The Impact of Energy System Modelling Tools for Policymaking

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DECLARATION

I confirm that this is my own work and the use of all material from other sources has been properly acknowledged.

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ABSTRACT

Industry is exposed to the consequences of Government energy policy. This project aims to improve the understanding of the energy system modelling tools used for the purpose of policy development. This is in order to help industry, including SSE, the industry sponsor, better understand future policy direction, and inform their future strategic planning.

This project used a multi-disciplinary approach to investigate this problem. A review was undertaken of the modelling tools used in academia and by Government, interviews were conducted to understand perceptions of the use of modelling, and finally representative versions of the core model types were developed to better understand the insights which they can provide to future system challenges.

A confusing landscape of model types and terminologies exist, many of which are used by Government. This research has identified a core set of models which are widely used in academic literature and are seen to be influential in the UK policy making agenda. The model types display differences in their representation of time resolution, the level of general unit detail and the operational strategies which they can consider.

This project has constructed simplified versions of each model type, either using open source tools, or developing code from first principles. Further adaptations were made to model the technologies present in the case study energy system of Shetland. Each model type was analysed to determine what insight it can provide to the Industry questions which were defined at the outset of the project.

Two attributes were identified which are important when modelling the impact of flexible technologies. These are:

i. The ability to reflect chronology and have visibility across time steps is important for any storage technology in order to ensure operational constraints are considered and to enable optimal charging profiles to be calculated.
ii. An understanding of the real demand for the technology is essential to represent its potential for flexibility. In the case study undertaken this was the separation of heat and power demand. Industry, with support from Government, needs to recognise the need for increased data on real demand for heat, as well as other demands to improve the modelling capability to represent the value of DSR technologies.

Stakeholder perceptions of these models were examined, in addition to a technical assessment of their ability to adapt and provide insight to future policy challenges. The work has demonstrated the value of simpler models. It recommends that Government increase their use of simpler models, to enable increased collaboration with stakeholders and improved confidence in Government modelling activities.

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Acronyms and Abbreviations

AEA	Association for Energy Affordability
BEAT2	Biomass Environmental Assessment Tool 2
BEIS	(Department for) Business, Energy and Industrial Strategy
BIS	(Department for) Business, Innovation and Skills
BRE	Building Research Establishment
BREDEM	Building Research Establishment Domestic Energy Model
CCC	Committee on Climate Change
CCGT	Combined Cycle Gas Turbines
CCS	Carbon Capture and Storage
CGE	Computational General Equilibrium
CHP	Combined Heat and Power
CPLEX	IBM ILOG CPLEX Optimization Studio, Mathematical programming software
CSE	Centre for Sustainable Energy
DDM	Dynamic Dispatch Model
DECC	Department of Energy and Climate Change
DNO	Distribution Network Operator
DSR	Demand Side Response
ED	Economic Dispatch
EGEAS	Electric Generation Expansion Analysis System

EIA	Energy Information Administration
ELMOD	European Electricity Model
EMF	The Energy Modelling Forum
EMR	Electricity Market Reform
EnergyPLAN	Advanced energy systems analysis model
EngD	Engineering Doctorate
ERP	Energy Research Partnership
ESME	Energy System Modelling Environment
ETI	Energy Technologies Institute
FES	(National Grid's) Future Energy Scenario
GDP	Gross Domestic Product
GLOCAF	Global Carbon Finance model
GNUMathProg	Linear mathematical programming model
IEA	International Energy Agency
LCNF	Low Carbon Network Fund
LEAP	Long-range Energy Alternatives Planning
MARKAL	MARKet-Allocation model
MESSAGE	Model Energy Supply Systems And their General Environmental impact model
MIDAS	Database of UK Meteorological Office land surface station data
N-DEEM	Non-Domestic Energy and Emissions Model
NG	National Grid

NINES	Northern Isles New Energy Solutions
N-Vivo	Interview Software
Ofgem	Office of Gas and Electricity Markets
OpenMOD	The Open Energy Modelling Initiative
OSeMOSYS	Open Source Energy Modelling System
PLEXOS	Integrated energy model
PV	Photovoltaic
RESOM	Redpoint Energy System Optimisation Model
RHI	Renewable Heat Incentive
SAP/rdSAP	Standard Assessment Procedure / Reduced Data Standard Assessment Procedure
SBEM	Simplified Building Energy Model
SO/NO	System Operators / Network Operators
SSEPD	SSE Power Distribution
TEMOA	Tools for Energy Model Optimisation and Analysis
TIMES	The Integrated MARKAL-EFOM System
UC	Unit Commitment
UKERC	UK Energy Research Centre
UKTM	UK TIMES Model
WASP	Wien Automatic System Planning
WeSIM	Whole-electricity System Investment Model
WholeSEM	Whole Systems Energy Modelling Consortium

1 INTRODUCTION

1.1 CONTEXT

It is widely recognised that energy systems, in the UK and beyond, require adaptation to meet growing concerns over climate change and to keep energy available and affordable to consumers. In order to ensure global and national momentum is maintained, the UK and many other countries have signed up to climate and emission reduction targets, for 15% of UK energy consumption to come from renewable sources by 2020 (European Commission 2009) and an 80% reduction in emissions by 2050 (HM Government 2008). Already the UK's energy system is beginning to change due to policy interventions to help us meet those targets such as emission level restrictions, resulting in closures of coal power stations and increased renewable generation at the transmission and distribution level incentivised through government renewable subsidies and carbon pricing.

Investments required to support this evolving energy system are likely to be capital intensive and have long term implications, and therefore they require complex decisions to be made both by Government, who are designing policy, and by industry, who are trying to adapt to the system needs and changing policy environment. The types of investment may include new power stations, infrastructure upgrades and technology development. In addition, change may be required or result from other system changes such as market design and consumer behaviour.

Many factors play into these decisions and energy system models are one of the tools being used to inform the evidence decision makers and policy makers use when developing new energy policy proposals. Energy system modelling outputs inform the design of future scenarios and strategies, such as the carbon budget analysis by the Committee on Climate Change (CCC) (Committee on Climate Change 2017), the National Grid Future Energy Scenario (FES) analysis (National Grid 2017a) and Government strategies, such as the heat strategy (DECC 2013c).

1.2 Rationale

Energy system models are used by a variety of energy system stakeholders including government, academia and industry, to inform system planning and for operational purposes. Energy system modelling tools vary considerably in their methods and assumptions. This has resulted in a confusing environment even for modellers to understand which is often worsened by poor communication. With advancing computational capabilities, the energy modelling landscape is becoming increasingly complex and hard to navigate.

The policy decisions which are being informed by energy system models affect many different energy system stakeholders. The uncertainty of what the future energy system might look like is a risk to industry when making new investment decisions. Companies need to understand the future energy system and the transitional pathway in order to adapt and succeed.

There is a body of literature which aims to improve models by adding further complexity or linking models together to get a more accurate representation of a part of the energy system. This adds to an existing field which is already very complex and hard to interpret by a non-modeller or a non-academic. These, often niche models with hybrid capabilities, are also not likely to be a model type which is regularly used by Government. There are also studies which look at classifying the types of energy system models to help better understand the field but they fail to provide a clear link to the policy landscape and examine their suitability and insights for emerging policy challenges.

1.3 AIM, SCOPE AND OBJECTIVES

This research aims to investigate the role which different energy system model types play in informing Government energy policy and the consequent options for a UK energy company to advise its strategic business planning.

The modelling landscape is full of different types of energy system models and it would not be feasible to investigate them all. Instead this research focusses on the models which consider the whole or a significant proportion of the energy system which are seen to play an important role in energy policy development. The purpose of the study is to understand in greater detail the core principles behind the models which impact policy development to understand the insights they can provide.

Past trends in model usage are analysed to understand the model types believed to be influential in policy making. However in terms of their usefulness and what insights they can provide for industry, their ability to consider future policy challenges is the core focus. Future challenges seen as important by stakeholders will be explored with industry as part of this project. Whilst many of the challenges are likely to exist and are impacted by other energy systems across the world, the focus is on those likely to impact UK policy development.

This project focusses on the core principles of the main model types used to influence policy design. It investigates how with an increased understanding of the modelling activities undertaken by Government, there can be improved stakeholder collaboration and provide industry with a greater understanding of their role in the future transition.

In order to meet the aim and stay within the scope outlined, the following research objectives have been defined:

1. Identify the range of energy system models being used and the previous classification approaches being applied, with particular regard to models used in relation to UK energy policy.

2. Explore how the identified models are being operationalised for UK energy policy development and the role which model outputs have played in informing recent energy policy decisions.

3. Identify relevant core model types and generate representative versions for the case study of Shetland.

4. Examine the strengths and weaknesses of each model type in responding to a range of identified business questions.

5. Advise the industry partner of opportunities to improve energy system capability, through enhancement or improved interpretation of existing tools, or through adopting new tools.

1.4 INDUSTRIAL CONTEXT

The Engineering Doctorate (EngD) combines the traditional academic research, associated with PhD programmes, with real industry need and expertise. Projects are designed with industry in order to advance their knowledge with the help of academic research. In this case the project sponsor is SSE, one of the UK's main utility companies, a vertically integrated company with interests across the sector including networks, generation and supply. SSE's operational and investment strategies are greatly affected by changing energy policy. Investments in network infrastructure, condensing and renewable generation plant all require long term certainty due to the high upfront cost. Adapting to meet future customer needs can be aided through a greater understanding of future policy and strategy. Additionally, in order for government to realise its ambitions it needs investment from the utilities. SSE is particularly concerned about how the changes will affect its business and how the current models being used by DECC/BEIS are fit for purpose.

SSE hope that with an increased energy modelling capability and improved understanding of the modelling landscape they can better facilitate dialogue with policymakers and explore their role in the future energy system.

At the outset of the project preliminary discussions were undertaken to assess the areas stakeholders in SSE believe are important to understand going forward. These are illustrated in Table 1.1.1.

TABLE 1.1: INDUSTRY QUESTIONS

	Industry Questions
Q1	What system benefits can electricity storage provide?
Q2	What effect will the increase in distributed level generation have on the system?
Q3	What is the effect of weather based renewables on the system?
Q4	What is the future for heat going to look like and what impact will that have on the electricity system?

It is not proposed that these questions will themselves be answered in this thesis, but they will guide the research and ultimately the conclusions from the study will provide recommendations regarding which model types would provide useful insights to them.

1.5 Thesis Overview

This thesis is broken down into eight chapters. Chapter 2 will identify who the users of models are, their core purpose, and highlight the range of tools and terminology being used. It will explore the development of policymaking and the role energy models have played. Finally, it will identify the future challenges for energy system models and how their uses and types of tools may evolve in the future.

Chapter 3 will compare previous attempts to classify energy system models to understand where there are agreements and inconsistencies. A detailed review of models which have been used by

Government for energy policy decisions since 2010 will be undertaken. The model methods are analysed and compared to the model classes previously identified. This comparative analysis leads to the identification of four core model types which are influential for policymaking and fit into a core modelling category.

Chapter 4 explores how energy system stakeholders perceive the usefulness of modelling for policy design. Twenty-one semi structured interviews are undertaken across the sector. Participants include Governmental organisations, consultancies and industry. The insights from the interviews are analysed to identify what energy system stakeholders see as the future key challenges for modellers and the policymakers. The insight from the interviews combined with the findings from the Government modelling review in Chapter 3 provides a unique interdisciplinary perspective of the challenges for policymakers.

Representative versions of the core models identified in Chapter 3 will be developed in Chapter 5 for the case study of Shetland. One model is created using an existing open source modelling tool, two were developed specifically for this study, and a further tool was developed in collaboration with other researchers, using Matlab and R software. Other existing tools were used to validate the representative models. The main differences in the method and data assumptions of representative model types will be explored and the impact on their results and the insights examined. Chapter 6 will make adaptations to the model structure to increase their capability in order to model the battery and smart storage heater technology which are present on Shetland. The two attribute themes; chronology/visibility across time steps, and the separation between heat and power demand; emerge in this chapter. These are important when considering flexible technologies. Recommendations will be made for modelling exercises which include similar technology types.

Figure 1.1 illustrates how the various outputs from the chapters feed into one another and meet the objectives of this research.

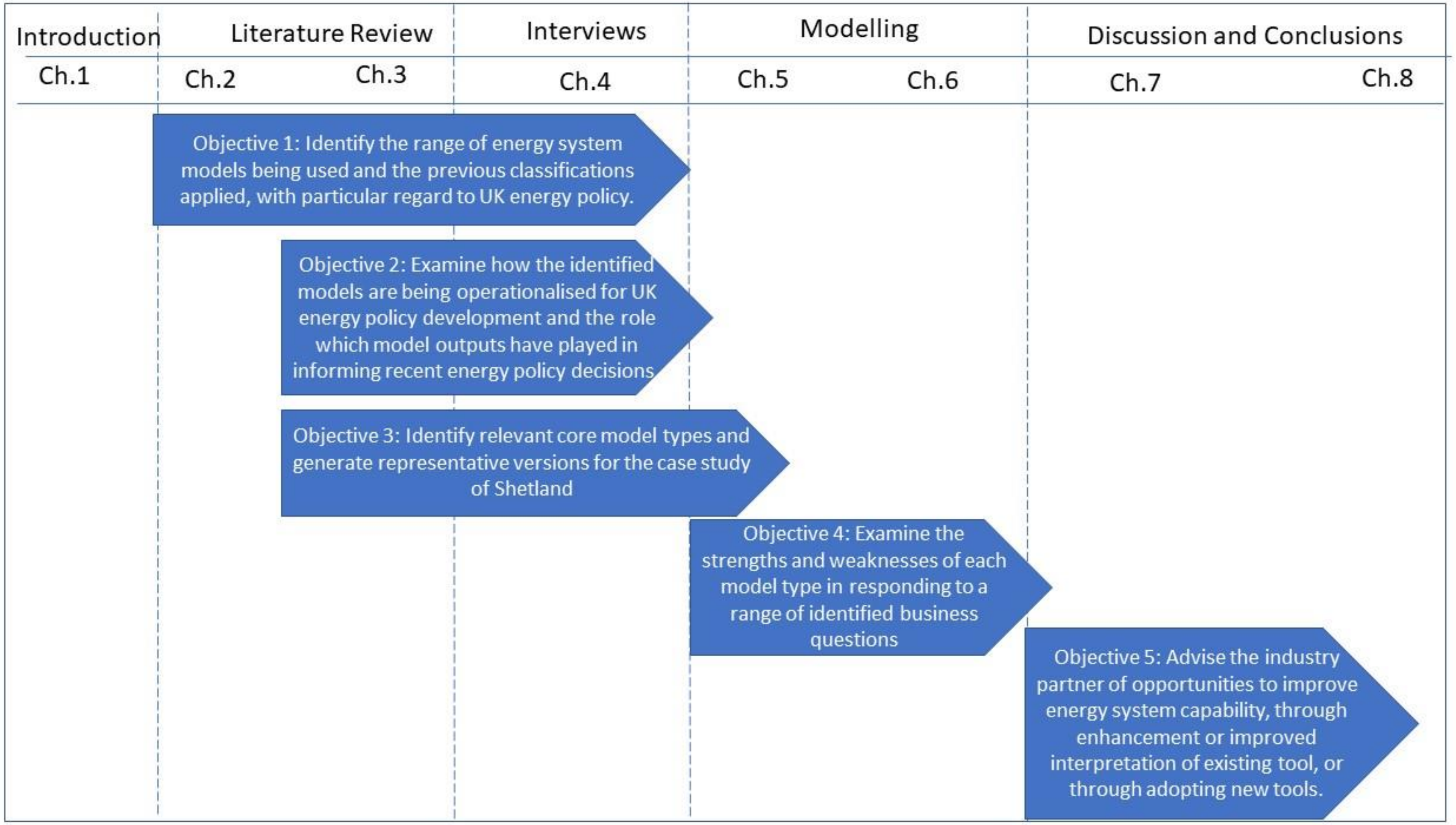

FIGURE 1.1: CHAPTER WORK FLOWS

Modelling Development

The Unit Commitment/Economic Dispatch model developed in Chapter 5 has been a collaborative effort between researchers at the University of Reading. This study defined the core structure and the specific adaptations which were required to enable representation of the battery and smart storage heaters, outlined in Chapter 6. The model development and coding expertise was provided by others in the team. This model was run in Matlab using the solver CPLEX.

SSE's economics team provided the software and support to run the PLEXOS model with the inputs required and the desired model structure was defined by this project.

2 LITERATURE REVIEW

This literature review will introduce the terms energy system and energy system model, with respect to the project's aims. It will explore how the energy system modelling landscape has evolved alongside the changing global energy system and drivers. This review will look at the types of models that are being used by the UK Government for the purposes of energy policy design and how these models are being used and communicated. Finally, it will use the academic literature to identify any similarities and inconsistencies between the types of energy system models being used by various stakeholders, and examine the terminology being used to describe them.

2.1 INTRODUCTION TO ENERGY SYSTEM MODELLING

2.1.1 WHAT IS AN ENERGY SYSTEM MODEL?

Jaccard (2005) describes an energy system as *'the combined processes of acquiring and using energy in a given society or economy.'* The activities involved between acquiring and using energy encompass the whole energy sector from upstream fuel exploration all the way down to the end user demand for energy. This includes: fuel extraction, energy transformation processes including electricity generation and distribution, through to the demand for electricity, heating fuels and technologies, and other transport and industrial fuels; as well as the associated market and economic interactions.

If a model can be described as a 'simplification of reality' (Huntington et al. 1982) then by definition an energy system model can be described as a simplification of an energy system. In addition to models which look at the interactions across the whole system, models exist which focus on, for example, just the supply or demand side in more detail, or which look specifically at the relationships for a particular fuel (Hoffman & Wood 1976). For these reasons they can vary considerably in their make-up including size, what is included and number of system interactions.

Many newly developed energy system models are far from simplistic, particularly with the recent advancements in computing power. The wide range of spatial and system boundaries a model can have, and at varying levels of computing power, highlights the broad nature which the term *energy system model* can reflect.

2.1.2 A RECENT HISTORY OF ENERGY SYSTEM MODELLING

As challenges such as climate change, increasing fuel prices and resource depletion have emerged, modelling tools that can help analyse the effect of these have become increasingly important. The requirement for sophisticated energy system modelling tools exists due to the complex system operational strategies and technologies present, and the knock-on effects energy has on the wider economy. These tools can help analyse the consequences that various changes might have on the system and can therefore be used to provide evidence about the future, providing model users with insight to aid future system planning, assess the role of different technologies and to guide and back up policy.

The use of modelling for energy planning and policy purposes developed in the 1970s as a result of the oil crisis (Huntington et al. 1982). It then re-emerged significantly with growing concerns regarding global warming in the 2000s. Models have adapted extensively over this period. In the 1970s the focus was the potential impact of oil prices, therefore the system boundary was more contained, today a greater range of energy system models are present including those which investigate the effects of intermittent technologies and balance the electricity grid with increasing demand variability. Developments in new technologies and energy management tools along with political and economic conditions continue to drive the ambition of advancing model capability. It was estimated that across the UK there were 53 energy models being used across 32 institutions in 2014, twice as many as in 2009, which highlights the focus of modelling within the academic community (@WholeSEM 2014b).

The recent challenges include balancing intermittent renewable generation, understanding the effect of increased generation at a distributed level which results in unpredictable demand, the development of smart demand side technologies, potential electrification of heat and transport and new and existing market policies which affect market interactions and will play a role in shaping the future system. As we move to a more interconnected electricity system and continue to rely on fuel imports, global issues will impact national systems more directly and will need to be explored through energy modelling tools.

2.1.3 What are energy system models used for?

There are a number of stakeholders engaged in energy system modelling activities including academic institutions, industry, governments and consultancies with varying objectives. Pfenninger (2014) groups the usage of energy system models into two broad categories, those used for planning purposes and those for operational purposes.

Models suited for planning purposes are likely to include those which inform policy direction and those used to make long term investment decisions. Examples of methods could include predicting future behaviours and demand (Suganthi & Samuel 2012), testing the effects of different scenarios (HM Government 2010) or analysing what the least cost design or strategy to a given problem would be (IEA 2011).

Long term energy system modelling is commonly undertaken by the academic community, governments and industry. Policymakers frequently use models which identify the least cost pathway to a particular goal such as achieving the climate change targets, whilst also ensuring that social objectives, security of supply standards and affordability targets are met. These are used to provide an indication of what technologies or investment are required and therefore what policies are required in order to incentivise this. Operational models are likely to be those with a much higher resolution and can analyse how the market would be likely to respond under given conditions. These are useful to guide operational decisions about plant and technologies. The method and technical capability of a model is likely to vary considerably depending on the problem it is intending to analyse.

2.2 The role of models in policymaking

Energy system models have been used by governments across the world since energy policy became an important issue in the 1970s. In the UK, a cabinet level Department for Energy was created in 1974 to coordinate energy policy development. In the following decades, energy policy became a lower priority and the Department of Energy was disbanded in 1992, following privatisation. Energy policy issues were subsequently divided between the Department of the Environment and the Department of Trade and Industry, additionally an independent regulator, Ofgem, was created to oversee the market. Energy policy then gradually increased in status due to the increased focus on climate change following the Kyoto Protocol which resulted in the creation of the Department of Energy and Climate Change (DECC) in 2008 alongside an independent body, the Committee on Climate Change (CCC), who have an advisory role. Currently energy sits in the remit of the Department of Business, Energy and Industrial Strategy (BEIS) following a restructure in 2016.

2.2.1 Energy system modelling landscape in the UK Government

Modelling tools are used in most Government departments, and in 2012, following concerns with the West Coast rail franchise competition process, a review was conducted of such activities (Macpherson 2013).

Figure 2.1 shows the range of modelling activities occurring across Government, as identified in this review. It shows a broad range of modelling uses across Government, however within the CCC and DECC, only three model types were recorded: policy simulation, forecasting and science based. It identified over 500 business critical models of which 28 were energy related.

Model type	Purpose	Examples
Policy simulation	Appraisal of policy options, analysis of impact on people, finances, etc	Intra Government Tax Benefit Model
Forecasting	Assessing the future, perhaps to provide base information for policy development or financial planning	State Pension expenditure forecast
Financial evaluation	Assessment of liability or future cost	Pension liabilities, higher education loan repayment model
Procurement and commercial	Evaluation of VfM or affordability and award of contracts	Awarding of rail franchises
Planning	Planning current actions based on future forecasts	Teachers, NHS
Science-based	Understanding and forecasting natural systems	Climate change
Allocation	Distribution of funding across organisations responsible for service delivery	Police allocation formula

FIGURE 2.1: MODEL TYPES IN GOVERNMENT (MACPHERSON 2013)

In 2014 it was estimated that DECC had over 31 models in active use (@WholeSEM 2014a; DECC 2014c). It is not clear what the ratio is of models which have been built internally, those which have been commissioned or those which are commercially available. It is understood that Government uses a range of all these types (DECC 2011e; DECC 2012d).

Subsequent conversations with officials in BEIS has identified that as of December 2016 there were 72 active energy policy models and a further 145 which they consider defunct or are models which are not owned or run by people in government (BEIS 2016b). This is an increase of over 50% in two years if it assumes that the definition has remained the same. It is not clear if this is all as a result of new models, or partly due to an internal review conducted by the 'Model Integrity Team' in BEIS to create a robust central record of all models in use. A central record was one of the suggested quality assurance measures that government departments were required to do following the MacPherson review of modelling in Government (Macpherson 2013).

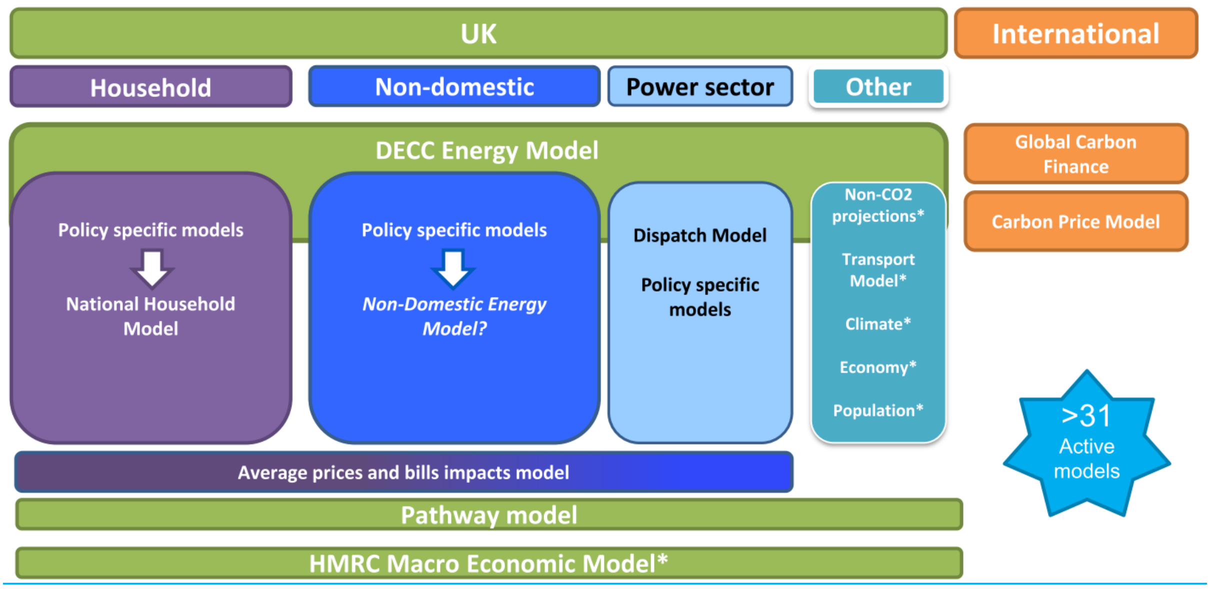

FIGURE 2.2: MODELLING LANDSCAPE IN UK GOVERNMENT IN 2014 (DECC 2014C)

Figure 2.2 illustrates the energy modelling landscape in Government in 2014. There are specific modelling activities in each the household, non-domestic and power sector as well as high level energy bill analysis and macro-economic modelling.

2.2.2 Application of Modelling

Models are used extensively to help governments understand these interactions and uncertainty in the transition to our longer term goals (Energy Research Partnership 2010). Both the risk of introduction of new energy policies and changes to existing energy policies can create significant uncertainty for stakeholders in the energy market. Energy system investment decisions typically require sufficient long term certainty in order to justify a business case. New plant, infrastructure and even energy efficiency measures are all likely to have high capital costs relative to their early revenue streams, and therefore need to carefully consider the future market in order to assess the risk and payback period. Government therefore has to consider not just what policy is likely to meet a given objective but also how it may impact the wider market. Designing policy is a balance; achieving the specific policy objectives which often work against each other, as well as keeping the UK market attractive to investors who ultimately are relied upon to deliver those objectives.

The current energy policy goals are to deliver a secure, affordable and low carbon energy system (DECC 2012c), and even these can pull against one another. One example would be a policy to help increase renewable energy will cost energy customers and therefore reduce short term affordability.

A number of different modelling techniques are used by Government for policy design as described in Figure 2.1. Modelling activities which guide policy direction, such as setting carbon budgets and identifying possible long term pathway scenarios, often use least cost optimisation tools which calculate the least cost system design to meet given targets (Hall & Buckley 2016). It is anticipated that these modelling activities, despite not accurately predicting a specific future output, produce benefits to the resulting policy design due to a greater understanding of the system and its associated uncertainties (Hughes & Strachan 2010). Much of this modelling is not published in Government Impact Assessment reports for external stakeholders and it is unknown to what degree such learnings and insights are passed on to future model users and policy makers.

Government Impact Assessment reports, which accompany the introduction of a new policy, frequently reference energy system models. The Reports outline the expected costs, benefits and likely consequences calculated as a result of energy system modelling analysis. Whilst the analysis may conclude that the new policy is effective in achieving its goal, it is often justified in such a report through simply quoting the results of a model. It is frequently argued that a numerical output of a model is meaningless without an understanding of its assumptions and the modelling process. Instead models should be used to develop insights rather than forecast numbers as the learning from the modelling process is more valuable that the output figure (Huntington et al. 1982; Hamming 1973). There is also a risk that documenting what appear to be very detailed results, could be incorrectly interpreted as an accurate forecast (McDowall & Keppo 2014).

2.2.3 Scenarios

A scenario is defined as '*a postulated sequence or development of events'* (Oxford English Dictionary 2016b). Energy system scenarios can be used by policymakers and industry decision makers to develop long term strategies and understand uncertainties in the future pathways. They often cover a time horizon of 20 or more years and lay out potential generation and demand portfolios.

Hughes and Strachan (2010) suggest that scenario production methods can be placed into two main categories; those formed from perceivable future trends, and those developed through back-casting from a desired future. Scenarios are often developed as part of a modelling study as well as being used as inputs for subsequent modelling activities.

A number of industry and governmental organisations produce scenarios for different purposes, including internal strategy, lobbying and policymaking (Cao et al. 2016). Below are some examples of scenario activities:

- National Grid produces four scenarios each year which are aimed to represent a range of different but possible future pathways to 2050. Their Future Energy Scenarios (FES) are produced to comply with their licence obligations and are used by National Grid themselves to aid their network planning as well as by other stakeholders as a benchmarking tool (National Grid 2016a). The scenarios do not use a back-casting technique to meet a certain goal; they instead are created through analysing likely trends and projections combined with stakeholder engagement producing a result which is supposed to represent 'credible' pathways.
- An example of a set of scenarios created using a back-casting method is the Energy Technologies Institute's (ETI) 'Clockwork' and 'Patchwork' scenarios (ETI 2015). They are created using the long term optimisation model, ESME, which takes the future carbon

reduction target as a requirement for 2050 under different technological portfolios and works back to identify the scenario projection between now and then.

