate energy consumption figures supplied by DECC. Aggregate demand estimates for space heating and each of the three different fuel categories were shown to be within a few percent of DECC aggregate consumption figures. Finally, the model was validated against the NEED database using different residential segments for both electricity and gas. The model was shown to predict energy consumption from the residential sector relatively well. In sum, the cross-sectional and inter-temporal detail provided by this new building stock model can offer new insight for how people actually consume energy in the home. Using this model it is possible to develop and compare future scenarios for the residential sector from which robust decarbonisation strategies can be formed.

Using the building stock model and assumptions about future construction and demolition rates it is possible to compare the carbon mitigation potential of different technology benchmarks. Several important findings from this analysis are found. First, decarbonising power generation, without parallel policies to address residential energy and emissions will be insufficient for meeting future climate change targets. Second, the only accurate way to model different energy efficiency technologies is to adopt the portfolio approach as modelling each technology individually will over estimate final energy and emissions savings. This implies the order in which technologies are deployed will result in differences to the relative amount of technology specific $CO_{2(eq)}$ emissions mitigated. Thirdly, as it is the stock of $CO_{2(eq)}$ emissions in the atmosphere that drives climate change, the sooner technologies are deployed for decreasing emissions the less cumulative $CO_{2(eq)}$ emissions will be able to build up in the atmosphere. This suggests it is important to implement technologies that have the most cumulative $CO_{2(eq)}$ impact, and not a simple focus on 'low-hanging fruit' policies. It also implies the logistic penetration rates of different energy efficiency technologies are very important factors for understanding the rate at which the residential sector can be decarbonised. Fourthly, the model highlights the importance of adopting a system approach to modelling energy demand as technologies that are considered in isolation may end up producing more emissions then they save. For example, it is shown that when electricity is decarbonised and energy used for home heating is not, energy efficient lighting and hot water tank insulation will result in an increase in $CO_{2(eq)}$ emissions. It is only through the implementation of connected up policy and integrated complex systems thinking that the interaction between policies and technologies can be properly analysed.

Moreover, it is increasingly important to understand how the timing of different policy options may affect final outcomes.

In conclusion, energy efficiency technologies offer a significant opportunity to reduce carbon emissions. External wall insulation offers the largest carbon abatement potential, but is also the most costly. This is closely followed by the combined effects of double and triple glazing and then an improvement in the air permeability of dwellings. However, even with the implementation of all these ambitious technology benchmarks, combined with complete decarbonisation of the power grid and zero carbon homes from 2016, emissions from dwellings still only decrease from 125.6 $MtCO_{2(eq)}$ in 2010 to 40.5 $MtCO_{2(eq)}$ in 2050. In 2050 space heating ceases to be the dominant source of emissions and is replaced by cooking, hot water and household appliances. If emissions targets are going to be met, retrofitting the building stock must be combined with a focus on decarbonising residential supply. As well as meeting all of the ambitious technology benchmarks it will also be necessary to produce an additional 200 TWh/year of low carbon energy in 2050 to meet the UK climate change targets.

9.2 Future research

The models developed for this thesis provide a powerful suite of tools for answering a multitude of different questions about energy and emissions from the English building stock. How these models have been implemented in this thesis barely touch on the potential for how they maybe used in the future.

Using the structural equation model approach it will soon be possible to apply this method to a more recent dataset of actual energy consumption. It will therefore be possible to test if any of the structural relationships between model variables have changed substantially over time. With a new dataset incorporating the material properties of the building and energy efficiency variables it will be possible to look at the effect of treating human behaviour as a latent variable to understand the structural relationship between behaviour, technology and energy consumption.

Panel models are a powerful tool for studying relationships over multiple observations and over time. In this analysis panel methods were used to predict mean daily internal temperatures but it is also possible to perform this at much smaller time steps (e.g. every hour). Segmenting the sample over different groups would make it possible to compare the heating profiles from different socio-demographic groups to target temperature profile behaviour.

The bottom-up building stock model represents the most significant piece of work completed for this thesis. The level of detail included in this model and the temporal granularity it offers opens up new research possibilities. Energy demand is estimated daily so the model can be used to predict peaks in energy demand over the network resulting from predicted changes to weather. In this model external temperatures were kept constant over the period of the study but it would also be possible to study the effect of increasing temperature due to climate change on overall energy demand. As the model is able to predict internal temperature for each dwelling it also endogenously allows for the rebound effect (e.g. as a dwelling improves its building fabric a higher internal temperature will be predicted by the model). Research may therefore focus on quantifying the rebound effect for different segments in society. The model may also be expanded to study cooling demand from the introduction of air-conditioners. Developing the model to handle air-conditioning would involve developing a new cooling demand module that is very similar to the heating demand module. However, the cooling demand module would use cooling degree days rather than heating degree days.

Ten major retrofit technological benchmarks were modelled in this study. However, it is possible (using the same model) to test the effects from a multitude of different technologies. Micro-generation was outside the scope of this research but can be included to understand what effect the interaction of distributed generation and energy efficient technologies might have on energy supply. It was assumed electricity generation was completely decarbonised by 2050 but it is also possible to run the model assuming the power sector was only partially decarbonised. Given the model represents a large heterogeneous sample it is possible to segment the dataset into any number of different ways to focus on particular groups. For example, an in depth study looking at the effects of fuel poverty, regional effects or demand led solutions might provide important insights for future energy policy.

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