- Centrica also create scenarios in a similar way, using RESOM, a tool which uses very similar techniques to the ETI's ESME model for strategy and lobbying purposes (Centrica 2014).
- The CCC likewise creates a number of scenarios to assess the UK's progress towards the future targets and inform Government policymakers (Committee on Climate Change 2015).
- Other more global examples include scenarios by Shell to help it understand its future role and the International Energy Agency's (IEA) higher level global scenarios which are widely used by other organisations as a baseline for their own analysis.

Another way of classifying scenarios is to divide them into the following categories; possible, probable and preferable (Börjeson et al. 2006). It could be argued that the preferable is likely to use back-casting style methods to meet desired futures, whereas those described as possible could align more with National Grid's approach. Depending on the level of detail and time horizon, labelling any scenario as probable could be misleading. There is a risk that when presented with a few scenarios that one is perceived as the central or most likely scenario (McDowall & Keppo 2014) and therefore used incorrectly by stakeholders.

Scenarios created by consortia including government and academic institutions from 1978-2002, as well as UKERCs own past scenarios were retrospectively examined by UKERC for the period 1990-2013 (McDowall & Keppo 2014). It revealed that often the actual future lay outside of the range of possibilities predicted by the model. This highlights the uncertainties and sensitivities in energy system modelling and that outputs need to be carefully analysed. It also illustrated the need to include various scenario approaches and methods to recognise future uncertainties. This review also highlighted the advantages in combining scenarios from multiple approaches to obtain a greater range of possibilities. It was suggested that another useful outcome from scenario analysis is that it can help facilitate conversation and debates about the future options for energy policy.

2.2.4 Challenges for modellers in Government

There are significant challenges facing government model users and policymakers. Two of these challenges are; harmonising model inputs and activities across teams, and providing transparency and communication to external stakeholders.

Figure 2.2 illustrates the range of energy modelling activities taking place in Government and the associated boundaries and overlaps. With over 70 active models in this field, documenting their assumptions and their interactions will be challenging, especially with frequent input data revisions. The 'Model Integrity Team' in BEIS, formed whilst part of DECC, have recently conducted an audit of models in order to create a central repository to monitor the various tools and their inputs to increase harmonisation of the Department's modelling activities (BEIS 2016b). There is also a central engineering team and an economics team in BEIS who assist with energy modelling activities.

Models are often created by external parties such as academics or consultancies. This creates a challenge when passing the analysis back over to Government, in ensuring that policymakers and other users fully understand the model and its various assumptions and its sensitivities are transparent. Often this is done by producing descriptions of the model methods in prose as well as numbers, key graphs, findings and logic maps (Macpherson 2013). An additional challenge is the frequent staff movements within Government and ensuring that knowledge of these models does not move with them (Centre for Sustainable Energy 2014).

As energy policy affects all stakeholders in the market including residential energy users, it could be argued that the models used and the accompanying assumptions used to back up any decision should be transparent. There is a community calling for increasing transparency and access to full model code, for modelling being undertaken across all parts of the energy sector including by policy makers (Huntington et al. 1982; DeCarolis et al. 2012). Transparency can range from a small disclosure of information to full reproducibility of a model (Cao et al. 2016). This can include the model source code, accompanying assumptions and the insights gained, such as the supplementary material provided by Pfenninger & Keirstead (2015). Cao (2016) creates a transparency checklist for scenario modellers which includes 20 criteria, including: aim, key term definitions, storyline construction, sensitivity and robustness analysis, model validation, model specific properties, uncertainty, and communication. The Open Energy Modelling Initiative (2015) (OpenMOD), recently established within the European academic community, encourages collaboration and provides a community for assistance to researchers using energy system modelling tools.

In addition to the call from stakeholders for increased transparency in Government, providing improved clarity of the modelling being undertaken could be beneficial to them by allowing increased dialogue with market stakeholders with regards to the accuracy of some of these assumptions. Three BEIS models are available open source for stakeholders to download and use. These are the DECC 2050 Pathways Calculator (HM Government 2010), the DECC Biomass Emissions and Counterfactual Model (DECC 2014b) (BEIS 2016c) and the National Household Model (DECC 2017). There is a long way to go if the future solution is to increase transparency and accessibility. Challenges due to complexity of models, such as MARKAL, makes documentation a challenge (McDowall & Keppo 2014). It is understood that UK TIMES will be open source. The goals of increased transparency and accessibility within government and externally are recognised by policymakers (@WholeSEM 2014b; DECC 2014c). DECC's current modelling strategy has developed to include quality assurance to ensure greater standardisation and a modelling forum to increase the skill base and support within the organisation (DECC 2014c).

There are some modelling communities which intend to increase the understanding of energy modelling techniques. The Energy Modelling Forum (EMF) was formed in 1976 at Stanford University (Huntington et al. 1982) with the aim to improve energy modelling techniques particularly their collective capabilities. The EMF produces reports which are publicly available and take into consideration views from a wide range of stakeholders (Stanford University 2017). In the UK, an academic energy modelling consortium, WholeSEM, was recently established with the aim to be a focal point for national energy modelling, develop new tools and build the capability of existing tools through increased collaboration and innovative thinking (UCL 2015).

There are areas of modelling which are under-represented, for example institutional and structural changes are not often captured by energy system models which can have significant impact (McDowall & Keppo 2014). Modelling tools are likely to develop when a need for them is identified. Flexibility in the energy system, particularly on the distribution and customer levels is increasing with the addition of policies to encourage demand side response. This has previously been identified as a gap in Government's modelling expertise (Centre for Sustainable Energy 2014) and the recent work commissioned by BEIS highlighted the complexity in modelling such complex interactions (Carbon Trust & Imperial College London 2016).

2.3 Modelling typologies

Typically a model can be broken down into three main parts: the inputs, the processing component, and the outputs (Macpherson 2013). What links these together can vary considerably in terms of the modeller's techniques, data, skill and computational requirements depending on the model's primary function and the system boundary. As a result energy system models possess a variety of attributes. DECC recognises the variations in modelling method in its definition of a model:

"A model is defined as a set of calculations, assumptions, or mathematical manipulations that supports a key business decision, including structured sets of assumptions about how some system operates which represent stakeholders' shared understanding of that system. This might in practice have more than one element of modelling (e.g. it might be a number of different spreadsheets, or a mind map or system thinking map with some calculations) but a cluster of such elements supporting a single set of decisions should be treated as a single model where possible.” (DECC 2014d)

The complex nature of a model means it can be hard to navigate and interpret what a given model is doing (Cao et al. 2016), however understanding what attributes are present in any model may aid comparisons between them. A number of studies have broken down the attributes which any given energy model may hold. This illustrates the diversity of models that could exist and the potential reason for the large number and range being used in the UK today (@WholeSEM 2014b). Table 2.1 indicates what attributes are considered by the five studies examined. It demonstrates the complexity and range of attributes a model may have. The different terminology used by the studies made the creation of a logical and comparative table a challenge.

	Connolly, 2010	Keirstead, 2012	Hawkes, 2014	Zeyringer, 2014	Kesicki, 2012	Cao, 2016
Analytical approach: Bottom-up and Top-down	Yes		Yes		Yes	Yes
Method (& programming technique)	Operation optimisation, investment optimisation, scenario and/ or simulation	Optimisation, simulation, empirical or econometric (further sub categorized)	Normative → Predictive	Optimisation or simulation (then sub-categorised further)	Optimisation or simulation (Including linear and non-linear programming techniques)	Input-output, spreadsheet, simulation, optimisation, economic equilibrium, econometric. Other (further categorised for Linear, non-linear, dynamic, mixed integer, other)
Equilibrium	Yes		Yes			
Spatial	Yes	Yes	Yes		Yes	Multi region or single region
Temporal	Yes	Yes				High, medium, Low
Time Horizon						Short, medium, long term
Level of detail						High, medium, low
Foresight (dynamic → static)			Yes		Yes	
Sectoral coverage	Yes		Central Planner → Self Interested	Yes		General: Economy, energy, environment Energy: Specific sector, All sectors
Treatment of uncertainty /logic			Yes		Yes	Stochastic, deterministic, Fuzzy or Interval
Supply demand focus		Supply & demand exo- / endo-geneous	Yes		Degree of endogenisation (fuel prices, economic growth, taxes and energy demand)	
Application / Purpose		1. Primary application (e.g. system planning, technology design, operational control) 2. Target audience (e.g. policy makers, engineers)				Forecasting, back-casting or exploring

TABLE 2.1: ATTRIBUTE COMPARISON. ***(CONNOLLY ET AL. 2010; KEIRSTEAD ET AL. 2012; HAWKES 2014; ZEYRINGER 2014; KESICKI 2012; CAO ET AL. 2016)***

All studies include an attribute to describe the model's method; this is generally considered to be optimisation or simulation with some further sub categorisation. Most studies included a spatial characteristic in their comparisons and whether the modelling took a bottom up or top down approach. Other attributes considered include: the level of equilibrium, presence of any stochastic methods, extent of the sectoral coverage, level of foresight and the temporal distinction. Two of these are discussed in more detail below.

2.3.1 Modelling Techniques

Simulation and optimisation methods are the most commonly referred to method attribute in Table 2.1, only excluded by Hawkes' method attribute comparison which instead comprises of a normative to predictive scale. Pfenninger (2014) suggests that simulation and optimisation techniques could be considered to be closely related to this distinction, the former creating forecasts or predictions whereas the latter creating normative scenarios. There are a number of other methods mentioned here such as econometric, the most common being regression analysis (Hoffman & Wood 1976) which is often used for demand forecasting, and sub categorisation of methods such as the different techniques for running an optimisation, including linear and non-linear programming. Zeyringer (2014) suggests that all models are either optimisation or simulation and subsequently lists a further set of modelling subcategories including: integrated assessment, input-output CGE, agent based and accounting. A more in depth discussion of modelling methods and the associated terminology can be found in Chapter 3.

2.3.2 Bottom up and top down modelling approaches

The attributes '*bottom up'* and '*top down'* refer to the general approach which the model takes. Typically bottom up models originate from the engineering discipline, are technology explicit and therefore generally disaggregated and require a large amount of technical detail (Kesicki 2012). Whereas a top down model is derived from the economics discipline and takes a more aggregated approach (Nakata 2004; Lanz & Rausch 2011). It can be argued that top-down models do not recognise the complexity in the demand and supply relationship although they are able to better adopt more reliable long term economic relationships (Nakata 2004). Hawkes (2014) considers models to be on a scale suggesting that they may not sit perfectly at one end or the other of the bottom up and top down extremes. A model can in fact be somewhere in the middle depending on, for example, the level at which the system is being modelled. Bottom up and Top Down are commonly used terms in the literature however not all the studies reviewing attributes consider them, potentially because it may be explicit from the method.

2.3.3 Hybrid modelling

Table 2.1 illustrates how models can differ from one another based on their basic attributes, however it can be argued that even splitting up the different types of attributes can still be misleading. Hawkes (2014) and Hoffman & Wood (1976) argue that it is imprecise to give an attribute a specific label, such as in its approach or method, as in reality a model often has multiple capacities. Hawkes (2014) uses a scaling system for each attribute where appropriate to highlight this, whereas Hoffman & Wood (1976) solely classify by primary objective but warn of its simplification. Hourcade & Jaccard (2006) highlight the recent increase in hybrid modelling methods which attempt to combine some of the strengths of a number of approaches or method to create a more realistic model for the problem being modelled.

The definition of hybrid is 'a thing made by combining two different elements' (Oxford Reference 2015) and therefore a hybrid model is assumed in this context a model that includes more than one type of technique. The most commonly referred to type of hybrid model in the literature are those which include top-down and bottom-up techniques and/or partial and general equilibrium properties. These properties are often used interchangeably as they are inherently linked in the case of energy system modelling. Partial equilibrium models balance the equilibrium of the energy system without taking the wider macro-economic system into consideration. They are generally bottom up models and therefore include a large amount of technical detail (Kesicki 2012). On the other hand top-down general equilibrium models take into account the full economic system and tend to aggregate electricity generation information therefore requiring less technological data (Lanz & Rausch 2011). The distinction between the ends of the spectrum have become less clear as models have adapted to be able to incorporate additional functionality, for example top down models with a greater degree of technological detail and bottom up models with some macro-economic effects such as price elasticity (Kesicki 2012). It is widely believed that there are strengths and weaknesses of each of these extremes and therefore trade-offs have to be established in order to choose the correct approach for the problem being modelled.

The main trade-off is between the amount of detail considered by the model for generation technologies and the inclusion of economic effects such as fuel costs. General equilibrium models can be mathematically complex and less transparent, (Rivers 2013) and therefore are not always the most cost effective models depending on the economy in question (Hertel 1985). Additionally due to the effect of aggregation they are unable to incorporate analysis such as technology learning (Böhringer & Rutherford 2009). Conversely a criticism of some bottom-up partial equilibrium models is that they do not take into account real world situations. They do not include wider economic effects and often include optimisation algorithms which are not always realistic, as they assume perfect foresight (Böhringer & Rutherford 2009). Other trade-offs include: accuracy vs complexity, cost, transparency, and time and computational constraints. This applies for other model attributes including resolution, time horizon etc. Hourcade & Jaccard (2006) have published a useful illustration of the trade-offs between bottom-up and top-down models which illustrates the diverse range of design a hybrid model could be, as shown in Figure 2.3.

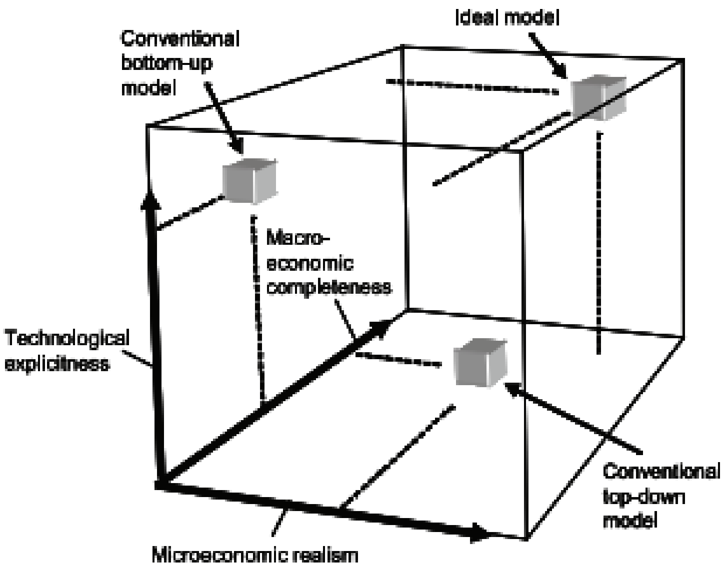

FIGURE 2.3: 3D ASSESSMENT OF ENERGY-ECONOMY MODELS (HOURCADE & JACCARD 2006)

Alterations have been made to the traditional bottom-up and top-down models to get closer to an 'ideal' model. Hourcade & Jaccard (2006) describe any model which 'has made at least one modification to shift them substantially away from their conventional placement in the cube' as hybrid models. It is likely that this assessment can be true for many more of the attributes outlined in Table 2.1.

2.3.4 Classifying models

Understanding what attributes a model contains can provide a useful set of criteria to assess whether a given model may be suitable for the problem being addressed, or at the very least narrow down from a larger group of potential models. However it is often not clear what attributes a model has as there is a lack of transparency and consistency in the way models are described in the literature (DeCarolis et al. 2012). This is illustrated by the difference in attribute labels provided by the studies for the methods in Table 2.1 and that the terms appear to be being used interchangeably despite not necessarily having the same meaning, for example normative and optimisation.

Another reason identified for different interpretations of model attributes can be due to models being further updated and evolving away from their original purpose. Dodds (2014) proposed a model archaeology system to track changes to models which would be particularly useful as models evolve and take on extra capability.

Even once the attributes of a model are established, interpreting which model is more suitable requires an understanding of the various terms and techniques and what the strengths and weakness of the model are in order to determine the appropriate trade-offs. This can be assisted by an understanding of the model purpose and a common modelling terminology and framework. Models can also be grouped into classes based on similar attributes or modelling objectives. This has been attempted in a number of studies and normally results in a grouping closely related to the modelling technique present (Pfenninger et al. 2014). This approach can assist a modeller in identifying what type of tool is appropriate for a given task. Access to such sophisticated tools is often limited due the skill, data and computing requirement of many of the models, particularly in developing countries (Gardner 2014), therefore understanding what is suitable would be valuable.

2.3.5 Demand modelling

Demand is a fundamental part of any energy system model, usually the variable the model aims to balance with supply, subject to further constraints. Despite this, demand is typically an input created outside of the model which may or may not be very well understood by the model user. Recognising the source of such input assumptions and the associated limitations and sensitivities which may impact the outcome is essential for a robust analysis.

Historically the main variables which impacted the level of demand at any given time were price and external weather conditions. As the system has evolved, demand forecasters have had additional factors to consider which have fewer data sources. These include:

- The rising number of distributed generation systems, such as solar PV, which result in demand from the grid decreasing in periods of high solar radiation,

- A change in who the large demand users are, for example new players such as data centres,
- The introduction of demand side incentives into the market.

2.3.5.1 DEMAND FORECASTING TECHNIQUES

Swan & Ugursal (2009) broke down the different modelling classes used for residential demand forecasting into two approaches, bottom-up and top-down and then sub-categorise further, see Figure 2.4.

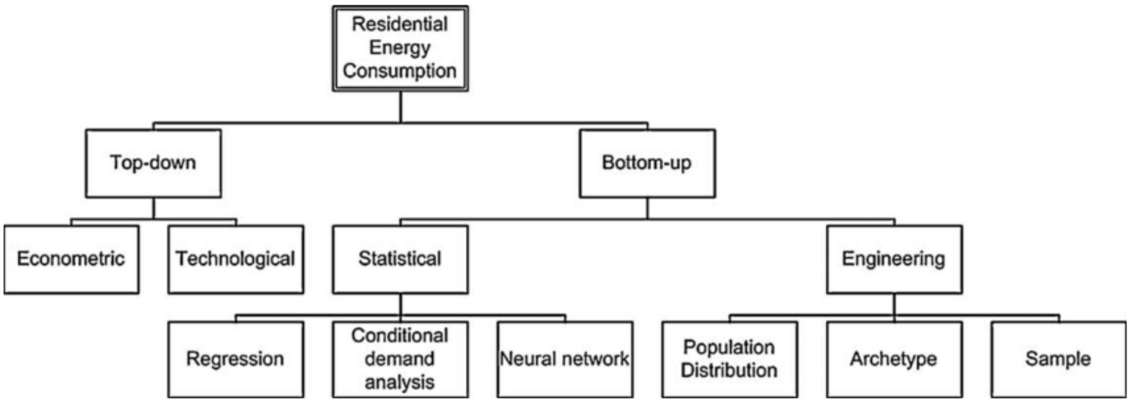

FIGURE 2.4: CLASSIFICATION SYSTEM FOR DEMAND FORECASTING (SWAN & UGURSAL 2009)

The top-down demand techniques are described here as econometric and technological and are calculated using historic consumption data. Econometric models analyse the relationships between economic characteristics such as price and income to forecast demand. Technological forecasting techniques here are those which consider the broad characteristics of the housing stock and how that may evolve over time. Swan & Ugursal (2009) group all remaining models into the category of bottom up and encompass models which use data from as detailed as household level and extrapolated to create a forecast that represents the full system being modelled.

Rhys & Rhys (1984) identify just three categories to distinguish between the different demand modelling techniques:

i. Statistical interpretations and projections of past trends,

ii. Examination through econometric analysis of fundamental economic factors believed to determine energy demand and electricity consumption,

iii. Detailed research into the nature of energy use at the customer level.

Methods 1 and 2 would be included in the top down category of models in the study by Swan & Ugursal (2009). Method 1 identifies the historic trend and then projects that trend into a future forecast with the inclusion of a weather corrected variable. It is noted that a potential flaw is that it is very dependent on the training years and that time is the only factor that has any influence on electricity consumption. Method 2 is broadly that described above as econometric. The final approach refers to bottom up or physical modelling and is likely to encompass a number of the end use research methods. Whilst the two classifications are likely to comprise of the same set of tools, their classification structure is very different. Swan & Ugursal (2009) include further detail in the bottom up or physical class of models.

A review by Bhattacharyya & Timilsina (2010) focuses only on econometric and end use techniques used in demand forecasting, methods 2 and 3 in Rhys & Rhys (1984). Whereas Suganthi & Samuel (2012) discuss a variety of different demand modelling techniques such as time series, regression, fuzzy logic, decomposition, artificial neural networks and agent based (Suganthi & Samuel 2012).

2.3.5.2 Aggregate demand modelling

In models such as long term optimisation tools, demand is an input variable in the form of annual aggregated demand. It is often accompanied by inputs to consider the seasonal and daily profiles and may, for example in the case of MARKAL, also include an elasticity assumption to recognise that as the supply mix changes, prices vary which could alter demand. However underlying annual demand still remains a core input (Loulou et al. 2004).

Many long term energy demand models use analysis of past trends to predict the future demand using techniques such as time series or linear regression (Swan & Ugursal 2009; Rhys & Rhys 1984; Bhattacharyya & Timilsina 2010b). Econometric methods take into consideration past trends and future economic outlook to forecast demand. They can be used to measure past relationships between factors, for example electricity sales, national economic growth and fuel prices (Rhys & Rhys 1984). Regression techniques analyse the past relationships between different variables such as day of the week, month of the year, and those that affect the amplitude of those trends such as temperature and wind chill which affect heating. Additionally, solar radiation not only affects solar gains in properties and therefore heating/cooling requirement, but also the level of PV production. Economic variables can also be considered which take into account future changes such as increased energy efficiency levels as a result of policy and the level of economic growth using factors such as GDP and population. However, as customers begin to use new demand and self-generation technologies there is not as much data to undertake analysis on past trends, particularly when much of this is impacted by the particular weather and market conditions.

Whilst all future inputs have a degree of uncertainty, for example GDP and population, the weather has a particularly high variability especially over longer time periods (i.e. years-decades). One way of understanding the impact of multi-year variability on demand could be to calculate a historic record of demand incorporating a range of meteorological conditions. This dataset could be used to understand the range of possible future changes in demand (Bloomfield et al. 2016). This is an example where understanding the limitations and sensitivity of the demand is important before using it as an input.

When using an econometric or regression tool the specific system being modelled needs to be considered. Inglesi et al (2010) explains that for South Africa temperature and price of raw fuel were decided not to be important variables when looking at the aggregate demand for electricity in South Africa. This is because electricity's main customer is the industrial sector which is not influenced by temperature, as perhaps a domestic customer would be, and secondly that there are no perfect substitutes for electricity raw fuel, i.e. natural gas is not a substitute for coal therefore demand does not vary significantly with the price of coal. The short term demand can be explained by GDP and population. In regions such as the Caribbean islands which have experienced quite significant shift in economic growth, past data may not provide suitable historical trends. Therefore Gardener (2014) suggests that bottom up scenario analysis may be more appropriate. In the Caribbean the variability in temperature has a smaller impact on demand than trends in human behaviour and tourism.

2.3.5.3 High resolution demand modelling

As has been identified above, longer term projections of demand, such aggregated annual and daily demand is often forecasted through an econometric or regression technique. However, often a more detailed temporal resolution is required when looking at system operation, in particular to identify peaks or ramping events. The output of a daily regression model can be combined with a typical daily profile to look at future hourly demand, such as in MARKAL where seasonal and daily trends are input separately to the predicted annual electricity and gas demand (Loulou et al. 2004).

LEAP breaks down the demand into different end use requirements such as heating, cooking and lighting within its energy system modelling tool (McPherson & Karney 2014). It considers future changes in economic variables such as population and GDP and, due to its aggregated nature, can assess the effect of the uptake of new technologies such as more efficient lighting. This could be useful to analyse the impact of demand side policies. This disaggregated or bottom up approach can be very data intensive as it requires a large amount of detail on future technologies and growth rates which can have a high degree of uncertainty and often require forecasting of their own.

Other techniques exist which can estimate future demand at a high resolution. These include those based on time use data from national time use surveys or by stochastic methods such as Markov or Monte Carlo analysis (Torriti 2014). Building physics models also give an indication of the energy requirements for future building types. Agent based modelling uses agents to represent likely behaviours and consequently demand (Ma & Nakamori 2009).

2.4 Chapter Summary

This review has highlighted the range of modelling tools that could be used for energy system modelling. The overlap between different techniques and attributes is likely to make comparisons between models confusing, due to the terminology or level of detail being shared as well as the complex landscape. There are a number of different terms being used to describe modelling methods and also the interchangeable use of terms to mean the same thing, for example bottom up models and partial equilibrium. There are the instances where a model does not fit neatly into certain attribute categories, such as bottom up or top down, as it could have some hybrid qualities, thereby leaving its interpretation down to the study describing it. This review has shown the importance of understanding the trade-offs of different attributes in order to choose the most suitable tool.

This review has illustrated a significant increase in the number of models which are actively used by Government. The internal perception of their importance has been demonstrated by the increased documentation and quality assurance occurring within BEIS. A number of challenges have been identified, notably around transparency of the underlying modelling methods.

This chapter has provided insight into Objective 1 which seeks to identify the range of models being used and how models are classified. As discussed above, this has been achieved through analysing the various modelling attributes and terminologies that exist in the landscape. Chapters 3 and 4 will continue to build on this knowledge. Chapter 3 will further explore the various terminologies being used by reviewing attempts to classify energy system models. It will also focus on the modelling types which are typically used for policymaking. Chapter 4 will then explore in more detail the relationship between the modelling undertaken by Government and the energy system stakeholders and any insight about model usage which may not be available in the literature.

3 CLASSIFYING ENERGY SYSTEM MODELS

3.1 CHAPTER OBJECTIVES

This chapter aims to identify the core model types which are commonly used to influence the direction of future energy policy. This is achieved by undertaking two types of model reviews. Firstly, previous attempts to classify energy system models in the academic literature are examined and areas of commonalities and differences between these approaches are identified. This will establish the broader energy system modelling landscape and where the emphasis lies in academic modelling activities. The second review identifies the specific modelling tools that have been used by UK Government for energy policy design since 2010. This will be achieved through a review of published Government report to identify which modelling tools have been referenced. The tools can then be referenced back to the academic review and the model types which are seen to be important for policymaking can be identified.

This chapter primarily addresses Objective 1 of this research, but also provides insights into Objectives 2 and 3.

- Objective 1: Identify the range of energy system models being used and the previous classification approaches being applied, with particular regard to models used in relation to UK energy policy.
- Objective 2: Explore how the identified models are being operationalised for UK energy policy development and the role which model outputs have played in informing recent energy policy decisions.
- Objective 3: Identify relevant core model types and generate representative versions for the case study of Shetland.

3.2 CLASSIFICATION THEORY AND APPLICATION TO ENERGY SYSTEM MODELLING

Chapter 2 illustrated the value of grouping models together and the importance of understanding model attributes to establish if a model is suitable for a task. Typologies create a common language and therefore improve communication and collaboration of methods between stakeholders (Börjeson et al. 2006).

Table 2.1 illustrated the different attributes used to describe models in a number of different studies. Having the ability to compare the different attributes of specific tools will assist a prospective model user when looking to choose an appropriate model for a task. However a model user will often not be familiar with what attributes are important, therefore being able to identify a model class will sometimes be more useful. A model classification system can help by grouping those by similar uses or techniques. This section examines the similarities and inconsistencies of commonly grouped energy system models from a number of studies. It aims to detect the different terminology being used across various studies, identify any common areas of misunderstanding and attempt to clarify the various terms.

3.3 ACADEMIC REVIEW

A number of examples of energy system model classifications were found in the literature and are displayed in Table 3.1. This list is not intended to be an all-inclusive review of classification studies, but to show a representative range to decipher probable models of importance to this project and an insight as to whether there is general agreement on the main model classes. The purpose and perspective of these studies vary; Loulou (2004), Pfenninger (2014) and Hoffman & Wood (1976) are looking at the more widely used energy system models, with Pfenninger focusing on policymaking and Loulou using its classification to highlight where the MARKAL models fit into the modelling landscape. Mischke & Karlsson (2014) group energy system models used specifically for the Chinese energy system and Bhattacharyya & Timilsina (2010b) look at those useful for system planning in developing countries.

TABLE 3.1: EXAMPLES OF ENERGY MODELLING CLASSES

Name of Study	**Categories used in study**
Hoffman & Wood (1976)	• Mathematical Programming (i.e. linear programming) • Input-output • Econometric • System dynamics • Game theory
Loulou (2004)	• Bottom-up, partial equilibrium optimisation • Bottom-up simulation • Top-down CGE • Top-down macro-econometric
Bhattacharyya & Timilsina (2010a)	• Bottom-up optimisation • Bottom-up accounting • Top-down econometric • Hybrid • Electricity system
Mischke & Karlsson (2014)	• Bottom-up optimisation • Bottom-up simulation • Bottom-up no further details • Top-down CGE • Top-down input-output • Top-down no further details • Hybrid
Pfenninger (2014)	• Energy system optimisation • Energy system simulation • Power systems & electricity market • Quantitative and mixed methods scenarios

Despite the differences in the aims of the five studies which have been compared, the compiled classes provide a useful data set of widely used model types. All studies grouped the models based on the core method used and therefore many of the terms used are comparable despite no classification being identical. In order to illustrate where there are similarities and differences between the classification approaches, the individual classes were plotted on a graph so that the areas of overlap could be explored, see Figure 3.1. This also enabled the most commonly cited energy system class types to be identified. Every class of model discussed in the seven studies, shown in Table 3.1, is plotted with the exception of hybrid model classes and the two classes by Mischke & Karlsson (2014) which were ‘bottom up no further details’ and ‘top down no further details’ as these were ambiguous. Hybrid models were excluded as without further information it was unclear which techniques they most closely characterise in the various studies. They are likely to represent models which use more than one technique and therefore cannot be placed into a single position on the grid.

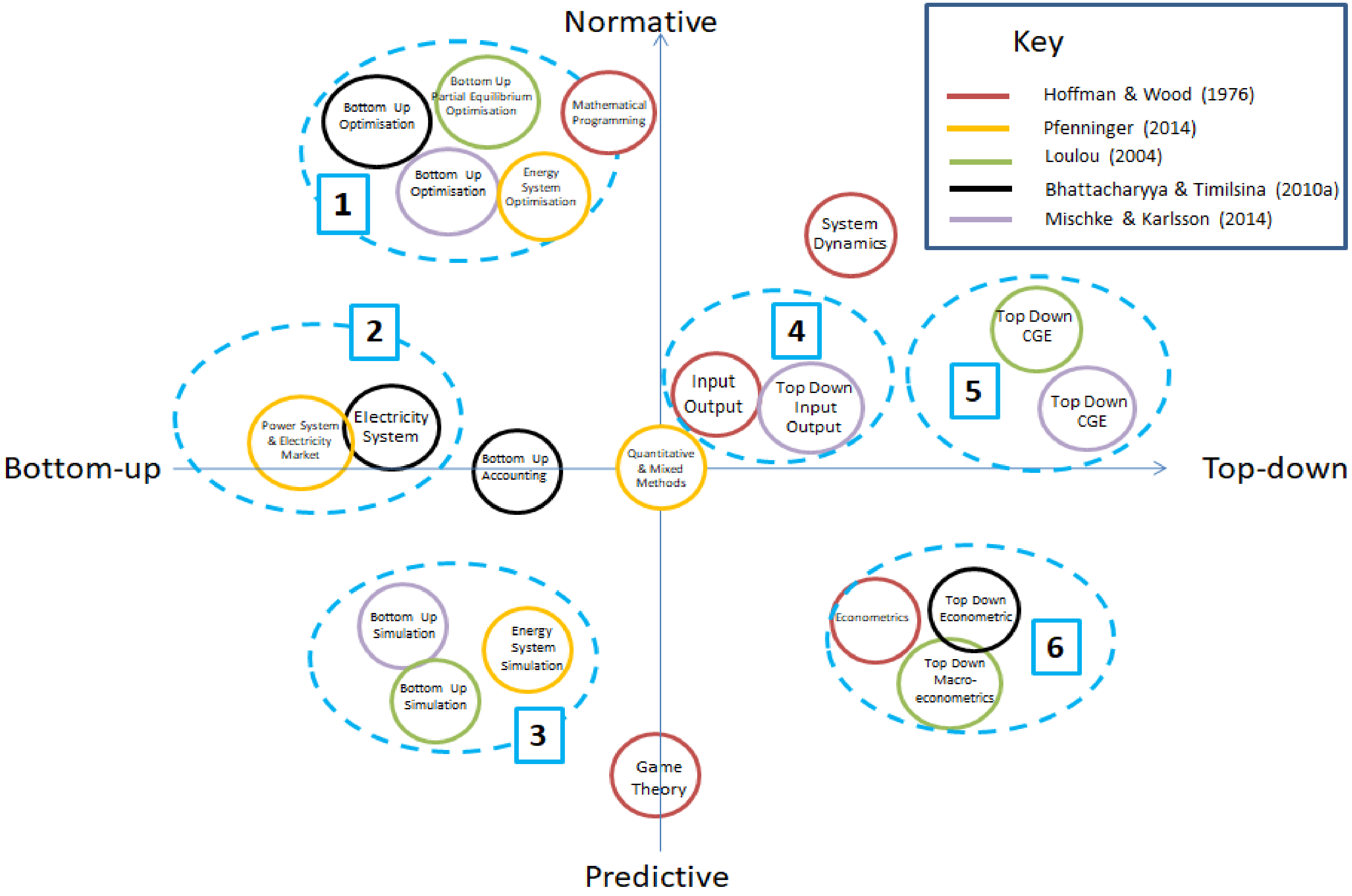

FIGURE 3.1: ENERGY SYSTEM MODELLING CLASSIFICATION COMPARISON (BASED ON TABLE 3.1.)

The colour of the circle in Figure 3.1 signifies the study the model class originated from, and where they sit on the plot represents a general indication of whether the model class typically takes a bottom up or top down approach, and if they are based on a normative or predictive approach. These axes are just for visual purposes to aid a general comparison of the classes, and are not to scale.

The terms bottom-up and top-down were discussed in section 2.3.2 and describe models which are based on a disaggregated or aggregated approach respectively. The terms normative and predictive require further explanation. In economics there are three theoretical standpoints; normative, descriptive and predictive. 'Normative' theory is how a person *should* make a decision, 'descriptive' theory is *how a person* does make a decision and 'predictive' theory actually accurately predicts the outcome of a person's decision (Briggs 2016). This implies that models which predict the likely outcome consider some descriptive theory in their method and therefore it is probable that there is some overlap. In the context of energy system modelling, Hoffman & Wood (1976) describe models as normative if they analyse the effect of a change at a point in time, whereas predictive models analyse the effect over a time period. Pfenninger (2014) contextualises further and describes 'optimisation' models as normative and 'simulation' models as predictive. It is elaborated further that optimisation modelling gives the perfect solution assuming that people are rational and act as they should, whereas simulation models aim to find the realistic solution. The descriptors 'optimisation' and 'simulation' will be discussed in more detail below. As this comparison is intended to demonstrate the theory in an energy system model, the axes of normative and predictive were chosen to align with the energy literature. However it is recognised that many models include elements of both theories so are often somewhere in the middle (Bhattacharyya & Timilsina 2010a).

Clusters of classes in Figure 3.1 have been identified where two or more classification names or descriptions in the study imply a similarity in the model class type. It is intended to aid comparison and highlight any trends. Six clusters were identified and these are illustrated in Figure 3.1 with a blue dotted circle and an associated cluster number.

Cluster 1 includes class types which all use optimisation in the descriptor, apart from the study by Hoffman and Wood (1976) that has a class called 'mathematical programming'. This study explains that linear programming techniques are frequently used for solving optimisation problems, therefore this class has been clustered together with the other optimisation models, although it is recognised that this could refer to a broader range of models. There were three references to simulation tools which cluster in the bottom-up predictive segment of the plot, see Cluster 3. On the top-down half of the plot the three main clusters were econometric models in Cluster 6, computational general equilibrium (CGE) models in Cluster 5, and input output models in Cluster 4. The former is based on predictive theories and the latter two are based on normative theories.

In the middle of the plot, there are some clusters and classes of models which could be either normative or predictive, or it was unclear from the study. These include the power system models in Cluster 2, accounting models and a mixed methods models, although Pfenninger (2014) did imply that accounting models were included in the mixed methods class. Other individual classes which were mentioned and feature on the plot were game theory and system dynamics.

3.3.1 Optimisation as a Descriptor

Optimisation is the descriptor cited most frequently across the classification names reviewed. The Oxford English Dictionary (2016b) describes optimisation as 'the action or process of rendering optimal'. More specifically, from a mathematical perspective an optimisation algorithm aims to find inputs which minimise or maximum the value of a function subject to constraints (Pardalos & Resende 2002). There are several methods being used to solve optimisation problems such as traditional linear and mixed integer programming, as well as those more heuristic methods such as particle swarm optimisation and genetic algorithms. The latter provide approximations for more complex problems which do not have a single solution (Baños et al. 2011). In the last decade there has been a ten-fold increase in the use of optimisation techniques to solve renewable energy problems (Baños et al. 2011). These models include a range of problems including optimal wind farm configuration or economic dispatch of electricity generation plants in a system.

The modelling tool EnergyPLAN is not discussed specifically in any of the studies in Table 3.1, but is an example of a tool described as an optimisation model in its model documentation and in a review of modelling tools for renewable integration (Connolly et al. 2010) (Lund 2013). EnergyPLAN does not use any formal complex programming techniques; instead it balances the system on an hourly time step over a given year. It runs through different scenarios based on user derived hourly distributions and capacities, balancing the system each hour with either the least cost power dispatch or the solution which reduces reliance on imports, exports and constraining of renewables (Østergaard 2009) (Lund 2013). It does this whilst considering just the hour in question as opposed to a longer time horizon, such as that for making investment decisions. So whilst it can be perceived to optimise, it is not strictly displaying mathematical optimising techniques such as the programming techniques described above, because it only considers a single time step of an hour and without perfect foresight. In addition, using the broad definition that Pfenninger (2014) provides of predicting or creating scenarios, EnergyPLAN does create scenarios and run those with an optimal algorithm, putting it in the category of 'Energy System Optimisation'. In another study Pfenninger describes EnergyPLAN as a 'short term operational model' (Pfenninger & Keirstead 2015). It is likely that it is more closely linked to the models described in the next section which use simulation methods, but with an element of optimisation within the basic model structure. This illustrates that despite frequently being used by the energy system modelling community to describe the model types found in cluster 1, 'optimisation' as a descriptor by itself is not sufficient to describe what class or type of model a given energy system tool is. It is a broad term which does not provide sufficient insight to the theory or the specific technique used.

3.3.2 SIMULATION AND ACCOUNTING MODELLING

Simulation modelling is defined as the imitation of a situation or process over time (Oxford English Dictionary 2017). Half of the studies reviewed in Table 3.1 cite 'simulation' as a method in their classification. Pfenninger (2014) describes these models as those which make predictions or forecasts of how the system may evolve. Loulou et al (2004) defines simulation energy models as those 'where the emphasis is on representing a system not governed purely by profit or utility maximizing behaviour', recognising that some technologies may attract investments which are not the cheapest available.

Whilst only three studies specifically state simulation in their class description it is likely that the remaining studies may have placed the tools described as simulation by others into different classes, such as accounting and hybrid. For example, Mischke & Karlsson (2014) and Pfenninger (2014) classify LEAP as a simulation tool whereas Bhattacharyya & Timilsina (2010a) classify LEAP as an accounting tool. The DECC 2050 calculator tool is also described differently between the studies. Mischke and Karlsson (2014) reference the DECC 2050 calculator tool as a simulation tool whereas Pfenninger (2014) puts it in the category of 'quantitative and mixed methods' which is described in that study as those which use simplistic quantitative methods with qualitative judgements.

One of the reasons for the opposing interpretations is that many of these models contain hybrid functionality or have sub modules which use different techniques. This includes models such as EnergyPLAN as discussed above, as well as the model NEMS, which is primarily a simulation tool, although it contains some optimisation techniques for generation calculations (Heaps 2011). This is understood to be why Pfenninger (2014) has classified it as a simulation tool whereas Hawkes (2014) refers to it as a hybrid simulation tool in another study.

LEAP can also fit into the criteria of multiple methods; it is based on an accounting framework whilst allowing users to add simulation techniques to their system. Heaps (2011) explains that in accounting frameworks, the modeller accounts for the output of decisions and the tool examines those outcomes, as opposed to a simulation tool which calculates the output based on behaviour of consumers and producers. In LEAP some of the electricity generation modules allow for simulation.

Another explanation is that the term simulation is often used as an overarching term for a number of methods, including accounting. Many of the examples in Table 2.1 based their method on either simulation or optimisation with further sub categorisation (Zeyringer 2014; Kesicki 2012). Pfenninger (2014) describes his classification as informal and only representing broadly the classes used for policy purpose. His distinction in the case of 'energy system optimisation' and 'energy system simulation' is that the former is creating scenarios whereas the second is predicting possible futures, which is similar to the normative and predictive attribute distinction explored previously. It is recognised that in reality these are not so clear cut.

3.3.3 Top-down energy system modelling

Three clusters of classes were identified which took a top-down, macro-economic approach to energy system modelling. These were macro-economic/econometric models (Bhattacharyya & Timilsina 2010b; Loulou et al. 2004; Hoffman & Wood 1976), Computational General Equilibrium (CGE) models (Loulou et al. 2004; Mischke & Karlsson 2014) and input-output models (Mischke & Karlsson 2014; Hoffman & Wood 1976).

Econometric modelling uses statistical techniques, often regression analysis, to hypothesise behavioural and technical processes (Hoffman & Wood 1976). Macro-econometrics consider aggregate economic behaviour and it is described by Loulou et al (2004) as simulating economic monetary flows between sectors. Aggregate economic behaviour is seen as being more closely linked with input output methodology than the CGE models, as they are not computing an equilibrium. However as econometric and input output modelling are separated in Hoffman and Wood's (1976), macro-econometric is grouped with econometric models in this study.

CGE models are based on microeconomic theory where consumers make decisions based on consumer choice theory and firms are profit maximisers (EIA 2013). CGE models can be used to understand the impact of policies on welfare and the production of goods in the economy. Input-output modelling considers the interdependencies between components of an economy. It is described as a matrix where the outputs of one economy can be the input for another. Therefore considering a broad economic system (Business Dictionary 2016). Zeyringer (2014) has combined the methods input-output and CGE models into one class, 'input-output CGE'. Potentially this is because CGE can be seen as an extension of input-output modelling which just simulates flows as opposed to computing an equilibrium. CGE models are used to consider the overall economic impact.

3.3.4 Power system modelling

Power system models are separate classes in two of the studies and refer to models which look specifically at power and electricity systems in more detail. They can be optimisation or simulation in technique but have been separated in two studies, most likely due to the focus of the study. Pfenninger (2014) looks specifically at models used for policy and Bhattacharya (2010a) is looking at those tools useful for developing countries in their system planning. Both of these reviews separated power models into individual classes, indicating that these were important models to consider in isolation. These models consider, albeit generally optimally, how the system can meet demand based on the operational constraints of the power stations and create dispatch solutions.

3.3.5 Summary of Academic Review

This review of academic studies has highlighted the vast array of terminology being used, resulting in many models being described by different studies in an inconsistent way. This interchangeability of terminology and even incorrectly used terms can be confusing to the reader and prospective model users, due to the subjective nature of these terms. As the development of more complex and hybrid models continues, largely due to computational power increases, understanding what different models do and the subtle differences between them is likely to become progressively more challenging.

The potential discrepancies and overlaps in the way simulation and accounting tools are grouped have been identified. The different types of optimisation tools that exist can also create confusion in the way the term ‘optimisation’ is used. Models which use programming to find optimal investment strategies are very different to those which optimise in a part of a model to provide short term optimal operational decisions; this was highlighted in the description of the EnergyPLAN model classification. Often further sub categorisation is required in order to fully understand the method of a given model and a high level of modelling knowledge is required of the prospective model user in order to recognise these differences.

This review has highlighted the difficulties in categorising models actually into a single classification due to the various techniques being used in each model. Identifying the specific attributes of a particular model could be complementary to a general model classification. This study does intend to create a new taxonomy of all energy model types, instead it identifies the core modelling theories which are being used for energy system analysis, as demonstrated by previous reviews and classification attempts:

3.3.5.1 Investment optimisation

An agreed class of models has been identified in Cluster 1. These models are generally used to identify least cost energy system pathways. The core concept behind these models is the energy balance, a simplistic representation of the flows in the energy system. An extension of this is the 'reference energy system' (Hoffman & Wood 1976), which is a network description of the energy system incorporating the activities and technological characteristics across the entire system and supply chain. These investment optimisation model types are commonly used by policy makers and planners, in order to identify the least cost future system design (Kesicki 2012).

The core economic theory behind these models is that they seek a partial equilibrium. This theory assumes that a single part of the economy, in this case the energy system, perfectly balances, and a price equilibrium is reached, and all actors behave relationally with perfect foresight. In reality this is not the case as system actors do not have visibility or the ability to predict what other actors may do, including policymakers. Policy will often change during the planning, design and construction period of a power station, resulting in an imperfect equilibrium. This longer-term view differentiates them from models which look in more detail at a shorter time scale, for example to consider how to dispatch plant or design a wind farm. As such, the term 'investment optimisation models' will be used to describe the modelling theory identified in Cluster 1.

3.3.5.2 Time Step Balancing

As described in Section 3.3.3, simulation tools attempt to create a view of how a system would evolve and can vary significantly in their resolution, complexity and scope. These models are often built in a modular way, unlike the investment optimisation models, from Cluster 1 which are created in a complex mathematical form. They can integrate sub modules which incorporate other methods, such as some optimisation techniques on specific parts of the model (Pfenninger et al. 2014). This means that in general they are less computationally complex and can be quicker and easier to use, however this can vary depending on the number of sub modules.

To eliminate the broad nature of the term simulation, this study considers a particular set of models, referred to here as 'Time Step Balancing Models'. This is because they make an assumption that the system, in general demand and supply, balance within a given time step, as opposed to over the long term with foresight like the 'Investment Optimisation' models in Cluster 1. This time step can vary, some models consider annual time steps as they look at multiple years, whereas other look at a year in isolation and will balancing on, for example, an hourly time step.

3.3.5.3 Unit Commitment/Economic Dispatch

Power system models, whilst often using similar techniques to the previous two model classes consider in greater detail the operational constraints of power plants. There are two main problems which are solved in a power system model; unit commitment and economic dispatch. Most sophisticated and proprietary tools will solve both the unit commitment and economic dispatch problems however they can be solved independently of each another. Most power system models solve the economic dispatch problem that identifies which plant should dispatch electricity and in what quantity in order to meet demand, subject to constraints including maximum power of each plant and cost. The unit commitment problem is solved first and, subject to constraints such as ramping and minimum on and off times of power plants, schedules which plant are on and producing power in a given time from which the dispatch calculation can be applied (Wood et al. 2014).

Dispatch models can vary in complexity, they can use similar techniques to the time-step balancing models discussed previously or more complex algorithm such as those used by Investment optimisation models. As discussed in section 3.3.5.1, optimisation techniques which consider central perfect foresight are not fully representative of how the system will behave. In the GB energy system, which is a market based system, there is no central dispatcher and therefore individual power stations are unlikely to operate to match a system cost optimised solution.

3.3.5.4 ECONOMETRIC MODELS

Econometrics are based on statistical techniques. Where econometric approaches are used for energy system modelling, it is generally to predict demand. They use past trends and relationships to determine future growth or decline in energy demand. They can also be used to examine the potential impact of change of an input, for example weather events on demand.

It could be argued that as our energy system is undergoing significant change, past relationships between variables may not continue to exist in the same form, therefore this needs to be considered when interpreting the results from econometric methods alone.

3.3.5.5 CGE/INPUT-OUTPUT MODELS

Both CGE and Input-Output models consider the wider economic impacts and therefore are grouped together for the purposes of this study. General equilibrium theory, like partial equilibrium theory seen in 'Investment Optimisation' models assume a price equilibrium is reached. However, it differs from partial equilibrium as it considers the whole economy, not just the energy system in isolation. Input-Output modelling, whilst also considering the whole economy, is less computationally complex because it uses an accounting/matrix style method to consider the impact of changes in one part of the system against another.

3.4 REVIEW OF ENERGY MODELLING TOOLS IN UK GOVERNMENT

As this project is primarily concerned with the types of models being used by UK Government, a review of models that have been used in recent policies was conducted. In order to identify the primary models being used for energy policy design, all models that have been referenced in a UK Government impact assessment or strategy document published by DECC or BEIS, since the coalition government was formed in 2010, were collated. In the case of policies still in development, and therefore presently without an impact assessment, the associated call for evidence or consultation document has been reviewed. This is notable in the case for the recent call for evidence on flexibility (BEIS & Ofgem 2016). Models are likely to be used at various stages of the policy development process. Therefore, it is anticipated that this list will not include every model which has been used, as some will be used in early analysis, which is too far removed from the final policy design outlined in the impact assessment. However, it is believed that this will provide a useful overview of the range of tools being used, which should be sufficient for the purposes of this review, which is to identify the types of models being used and not the individual tools.

It is acknowledged that by solely looking at models referenced within DECC/BEIS documentation, the review may not encompass all specific models and tools used to inform a given policy. It is likely that there will be models that have been used by National Grid, Ofgem, and other associated energy system actors which have contributed to knowledge and informed the need for a new policy. Ofgem's role is to ensure the market is operating fairly and in the interest of consumers and therefore use models for different purposes, to identify risk and set regulation. National Grid similarly act to ensure the system is balancing and network infrastructure is sufficient. Neither directly set policy and therefore have been determined to be out of scope for this analysis. There may also be insight from other government departments setting policy in areas which impact energy, such as an output from a Department for Transport model. However, for the purposes of this research it is assumed that any models of critical significance to a policy would be referenced in the associated impact assessment and policy papers.

3.4.1 Model Review

The review was conducted by using the UK Government website (HM Government 2017) and searching for publications using the following fields:

i) Publication types: 'Impact Assessments'

ii) Policy area: 'Energy'

iii) Published after: 11/5/2010

This produced 37 results, some of which had multiple impact assessments such as Energy Bills or Acts. Each of these impact assessment documents was reviewed to identify any references to energy system modelling activities. These were recorded and a database created. Strategy documents were collated using a similar method, in this case the fields were:

i) Keywords: ‘Strategy’
ii) Publication types: ‘Policy Papers’
iii) Policy area: ‘Energy’
iv) Published after: 11/5/2010

This produced 55 results, however only the reports which were stand-alone long term strategy documents were analysed, thereby excluding reports which had periodic editions or policy briefs. This left 12 to analyse in more detail. Finally the call for evidence on ‘A Smart, Flexible Energy System’ was analysed as this is likely to result in new policies in the near future.

The review identified 26 models. As already identified in Chapter 2, BEIS currently have 72 active models and a further 145 in its model log, therefore the list produced in this review is far from exhaustive. Nevertheless it should represent a broad overview of the modelling types which are being used.

Table 3.2 illustrates which reports have referenced the energy models identified in the review and which Government report they were referenced in. It also displays the number of models referenced in each report and how many reports each model was referenced in. Finally each modelling tool is colour coded to identify what model class it most closely corresponds to. This is either the model class identified in section 3.3.5 or where not appropriate, the class name most commonly discussed in the reviews and policy papers where referenced.

TABLE 3.2: MODELS REFERENCED IN GOVERNMENT REPORTS SINCE 2010 ***(BEIS & OFGEM 2016; DECC 2011B; DECC 2014A; DECC 2011F; EA TECHNOLOGY 2014; DECC 2013A; DECC 2011A; DECC 2013B; DECC 2010A; DECC 2010B; DECC 2012B; DECC 2012A; DECC 2012D; DECC 2011C; DECC 2011D; DECC 2010C; DECC 2012E)***

Key - Model Types
Calculator tool – simulation/accounting
Power system model
Investment optimisation model
Econometric
Building level models
Network model
Other policy specific cost benefit analysis

Government Report \ Model	DECC 2050	DECC DDM	Redpoint Dispatch Model	ESME	RESOM (Redpoint)	UK MARKAL	WeSIM	DECC Energy Demand and Emissions Model	BREDEM	DECC Green Deal Household Model	National Housing Model (CSE)	N-DEEM	SAP/rdSAP	SBEM	Transform (EA technologies)	AEA Biomass Model	BEAT2	BIS Standard Cost Model	BRE Standard Cost Model	DECC CHP Model	DECC Heat Network Model	DECC Smart Meter Model (various consultancies)	GLOCAF	NERA Heat Model	Parsons Brinckerhoff Electricity Cost Model	Redpoint Appropriate Use of Bioenergy Model	**Total number of models used in report**
Call for evidence on Smart, Flexible, energy system							×																				**1**
Carbon Budget						×																			×		**2**
Community Right to Buy into Renewable energy Developments	×		×			×		×								×	×						×				**7**
Carbon Reduction Commitment								×				×						×									**3**
EA Technology impact report on Distributed Generation								×							×												**2**
EMR Capacity market		×						×																			**2**
EMR Delivery Plan		×										×															**2**
EMR Electricity Demand Reduction		×																									**1**
EMR Emissions Performance Standard		×	×																						×		**3**
EMR Investment Contracts		×						×																			**2**
Energy Act 2008 amendments, Nuclear Decommissioning		×	×																				×				**3**
Extending Carbon Emission Reduction Target									×																		**1**
Gas Generation Strategy																									×		**1**
Green Deal and Energy Company Obligation									×	×		×	×	×					×								**6**
Heat Strategy				×	×						×	×	×	×	×					×	×						**9**
Microgeneration Strategy									×				×														**2**
Renewable Heat Incentive																		×						×			**2**
Severn Barrage Impact Assessment			×																								**1**
Smart meters			×					×							×							×					**4**
UK Bioenergy Strategy				×												×	×							×		×	**5**
Total references per model	**1**	**6**	**5**	**2**	**1**	**2**	**1**	**6**	**3**	**1**	**1**	**4**	**3**	**2**	**3**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	**2**	**2**	**3**	**1**	

The right hand column of Table 3.2 shows that the heat strategy impact assessment referenced nine models, which is greater than any of the other reports, most likely because it is a policy area which has significant overlaps with many parts of the energy system. This is closely followed by the carbon budget for similar reasons. It details the number of times that each model has been referenced in different reports.

The bottom row of Table 3.2 shows that the DECC DDM model and the DECC Energy Demand and Emissions model were referenced the most frequently, at six times each. The former is likely to be referenced frequently because it was used for the Electricity Market Reform (EMR) project which had a large number of impact assessments produced. DECC's Energy Demand and Emissions model is likely to be referenced frequently as demand is a core input to many different models in different energy policy areas.

The colour coding of the modelling tools in Table 3.2 shows that majority of classes identified in the academic review are present here, apart from the CGE/input-output models. In addition there are some models present which do not appear to fit perfectly into the model classes previously identified. Many of the models referenced in the model review are not publicly available, and therefore it is difficult to fully understand their methodology with limited information provided in the policy documentation.

The DECC 2050 calculator tool is described as an accounting tool. This model was also referenced in the academic review. The following class includes two models, the DECC Dynamic Dispatch Model (DDM), and the Redpoint Dispatch model which both consider the power system in isolation. Between them they were referenced 11 times, predominately in EMR impact assessments but also in other reports, such as the Carbon Plan and the assessment of the Severn Barrage. It was discussed in the academic review that power system models can use different techniques and this is likely to be the case here. The DECC DDM predominately uses simulation techniques, whereas the Redpoint Dispatch model uses programming techniques to consider optimal dispatch.

The next class is investment optimisation. MARKAL is referenced here, as well as frequently in the academic studies; however the other three models referenced here are similar in their techniques. WeSIM uses inputs from MARKAL and DECC's Energy and Emissions Model and runs the model to find optimal investment strategy under different constraints (Carbon Trust & Imperial College London 2016). These investment optimisation models were referenced a total of six times over a range of policy areas, including flexibility, heat and biomass. They are frequently cited in strategy documents due to their long-term outlook.

The econometric model, DECC Energy Demand and Emissions has already been identified as being widely used. It is a continuously updated model in DECC which provides inputs for many modelling activities. It is likely that this uses a lot of macro level inputs to form its forecasting of future demand and emissions.

The final three categories do not directly overlap with those identified in the academic review. There are six models which are used for energy efficiency and building policies. They are used to calculate the likely energy savings of different measures and future building stock. The Transform model looks specifically at networks; there was no mention of network models in the academic review. Finally the models which remain in white appear to be models which are very policy specific and tend to take a cost benefit approach. Some non-energy specific models were referenced such as the BRE and BIS Standard Cost Models as they were used as inputs for other energy models discussed.

3.4.2 Review Results

The review shows a strong link with the academic review and Figure 3.2 shows the Government models which fit into the clusters identified in the academic review. Classes mentioned in both are; accounting, unit commitment/economic dispatch, investment optimisation and econometrics.

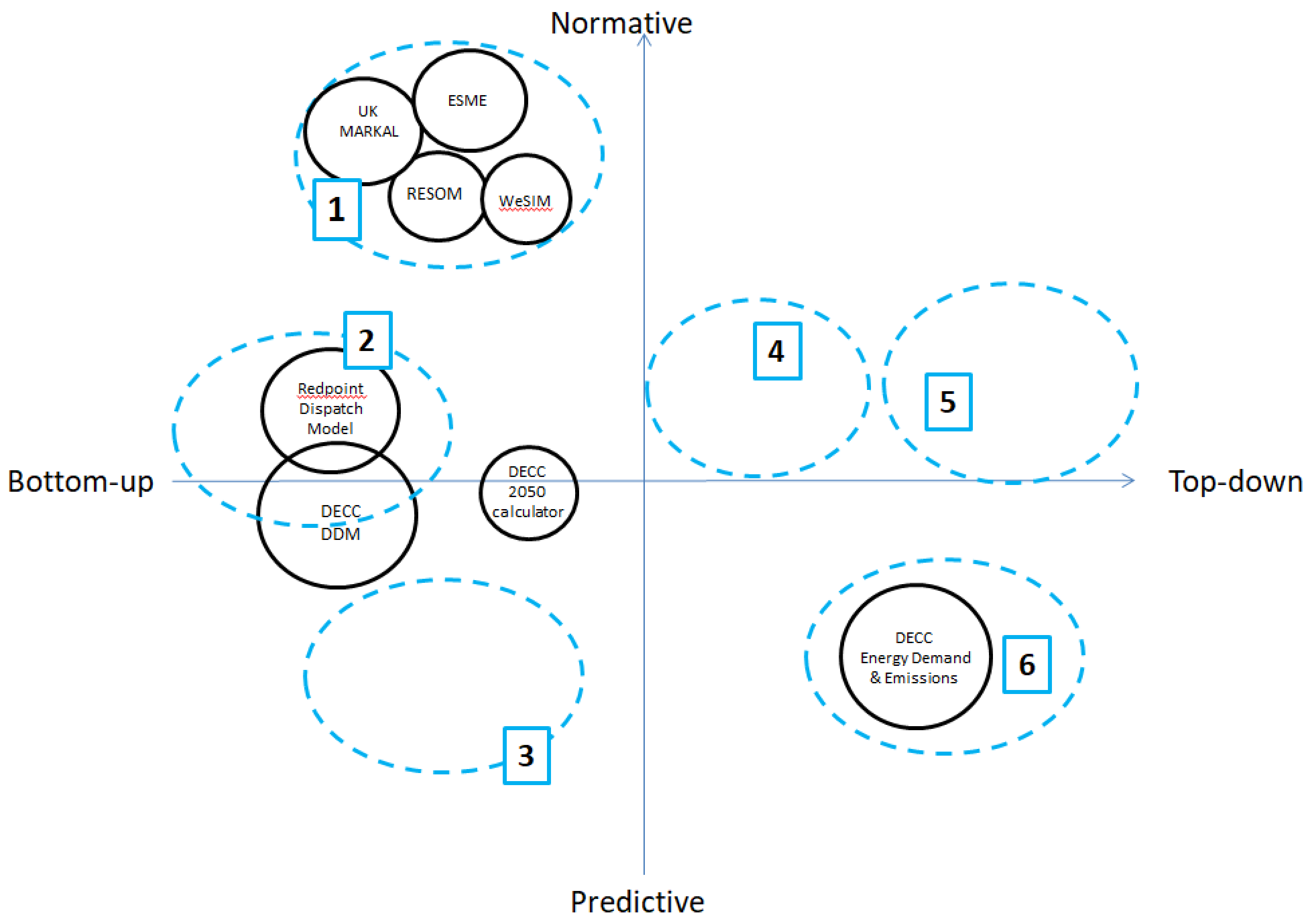

FIGURE 3.2: GOVERNMENT MODEL TYPES

The models which are missing from the Government review but are present in the academic review are CGE/input-output models and time step balancing tools. It has already been acknowledged that there are some gaps in this review as the list of 26 models is far fewer than the number currently present in Government modelling. It is possible that some of these models, which are comparable to these missing model types, are present in Government modelling work just not referenced in the types of reports analysed here. Alternatively they may be the types undertaken by consultancies and it was not clear in the reports that these classes of models were being used as there was limited information in the Government documents. CGE models are used by the Energy Information Administration (EIA) in the USA (EIA 2013) therefore are used in energy policy design by other governments and likely to be used by UK Treasury to look at the impact of overall economic landscape.

In addition there are some models types referenced here which are absent from the academic review. The building level models are out of scope of the academic review as they are a small part of the energy system, whereas those explored by the academic studies were high level, whole system models. This is the same for the policy specific cost benefit type models. However, the energy network is fundamental to the system operation and it is perhaps more surprising that there were no energy network models discussed. Although it is likely that network models may become more important with increasing intermittent and embedded generation and demand response. For example distribution network models are important for understanding local level benefits which you cannot see in whole system models. It is likely that more network models would be highlighted if considering Ofgem and National Grid models.

3.5 Discussion

Numerous previous studies have tried to propose classification groups and names for energy system models, illustrating the complexity in finding a perfect set of labels. In this chapter, five core model classes were identified from the clusters created from the academic classification studies. These were 'Investment Optimisation', 'Unit Commitment/Economic Dispatch, 'Time-Step Balancing', 'CGE/input-output', and 'econometric' models. The most commonly referenced classification was the investment optimisation category, which all studies included in their classification attempts, albeit with different class names and descriptions.

Models referenced in published Government reports were reviewed and compared to the academic literature. Of the five core classes found in the academic review, four were also present in the Government review, with CGE/Input-Output being the class not referenced in the Government documents reviewed. Accounting models were referenced once in both the academic and government review and referred to the same tool, the DECC 2050 calculator which is seen as an educational tool, highlighting the generation mix required in 2050 to meet carbon targets. Additional model types used in policymaking which did not clearly fit into the academic classifications were building level models and network models.

The insights from these two reviews have been used to identify a core set of model classes commonly used to inform energy policy and are likely to provide insight to the industry questions documented in Chapter 1. As a result, four modelling classes have been identified here for further discussion and analysis in this thesis. As previously discussed, this study does not intend to produce a new classification system or create new labels, but it instead aims to identify models seen as influential or commonly used in the policy development analysis. These model classes are:

- **Investment Optimisation Models** - This is based on the optimisation class referred to in Figure 3.1; however this includes the description of investment to clarify that these models take into account longer time horizons and therefore are likely to be complex programming tools. These models are based on partial equilibrium theory, which assumes that an equilibrium is reached within a part of the economy, in this instance the energy system. Examples of these are MARKAL, ESME and RESOM. All of the academic studies referred to this type of model and it was also present in a number of Government policy and strategy reports.

- **Unit Commitment/Electricity Dispatch Models** – These models focus on the power sector in considerably more detail. They focus on the problems of dispatching and scheduling generation plant, taking into consideration technical constraints such as ramping rates, closures and availability. PLEXOS is an example of this model type. There were two references in the academic literature to power system models as a discrete class and within the government review, two models were referenced in the Electricity Market Reform policy documentation.
- **Time Step Balancing Models**– This class includes models which balance demand and supply within a defined time step, based on the input properties provided by the modeller. These can be over a range of time steps including hourly or annually. These models use simulation techniques and whilst this broad model class was referenced significantly in the academic review, it was not specifically referenced in the government review. Examples of these are LEAP and EnergyPLAN.
- **Econometric Demand Forecasting Models** – These tools forecast future demand which can be used to inform the other energy system tools. A wide variety of techniques exist in the demand forecasting space and therefore it could have its own classification system. There were three references to econometric techniques in the academic classification review and DECC has used a model of this class, the Energy Demand and Emissions Model, which was the most commonly referenced model in the Government policy literature reviewed.

3.6 Chapter Summary

This chapter reviewed energy system models referenced in both the academic literature and in published Government reports. Across both sectors there was a wide range of model types being used. Determining their core methods and theories can be challenging due to the number of and interchangeably used terminologies for different techniques as well as models with hybrid qualities.

Through its review of previous classification attempts and cross referencing with the models identified as being used by Government for UK energy policy, this chapter has met Objective 1 of this research. It has also provided insight to Objective 2 which seeks to understand how models are used by Government. This chapter has explored what types of models are being used for various policy decisions and where there are gaps compared to the wider modelling landscape. Chapter 4 will add further insight to Objective 2 through interviewing energy policy stakeholders to understand their perception on how models are used by Government and the impact they have on policymaking.

This chapter has also achieved the first part of Objective 3 which is to identify relevant core model types for further research. Four core model types have been identified due to presence across both the academic review and the Government review and suitability to provide insight to the defined thesis questions. These are: Investment Optimisation, Time Step Balancing, Unit Commitment/Economic Dispatch and Econometric Demand Forecasting Models.

4 PERCEPTIONS ACROSS THE INDUSTRY

4.1 CHAPTER OBJECTIVES

Chapter 3 explored the energy modelling landscape utilised by UK Government policy makers and has identified the model types which are commonly used. In order to understand how these model types are used in greater detail and how the energy system stakeholders perceive their impact and usefulness, semi structured interviews were conducted with various stakeholder types. This chapter explores how energy system stakeholders engage with government in the policymaking process, their views on the tools being used and the policy development process, and finally where change is required to tackle future policy and system challenges. This chapter provides further insight to Objectives 1 and 2:

- Objective 1: Identify the range of energy system models being used and the previous classification approaches being applied, with particular regard to models used in relation to UK energy policy.
- Objective 2: Explore how the identified models are being operationalised for UK energy policy development and the role which model outputs have played in informing recent energy policy decisions.

4.2 METHOD

A qualitative semi structured interview approach was chosen to collect insight from stakeholders. This less structured method had a number of advantages which made it suitable for this evidence gathering process. It encourages honest and open observations from participants with fewer restrictions on the conversation structure which was important due to the varying backgrounds and interests of the participants.

The semi structured interview design used here includes a basic construction of key questions followed by several sub questions which can be used in the event of little input from the participant to help encourage, but not guide, their responses. The sub questions could vary depending on the direction the interview took and the background of the interviewee, as not all were relevant to all participants. All questions were open ended in order to avoid prompt or bias of the answers but instead encourage a free-flowing conversation with real insight from the participants. Themes explored during the interview include the communication of modelling, how well the tools which are used by government are understood, future challenges for existing modelling methods, gaps in modelling capability and how useful models are perceived to be for different system challenges. The interview question template can be found in Appendix A.

4.2.1 Participants

The sample set of participants interviewed was chosen based on the relevance of their interests and roles to the subject area. The participant sample set emerged over the course of the process as early participants recommended further participants for the study. This technique for generating samples is often referred to as snowballing (Bryman 2016).

In total 21 stakeholders were interviewed from across the sector, including participants from academia, consultancies, government and industry. These organisations were grouped into types to ensure they were anonymous but also to see if there were any common trends in their perceptions by individuals from similar organisations. The groupings were:

- ‘Government Organisation’ which includes any participant who is considered a civil servant,
- ‘SO/NO’ which includes participants from a system and network operators,
- ‘Consultancy’ which encompasses academics, participants from traditional consultancies and non-academic research centres
- ‘Industry’, which is any private company

It is likely that the consultancy grouping in particular could have different views as the organisations encompassed are varied. This group could be broken down further if a greater sample size was used.

Participants were also asked whether they considered themselves to be a modeller or a user of model outputs. This was to gain an understanding of their role type and whether that played a part in their opinions and to ensure there were a variety of participant types. Model output users are defined in this study as those who for example engage with policymakers about policy development and read reports which are based on modelling activities. Whereas many of the modellers are likely to do this too they also engage in modelling of their own. Some participants stated that now they would consider themselves a user of model outputs, however in the past were modellers. In this instance they are still classed as a 'modeller' as they have been in previous roles and have a greater understanding of model creation and analysis. This was further justified by the experience of one participant:

'I regularly get told when I say I am an ex modeller that there's no such thing as an ex modeller!'

(Government Organisation, Modeller)

TABLE 4.1: INTERVIEW DATE AND PARTICIPANT INFORMATION

Interview Date	Organisation type	Role type
22/08/2016	Consultancy	Model output user
22/09/2016	Industry	Model output user
20/10/2016	Industry	Model output user
20/10/2016	Consultancy	Modeller
26/10/2016	Industry	Model output user
01/11/2016	Governmental Organisation	Modeller
01/11/2016	Governmental Organisation	Modeller
07/11/2016	Industry	Modeller
08/11/2016	Industry	Model output user
14/11/2016	SO/NO	Model output user
15/11/2016	Industry	Model output user
15/11/2016	SO/NO	Model output user
15/11/2016	Industry	Modeller
15/11/2016	Industry	Model output user
21/11/2016	Consultancy	Modeller
22/11/2016	Consultancy	Modeller
23/11/2016	Governmental Organisation	Modeller
24/11/2016	Industry	Model output user
05/12/2016	SO/NO	Modeller
01/02/2017	Consultancy	Model output user
16/02/2017	Consultancy	Modeller

4.2.2 Ethics

The semi structured interview method was approved by the University of Reading’s ethics approval process prior to any being undertaken. This included details about the planned communication with participants, the process for maintaining confidentiality and any risks that could result. The participant information sheet and consent form which were sent to all participants can be found in Appendix B and Appendix C.

Interviews were recorded using a speech recording device so that the interviews were not disrupted by note taking, allowing a more natural conversation whilst ensuring that all the messages and learnings were captured. Interview recordings were transferred to a password protected computer and removed from the recording device as soon as possible to maintain secure and confidential practices. The interviews were manually transcribed into a word document and then uploaded into the software tool, N-Vivo for analysis. The transcripts were saved with a numerical code, not the participant's name or organisation, which ensured that the conversations remained confidential.

4.2.3 Analysis

All of the interviews undertaken followed a broad structure. Firstly, information about the participant was obtained such as their interaction with policymakers, then picking on some examples from their experiences, questions were asked to understand their awareness of the modelling that was undertaken and their views on the communication and methodology. For those who engaged in modelling themselves a more detailed discussion was had around the tools they use. Finally challenges for future policymaking were discussed.

The results were analysed using a 'thematic analysis' method where common trends from the data are grouped and analysed (Bryman 2016). This does not follow the same structure as the questions asked as insights were often found across answers to different questions. The transcripts were coded using the N-Vivo software by identifying common themes and key words which were frequently discussed by participants. Those comments were then analysed to see where there were agreements, differing views and interesting insights.

4.3 Stakeholder Views

In this section the key areas discussed by the participants are brought together and areas where there is agreement or contradicting views are highlighted. In some instances, quotes are included to illustrate a line of argument in greater detail. The comments cover interactions with government and the modelling they undertake as well as suggestions for how to improve the modelling undertaken both for policy making and more generally best practice principles.

4.3.1 Government Modelling Expertise

> ‘*My feeling is that they have good tools but probably insufficient personnel to really make good use of it.’* **(Consultancy, Model Output User)**

Overall participants were confident that Government have access to the right suite of modelling tools. Despite this, it was believed that they lack the resources to fully utilise them. This includes time, cost and the internal technical skills required in order to keep them up to date and analyse the results thoroughly. Even though it was thought Government had the right modelling tools, participants felt that they were actually unable to name many of these tools. With the exception of when a participant who was closely involved in following a policy development, was aware of a specific tool used but even then they did not have a detailed understanding.

There was also a concern by some that the models are not being used appropriately. One participant felt that the policymaking process was not scientific enough and that currently government made the evidence fit the policy rather than conducting policy making based on the evidence.

4.3.2 Outsourcing Modelling

It was noted that Government, namely BEIS, is working hard to build up internal capacity and focus on a small number of models that they understand well. However, a large amount of modelling work is currently tendered out to external consultants and academics, likely due to the internal time and cost constraints in government which were highlighted above. The usefulness of this modelling being undertaken externally was disputed.

> ‘*Consultancies are helpful for a notionally independent view, although not always independent as they are paid by someone. You would hope if commissioned by Ofgem/BEIS however they would be neutral. Well known consultancies, such as Baringa/Poyry have a high reputational risk if not seen to be impartial.*’ **(Industry, Modeller)**

Three participants suggested that having external consultants and academics doing the work was positive as it was thought they generally have greater modelling expertise and a reputation of their own to uphold. One of these participants emphasised that they actually have more confidence when modelling is outsourced as they are more likely to know and have access to their modellers, or at least the confidence that they would be using a robust approach.

Conversely there were also concerns that modelling work being done externally resulted in reduced transparency and less centrally held knowledge. One participant also highlighted that the reduction in expertise to review modelling work, within both Ofgem and Government, has resulted in new models and analysis not just being built by external organisations, but also reviewed by them.

External consultants also conduct modelling on behalf of other organisations such as industry and trade associations to provide evidence to government. In this instance there was more concern by participants regarding the impartiality of the modelling. A number of participants raised the importance of understanding who commissioned the work and its aim.

4.3.3 Transparency of Modelling Activities

There is a push, both within government and by the wider energy policy community, for increased transparency of modelling activities. However, for external organisations, such as academics and consultancies, who are contracted to undertake analysis, their models and knowledge are their intellectual property and their business which causes difficulties for both parties in working together.

'When we do a project with DECC we bring a lot of our own intellectual property and knowledge which we build up…it genuinely does stop us working for government bodies from time to time when the level of disclosure required doesn't fit with the realities of running a commercial consultancy' **(Consultancy, Modeller)**

In terms of how transparent these models should be, a range of views was expressed. These views range from wanting the modelling activities to be accountable and key steps made clear, to strongly believing that all models used for policymaking should be completely open source, including the model code and documentation.

'*They [models] need to be credible and stand scrutiny and therefore important they show intermediary steps and results'* **(Industry, Modeller)**

'I think all models used for policymaking should be in the public domain, the more peer review you have the better…as its public policy making it should be replicable by anyone. There's a risk that if someone has a particularly brilliant proprietary model which you would really like to use and would suit the purpose well that you might find you aren't able to use it. To me I think the benefits would outweigh the risks.' **(Industry, Model Output User)**

In general, most participants were strongly in favour of increased open source modelling. However due to concerns about open source requirements possibly ruling out access to good tools and analysts, along with the likely additional time and cost implications, full open source modelling was not always seen as the right approach.

'In terms of transparency, it's a good objective to have. It may aid a little but some models are so complex and you would have to devote so much time and probably quite a few would use it.' **(Consultancy, Modeller)**

'If something is open source it has to be relatively simple in its approach. As it gets more and more complicated the number of people able to comment on it and use it effectively decreases very rapidly so if there are any open source models it would have to be basic.' **(Consultancy, Modeller)**

It was noted that many modelling tools are extremely complex and therefore there are significant costs and risks associated with making them open source. This includes keeping input files up to date and preventing the misuse of the models when used by non-experts. One participant noted in the past this may not have been such as issue, as Government used to publish more, such as econometric equations for demand, but that now it is much more difficult due to the increasing complexity of forecasting demand.

It was also suggested that model complexity influences which model will be used at all. For example DECC's Biomass Counterfactual Model was made open source by DECC along with detailed documentation, however not a single user downloaded and used the model and it was argued that this was due to the complex nature of the model. The DECC 2050 calculator on the other hand was meant to be an educational and simplistic tool and consequently it was used and downloaded by many stakeholders. Another reason for this could be the broader subject matter. It was noted however that even simple models still can get misused. Some participants mentioned that outputs from the DECC 2050 modelling activities have been used as assumptions which is not its purpose.

An additional challenge discussed was whether some data can be made public. Government use data in their models which is commercially sensitive and provided confidentially by market players such as industry and the system and network operators. The DECC Dynamic Dispatch Model was quoted as one model which could not be made public as stakeholders might be able to use it to gain commercial advantage.

4.3.4 Communication

As well as mixed views of the level of transparency of the models themselves, transparency is wider than just the model code. Currently it seems that government are not providing a sufficient level of engagement or even visibility of policymakers and the modellers themselves, which stakeholders would like to see. Several participants said that Government believe they are more transparent than they are, and that often insights come through informal conversations as opposed to published material or formal forums. Another thought that policymakers like to keep themselves distant so they do not feel like they have been influenced.

> *'..the people who do the modelling and stuff, in fact I have even heard this directly, say it's not really 'in their job description' to engage with stakeholders..'* **(Industry, Model Output User)**

Participants felt that this increased engagement would increase their confidence in the modelling being undertaken and the methods and assumptions used.

> *'I do not think it's the documentation, it's meeting the modellers and understanding, so seeing the modellers standing up in conference and saying this is what I did and being asked about their assumptions. It builds confidence that they have looked at the sorts of issues you run up against when you are a modeller…the modelling is only as good as the modeller'.* **(Consultancy, Modeller)**

There was a similar view when modelling is conducted for Government by other stakeholders. Increased narrative was seen as important, but specifically the consequence of the modelling output as opposed to the modelling method itself. It was thought that sending a complex report was unlikely to be beneficial without clearly outlining the insights and implications on policy direction.

'The communication is not, we did that modelling and here are the results that should be in your strategy, it is much more setting out a narrative for what the transition looks like, what the key decision points are, what are the changes people need to make to their behaviours, the investment Government needs to enable etc... It is not enough to say our analytical conclusions are this, you need to tell a bit of a story.' **(Government Organisation, Modeller)**

'I think it's down to as much the modellers to explain their outputs really, I do not want to say simplistic, but the language a policymaker uses and I do not think the modelling community is very good at that. The reason models do not have much traction with some people is because as a community the modellers are not very good at explaining outputs in nice simple terms. Sometimes we express overconfidence in our models …' **(Consultancy, Modeller)**

'To get decision makers to do something they need to come on the journey with you, not just see a report. They need to champion it in their own departments for decision making. All organisations have their own processes and changes take a long time so the whole thing needs to be iterative. There is no common language, need long term engagement, and no institutional memory as Government staff change so frequently. Need to present messages to suit decision makers, language that everyone can interpret. Integration piece, here is a soundbite.' **(Consultancy, Model Output User)**

4.3.5 Model Uses

When discussing the usefulness of models and best practice principles, it was highlighted that no single model is perfect. Instead a model aims to provide an understanding of the problem and insight into likely impacts of various future scenarios. Modelling is about exploring the problem and possible futures.

> ‘*All models are useful to provide views on what might be possible but can only tell you plausible pathways*.’ **(Consultancy, Model Output User)**
>
> **‘***Models are themselves a process to codify your thinking so they make you write down in data and a code of equations exactly how you see the future of the energy system so one model is not inherently better than another model. Having a small number of models that are well understood by government, the technical people and has the data passed though all their internal processes including different departments are very useful.***’ (Consultancy, Modeller)**

Communicating the limitations of models was raised by most participants. Models are often highly assumption driven and the more assumptions there are the greater the uncertainty. When this is not communicated there is a risk that users treat them as being faultless and do not consider their uncertainties, sensitivities and generalisations.

> *‘..the limitations and purpose of them I think gets a bit lost between the modellers. I think the modellers themselves understand quite well but not sure about the users of the output necessarily’* **(Industry, Model Output User)**
>
> *‘I think actually the people who actually are the end users have more faith in the them than the actual modellers’* **(Consultancy, Model Output User)**

Three participants commented on the value which can be achieved from relatively simplistic models and that often we over complicate our models. However, some participants did indicate that the appropriate level of simplicity varies depending on the nature of the question as sometimes important interactions could be missed from over simplification. Identifying the suitable level of complexity may be a challenge and the possible uncertainties need to be recognised when interpreting results.

> *'My view is that you could spend 20% of the same amount of time and get the same answer, the rest of the 80% you are just tweaking things.*' **(Industry, Model Output User)**
>
> *'My view of modelling is that it should be kept to the simplest and lowest level you can get away with that is sufficient to model and understand the effects you are looking for. I think too often there's an emphasis on we need to do more modelling or we need more modelled, you build fantastic models because that is what modellers like to do that are over spec'd beyond what is needed…'* **(Consultancy, Modeller)**
>
> *'People who sit on the edge like me get model fatigue'* **(Consultancy, Model Output user)**

4.3.6 Use of Scenarios

Published future energy system scenarios with detailed narratives are used as a method to better understand the implications of future scenarios and to inform system pathway options. The National Grid Future Energy Scenarios (FES) is one of most commonly known system scenario publications and was discussed by a number of participants in this study. There were some strong views on its usefulness, which were not always aligned. Some were very critical of the way the FES is created, particularly that the methodology is largely built around stakeholder views. There were concerns that this could lead to bias as stakeholders all have their own business model to protect and that key technologies may be missed which are not in the interests of the stakeholders asked or just not known by them. It was suggested that depending on when the scenario exercise was created that the 'trendy' technology at that time may be more prevalent than in the years preceding or following.

One participant was concerned that some basic economics might be missing and uncertainty whether it could ensure the system was balanced in each of the scenarios, another thought the fact that they do not meet the carbon target is unhelpful and not progressive. Despite these critical views some participants were particularly complementary of National Grid's communication and engagement strategy.

> *'It is very difficult to model the future without scenarios. National Grid are going around every year refreshing their assumptions, using a process miles ahead of academia in communicating'*
>
> **(Consultancy, Model Output User)**

Despite National Grid's efforts in the communication and the extensive narrative published alongside the scenarios, a concern was raised about how these scenarios are being interpreted and used by stakeholders. It was noted that these scenarios are frequently being used as inputs to other pieces of analysis without their uncertainties being recognised. Many emphasised that these scenarios are example pathways and intended to give you a sense of the range of possible futures, but as with all modelling activities these are heavily assumption driven.

Multiple scenarios illustrating a range of possible futures are seen to have two main advantages. Firstly, that it reduces the chance of a single scenario being considered truth. Secondly that comparing scenarios within one publication and those produced from different organisations through different methods may produce some trends which can provide a degree of confidence or help understand what might be achievable. One participant noted that comparing scenarios can also help provide insight into the balance between cost and likely success of different pathways.

'If you only produce one scenario then people think that is what you think should happen…' **(Governmental Organisation, Modeller)**

'You can have two scenarios come out of a model with different assumptions and one might be much more deliverable than another from a political or behavioural perspective but it does make sense to make that assessment and say well this target seems 10% more expensive but a lot more deliverable than that one.' **(Government Organisation, Modeller)**

It was noted that despite the computational techniques having advanced to allow multiple scenarios to be run, significant time is still required to design and analyse model runs and the system and societal consequences. Running multiple scenarios does not necessarily mean variability is being captured as it depends on the scenario's design.

'In the past scenarios were expensive and hard to do, these have had work spent on being consistent. Now setting up scenarios is easy and analysing runs is expensive.' **(Consultancy, Modeller)**

4.3.7 Government Strategies

Four participants specifically raised concerns about the lack of joined up strategic approaches between Government departments. A collaborative approach was seen as important because energy is fundamental to so many other department strategies.

'*One of the problems government has is it is very slow in terms of its strategies so each bit of Government might be thinking broadly sensibly about its own bit but there is very little evidence that they join up*.' **(Governmental Organisation, Modeller)**

'I have always been fascinated by the fact that DECC, Ofgem, NG can all come out with such different view for example on capacity requirement, outlook on security of supply, maybe they use different assumptions but I imagine it's because they use different modelling approaches, there is not really consistency across those.' **(Industry, Model Output User)**

One of the reasons for this disconnect and also a concern in the way Government conducts its modelling is that the modelling activities and strategies designed by a given department assume that their policies work. This can result in optimistic assumptions being used as inputs, the Green Deal being used as an example, where the resulting energy efficiency savings from the impact assessment were being used as an input in whole system models.

'Government models tend to assume that their policies work and they do their cost benefit analysis on their policies working and you can look at policies like the Green Deal and RHI which failed to deliver…' **(SO/NO, Modeller)**

It was discussed that Government strategies and the pathways are often idealistic and do not realistically consider what industry can deliver in terms of skills. For example, models may suggest that at some point domestic customers are going to switch over to heat pumps but there is not seen to be enough consideration of how to convince the public and the phased switch duration. It was suggested that modelling exercises need to have constraints in place to ensure that examples such as electric vehicles or heating technologies do not go from 0 to 100% penetration in too short a timeframe.

> ‘*Industry doesn’t just gear up to deliver one generation of a technology and if they do they work really hard to make sure that technology persists so I think those sorts of things get missed in the modelling*.’ **(Industry, Model Output User)**
>
> *‘Skills and talent workspace is poorly modelled. I see reports where we are going to build X number of heat networks, great but we couldn’t build a tram in Edinburgh.’* **(Consultancy, Model Output User)**

In terms of strategies, an industry participant commented that no model or scenario is ever going to be correct, but at some point we just need to make some decisions and see what emerges. There is the opportunity to tweak along the way but we have a lot of insight already and that running more model runs is likely to have limited value, especially if it delays decision making. There was a call particularly from industry participants for a level of certainty or a pathway/trajectory to provide confidence to industry. Many of the options require long term decisions, such as heat networks, and industry needs some certainty to make investments. Another argument was that we have to reduce emissions further so what we focus on for 2050 does not need to be overly detailed. We just need to aim to go as low as possible in all areas. Another gap mentioned was the lack of models which analyse the effect of different policies and strategies to local economies or UK plc more broadly.

One participant remarked that energy system models are not scientific models as they contain many behavioural assumptions. This means that there will always be disagreement which makes decision making challenging.

> *‘People have an opinion on energy or the environment in the way that models of basic science do not.’* **(Consultancy, Modeller)**

4.3.8 Modelling Challenges and Gaps

Participants were asked what they thought were the main challenges facing modellers. This applied to modelling completed or contracted by Government, but also wider modelling activities conducted in the sector.

4.3.8.1 Data Gaps

Data availability was cited as a key challenge for most modelling activities. As shown in Figure 4.1, the most commonly mentioned data availability challenges for modellers were those at household and distribution levels. This includes data on how we use energy in the home, both now and in the past, and data on the amount and location of embedded generation and how that impacts local level network flows.

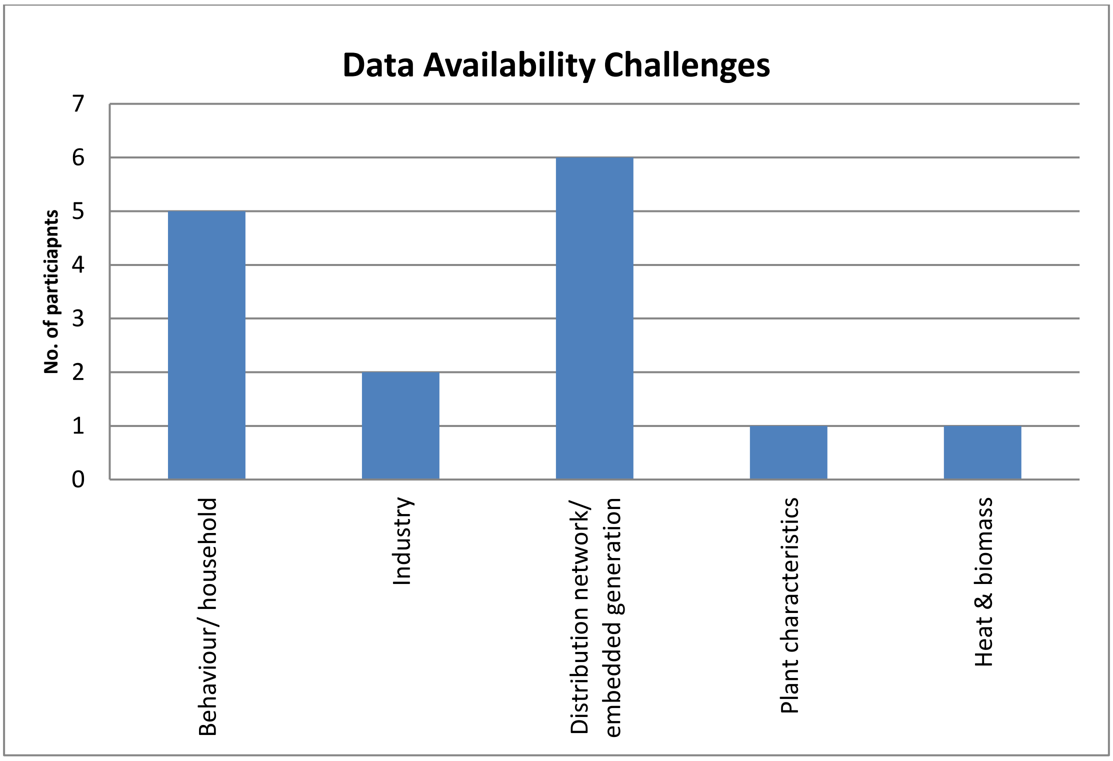

FIGURE 4.1: DATA AVAILABILITY CHALLENGES

Reliability of data and assumptions was discussed as their uncertainty can have a large impact on the output. Many participants recognised that models require a vast amount of data even if it is available and there is a risk in the significance of cumulative effects from multiple uncertain data assumptions and the impact on model outputs. Data assumptions require regular updating as many are constantly changing, which presents a huge resource required in terms of time and cost and a risk that out of date numbers are being used.

'A lot is in the data therefore assumptions and when wrong they can be amplified in the model. Data is so important.' **(Consultancy, Model Output User)**

Some Government specific data challenges were mentioned. It was suggested that Government often have difficulty obtaining commercial data and interpreting it. This is because industry does not always want to share commercially sensitive information and when they do it can be hard to interpret as industry provides data to them in different ways. An example given was how plant costs are lumped together differently by different companies. Another concern was Government analysts inheriting and recycling bad data. This was mentioned by one participant as a particular problem for Government as personnel movements make it harder to retain knowledge and understanding of the purpose of sensitivities of data sets. It was mentioned by one participant that this has been a particular issue in heat policy due to the absence of new data.

'It is probably hard for Government due to lack of access to data. Companies like us have the knowledge.' **(Industry, Model Output User)**

'Institutionally difficulties in getting right inputs and outputs as inherit bad data which hasn't been updated i.e. heat, biomass.' **(Government Organisation, Modeller)**

There was a comment regarding near term data availability issues such as information on energy efficiency. Both that some data does not exist and others are being held by Government and cannot be shared. This affects the efficiency of policy roll out today, such as the Energy Company Obligation, where information on the state of energy efficiency in domestic homes could help suppliers and their contractors deliver their energy efficiency obligations far more efficiently in terms of cost and carbon savings. The roll out of smart meters in UK homes was considered a great opportunity for quality data at the local level. However, there was a concern as to whether this opportunity would be realised.

4.3.8.2 Representing Flexibility

Almost all participants mentioned embedded generation as a challenge either in terms of data, change or specifically as a modelling challenge due to their dynamic qualities and knowledge of how they will be treated in the market going forward. It was noted that no one has a good disaggregated data set on embedded generation.

> *'Embedded generation is hard to see, just a decrease in demand and in the winter it is hard to see peaks.'* **(Industry, Model Output User)**
>
> *'Embedded generation having an impact…it all becomes more difficult and fragmented and will probably require more nimble forecasting methods, methods that adapt quickly to small amounts of data or perhaps real time updates…'* **(Industry, Model Output User)**

Flexibility in terms of variability was mentioned but not as passionately as the issues around embedded generation. This could be to some degree due it being a topic on policymaker's agendas currently and a recent consultation therefore many are familiar with the challenge.

One of the important areas to consider when looking at the impact or need for flexibility is time resolution. One participant mentioned the importance of recognising what model type or technique is required for the problem as models which look at averages over a season or a day may miss extreme peaks at specific times. An example was given of some MARKAL modelling being undertaken which failed to capture the consequence of peak heat demand at certain time slices.

Despite the high level of concern by the majority of participants, one participant thought we had plenty of modelling expertise regarding flexibility.

> *'…If I read one more paper on intermittent renewables and demand shifting, I mean we are not short on studies there, absolutely not.'* **(Consultancy, Modeller)**

4.3.8.3 Networks and Cross Vector Modelling

Modelling the interaction between the distribution and transmission levels is thought to be important going forward, particularly with increased embedded generation, electric vehicles and demand side response, but also the impact of interconnection with neighbouring markets going forward. It was noted that the information held at the distribution level in terms of profiling energy use could be of high value to modellers. Similarly data regarding private networks, such as those for heating, was sought by one participant.

'There is lots of useful data we would like about the energy system close to consumers like distribution level gas and electricity networks to understand pinch points.' **(Consultancy, Modeller)**

'I think modelling the effects of more flexible assets in the network and the value they add or detract from the system that is going to be more difficult going forward as their share of generation and demand goes up. I think that is going to cause some issues as it becomes more complicated and complex, the amount and varying types and the fact that there will be more automated in terms of how they are managed.' **(Industry, Model Output User)**

Network modelling is important especially as large infrastructure decisions are required. Both of the industry participants who mentioned the model Transform, a model created collaboratively between Ofgem and the DNOs, said that it was driven heavily by uncertain assumptions. The collaborative approach was considered to be a good idea however there was much disagreement with the modelling process. One participant thought that because it was so reliant on assumptions which were disputed by all stakeholders, therefore created by those with no expertise, greater sensitivity analysis was required to provide the model output with some useful insights.

More detailed regional modelling was called for by a number of participants to understand local constraints and opportunities as well as increased cross-vector modelling. This is because changes such as the electrification of heat and transport, or increased district heating or biofuels could result in challenges for the power system. It is important models can step between these systems and understand the effect a change in one can have on another. An example which was discussed by one participant was the impact a change in projection in a completely different sector could have on the energy sector, such as an increase in kindles and tablets resulting in a reduced demand for biomass for books and therefore less competition in biomass for fuel.

It was commented that Government are not doing enough to better understand the cross vector impacts. One participant mentioned that recently Ofgem has turned down funding for certain innovation projects because they are looking across sectors as opposed to focussing on one. This implies that Ofgem do not see cross vector challenges as such an important issue.

4.3.8.4 BEHAVIOURAL CHANGE & TECHNOLOGICAL BREAKTHROUGHS

Five participants discussed the lack of data on consumer behaviour, such as how people live an use energy throughout the day, as well as their level of acceptability of new technology. This has an impact in our ability to forecast how we will use energy in the future, both at home and in the work place.

'*The demand side is interesting because it is data poor, we do not have great data of how people actually live, work, play and socialise and it is also policy difficult to tell people to change their daily habits.'* **(Consultancy, Modeller)**

It was thought that the modelling currently being done by Government fails to consider future demand uncertainties appropriately. In particular the use on economic methods and past data to understand the future was disputed. It was agreed that the past is not going to be a good indicator of the future.

'The Government doesn't understand people, it has an economics service…' **(Consultancy, Modeller)**

'The economic answer is one thing, but it may not trump the emotive side.' **(Consultancy, Modeller)**

One participant mentioned that demand was so uncertain it was not seen as worthwhile trying to forecast in detail, instead just run scenarios. Another participant thought that running scenarios for demand was important but in order to consider the unknowns and possible future behaviours modelling should be undertaken which considers extreme future societal structures and the possible impact which this could have. This will enable behavioural uncertainties to be considered.

Technology change is one of the causes for future behavioural uncertainty, particularly understanding what technology is going to be on offer and foreseeing the winners. Predicting consumer choice, such as for a long term heating technology or a phone, is not always what economics would tell you, as the previous section discussed. The iPhone was used as an example, not the cheapest but the market chose it. The emotive side of modelling was also mentioned by another participant who believed that Government struggles to understand two ends of the modelling spectrum: the social practices and people, and the macro-economics.

This is seen as the big challenge because even with good past data there are still future unknowns which could have a significant impact on how we use energy in the future. Many participants spoke about game changing technology breakthroughs in significant detail as they saw that as being a big risk. It was noted that the uptake and consequential effect of new technologies or products never occurs in a straight line, they either increase exponentially or die. The examples given to illustrate this analogy was the transition from the horse and cart to cars, the introduction and rapid uptake of smart phones and the same with PV uptake. The future brings a few known unknowns, such as 3D printing and electric vehicles, but also a large number of unknown unknowns. Credible future forecasts can still be made but technology jumps are likely to impact on the profile, for example with the increase of tablets and TV on demand we no longer see the historic TV pick-ups. Future ownership may affect our usage such as whether we will own our houses and cars in the future or if we will become a renters market.

'Modelling behaviour is always a tricky one…some stuff we have data on so fridges, washing machines, traditional appliances, lights bulbs etc so we can put a credible forecast forward but technology jumps. We are all using iPads and stuff now, a few years ago it was all laptops and before that desktops so the way we use energy is changing.' **(Industry, Modeller)**

'Energy world is moving slowly yet digital world is moving very fast' **(Consultancy, Model Output User)**

Almost all participants specifically mentioned electric vehicles as a disruptor and challenge for designing our future system. There are unknowns in terms of uptake but also how much control people will give the grid of their batteries. Modelling a technology like this is extremely useful and despite all the uncertainties it provides insights into the consequences of different uptake scenarios.

4.3.8.5 Policy Uncertainty

Incorporating policy uncertainty into models was mentioned by a large number of participants, with some considering it the greatest uncertainty of all. One participant remarked that he did not trust any models that looked more than five years ahead because of the level of uncertainty. Specifically on the theme of storage and flexibility, a few participants mentioned the dependency on how it is treated in the market as to the growth rate and whether it will follow wholesale prices or policy avoidance costs. This uncertainty is a significant risk to industry and investors.

'I am generally sceptical of modelling. They can be good for generating scenarios though it is so subsidy reliant. I am particularly sceptical of investment outlook models as the assumptions about their usage etc. are so sensitive so I do not trust more than 5 years.' **(Industry, Modeller)**

'For me the hardest one is policy uncertainty and policy consistency because we tend to build models which assume long term policy structures are in place and often this is some sort of normative process right so you say this is the best solution and if you started now and had a consistent policy and everyone agreed this is where you'd get to….' **(Consultancy, Modeller)**

It was noted that models tend not to consider the impact of a change in administration despite the often long term time horizon of the model.

4.3.9 Impact on Policy Making

There were a number of comments made about the impact modelling has on policymaking. Some thought it simply set the direction, others thought they were generally just used as add-ons and can be ignored when it does not suit policymakers due to their electoral timelines.

In the area of heat policy one participant explained that there were instances where DECC did not believe particular scenarios which consultancies had modelled for future heat policy pathways and therefore did not have much traction. Despite this it was believed that modelling played a vital role in the RHI review and setting tariff levels. In this instance it shows that it had an impact on the finer details of policy design but less so on the strategy for heat policy.

This viewpoint was further substantiated with a remark by a participant who said that no modeller would have proposed that Hinkley Point C would be the best choice for our future energy system. Another participant said that CCS was favoured by most energy system models yet

Government have not supported CCS development. It was thought that big decisions such as technology winners were guided more by politics than the analytical evidence itself.

'No one in the modelling world would have told you to build Hinkley' **(Consultancy, Model Output User)**

'If spoke to the modelling community they would all say CCS to hit targets. It was a devastating blow when they CCS grant got taken out…felt worthless'. **(Consultancy, Model Output User)**

4.4 DISCUSSION

4.4.1 ROLE OF MODELLING

In general many of the comments about the role of modelling are quite critical, particularly around communication of the usefulness of modelling outputs and recognition of their limitations. Despite this critique many of the comments point to the value modelling has when used appropriately, particularly in forcing the modeller to think more deeply and better understand the questions and possible future outcomes.

Stakeholders showed a desire for trajectories and joined up strategies from Government to provide confidence in their future business model and to make investments. This absoluteness does not fit with the uncertainties highlighted in modelling the future and is why investors still seek Government risk control when developing major projects like Hinkley Point C as they cannot rely on Government roadmaps alone. It was highlighted by participants that whilst they help provide a guide there are risks when using Government projections as the political party may change and Government are often optimistic of the success of their policies.

Participants from consultancies were the most critical of the impact models have on policy making. Providing quality modelling analysis is part of their role and therefore they are likely to be critical when their analysis is used differently to their findings. It was noted that a modeller would never have said Hinkley Point C was the right decision. It is likely that modelling played a part in the insight, but not the only influencing factor for those making the decision. It is also important to recognise that people are more likely to have stronger negative than positive views.

4.4.2 Communication

Participants who were specifically asked if Government were employing the correct range of models generally agreed that they were. The concerns were more on how the outputs were being interpreted and communicated, particularly when some of the input assumptions were seen to be inaccurate. This is a challenge for all modelling activities but particularly for policymaking due to the stakeholder interest and potential impact. One of the challenges in greater transparency is in communicating the complex nature of many models and where perhaps there should be a push in some instances for simpler more transparent models with greater narrative.

Terminology and transparency have been a common thread in this thesis so far. When reviewing the academic literature, it was found to vary by discipline and model focus. It was further cited as a concern by many of the participants interviewed and appeared to add an element of distrust in some model outputs. It is likely this is a contributing factor to the contested views on the value of energy system modelling for policy design, and the relevance of the outputs to policy questions.

Some participants thought the value provided by modelling lies with the plausible future scenarios, whereas others thought it comes from the process of modelling and the thinking it made the modeller undertake. Participants highlight that as so much of the learning happens during the modelling process it can be a challenge to communicate that insight to other model output users. This is likely to also be a concern with the amount of modelling which is outsourced by Government, resulting in much of the insight being lost.

4.4.3 Modelling Best Practice

Using the insight obtained from the conversations some principles have been identified to help modellers make models which are fit for purpose:

- There are multiple objectives to consider when looking at our future energy system design. Be aware that the cheapest scenarios may not be the answer. One scenario may be slightly more expensive but be politically and/or behaviourally easier and therefore more likely to achieve results.
- Be alert to uncertainties. All scenarios are just a single scenario and not a prediction therefore care must be taken when using as an input for further modelling.
- It can be useful to compare the common strands of various scenarios created by different stakeholders. These trajectories and alignment of views can be useful to provide a guide for industry, but be aware of the scenario creation methodology.
- Compare the ranges and understand where there are significant uncertainties.
- Be aware that what is currently ‘trendy’ often skews scenarios (for example electric vehicles or hydrogen).

4.4.4 Current Challenges

The prevalence of current fashionable technologies in scenarios was noted as something to be aware of when considering the uncertainty in future system outlook. The fashionable themes from participants in this study when discussing current challenges were modelling the implications of embedded generation and future demand forecasting, and the uptake of technologies such as electric vehicles. Intermittency caused by renewable generation was mentioned by few participants, and the focus instead being on demand side flexibility. This is likely to be a change in focus from a few years ago and perhaps influenced by current policy goals.

4.5 Chapter Summary

This chapter has explored the role that models have or are perceived to have in policy making by stakeholders impacted by their outcomes. There is some disconnect between models and the policy environment which is illustrated by the relatively poor knowledge of the models being used by Government by those stakeholders impacted by their results. Despite being somewhat removed from the models themselves, participants still have a view on the modelling process. Efforts to improve communication and modelling best practice may help the models to better serve the purpose intended. Knowledge and communication can be improved though greater transparency, increased narrative around the method and assumptions. The use of simple models can have significant advantages in improving the communication of modelling results and often provide as much insight as more complex modelling tools.

Understanding how we use our homes and consequential demand for energy was seen as a significant challenge for modelling, particularly as it means it is difficult to measure the impact of new smart technologies and how they may impact demand. Distributed generation was also seen as a challenge but mainly due to the lack of monitoring. Representing the potential for technologies which can provide flexibility services was also seen as an important modelling challenge going forward.

This chapter provides insight into how stakeholders interact with the policy development process and how they believe models are used by government. This complements the government literature review in Chapter 3 and together they meet Objective 2 of this research. This chapter has also validated the previous findings for Objective 1 because no further model types have been discussed in Chapters 2 or 3 that were not already described in the literature.

5 GENERATING REPRESENTATIVE MODELS

5.1 CHAPTER OBJECTIVES

Chapter 3 identified a set of core model types which are widely used for policy development or are considered influential in policy design. This list of core model types was created by conducting a review of the common model types and classification attempts identified in the academic literature as well as a review of the models being used by the UK Government. The four model types identified were:

i. Investment Optimisation
ii. Time Step Balancing
iii. Unit Commitment/Economic Dispatch
iv. Econometric Demand Forecasting

This chapter examines the fundamental principles behind these models by creating representative versions of each model type to better understand the core purpose of each and allow for a comparison of their structure and likely insights. These simple models provide a structure for further adaptations to be developed to assess their strengths and weakness when representing future energy system developments and challenges. These adaptations and a more detailed analysis of their strengths and weaknesses will be implemented in Chapter 6.

This chapter primarily addresses Objective 3, to generate representative versions of the model types. However, the learning from this activity also feeds into Objective 4.

- *Objective 3: Identify relevant core model types and generate representative versions for the case study of Shetland.*

- *Objective 4: Examine the strengths and weaknesses of each model type in responding to a range of identified business questions.*

5.2 Representative Models

In order to test the suitability of the different model types for future policy and system challenges, simple but representative versions are generated for each of the core model types which have been identified to allow a more thorough review of the example tools to be undertaken.

These representative models can then be used to answer a number of case study questions and their method examined in detail to understand their strengths and weaknesses. Using basic versions of these model types as opposed to complex proprietary tools has a number of advantages:

- Only including the core principles of each model type allows for greater distinctions between them. Many proprietary and more complex tools include additional features, often hybrid in nature, which makes the boundary between model types less clear, as explored in Chapter 3.
- The less complex nature will result in a reduced learning time and allow for a deeper understanding of the core model methods. This increased insight will aid comparison of these representative models and will result in a greater understanding of complex versions of these tools in future studies and real life problems.
- A model which is simple and only models the essential components can be more easily adapted in order to test specific case study questions. Starting simple and building up the complexity to the level required is widely considered best practice (Kendall 1968). Simple models were also widely considered beneficial by those interviewed in Chapter 4.

For each of the model types selected to be examined, a bespoke model will be created or adapted based on an existing model tool of that type.

5.3 Case Study: Shetland Energy System

Shetland has been chosen as the case study energy system for the representative models. It is a small energy system, enabling the fundamental modelling approach and results to be compared in greater detail. Despite the size, Shetland has some interesting system challenges which are highly relevant to the industry questions identified at the outset of the project.

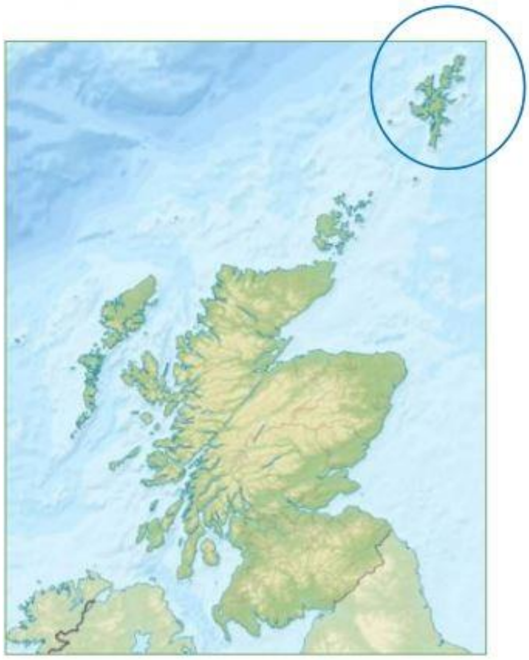

FIGURE 5.1: LOCATION OF SHETLAND

Shetland is an island located 130 miles off the coast of Northern Scotland, see Figure 5.1, which is not interconnected with the mainland GB electricity grid. In the absence of a gas network, islanders have adopted high levels of electric heating, commonly with night storage heaters, resulting in significant seasonal fluctuation in electricity demand. Demand varies from an annual peak of 45.5MW to a summer night low of 11MW, and this peak demand on Shetland is projected to increase to 57MW in 2019 and 68MW in 2033 (SSEPD 2014).

Shetland also has a high wind generation potential, with its main wind farm, Burradale, reporting load factors of over 50% (Shetland Aerogenerators 2017), compared to a GB onshore average of nearly 25% (BEIS 2016a). Despite this resource, Shetland is experiencing difficulties connecting more wind to the system whilst retaining system stability.

Shetland's main power station is Lerwick Power Station, an oil fired power station with 11 units, capable of providing a combined 67MW. There is a second power station, Sullom Voe, which is a 100MW natural gas power station, operated by the oil and gas terminal. A commercial arrangement exists between Shetland's system operator and Sullom Voe to allow for 15MW of the generation capacity to serve Shetland. However Sullom Voe does not operate like a normal power station, due to various contractual and operational constraints, and as a result is hard to accurately represent in an energy system model. In the modelling undertaken in this study, the units at Lerwick Power Station are labelled U1 to U11 and the Gas Power station, Sullom Voe, as the 'Gas Plant'. In addition to the two main fossil fuel power stations there is a 3.68MW wind farm, Burradale, and a number of smaller renewable generator projects which have been added to the network. These power stations are displayed in Figure 5.2.

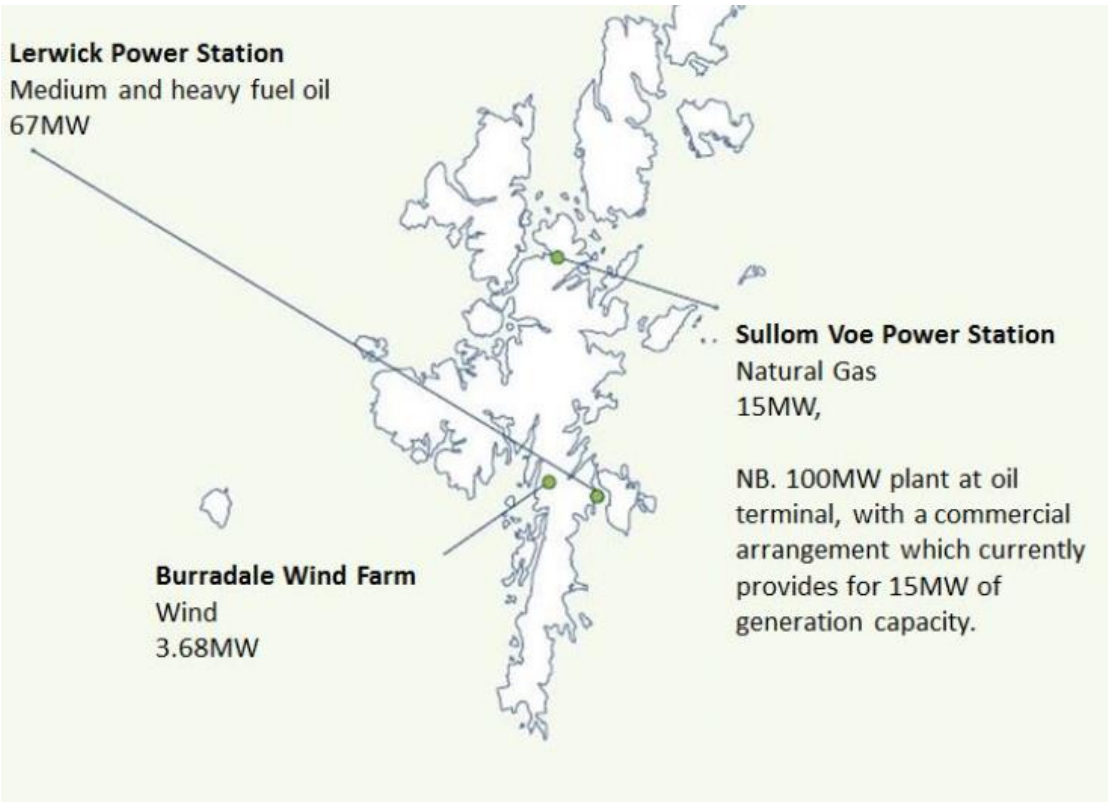

FIGURE 5.2: LOCATION OF SHETLAND'S MAIN POWER STATIONS

The recent increase in renewable generation has been facilitated by a new active network management system, part of an innovative demonstration project NINES (Northern Isles New Energy Solutions), funded by Ofgem's Low Carbon Network Fund. This project also saw a 1MW/3MWh lead acid battery installed at Lerwick Power Station along with smart electric thermal storage heaters installed in 234 homes on the island, to help increase system flexibility (Scottish and Southern Electricity Networks 2017). Other renewable generation exists on the distribution network, such as household solar and wind, however this is embedded within the demand profile. The Feed in Tariff statistics up to the end of June 2017 illustrate that Shetland has on average 0.131kW of generation installed per household under the Feed in Tariff scheme which is higher than the average UK figure of 0.102kW (BEIS 2017b). This creates an extra challenge in forecasting demand on Shetland.

Shetland has many qualities that make it suitable to be a case study for this research, most notably the challenges it faces in terms of renewable generation and flexibility. This challenge is comparable to that faced in GB. However, there are noticeable differences between the two systems, with size being the most apparent difference. The geographic scope and complexity are far reduced for Shetland compared to GB. The smaller scale is also a benefit as it provided a simpler case study to fully analyse the models in more detail and to understand the outputs. However, when interpreting results any system specific learnings should be identified and the impact if a GB size system model was considered.

5.4 Model Types

This section outlines the core principles behind the different model types which have been identified and the design of the representative models for Shetland.

5.4.1 INVESTMENT OPTIMISATION MODELS

In this study Investment Optimisation models refer to those which, with the use of optimisation algorithms, calculate the least cost investment pathway over a prescribed time horizon, typically 20 to 50 years. Outputs include the amount of production from each generation type, what new plant should be built, and the total system cost. The most common tool in this category is the MARKAL/TIMES family of models which were developed and maintained by the IEA (2017) and widely used by many governments and organisations around the world. Other examples include MESSAGE, TEMOA, OSeMOSYS and RESOM. This family of models have been given various titles, including 'energy system optimisation' models (Pfenninger et al. 2014) and 'partial equilibrium optimisation' models (Loulou et al. 2004).

OSeMOSYS is an example tool of this type which is free to download and open source in its structure. As such this allows greater transparency of its method to its users (Howells et al. 2011), thus it provides the potential to adapt the model to the system being studied. This flexibility to allow more technologies and processes, whilst the core model being relatively simplistic, means that the user is better able to fully understand the method and adapt to their case study. OSeMOSYS treats everything as a technology in the model with associated efficiencies. Example time slices are used to outline how demand is spread across the year. Other inputs include types of technologies and their associated inputs, outputs, efficiencies and where appropriate, capacity and availability factors. The model runs an objective function to minimise the total cost, subject to a number of operational and balancing constraints.

As the raw code files are readily available, there is little advantage in making a bespoke model for this model type. Instead OSeMOSYS is used and adapted to build a representative Investment Optimisation model for Shetland.

5.4.2 Time Step Balancing Models

In this study 'Time Step Balancing' models refers to those which perform a calculation on each successive time step, over a time horizon such as a single year. They typically balance demand and supply, usually with the objective of minimising running costs or increasing the share of renewable generation. This model type is an example of those encompassed by the broad energy system simulation class of models, referenced in a number of reviews (Connolly et al. 2010; Pfenninger et al. 2014; Loulou et al. 2004).

It was decided that a bespoke tool would be built based on the existing model, EnergyPLAN. EnergyPLAN itself is freely available but not open source, therefore the code cannot be adapted by the user. Despite this, the documentation and supporting user guide details the mathematical approach and therefore for a simplistic system the method can be reproduced (Connolly 2010; Lund 2013). EnergyPLAN simulates the generation produced from the fossil fuel plant in each hour, depending on its objective function. It has no foresight therefore calculates the result in each discrete time step independently. It can run in two main modes:

i. To minimise the amount of renewable supply curtailed
ii. To minimise operational costs in a market where all plant operators seek to optimise their business economic profit

In this study the model is recreated with the aim to reduce renewable curtailment as this is its more simplistic version and provides an interesting comparison to the other models analysed.

5.4.3 Unit Commitment/Economic Dispatch Models

Power system models focus on the operation of electricity generating plant. Power system models come in many forms but one of the most common of these forms is to schedule the dispatch of different units and plant on the system. Generally, this is done in two stages; firstly a unit commitment calculation using a demand forecast, reserve requirements and plant constraints, such as minimum on/off times and start costs, which schedules which units should be on at a given time, and then an economic dispatch calculation provides the exact amount of generation each unit should produce. Both of these algorithms typically optimise with the intention of reducing cost (Wood et al. 2014).

Unit Commitment/Economic Dispatch (UC/ED) models are capable of computing over longer time scales and therefore informing investment decisions. However, this is not their core purpose but more likely a hybrid adaptation. When run over a longer time horizon, example time slices are used, similar to those used in the Investment Optimisation model. The UC/ED model however still includes greater detail of the power system.

There are a number of different techniques that can be used for the UC/ED problem; mixed integer linear programming, priority list and dynamic programming to name a few. Other less conventional methods which solve the UC/ED problem include particle swarm optimisation, genetic algorithms, game theory, and optimisation neural networks (Wood et al. 2014). The most straight forward method is a priority list algorithm to first solve the UC problem, followed by linear regression for ED. The priority list method uses a more heuristic approach as opposed to performing an optimisation calculation through programming software. A merit order list is established based on average production cost and then a shutdown algorithm is used to schedule units. If the load is lowering in the following hour, it establishes whether dropping a unit will leave sufficient generation to meet the demand and the reserve requirement. If not then it will remain on, if yes then it identifies if forecasted demand will rise again before the end of the minimum shutdown period of the unit. If it does then the unit must remain on, if not then the hourly production costs of that unit for the hours it would be kept on despite not being required is compared to the cost of shut down and start up. If keeping it on is cheaper than switching it off and on then the unit remains on until next required, if not it is shut down. This process is repeated for each unit down the priority list. To model the main short to medium term power system operational problems, the UC algorithm schedules the mixture of generating units to be online to ensure that there is enough supply to meet forecasted demand and reserve requirements. Plant restrictions are considered, such as minimum run time, minimum down time, start-up cost, shut down cost and minimum and maximum load capacities. Economic dispatch then optimises the generation load from each of the available plants from the unit commitment process to meet demand in each time period, at lowest cost, based on capacity limits and running costs (Wood et al. 2014).

The academic review conducted in section 3.3.4 found that two studies considered power system models as individual classes and the models referenced in those reviews were WASP, EGEAS, PLEXOS and ELMOD (Bhattacharyya & Timilsina 2010a; Pfenninger et al. 2014). The Government review identified two power system models, DECC's Dynamic Dispatch Model (DDM) & the Redpoint Dispatch Model. The DDM focuses on investor behaviour and hurdle rates, whereas the Redpoint Dispatch Model is understood to be similar to the PLEXOS style of model, which is a proprietary tool using a mixed-integer linear programming model to solve the UC and ED problems.

For this study a linear programming model is built in Matlab to represent the commonly used UC/ED models. It uses binary integer linear programming using the CPLEX solver to solve the unit commitment problem, followed by a linear optimisation algorithm to dispatch generation.

5.4.4 Econometric Demand Forecasting Models

Electricity demand is normally an important input to any energy system model. It is what the power system, through its generation fleet and balancing services, needs to meet. Electricity demand consists of electricity for power, heat and transport needs across all types of customers. Electricity demand is dependent on several factors, such as; human behaviour, weather and price elasticity.

Chapter 2 highlighted the variety of demand forecasting modelling methods which range from top down approaches which look at past trends to consider the future, to bottom up approaches which consider technology use and human behaviour trends. It was documented in Chapter 3 that the UK Government publishes annual electricity demand forecasts out to 2035, broken down by sector, using a macro-econometric methodology (BEIS 2017a). It is understood that National Grid also use this type of model, specifically multiple linear regression modelling to forecast electricity demand at daily resolutions (Taylor & Buizza 2003). Regression analysis explores the past relationships between different variables, such as weather and GDP, to predict what the future demand could be. The variables used within a multiple linear regression model depend on the demand resolution being modelled, for example longer term models considering annual aggregate demand over 50 years are likely to include variables such as population and GDP, whereas daily demand is likely to be impacted to a greater degree by temperature. Demand models can be created for different sectors independently as they often have different relationships between variables. For example weather is more of a driver for residential demand than in the case of industrial demand (Elkhafif 1996).

The representative electricity demand model created for this research uses a multiple linear regression technique to forecast future electricity demand at a daily resolution. A daily resolution is more in line with the themes of this research, such as looking at the impact of flexible technologies, which requires an understanding of how demand changes within a year as well as between years; it also requires data that is more readily available. The programming tool chosen for this model is R, a recognised software program for statistical analysis which is freely available to download.

5.5 Reference case models

The process of creating each of the representative models for Shetland is detailed below. For the purpose of the representative model created in this chapter, it is assumed there is no battery storage or flexible technologies present in the system. This is in order to validate the various models prior to adding additional capabilities to the models and to better understand the core method within each of the model types. The reference case year is 1st April 2014 – 31st March 2015 and in this year the battery was not yet fully operational therefore is a suitable reference year to validate the system prior to the addition of storage and flexible heating technologies. Chapter 6 will explore the ability of these model types to represent electricity storage and other flexible technologies.

5.5.1 Investment Optimisation Model

The existing tool, OSeMOSYS, is used to illustrate the capabilities that an investment optimisation type of model has to answer questions about the future of Shetland. OSeMOSYS is a linear optimisation model written in GNUMathProg and is open source allowing for alterations to be made to adapt it to the system in question. It is structured so that everything is treated as a technology with a conversion, as illustrated in Figure 5.3. All of the rectangular boxes represent technologies, for example, 'E_Gas' is a gas power station which converts gas to electricity and the flows go from left to right, as demonstrated by the arrows, from raw fuels to electricity demand on the far right. Two versions were created for Shetland, one with the power stations aggregated and one where the individual units were disaggregated to understand the effect this extra detail could provide. For the case study of Shetland, there are 12 units, 11 of which represent the different units at Lerwick Power Station and the other represents Sullom Voe power station. These two versions are illustrated in Figure 5.3 and Figure 5.4.

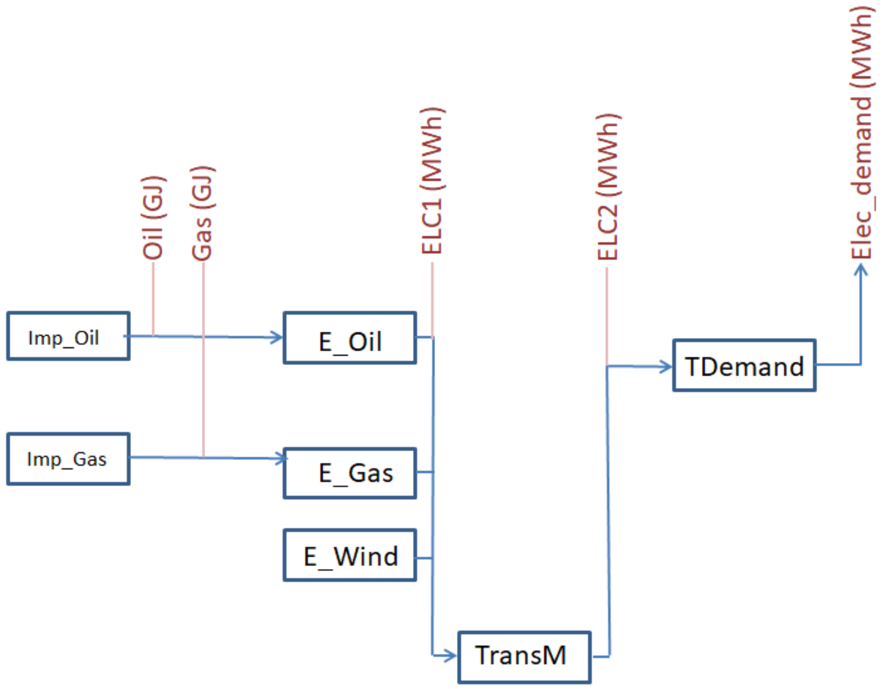

FIGURE 5.3: OSEMOSYS-SHETLAND STRUCTURE

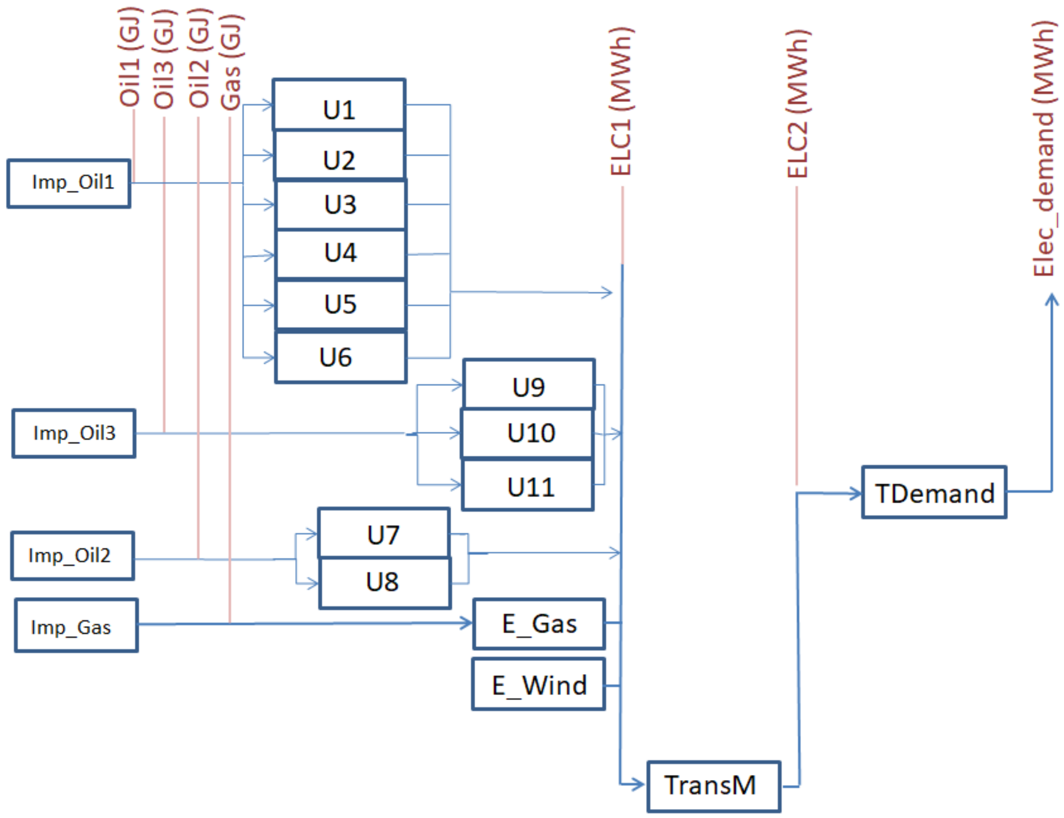

FIGURE 5.4: OSEMOSYS DESIGN WITH DISAGGREGATED UNITS

5.5.1.1 Model Method

The model aims to reduce the total discounted costs, which includes investment and operational costs over the predefined time horizon. This is outlined in Equations 5.1 and 5.2.

$$Minimise \sum C_{y,t,r} \qquad (5.1)$$

Where,

$$C_{y,t,r} \ = \ OC_{y,t,r} + I_{y,t,r} \ + TEP_{y,t,r} + SV_{y,t,r} \qquad (5.2)$$

$C_{y,t,r} \ = Total\ Discounted\ Cost\ at\ year\ y, time\ slice\ t\ and\ region\ r$

$OC_{y,t,r} = \ Discounted\ Operation\ Cost\ at\ year\ y, time\ slice\ t\ and\ region\ r$
$I_{y,t,r} \ = \ Discounted\ Capital\ Investment\ at\ year\ y, time\ slice\ t\ and\ region\ r$

$TEP_{y,t,r} \ = \ Discounted\ Technology\ Emission\ Penalty\ at\ year\ y, time\ slice\ t\ and\ region\ r$

$SV_{y,t,r} = \ Discounted\ Salvage\ Value\ at\ year\ y, time\ slice\ t\ and\ region\ r$

The units are aggregated by plant type and the total capacity across years depends on the investment decisions made within the model. Due to the long time-horizons the model is designed to calculate over, the input data required is in the form of user specified seasonal and daily time slices.

This representative model for Shetland is created over a time period 2014 – 2030 using 2014/15 inputs and assumes that all data inputs, such as cost and demand, remain the same across the time horizon apart from the plant mix. However, the expected lifetime of the existing plant is included; therefore the model will have to make investment decisions before the end of the time horizon. The model restricts any new capacity being built between 2014 and 2017, as it is known that the system did not build any in this period.

Other models of this type such as MARKAL/TIMES have a number of additional qualities which are not replicated in this simplistic version. These include price elasticity, therefore how demand may change as a result of price, and a representation for peak demand.

5.5.1.2 DATA ASSUMPTIONS

ELECTRICITY DEMAND

OSeMOSYS requires demand to be set out annually and then proportioned into time slices. To illustrate demand on Shetland, four time slices are used to represent the two seasons, summer and winter, and two daily time slices, day and night. The average temperature trends on Shetland are used to distinguish between the summer and winter on Shetland. June, July and August have higher average temperatures, above 10˚C, and therefore are classed as summer and September to May as winter (Shetland Islands Council 2012). Temperature is used as the distinguishing factor between summer and winter as opposed to daylight hours as the energy consumption is higher due to the high electric heating demand on Shetland, however the cool temperatures even in the summer may result in heating being active for much of the year. ESME, a model which uses a similar method to OSeMOSYS, uses March to September as the summer for their GB model however as the temperatures are lower in Shetland the heating season is likely to be significantly longer (Heaton 2014). For the day and night time slices, night is considered 0000 until 0600 which is broadly in line with the ESME's overnight time slice definition of 2300 to 0600, however the ESME model has four time slices within the day to represent morning, midday, early and late evening. This added temporal resolution creates a profile which is more representative of how demand varies across the day. Midnight was used at the beginning of the night time slice to reflect when storage heaters can begin to charge.

The average demand in each of these four time slices is calculated using 2014/15 data. In the absence of any future forecasts, it is assumed that this remains the same each year. When considering future years or years without data, scenarios can be run to analyse the effect of different demand levels and time slice profiles. These scenarios could be based on projected annual demand growth and past years demand profile trends.

Plant Characteristics

For each unit a number of technical inputs are required. The input capacity values represent the current plant stock in Shetland, 67MW at Lerwick Power Station, or split into its individual units when in its disaggregated form, and 15MW at Sullom Voe. The individual unit costs and efficiency assumptions were provided by SSE based on real data and SSE's own assumptions. These figures are commercially confidential therefore the full disaggregated data set is not published in this thesis. For the aggregated version, the average efficiency and costs from each unit in Lerwick Power Station are used and an SSE provided estimate for Sullom Voe. OSeMOSYS requires efficiency in the form of an input activity ratio, which is calculated from fuel use and efficiency. An availability factor and capacity factor of 1 for gas and oil plant has been assumed for this case study.

Costs provided by SSE include fuel costs only and have not accounted for fixed or other, non-fuel, variable costs. This is because for the fuel costs are higher on Shetland therefore represent an even greater proportion than they do on GB and as result is the main driver. For the investment calculations, capital costs, plant build limits and a percentage capacity reserve are required to ensure there is enough capacity installed.

As the transmission network is modelled as a technology too there is the ability to input an efficiency value for the network to represent transmission and distribution losses. National Grid (2016b) estimate that GB transmission network losses are on average 1.77% and UK Power Networks (2014) estimate that average GB distribution losses are 9% in rural areas. Rural was used as a proxy for the Shetland grid as opposed to urban due to the spread of customers across the islands. For this study an aggregate figure for network losses of 10.61% has been assumed for Shetland. This corresponds to an efficiency of 89.39%.

Renewable generation

Historic wind generation data has been provided by SSE at a half hourly resolution. OSeMOSYS only requires the total capacity of the wind generation and the capacity factor in each time slice. The capacity factors are calculated from the half hourly data set for 2014/15.

TABLE 5.1: INPUTS REQUIRED FOR OSEMOSYS MODEL

Inputs required	Source
Annual electricity demand (MWh)	Half hourly demand 2010-2016, provided by SSE (Confidential)
Electricity demand proportion/ time slice (%)	Calculated from actual demand
Plant capacities (MW)	SSE, publicly available (SSEPD 2014)
Plant efficiencies (%)	Provided/estimated per unit from SSE (Confidential)
Plant Variable costs (£/MWh)	Provided/estimated per unit from SSE (Confidential)
Discount Rate	Assumed 10% (Mott MacDonald 2010)
Capital Costs (£/MW)	Publicly available, assumed nth of a kind, medium estimate. Coal estimate used for oil. (Mott MacDonald 2010)
Operational life of plant (Years)	publicly available, assumed nth of a kind, medium estimate. Coal estimate used for oil. (Mott MacDonald 2010)
Plant Build Limits (MW)	N/A
Emissions	N/A (excluded in this study)
Capacity Reserve (%)	UK actual estimate, publicly available from National Grid (2017)
Network losses (%)	Estimated from GB losses (UK Power Networks 2014; National Grid 2016b)
Wind capacity (MW)	SSE, publicly available (SSEPD 2014)
Wind average capacity factor per time slice (%)	Calculated from half hourly wind generation from Burradale wind farm provided by SSE (Confidential)

5.5.2 Time Step Balancing Model

The Time Step Balancing model is recreated in Matlab to reflect the Shetland system, using the EnergyPLAN documentation as guidance for the method, to allow for future adaptations and tests which the existing interface would not allow. The model is recreated with the objective to reduce renewable energy curtailment.

The model is created using EnergyPLAN's native hourly resolution and runs in a chronological manner but with no foresight of future time steps, only the initial conditions of the hour it is simulating. For each hour it considers the demand, any renewable generation which in the case of Shetland is just wind, and the stability requirements. The total fossil fuel plant generation is then calculated as the maximum of either the difference between demand and wind generation or the level required to ensure grid stability. If the latter is true then this will result in some wind generation being constrained off.

$$e_{pp}(t) = Max\begin{cases} D(t) - e_{wind}(t) \\ (e_{wind}(t) * STAB) \ / \ (1 - STAB) \end{cases} \qquad (5.3)$$

Where,

$e_{pp} = Generation\ required from\ condensing\ plant, in\ each\ hour\ (MW)$

$D = Total\ demand, in\ each\ hour\ (MW)$

$e_{wind} = \ Wind\ generation, in\ each\ hour\ (MW)$

$STAB = Demand\ for\ grid\ stabilising\ units\ as\ a\ \%\ of\ total\ electricity\ generation\ (\%)$

$t = Hourly\ time\ step$

This model is able to compute on an hourly timescale how much power generation is required from fossil fuel plant to balance demand, subject to demand side and flexibility solutions, and the intermittency of renewable supply. It can include for example CHPs, vehicle to grid and district heating. However it does not distinguish between plant and/or units, just calculates overall fossil plant required. The model structure is displayed as a flow diagram in Figure 5.5.

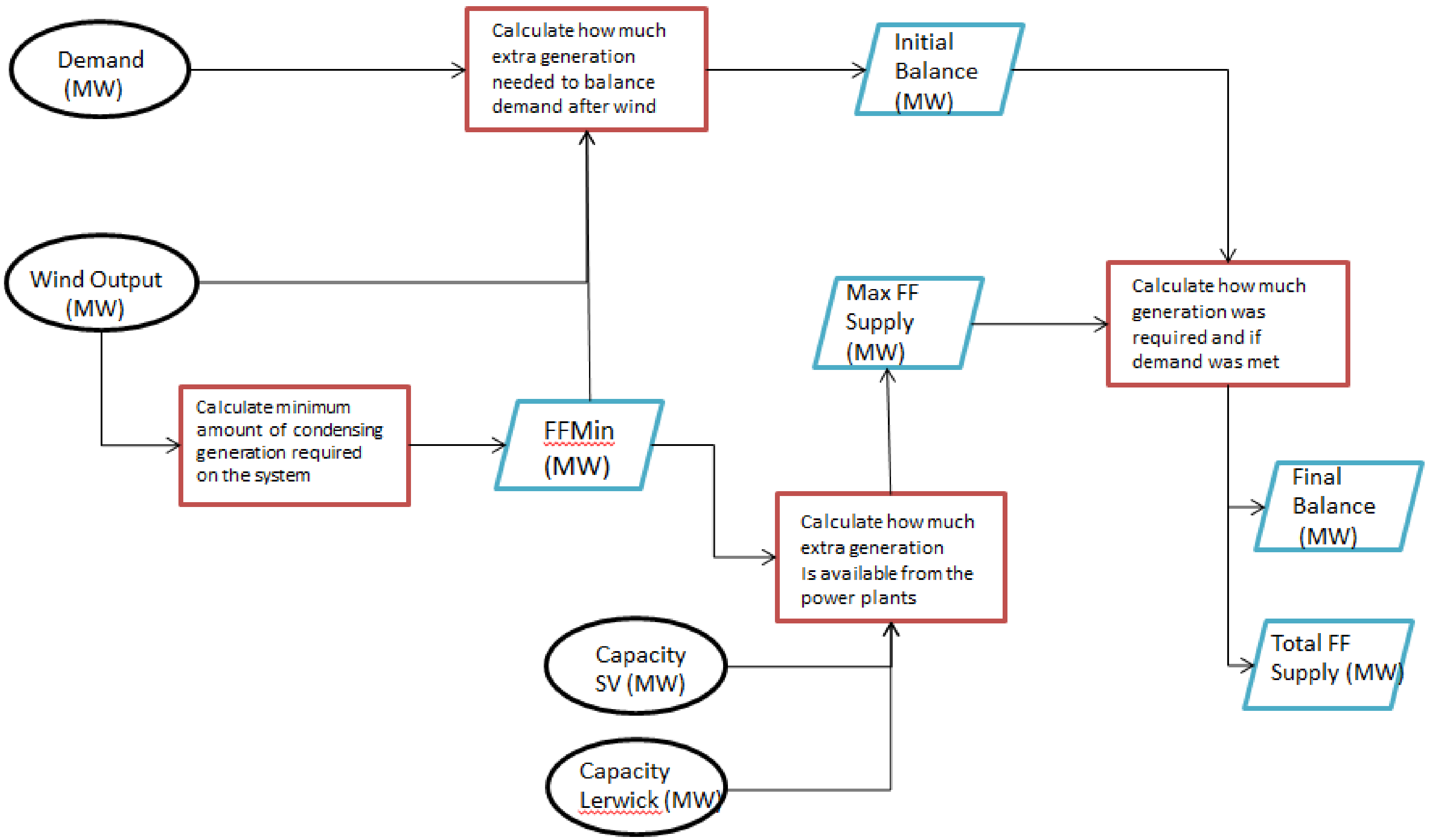

FIGURE 5.5: TIME-STEP BALANCING MODEL - SHETLAND (REDUCING EXCESS WIND MODE)

5.5.2.1 Data Assumptions

Table 5.2 displays the inputs required for the Time Step Balancing model. Electricity demand is required in an hourly time series and this was provided by SSE. Capacity and efficiency of the two power plants are single value inputs. An average efficiency is used from the unit efficiencies provided by SSE, these are created in the same way as for the Investment Optimisation model. The cost assumptions are explained later in section 5.6.1. Historic renewable generation output was provided by SSE and made into an hourly time series for this model.

TABLE 5.2: INPUTS REQUIRED FOR TIME STEP BALANCING TOOL

Inputs required	Source
Annual electricity demand (MWh)	Created from half hourly demand 2010-2016, provided by SSE (Confidential)
Hourly distribution of demand (%)	Calculated from actual demand
Plant capacities (MW)	SSE, publicly available (SSEPD 2014)
Plant efficiencies (%)	Provided per unit from SSE & aggregated for this model (Confidential)
Plant running cost (£/MWh)	Provided per unit from SSE & aggregated for this model (Confidential)
Wind capacity (MW)	SSE, publicly available (SSEPD 2014)
Hourly wind generation distribution (%)	Calculated from half hourly wind generation from Burradale wind farm provided by SSE (Confidential)

5.5.3 Unit Commitment/Economic Dispatch Model

The UC/ED model is split into two algorithms; UC and then ED. The objective of the UC stage is to schedule which power plant or units are committed, i.e. 'on' and generating in any given time period. The ED stage then calculates the amount of electricity generated from each unit which is committed at each time period, both with the objective of reducing the operational cost. A UC/ED model was created in Matlab and run over a one year time horizon at half hour time intervals. The model creation was a collaborative effort between University of Reading researchers, as described in Chapter 1.

5.5.3.1 Unit Commitment Calculation

The output of the UC stage is a binary ‘on’ or ‘off’ decision for each unit for each time slice, which is represented as a 1 or 0 respectively in the model output. To solve this problem the CPLEX solver was installed within Matlab and run using its Binary Integer Linear Programming function. The function is similar to Matlab’s mixed integer linear programming function but the CPLEX solver can compute at a faster speed.

The UC optimisation calculation aims to minimise the operational cost in each half hour time period subject to a number of constraints, as shown in Equation 5.4. The constraints which have to be met within the calculation are:

- The output has to be an integer and between 0 and 1 inclusive. This ensures that the only possible outputs are 1 or 0 which corresponds to whether the unit is on or off.
- The sum of the maximum capacity of each committed generating unit must be greater than or equal to the forecasted demand, plus a fixed level of reserve. This ensures that the committed units are capable of meeting demand with headroom in case the demand is higher than forecasted.
- As the units which are committed have to run, the sum of the minimum stable operating level of all plants must be less than or equal to the forecasted demand.

$$min_x(f^t x) \ subject \ to \begin{cases} x(t) \in Z \\ Gmax(u).x(t) \geq -(d(t)+r(t)) \\ Gmin(u).x(t) \geq d(t) \\ 0 \leq x(t) \leq 1 \end{cases} \qquad (5.4)$$

Where,

$$f = (C_{AV}(u) \, . \, x(t)) + C_{starts}(u) \qquad (5.5)$$

$x = Unit\ State\ (1\ if\ on\ or\ 0\ if\ off)$

$Z = An\ Integer$

$Gmax = Maximum\ capacity\ of\ a\ unit\ (MW)$

$Gmin = Minimum\ stable\ operating\ level\ of\ a\ unit\ (MW)$

$d = Demand\ (MWh)$

$r = Reserve\ (MWh)$

$C_{AV} = Av.variable\ cost\ of\ a\ unit\ operating$ (£)

$C_{Starts} = Start\ up\ cost\ of\ a\ unit$ (£)

$t = Half\ hourly\ time\ step$

Minimum on and off time periods for each of the generating units can be added to the model however they have not been for the case study of Shetland. Due to the small size of the units it is unlikely the constraints would be greater than 30 minutes which is the resolution of the model.

There are two costs associated with each unit, the variable running cost when it is in an 'on' state and the cost associated with turning on a generator, known as the start-up cost. Therefore the total cost is the sum of the costs of each start-up per unit and the sum of the variable costs for each generating unit. The UC model flags when a unit changes state to identify the number of start-up and shut down events.

Other models of this kind such as PLEXOS have additional functionality including the constraints of ramping rates of units and outages.

5.5.3.2 Economic Dispatch Calculation

The ED calculation takes the output from the UC calculation, the committed state of each unit at each half hour, and calculates the actual electricity generation dispatched from each unit. An optimisation function is set up in Matlab, using the 'fmincon' function. It aims to meet demand at lowest running cost. In this instance the upper and lower bounds are the maximum and minimum stable limits of the unit if it is switched on, and the variable costs are calculated more accurately depending on the exact amount of electricity generated per unit. In the economic dispatch calculation no reserve is accounted for, just the actual demand.

$$min_g(f^t g) \ subject\ to \begin{cases} x(t).g(t) = d(t) \\ x(t).Gmin \ \leq g(t) \leq x(t).Gmax \end{cases} \quad (5.6)$$

Where,

$$f\ (t) = \ g(t).C_V \quad (5.7)$$

$g = electricity\ generated\ from\ each\ unit\ (MWh)$

$C_V = Variable\ Cost\ (£\ /MWh)$

Overall the total system cost of meeting demand is the sum of the variable costs in the ED solution plus the sum of the costs of all unit start-ups in the UC solution.

$$C_{Total} = g(t).C_V + \ C_{starts}(u) \ (5.8)$$

Where,

$C_{Total} = Total\ System\ Cost$

For the economic dispatch the variable cost is calculated with greater accuracy as the power generation of each unit at each time step is calculated. For the unit commitment the variable cost is represented as an average variable cost and is calculated using a mean generation level for each unit and does not include the no load fuel.

$$C_V = C_F(F_B + g(F_I /e)) \qquad (5.9)$$

Where,

$C_F = Fuel\ Price$ (£/GJ)

$F_B = No\ load\ Fuel$ (GJ/h)

$F_I = Incremental\ Fuel\ Usage$ (GJ/MW)

$e\ = Efficiency$ (%)

5.5.3.3 DATA ASSUMPTIONS

Table 5.3 displays the inputs required for the UC/ED model. Half hourly demand data provided by SSE for 2014/15 is used with a reserve assumption of 7.2% based on estimates from National Grid (2017). The 12 units, 11 for Lerwick Power Station and 1 for Sullom Voe are modelled individually with their own associated costs and efficiencies. Half hourly wind output is also required to represent the renewable generation.

TABLE 5.3: INPUTS REQUIRED FOR UC/ED MODEL

Inputs required	**Source**
Half hourly demand (MW)	Half hourly demand 2010-2016, provided by SSE (Confidential)
Reserve demand (%)	UK actual estimate, publically available from National Grid (2017)
Max Capacity /unit (MW)	Provided by SSE (Confidential)
Minimum stable level /unit (MW)	Provided by SSE (Confidential)
Fuel Price (£/MWh)	Provided by SSE (Confidential)
No load & Incremental fuel use (GJ)	Provided by SSE (Confidential)
Unit efficiencies (%)	Provided by SSE (Confidential)
Start and shutdown costs /unit (£)	Provided by SSE (Confidential)
Minimum on & off times /unit (Hours)	Provided by SSE (Confidential)
Wind Capacity (MW)	SSE, publically available (SSEPD 2014)
Half hourly wind generation (MW)	Half hourly wind generation from Burradale wind farm provided by SSE (Confidential)

5.5.4 Econometric Demand Forecasting Model

The electricity demand model created in this study for Shetland uses a multiple linear regression technique to forecast daily electricity demand. The regression model created uses a method similar to that of Taylor and Buizza (2003) and is provided in Equation 5.10.

$$Demand(t) = \alpha_0(t) + \alpha_1 DT(t) + \alpha_2 MT(t) + \alpha_3 SR(t) + \alpha_4 T_{MAX}(t) + \alpha_5 WC(t) \quad (5.10)$$

Where,

$DT = Day\,Type\ (Type\ 1 = Monday\ or\ Friday.\ Type\ 2 = Tuesday \rightarrow Thursday.\ Type\ 3 = Saturday, Sunday\ or\ bank\ holiday.$

$MT = Month\,Type\ (Month\ of\ the\ year, 1 \rightarrow 12)$

$SR = Solar\ Radiation$

$T_{MAX} = Maximum\ Temperature$

$WC = Wind\ Chill$

$t = Daily\ time\ step$

Actual daily demand from 25th August 2010 to 31st March 2014 was trained with the corresponding regression variables and the 'α' regression coefficients calculated. Training regression runs were conducted to analyse the strength of the relationships and combinations of variables by measuring the correlation in the form of the adjusted R^2 value. Any variables which were not significant were removed one by one to produce a final regression equation. In the final model the variables included: day type, month, solar radiation, temperature at 6pm and wind chill. Other variables considered were maximum and minimum temperatures, sun rise and sunset, sine and cosine curves, but these were not required to create a model with sufficient correlation. It is likely that solar radiation relationship provided the daylight hour proxy as well as an indication of embedded solar generated, the day type has a strong relationship as more electricity is used in the middle of the week than the weekend for example. The evening temperature and wind chill are likely to impact on the electric heating demand, as well as giving an indication of the seasonal variation in demand when combined with the month. The adjusted R^2 value in the final model is 91%, which shows a high level of correlation between variables, comparable to that found in other studies (Thornton et al. 2016).

5.5.4.1 DATA ASSUMPTIONS

Table 5.4 displays the inputs required for the Econometric Demand Forecasting model. Historic demand data, provided by SSE, was aggregated to create daily electricity demand for the time series required. Meteorological data including wind speed, temperature and solar radiation for Lerwick, Shetland is available from the Met Office MIDAS database (BADC 2015). Data was available in .csv format and the data fields extracted and converted into daily rather than hourly to be consistent with the daily forecast. Wind Chill was calculated using average temperature and wind speed from an equation taken from Environment Canada (2015).

$$WC\ (t) = 13.12 + 0.615T_A(t) - 11.37WS^{+0.16} + 0.3965T_A WS^{+0.16}\ (t) \qquad (5.11)$$

Where,

$T_A = Average\ daily\ temperature$
$WS = Average\ daily\ wind\ speed$

TABLE 5.4: INPUTS REQUIRED FOR ECONOMETRIC DEMAND FORECASTING MODEL

Inputs required	**Source**
Daily demand (MWh)	Created from half hourly demand 2010-2016, provided by SSE (Confidential)
Temperature in Lerwick (˚C)	UK Met Office MIDAS database (BADC 2015)
Wind Speed	UK Met Office MIDAS database (BADC 2015)
Solar Radiation	UK Met Office MIDAS database (BADC 2015)

5.6 HARMONISING ASSUMPTIONS

In order to ensure that fair comparisons can be made between the model outputs, the input data and assumptions need to be consistent and harmonised across the models. Table 5.5 sets out the input assumptions used in each model type created. It shows that few of the input parameters are identical between models. For example the Time Step Balancing and UC/ED models both require time series data, albeit at different resolutions. The Investment Optimisation model requires demand to be set out in example time slices so average trends had to be found in the raw demand data.

TABLE 5.5 MODEL INPUT ASSUMPTIONS COMPARISON

	Investment Optimisation	Time-step balancing	Unit Commitment / Economic Dispatch	Econometric Demand Forecasting
Demand	• Average Demand consumption per time slice (MWh)	• Hourly demand time series (MWh)	• Half hourly demand series (MW) • Reserve (%)	• Daily demand consumption series (MWh)
Meteorological data				• Wind speed, Visibility & temperature
Wind operation	• Capacity (MW) • Availability and capacity factors per time slice	• Hourly wind generation (MWh)	• Half hourly wind generation (MW)	
Plant data	• Capacity (MW) • Average capacity factors per time slice • Activity ratios (overall efficiency) • Average availability factor per time slice	• Capacity (MW) • Overall efficiency	• Capacity (MW) • Min stable level (MW) • Min on/off time (min) • Incremental fuel efficiency • No load fuel use (J/h) • Incremental fuel use (J/MWh)	
Costs	• Variable costs (£/MWh)	• Variable costs (£/MWh)	• Start-up costs (£) • Fuel price (£/MWh)	
Investment of plant (including wind)	• Capital cost (£/MW) • Plant built limits (MW) • Reserve margin (%)			

The Investment Optimisation model can include availability factors to address maintenance and other likely outages. The other models do not include availability factors; however more complex versions of UC/ED models, such as PLEXOS, do include this in greater detail. Plant operation is considered in most detail in the UC/ED model, it includes minimum capacity levels for each unit as well as start-up costs and the fuel usage and efficiency broken down into no load, incremental fuel and incremental efficiency. The other models only consider an average variable cost and overall efficiency.

5.6.1 COST DATA ASSUMPTIONS

The data required in terms of cost varies in each of the model types which can make harmonisation of the input data problematic. Costs are usually split into fixed and variable costs both of which typically require a single, £/MWh, value. Fixed costs refer to those which occur regardless of whether the plant is running or not, which were not included in this study, and the variable costs which are those which only occur when the plant is producing electricity. Variable costs can include the cost of fuel, carbon and operation and maintenance.

For this study the variable cost is assumed to be made up of only fuel costs, as explained in Section 5.5.1, this is because the fuel costs are higher on Shetland therefore represent an even greater proportion than they do on GB and as a result is the main driver. However even this simplified cost assumption is represented in varying levels of accuracy across the different model types.

In the UC/ED model, the fuel cost is calculated in the ED algorithm as the sum of the no load fuel plus the incremental fuel usage which varies depending on the generation level and the incremental efficiency. This is then multiplied by the fuel price to give the fuel cost. This is illustrated in Equation 5.9, which is repeated here:

$$C_V = C_F(F_B + g(F_I/e)) \qquad (5.9)$$

Where,

$C_F = Fuel\ Price$ (£/GJ)

$F_B = No\ Load\ Fuel$ (GJ/h)

$F_I = Incremental\ Fuel\ Usage$ (GJ/MW)

$e = Efficiency$ (%)

As this is the most detailed fuel calculation it is used as a proxy for calculating variable costs across the other model types.

The UC part of the UC/ED model required a single value variable cost, but as it does not calculate the amount of generation used a mean generation level was assumed. The variable cost in the UC model is therefore not variable.

$$C_{AV} = C_F((0.5GMax)(F_I/e)) \qquad (5.12)$$

In the Investment Optimisation and the Time Step Balancing Tool there is a single variable cost depending on the amount of electricity generated. This is similar to Equation 5.12 but with the accuracy of exact electricity generation. Equations 5.12 and 5.13 do not account for a fixed no load fuel usage when operating. As the amount is small compared to the incremental fuel use it has been excluded as opposed to a variable proxy created.

$$C_V = C_F(g(F_I/e)) \qquad (5.13)$$

When the units were aggregated for Lerwick Power Station, the weighted average was found for the incremental fuel use, the fuel price and the efficiencies based on the maximum generation of each unit. Whilst the same efficiency value has been used across all calculations it should be noted that this efficiency does not represent the same value. In Equation 5.9 this is incremental fuel efficiency however the other equations require an overall efficiency, which takes account of no load fuel use. It is important that the difference in the basis of efficiency is recognised as the potentially inaccurate fuel cost calculations could impact on the model outputs.

Start-up and shut down costs are also absent from the system costs in all models apart from the UC/ED model. Only the UC/ED flags when units change from an on to an off state and vice versa allowing for these costs to be included. The absence of these start up, shut down and base load fuel costs would suggest that both the Investment Optimisation model and the Time Step Balancing Model have the potential to underestimate the cost of plant operation.

Carbon and/or emissions costs are not considered in this study, but all models have the ability to include them in the same way as the fuel costs. If included this would result in higher operating costs and potentially a change in the dispatch priority between fuels. The Investment Optimisation model also requires capital cost in order to make future investment decisions.

5.7 Reference Year Results and Validation

This section will discuss the assumptions used in the models, validate each of the model types against a similar tool and/or actual values where appropriate, and finally compare with one another.

5.7.1 Individual Model Results and Validation

As the models vary both in their structure and the method of generation, the validation technique depends on the model. The year from 1st April 2014 to 31st March 2015 is used as the reference year to validate and compare the models to one another. The financial year is used instead of the calendar year so that one complete winter season was considered.

5.7.1.1 Investment Optimisation Model

As the existing tool OSeMOSYS was used and inputs updated for the Investment Optimisation model, the code is already peer reviewed and verified. The only validation undertaken is to compare the reference year results to the actual results to sense check the output. Table 5.6

shows that for the reference year, 2014/15, the Investment Optimisation model overestimates the amount of generation required from the gas plant and from Lerwick Power Station.

TABLE 5.6: OSEMOSYS RESULTS AND VALIDATION

FF Generation 2014/15	Aggregated unit model run	Disaggregated unit model run	Actual 2014/15 output
Gas Plant (GWh)	60.01	60.01	
Lerwick Power Station (agg) (GWh)	182.36	U9 – 16.50 U10 – 55.15 U11 – 110.41	
Wind	16.80	16.80	16.80
Total (ex. Wind)	242.37	242.04	200.48

In both the aggregated and disaggregated models 31MW of wind capacity is added to the system in 2018, the first year there was no capacity limit set, and a further 1.1MW in 2025. The addition of a 7.11MW gas plant is also seen in 2021 when the oil plant is set to come offline. In the Investment Optimisation model there is no constraint parameter for grid stabilisation. There is a maximum activity limit which can be specified for a technology and maximum build limits but nothing to restrict renewable generation output as a proportion of fossil fuel generation. This is a recognised flaw in the medium to long term models despite some basic representation in some tools of this type (Welsch et al. 2012a). The significant investment in wind from 2018 onwards results in a solution where the demand is met almost exclusively from wind power, at 95%. Constraints need to be included to account for the grid stabilisation and uncertainty of wind generation.

5.7.1.2 Time Step Balancing Model

The Time Step Balancing model is based on the existing EnergyPLAN tool, a peer reviewed model. Therefore the Time Step Balancing model is validated by running the same 2014/15 data set through the EnergyPLAN interface. The input data is in the same format, hourly time series data for demand and wind generation and plant capacity and efficiencies. These results are compared to ensure they are sufficiently similar and again sense checked with the actual system data. Table 5.7 shows that the Time Step Balancing model accurately replicates the EnergyPLAN simulation as both the wind and power generation have exactly the same values across both versions.

TABLE 5.7: TIME STEP BALANCING TOOL VALIDATION (CORRECT TO 1 D.P.)

	EnergyPLAN	Time Step Balancing
Total wind (GWh)	16.8	16.8
Total FF (GWh)	201.3	201.3

5.7.1.3 Unit Commitment/ Economic Dispatch Model

The UC/ED model can be validated by running the same data through another model of the same type. The proprietary model, PLEXOS, was used for this validation. The PLEXOS software and the support in running it was provided by SSE's economics team, as described in Chapter 1. Table 5.8 shows that the UC/ED and PLEXOS calculated the same wind and fossil fuel generation for the reference year. Figure 5.6 compares the generation per unit in the UC/ED model and the PLEXOS model.

TABLE 5.8: PLEXOS AND UC/ED MODEL COMPARISON

	PLEXOS	UC/ED
Total wind Generation (GWh)	16.8	16.8
Total Fossil Fuel Generation (GWh)	201.3	201.3

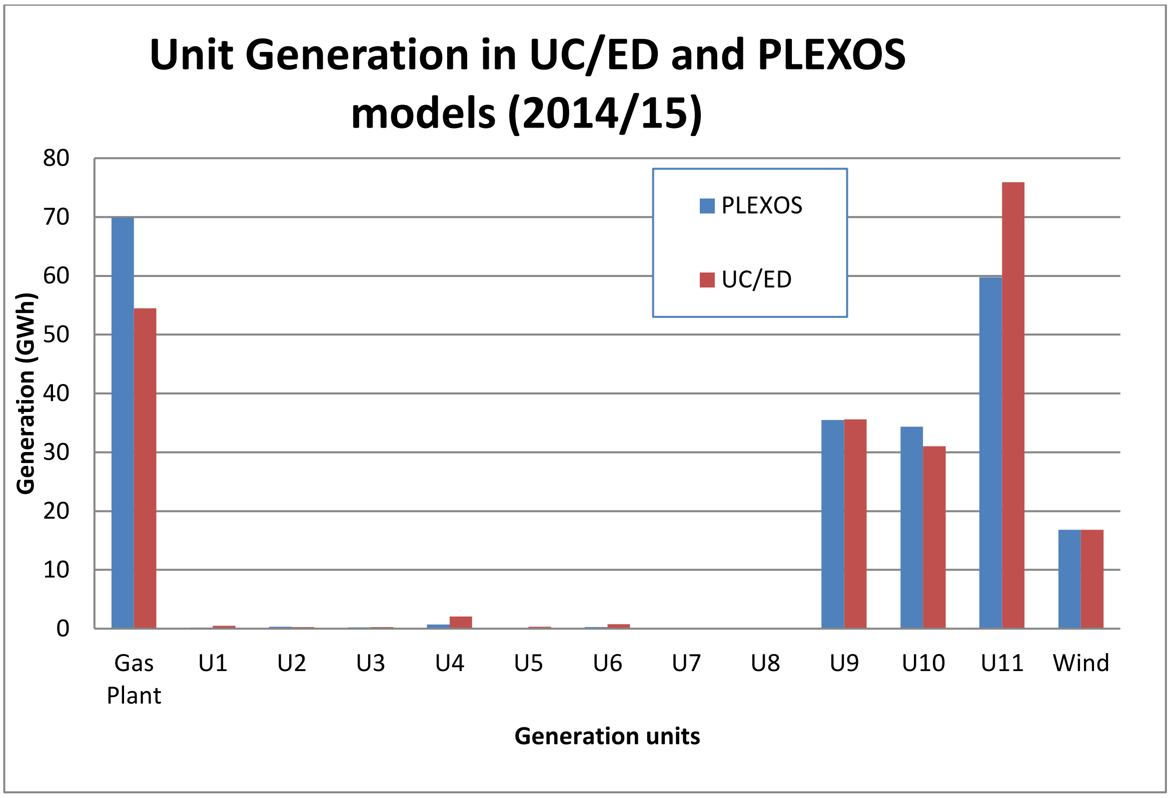

FIGURE 5.6: UC/ED AND PLEXOS UNIT GENERATION COMPARISON

There are some differences in the inputs for PLEXOS compared to the UC/ED model which may explain some of the variation. PLEXOS includes extra detail such as maintenance days and other outages which may account for some variation. The difference between U11 and the Gas Plant in the two models is due to two factors, the extra detail PLEXOS is able to include to more closely mirror the commercial arrangement that exists and also because the fuel costs are very similar between the two units therefore can be dispatched roughly as alternatives. This may account for some of the extra generation from the gas plant in PLEXOS compared to the UC/ED model. In both models the same main units were prioritised and two units, U7 and U8, were not required.

5.7.1.4 Econometric Demand Forecasting Model

The linear regression model used for modelling demand can be validated by saving a year of data, in this case the reference year 2014/15, from the training data and instead use that to test the model and see how close it is to the actual demand. Table 5.9 shows the sum of the forecasted daily demand for the year 2014/15 and the actual demand. It demonstrates that the econometric electricity demand model provides an accurate forecast of demand. It should be noted that in this example actual weather data was known, when forecasting future demand there will be greater uncertainty.

TABLE 5.9: FORECASTED AND ACTUAL DEMAND 2014/15

	Total demand 2014/15 (GWh)
Econometric Demand Forecasting Model	218.2
Shetland Actual	218.1

5.8 DISCUSSION

5.8.1 GENERATION OUTPUT

The outputs of the three energy system models, which excludes the Econometric Demand Forecasting model, can be compared. The models showed good agreement with tools of the same type and when compared to the actual overall generation figures for 2014/15. Table 5.10 details the aggregate model outputs and the actual Shetland generation for comparison.

TABLE 5.10: COMPARISON WITH ACTUAL 2014/15 VALUES

	Investment Optimisation	Time Step Balancing	UC/ ED	Actual
Total Fossil Fuel Generation (GWh)	242.7	201.3	201.3	200.5

All model types calculate the total amount of electricity generation required from fossil fuel plant to be higher than the amount actually generated on Shetland in 2014/15. The Time Step Balancing model and the UC/ED model provide values which are 0.8GWh above the actual generation, whereas the Investment Optimisation model gives a result 42GWh higher than the actual generation. Over half of the extra generation calculated in the Investment Optimisation can be accounted for by the transmission losses present which are not present in the Time Step Balancing or UC/ED model.

The Time Step Balancing model does not dispatch the generation plant, it only calculates the amount of generation required from fossil fuel plant. A dispatch model which implements a merit order could be achieved through a post process approach but this would not be part of the core model calculation. Figure 5.7 illustrates the results of the individual unit generation in the Investment Optimisation model and the UC/ED model in order to make comparisons.

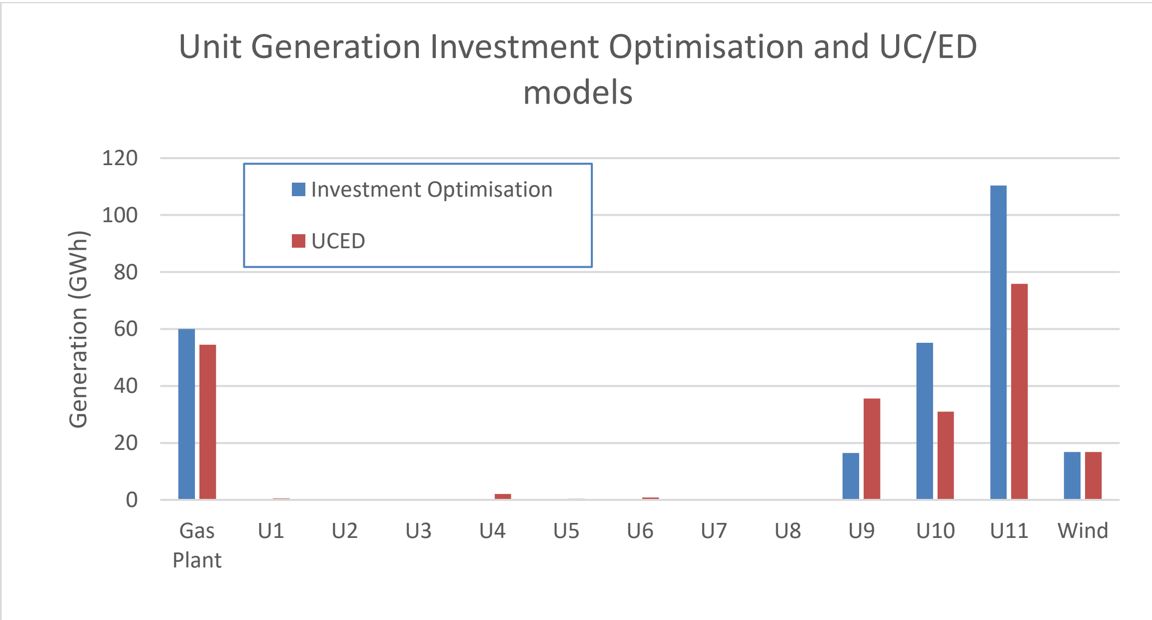

FIGURE 5.7: UNIT GENERATION OUTPUT IN UC/ED AND INVESTMENT OPTIMISATION MODELS

The same units are prioritised in both the Investment Optimisation model and the UC/ED model. Units U9 and 10 are interchangeable in terms of cost for the Investment Optimisation model as the fuel price and efficiency is the same whereas the UC/ED model also considers the start-up costs of the units and optimises the number of times each is switched on. The extra unit cost characteristics considered in the UC/ED model explains this variation. The extra generation seen in the Gas Plant and U11 in the Investment Optimisation model is due to the increased overall generation that is calculated in this model.

Despite not calculating the unit dispatch in as much detail as the UC/ED model, the Investment Optimisation model has identified the main units required to meet the demand in order to make future investment decisions. However, the Investment Optimisation model does not identify the need for infrequent generation from the more expensive units, such as for units U1 to U6, displayed in the UC/ED model result. This is because the average time slice temporal resolution results in a levelling out of the peaks and troughs in demand and wind generation and therefore a lack of visibility of the peak demand. This is important to recognise if the result is being used to determine the number of units or total capacity required to meet the system needs. MARKAL, a more complex tool of this model type, overcomes this limitation by introducing a peak requirement to ensure enough capacity is present to meet the peak demand (Loulou et al. 2004). As the Investment Optimisation model is only able to identify trends in units required, the added resolution of individual units does not add significant insight and could be achieved outside of the model through a basic merit order assessment.

5.8.2 System Costs

Making comparisons between the system costs calculated in each of the model types is not straight forward due to the differing approaches to cost. The Investment Optimisation model calculates a total discounted cost encompassing both the investment and operational costs of each unit. The Time Step Balancing model does not include a system cost in its native form. Instead a calculation is added to determine the cost of the fossil fuel generation required based on an average cost of the Shetland plant mix. As the model does not distinguish between units the cost is directly proportional to the amount of electricity generated. The UC/ED model calculates operational cost for the year based on the fuel and start-up costs of each unit. Section 5.6.1 outlined the different data assumptions for cost and plant efficiencies between the different model types.

Table 5.11 displays the system costs from each of the model types. It shows that the Investment Optimisation cost cannot be compared with the cost from the Time Step Balancing model or the UC/ED model as it is considering a longer time horizon and plant investment in addition to operational costs. This is illustrated by its significantly larger value. The Time Step Balancing model and the UC/ED model produce different operational cost values for the year 2014/15. The reason for this is the inclusion of start-up costs and greater accuracy in the individual unit costs in the UC/ED model.

TABLE 5.11: SYSTEM COST RESULTS

	Investment Optimisation Model	**Time Step Balancing Model**	**Unit Commitment/ Economic Dispatch Model**
Total Investment and Operational cost 2014-2030	£241.7M		
Operational Cost 2014/15		£36.1M	£55.7M

The different approaches present in all of three model types result in system costs which cannot be directly compared. The simplifications in cost in the Investment Optimisation and Time Step Balancing models mean that the system cost is less accurate however comparing the change in cost when changing variables within the model and running scenarios will provide useful insight.

5.8.3 Model Methods

Inconsistencies in model outputs are a result of the different methods present in the model types.

Table 5.12 sets out the main characteristics of the Investment Optimisation, Time Step Balancing and UC/ED models to clearly illustrate how the three system models differ in their structure.

TABLE 5.12: MODEL CHARACTERISTICS COMPARISON

	Investment Optimisation	Time Step Balancing	UC/ED
Objective Function	Minimise investment and operational cost	Minimise renewable curtailment	Minimise operational cost
Time horizon	Typically 20 years+	1 year	1 year
Temporal representation	Seasonal time slices	Hourly time series	Half hourly time series
Optimisation & foresight	Perfect foresight over time horizon	Optimises within hour, no foresight	Perfect foresight over time horizon
Demand structure	Total demand & distribution across time slices	Hourly demand profile	Half hourly demand profile
Representation of intermittency	Average capacity factors across time slices	Hourly distributions	Half hourly distributions
Stability	No specific inclusion, can include capacity limits on renewables	% fossil fuel requirement	Not included
Inclusion of Transmission Losses	Yes as %	No	No
Level of plant detail	Low	Medium	High
Input Costs	Variable fuel cost Overall efficiency	N/A	Variable fuel cost calculated from no load and incremental fuel usage Incremental efficiency Start up and shut down costs.

The variations which appear to have had an impact in the reference year outputs were the representation of temporal resolution, average time slices compared to time series, and the level of plant detail, for example the inclusion of start-up constraints and costs. Other characteristics may be more important when considering specific modelling problems.

The Time Step Balancing and UC/ED models use a time series approach, which provides increased consideration of the variability of renewable generation and demand profiles. The Investment Optimisation and UC/ED models do not consider grid stability constraints. In the Investment Optimisation model this impacts the model's investment decisions. The result is a solution which builds a fully renewable system, despite this not being operationally plausible. The UC/ED model does not consider stability and assumes what is included in the input is available. If testing scenarios with high wind capacity this would have to be considered. The Time Step Balancing model includes a requirement for a percentage of generation to be from fossil fuel plant, which is important as it is designed to explore the potential for high renewable capacity systems. All of the models assumed a central dispatcher or system planner and did not account for generator behaviour.

Future years are modelled in the Investment Optimisation model within a single scenario whereas the Time Step Balancing model and the UC/ED model only calculate one year at a time. If multiple years are to be explored then individual model runs are required which state the plant capacity and the mix that will be operational. All three models require future demand for the year being modelled. The Econometric Demand Forecasting model can be used to forecast future demand time series for various weather scenarios. Alternatively the future aggregate annual demand forecasted from annual regression models can be overlaid onto past demand profiles.

5.8.4 Suitability of Model Types for Identified Challenges

Based on the development of the identified model types in their core form, their ability to provide insight to the industry questions was explored. Table 5.13 compares the potential of each model type to provide insight to each question using a colour coded key.

TABLE 5.13: SUITABILITY TO PROVIDE INSIGHT TO INDUSTRY QUESTIONS

Key
Good representation
Poor representation
Existing capabilities present which could be explored

Industry questions / Model type	Investment Optimisation	Time Step Balancing	UC/ED	Econometric Demand Forecasting
What system benefits can electricity storage provide?				
What effect will the increase in distributed level generation have on the system?				
What is the effect of weather based renewables on the system				
What is the future for heat going to look like and what impact will that have on the electricity system?				

The OSeMOSYS and EnergyPLAN tools which inform the Investment Optimisation and Time Step Balancing model types in this study include the ability to represent storage. The UC/ED model does not include electricity storage but other models of this type such as PLEXOS can include storage. The ability to model storage will be explored in Chapter 6 using the battery present on Shetland as a case study technology.

None of the models in their current form consider distributed generation in any form. It is assumed to be embedded within the demand profile in all models. The econometric model has illustrated the correlation between demand and the weather and therefore scenarios being run for wind generation could impact the demand forecast. This is also important as distributed generation is assumed to be accounted for within the forecasted demand. It is not clear how distributed generation could be included in the model types. There may be value in a further adaptation to create a version of the Econometric Demand Forecasting model on a case study known to have no distributed generation to understand underlying demand.

The Investment Optimisation model considers renewable generation but has poor visibility of its intermittent nature. The Time Step Balancing model is designed to explore how higher renewable penetrations can be achieved. It can run multiple wind scenarios with various capacities and profiles in scenarios which include the presence of various technology mixes to explore the effect on increasing the percentage of renewable generation. The UC/ED model allows for different wind output scenarios, although relies on realistic scenarios due to the absence of grid stability constraints. It can analyse the impact this would have on the system cost and unit generation scheduling.

None of the models studied account for the behaviour of the end user or building level technologies in any detail, therefore they are unable to identify the demand for heat independently. Energy system models tend to include more detail on electricity generation than electricity demand.

5.9 Chapter Summary

This chapter has developed representative models of each of the four model types that were identified as influential in policy development in Chapter 3. This meets Objective 3 of this research which was to generate representative versions of the core model classes identified for the case study of Shetland. These models have been designed to be simple in their approach to allow them to be understood in detail. The models created in this chapter have been validated through a combination of comparisons with other peer reviewed models and actual reference year outputs. This has demonstrated the potential for some useful insights from these simpler model versions.

Shetland was chosen as a case study for this research. Its small size but significant system balancing challenges makes it a suitable energy system to analyse the industry questions identified in Chapter 1 and the emerging modelling challenges from the interview analysis in Chapter 4.

Two attribute differences were noted between the Investment Optimisation model, the Time Step Balancing model and the UC/ED model which resulted in appreciable differences in model outputs. These were:

i. Temporal representation, i.e. time slices or time series.
ii. Level of individual unit operational characteristics, such as efficiencies and start-up costs.

In their current form, the models do not appear to be able to provide significant insight to the industry questions. The time series models (the Time Step Balancing and UC/ED models) are better suited to assessing the impact of renewables. This is due to added representation of intermittency. The Investment Optimisation can consider the average seasonal effect but not extreme scenarios. In their current form none of the models consider electricity storage or distinguish between electricity demands for different purposes.

This chapter has provided a better understanding of the differences between the model assumptions and structures. This provides early insight into Objective 4 of this research which is to examine the strengths and weaknesses of each model type. This will be developed further in Chapter 6 which will look in more detail at how these models can consider battery storage and flexible electric heat demand.

6 MODELLING FLEXIBILITY FOR SHETLAND

6.1 CHAPTER OBJECTIVES

The energy system models created in Chapter 5 represent the core model types which have been identified in this study as being influential for policy development. This chapter will make adaptations to these tools to explore how they are able to model the battery and smart electric storage heaters which exist on Shetland. Their ability to provide insight to the industry questions will then be re-examined based on these adaptations to see if there have been substantial improvements.

- Objective 4: Examine the strengths and weaknesses of each model type in responding to a range of identified business questions.
- Objective 5: Advise the industry partner of opportunities to improve energy system capability, through enhancement or improved interpretation of existing tools, or through adopting new tools.

6.2 REVIEW OF FLEXIBILITY MODELLING

The European Smart Grids Task Force defines flexibility *'as a service provided by a network user to the energy system by changing its generation and/or consumption patterns in response to an external signal*' (European Smart Grid Task Force 2015). Encompassed within the term 'flexibility' are technologies including: electricity storage, DSR and interconnectors, as well as thermal generation such as new CCGTs (Carbon Trust & Imperial College London 2016). The UK Government recognises the potential value that these flexible technologies can provide to security of supply and meeting its carbon reduction commitments. Reducing the barriers to flexible technologies was a theme in their recent call for evidence on a 'smart, flexible electricity system' (BEIS & Ofgem 2016). Additionally, the ancillary service market is opening up access to a broader range of smart technologies as demand is increasing for services which provide back up for both predictable and unexpected events. This increase in demand is due to the increase in variable and non-dispatchable renewable generation, and because the traditional suppliers of these services, primarily coal plant, are closing down. With this increasing focus by Government and the consequential increase in deployment, understanding how these core models can provide insight to the role of these flexible load technologies is important. Characterising their use through running different modelling scenarios can demonstrate their benefits, limitations and guide investment.

One way to distinguish the type of electricity storage in energy systems is to separate between bulk and distributed storage. Bulk storage is connected directly to the National Transmission Grid, and distributed storage is connected to the distribution network or individual households. This distinction can also be made for other flexibility technologies.

Fossil fuel power stations can provide many ancillary services, as can other distributed generation and DSR technologies. The type of services which flexible technologies can provide varies depending on whether it is for the benefit of a network operator, system operator, generator or the energy user. Types of benefits include reducing renewable curtailment, reducing peaks and troughs to maintain bulk generator efficiency, emergency response to power cuts, and other reserve timescales (Pearre & Swan 2015). Different technologies are feasible for different services, but as capital costs are high investors need to know they will be contracted (Pearre & Swan 2015).

The main tool used for storage analysis in policy making, as determined in the review of models in Government Impact Assessments and policy reports in Chapter 3, is the WeSIM model. The WeSIM model is an optimisation model created by Imperial College London (2016). It considers the distribution and transmission levels at up to sub second time scales and aims to identify the 'least worst regrets' investment decisions. DECC also commissioned Frontier Economics (2015) to advise on how to integrate DSR assumptions in their Dynamic Dispatch Model following a report by CSE (2014) which identified the poor representation of DSR, distributed generation and demand reduction within Government models. One of the causes for the lack of representation is suggested to be the complex programming tools required for such complicated interactions, correlated with the internal modelling preference for tools like excel.

The Energy Research Partnership (ERP), an organisation partly funded by Government, undertook a project on flexibility with the aim to inform policy direction (Energy Research Partnership 2015). A model was developed, named BERIC, a linear programming optimisation model whose objective function is to minimise short run costs at each scheduling time step. Using National Grid's Slow Progression scenario as a starting point the model balances demand, which uses the forecasted 2030 peak demand over a 2012 demand profile. Its constraints are that there must be adequate reserve for services to cover response requirement down to second by second granularity, and sufficient inertia. The generation is grouped by plant type, not by individual plant or units. This model did not include new storage and DSR technologies, instead it was limited to main plant types and some existing storage was modelled as generation.

UKERC (2014) noted that it is common to use optimisation modelling to assess the value of smart technologies in future transitions. This results in important behavioural and social interactions being missed. However, network models and building physics models are being used to assess the full end to end impact of smart storage heaters in the Horizon 2020 funded consortium project, RealValue (Anwar et al. 2016; Bakhtvar et al. 2017).

Patteeuw et al. (2015) compared two of the main modelling approaches and how they represent DSR. The first type are models which focus on the demand side and consider in detail the building level physics and human interaction of these systems, but are unable to reflect the impact DSR could have on the wholesale price. The second type models the supply side and explores DSR either through changes to price elasticity or by modelling DSR as a storage technology with negative output. This approach is unable to capture the effect of uncertain inputs such as behaviour, occupancy and weather, as they have a high level of aggregation. The distinction of the market being affected or not by the storage investigation was also highlighted by Pearre & Swan (2015). The models in this study; the Investment Optimisation model, the Time Step Balancing Tool and the UC/ED model, are all more aligned with the supply side modelling method and how it may impact on the market conditions.

6.3 Case Study Modelling

In this chapter the representative models created for Shetland in Chapter 5 are adapted to model the flexible technologies present on Shetland. Some changes in input data are required and significant changes to the code are necessary in all cases.

Shetland provides a suitable case study for this project to assess the ability of the different model types to provide insight into to the industry questions. Shetland has electricity storage, a high renewable generation potential and demand side response in the form of storage heating. Electric storage heating is a relevant challenge as increasing the proportion of electric heating was prioritised in the UK Government heat strategy (DECC 2013c). Since 2013 the focus on electric heating has reduced but it is still a major focus. Most of the focus in the Government pathways has been for heat pumps, however it has been argued that storage heaters, and other technologies with thermal storage, should be part of the mix (Sustainability First 2014).

Smart storage heaters have been rolled out to a number of households on Shetland as part of the Low Carbon Network Funded project, NINES (Scottish and Southern Electricity Networks 2017). These storage heaters are more dynamic than the traditional storage heaters and can respond to market signals to charge when the price is low and not just from a pre-defined time of night. They can also forecast the exact amount of store they require based on the weather.

Modelling the case study of Shetland provides the opportunity to explore the system benefits electricity storage could provide and how domestic demand shifting and DSR in the form of electric storage heaters could help increase renewable penetration and reduce reliance of fossil fuel generation. Storage heaters are likely to provide useful insights to the value of these model types for other technologies, such as electric vehicles and other DSR enabled smart appliances. These technologies all exhibit similar challenges regarding understanding the underlying demand profile and the potential to shift that consumption whilst meeting end users expectations regarding level of service.

The suitability of each of the model types are examined based on the level of insight which it can provide for the inclusion of these two technologies. The outputs of the models will be compared with each other to identify any consistencies or discrepancies between the insights and the reason for any differences will be analysed.

6.4 Representing Battery Storage

The battery connected to the Shetland electricity network is a 1MW/3MWh lead acid battery. It was installed in February 2014 with the aim of facilitating increased renewable generation onto the Shetland system (Scottish and Southern Electricity Networks 2017). How this technology can be included in the model types and the comparisons between their results is explored in this section.

6.4.1 Investment Optimisation Model

The OSeMOSYS model used as the example tool for the Investment Optimisation model does not have embedded functionality to model storage on a daily time step. It does have the ability to model storage at seasonal and weekly time scales, however for Shetland seasonal storage does not reflect the purpose of the battery, and as there is no distinction in the model for day types, weekly storage cannot be run. Therefore, the battery is not run for the Investment Optimisation model type.

MARKAL, a well-known model of this type which has a similar set up to OSeMOSYS, does include functionality for storage devices and states charging and discharging constraints for time slices, i.e. it can only charge at night and discharge in the day to reduce peak generation (Loulou et al. 2004). In OSeMOSYS if it were to include daily storage it would be aiming to optimally charge and discharge between the day and the night time slices within the two seasons, as illustrated in the MARKAL model. In contrast with time series models, such as the UC/ED and Time Step Balancing models, which can see the state of charge from the previous day to calculate the battery behaviour, the Investment Optimisation model will provide the same solution for each day and night within each season. This means the potential of the battery to provide back up at extreme peaks will not be seen in the model as the peaks are not visible in the average demand time slices. Figure 6.1 illustrates where the battery technology would fit within the Investment Optimisation structure for Shetland, based on the method outlined for the other storage technologies in the OSeMOSYS code. This is because the battery is used at the system level before transmission losses are accounted for.

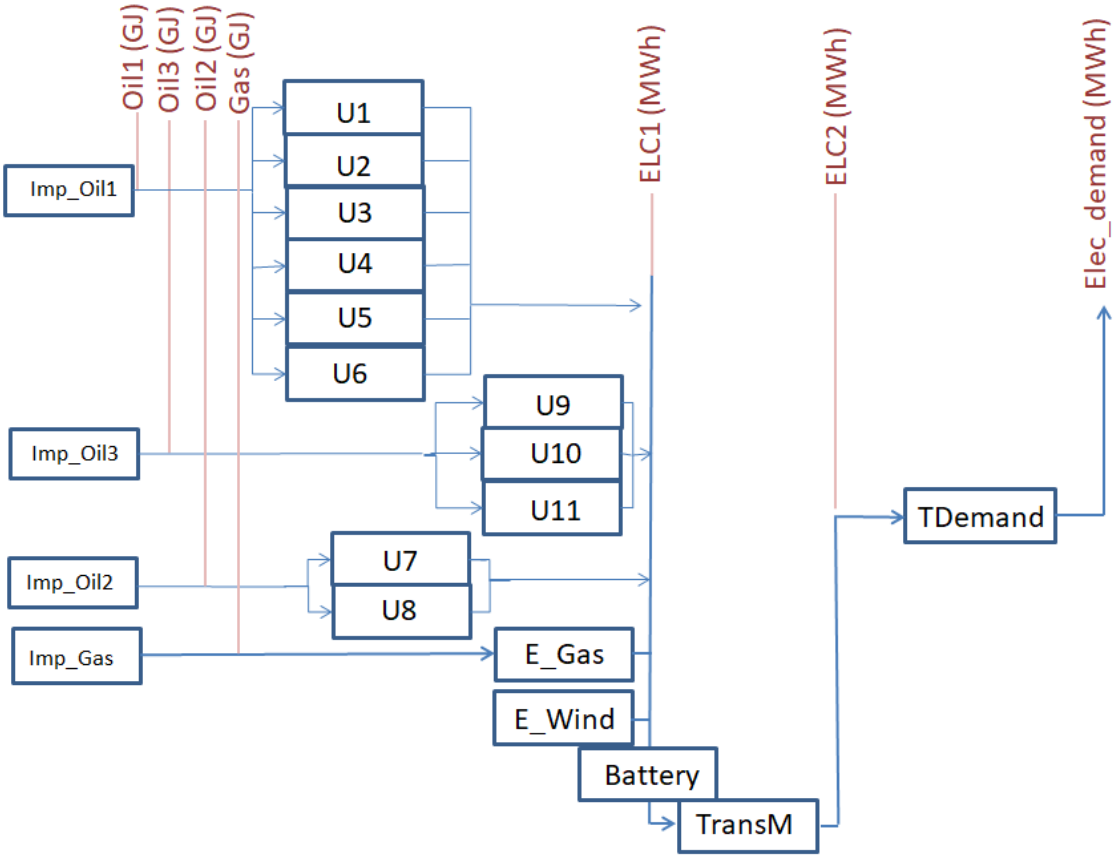

FIGURE 6.1: INVESTMENT OPTIMISATION MODEL WITH BATTERY

6.4.2 Time Step Balancing Tool

EnergyPLAN has the functionality in its existing interface to run a battery and therefore the same method is replicated in the Time Step Balancing model created for this study. It calculates the battery operation in each time step with visibility of the previous time step only.

Where there is excess supply in a given time step (the time step is hourly in this model) the battery charges subject to constraints on the power of the battery and available capacity space in the battery, see Equation 6.1.

If: $e_{wind}(t) + e_{pp}(t) - D(t) > 0$

$$e_{PUMP}(t) = min\begin{cases} e_{wind}(t) + e_{pp}(t) - D(t) \\ (C_{BATT} - S_{BATT}(t-1))/\mu \\ (P_{BATT}) \end{cases} \qquad (6.1)$$

Where,

$$e_{PP}(t) = Max\begin{cases} D(t) - e_{wind}(t) \\ (e_{wind}(t) * STAB) \,/\, (1 - STAB) \end{cases} \qquad (5.3)$$

$$S_{BATT}(t) = S_{BATT}(t-1) + e_{PUMP}(t)/\mu \qquad (6.2)$$

$D = Total\ electricity\ demand, in\ each\ hour\ (MWh)$

$e_{wind} = Wind\ generation\ (MWh)$

$STAB = Demand\ for\ grid\ stabilising\ units\ as\ a\ \%\ of\ total\ electricity\ generation$ (%)

$e_{pp} = Generation\ required from\ condensing\ plant, in\ each\ hour\ (MWh)$

$e_{PUMP} = Electricity\ demand\ from\ the\ pump\ (MWh)$

$C_{BATT} = Capacity\ of\ the\ battery\ (MWh)$

$S_{BATT} = State\ of\ charge\ of\ the\ battery\ (MWh)$

$P_{BATT} = Battery\ power\ rating\ (MW)$

$\mu = Efficiency\ of\ the\ battery$ (%)

In contrast the battery will discharge when there is not enough supply (from both the renewable generation and the minimum fossil fuel generation which is required for stability) to meet demand. This is again subject to available energy stored in the battery and the power characteristics. This is illustrated in Equation 6.3.

If: $e_{pp}(t) > 0$

$$e_{TURBINE}(t) = min\begin{cases} (D(t) - e_{wind}(t)) \\ (C_{BATT}(t)) * \mu \\ (P_{BATT}) \end{cases} \quad (6.3)$$

Where,

$$S_{BATT}(t) = S_{BATT}(t-1) - e_{TURBINE}(t)/\mu \quad (6.4)$$

$e_{TURBINE} = Amount\ of\ electricity\ being\ discharged(MWh)$

After the battery has been scheduled the remaining amount of electricity generation required from the fossil fuel plants is calculated, as shown in Equation 6.5.

$$e_{PP2} = D(t) - e_{wind}(t) + e_{PUMP}(t) - e_{TURBINE}(t) \quad (6.5)$$

Where,

$e_{pp2} = Generation\ requiredfrom\ condensing\ plant, after\ battery\ (MW)$

The additional input data required for the battery in the Time Step Balancing model is detailed in Table 6.1.

TABLE 6.1: ADDITIONAL INPUTS REQUIRED FOR THE BATTERY - TIME STEP BALANCING TOOL

Data Type	Reference
Battery Power (MW)	SSE, publicly available (Scottish and Southern Electricity Networks 2017)
Battery Storage Capacity (MWh)	SSE, publicly available (Scottish and Southern Electricity Networks 2017)
Efficiency of Battery	SSE data, confidential

The model was run using the 2014/15 reference year data to compare the output with and without the battery. Table 6.2 displays the total fossil fuel generation required, the peak generation and how much wind was curtailed for each scenario. The results show that the model does not utilise the battery capacity at all. The lack of battery use is because it is not required to facilitate the existing wind capacity as no wind is curtailed. As the input was based on actual wind generation, if any wind curtailment did occur in this year it would not be present in the data.

TABLE 6.2: RESULTS FROM TIME STEP BALANCING TOOL WITH BATTERY

Battery Usage	Total Fossil Fuel generation (GWh)	Peak Fossil Fuel generation (MW)	Total Wind Output (inc. curtailment) (GWh)	Wind Output Curtailed (GWh)
No	201.3	43	16.8	0
Yes	201.3	43	16.8	0

To explore how this model can demonstrate the potential for the battery to help facilitate more renewable generation onto the system, further model scenarios are run altering the level of wind capacity. Table 6.3 documents the total generation, peak generation and wind curtailment for each wind capacity scenario with and without the battery. It illustrates that a battery of this specification can help reduce the amount of wind constrained off the system. When there is 20MW of wind capacity on the system the battery reduces the wind which is constrained off by 0.5GWh, or 7.5%. When there is 30MW of wind capacity, 0.6GWh of extra wind is able to be utilised but this only represents 1.4% of the total constrained off. This indicates that a battery of this specification is more effective at complementing wind at 10MW compared to 20MW wind capacity. In general the battery has no impact on the peak fossil fuel generation but it does reduce total fossil fuel generation with the battery when it is reducing wind curtailment.

TABLE 6.3: IMPACT OF BATTERY ON UTILISATION OF WIND IN TIME STEP BALANCING MODEL

Wind Capacity (MW)	Battery Usage	Total Fossil Fuel Generation (GWh)	Peak Fossil Fuel Generation (MW)	Total Wind Output (inc. curtailment) (GWh)	Wind Output Curtailed (GWh)
10	No	174.5	41.6	43.5	0
	Yes	174.5	41.6	43.5	0
20	No	137.1	41.3	80.9	6.2
	Yes	136.7	41.2	81.3	5.7
30	No	137.1	40.8	87.5	42.5
	Yes	129.4	40.8	88.1	41.9

The amount of wind constrained in the model is subject to the value of the stability assumption and calculation in Equation 5.3. In this model the minimum fossil fuel generation required is subject to wind only, however in reality this will be down to more factors such as demand and the number of units which are on.

As this model only deals with the one constraint, the wind, it is limited in its use to analyse the benefits of the battery when there is no wind constraint as it does not consider other factors such as the economics of the system and plant dispatch impacts. This is illustrated in this case where the battery never charges as there is no wind constrained off to utilise, so the battery remains unused for the whole year. This model could be used to help get the correct balance between the size of the battery and amount of wind capacity by running scenarios to get the maximum extra capacity which results in no wind constrained off with the battery active. This can be run with a number of different wind distribution profiles to see the effect of different weather conditions. However the simplifications in terms of system operation must be considered.

6.4.3 Unit Commitment/ Economic Dispatch

Representing storage in the UC algorithm is challenging as it does not conform to the native on/off integer state, which is the core of the UC solution. The solution implemented for this study in the UC/ED model was to introduce options for the number of power levels for the battery. The higher the number of power levels set, the greater the complexity of the optimisation. For example if it is programmed to have one power level it can charge and discharge at full power only, if it has two power levels then it can charge and discharge at full power or at half power. The battery power level can also remain unchanged in all scenarios. The model optimises the battery usage to reduce cost and it calculates an optimal battery charging and discharging profile, alongside the normal integer UC solution for the remaining plant. The revised model is illustrated in Equation 6.6.

$$min_x(f^t x) \ subject\ to \begin{cases} x(t) \in Z \\ Gmax(u).x(t) \geq -(d(t) + r(t)) \\ Gmin(u).x(t) \geq d(t) \\ 0 \ \leq x(t) \leq 1 \\ |p_{BATT}| \leq P_{BATT} \\ 0 \leq E_{BATT}(t) \leq C_{BATT} \end{cases} \qquad (6.6)$$

Where,

$$f = (C_{AV}(u)\ .x(t)) + C_{starts}(u) \qquad (5.5)$$

$$p_{BATT}(t) = \begin{cases} \mu.p_{BATT}(t)\ , \quad if\ p_{BATT}(t) \leq 0 \\ \frac{1}{\mu}p_{BATT}(t)\ , \quad if\ p_{BATT}(t) > 0 \end{cases} \qquad (6.7)$$

$$E_{BATT}(t) = \sum_{t=0}^{t} p_{BATT}(t) \qquad (6.8)$$

$x = Unit\ State\ (1\ if\ on\ or\ 0\ if\ off)$

$Z = An\ Integer$

$Gmax = Maximum\ capacity\ of\ a\ unit\ (MW)$

$Gmin = Minimum\ stable\ operating\ level\ of\ a\ unit\ (MW)$

$d = Electricity\ Demand\ (MWh)$

$r = Reserve\ (MWh)$

$C_{AV} = Av.variable\ cost\ of\ a\ unit\ operating$ (£)

$C_{Starts} = Start\ up\ cost\ of\ a\ unit$ (£)

$t = Half\ hourly\ time\ step$

$p_{BATT} = Power\ state\ of\ the\ battery\ (MW)$

$P_{BATT} = Battery\ max\ power\ (MW)$

$E_{BATT} = Energy\ stored\ in\ the\ battery\ (MWh)$

Table 6.4 documents the additional inputs data required for this adaptation and the data source used.

TABLE 6.4: ADDITIONAL INPUTS REQUIRED FOR THE BATTERY - UC/ED MODEL

Data Type	Reference
Battery Power (MW)	SSEN, publicly available (Scottish and Southern Electricity Networks 2017)
Battery Storage Capacity (MWh)	SSEN, publicly available (Scottish and Southern Electricity Networks 2017)
Efficiency of Battery	SSE data, confidential

The addition of the battery added significant computational requirements to the UC algorithm. Without the battery the number of unknowns which the model was calculating was:

$$No. of\ Generation\ Unit\ Unknowns = No. of\ Units\ x\ No. of\ Time\ Steps\ x\ 2$$

This represents the on and off state of each unit which can occur in each time step. With the battery an extra set of unknowns are calculated which is added to the number of generation units unknowns calculated above.

$$No. of\ Battery\ Unknowns = No. of\ Time\ Steps\ x\ (\ (No. of\ Power\ Levels\ x2) + 1)$$

The number of power levels is multiplied by two to reflect charging and discharging and the addition of one is to reflect the option to do nothing. As a result of the increased flexibility only a four day time horizon is able to be computed in a similar length of time to a whole year in the absence of a battery.

Table 6.5 illustrates the total number of unknowns in the optimisation calculation broken down by generation units and for the battery for the four day time horizon modelled. It shows a 21% increase in unknowns between the scenarios with no battery compared to a battery with two power levels. This highlights the complexity that could be added to the model if the number of power levels were increased further.

TABLE 6.5: NUMBER OF UNKNOWNS RESULTING FROM BATTERY POWER LEVELS

	No. of Unknowns for generation units (12 units)	**Extra no. of Battery Unknowns**	**Total Unknowns**
No Battery	4608	0	4608
Battery 1 Power Level	4608	576	5184
Battery 2 Power Levels	4608	960	5568

The UC solution is then used as the input to the ED calculation as normal, however the demand used is an amended demand following the subtraction of the battery charging profile.

$$d_{ED}(t) = d(t) - \ p_{BATT}(t) \qquad (6.9)$$

Where,

$d_{ED} = Demand\ to\ be\ met\ in\ the\ ED\ calculation\ (MW)$

Different levels of complexity can be included for the battery by altering the number of levels it can charge and discharge at, resulting in more or less computational power required to solve the equation. The impact of the battery having one or two charging levels is assessed.

Figure 6.2 plots the distribution of geneation across units a as result of the addition of a battery in the four day period analysed. It shows that there is a change in the distribution between units U9 and U10. These units have the same cost and therefore this change is likely to be caused by a more optimal unit schedule due to start-up costs. The increase battery power levels from one to two emphases this change more and further reduces the need for expensive back up generation as in unit U4.

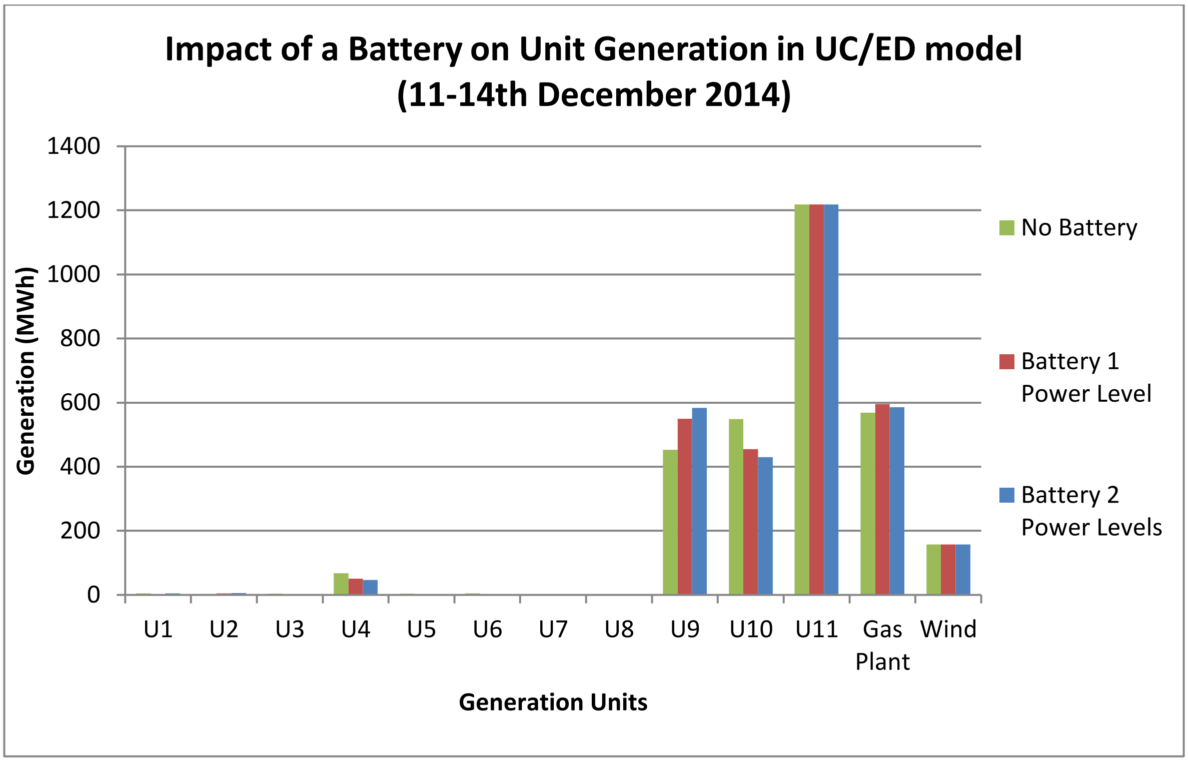

FIGURE 6.2: IMPACT OF A BATTERY ON UNIT GENERATION IN THE UC/ED MODEL

Table 6.6 illustrates the total amount of fossil fuel required to balance demand and supply in the four day period, the peak generation level and the system cost. It shows that the battery has no impact on the total amount of fossil fuel generation required nor the peak generation level. However it does reduce the cost by a small amount which is likely to be due to optimising the use of cheaper units to meet demand. The cost further reduces with increased battery power levels. This is because it can operate closer to the optimal solution.

TABLE 6.6: IMPACT OF BATTERY ON GENERATION AND COST IN UC/ED MODEL

	FF generation (MWh)	**Peak generation (MW)**	**Cost (£M)**
No battery	2875.7	36.4	0.783
Battery 1 level	2875.7	36.4	0.778
Battery 2 levels	2875.7	36.4	0.777

Figure 6.3 plots the battery activity across a single day. A negative power value indicates that the battery is charging. It shows that the battery has a high activity level and charges and discharges frequently within a single day. When the battery charging flexibility is increased by increasing the

number of power levels, its activity follows the same profile but does not always charge and discharge at full capacity. No limit is imposed on the battery operation which is the cause of the over use. Constraints could be added to allow the battery to only complete, for example one charge and discharge cycle within a day.

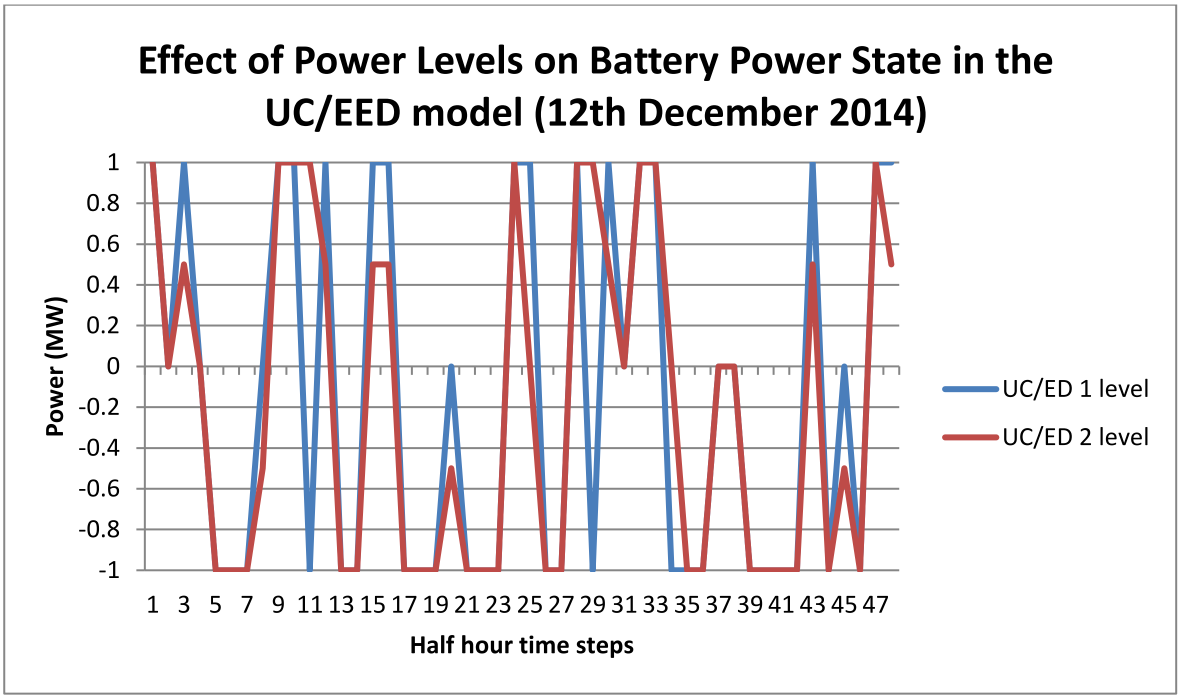

FIGURE 6.3: EFFECT OF POWER LEVEL ON BATTERY POWER STATE IN UC/ED MODEL

Comparison with PLEXOS

Only four days could be run with the UC/ED model in the Matlab/CPLEX model, therefore the proprietary model of the same type, PLEXOS, was also run to understand the impact over the full year, 2014/15. Table 6.7 shows the total fossil fuel generation required in the 2014/15 year and peak generation over the 2014/15 year with and without the battery operating in PLEXOS model. It shows that the battery also had no impact on the overall generation requirements.

TABLE 6.7: IMPACT OF THE BATTERY IN PLEXOS

Battery Usage	Total Fossil Fuel Generation (GWh)	Peak Generation (MW)
No	201.3	43.7
Yes	201.3	43.7

Figure 6.4 plots the generation of each unit calculated by PLEXOS with and without the battery. Similarly to the UC/ED model, PLEXOS also shows little impact on the level or distribution of generation across units from the presence of a battery.

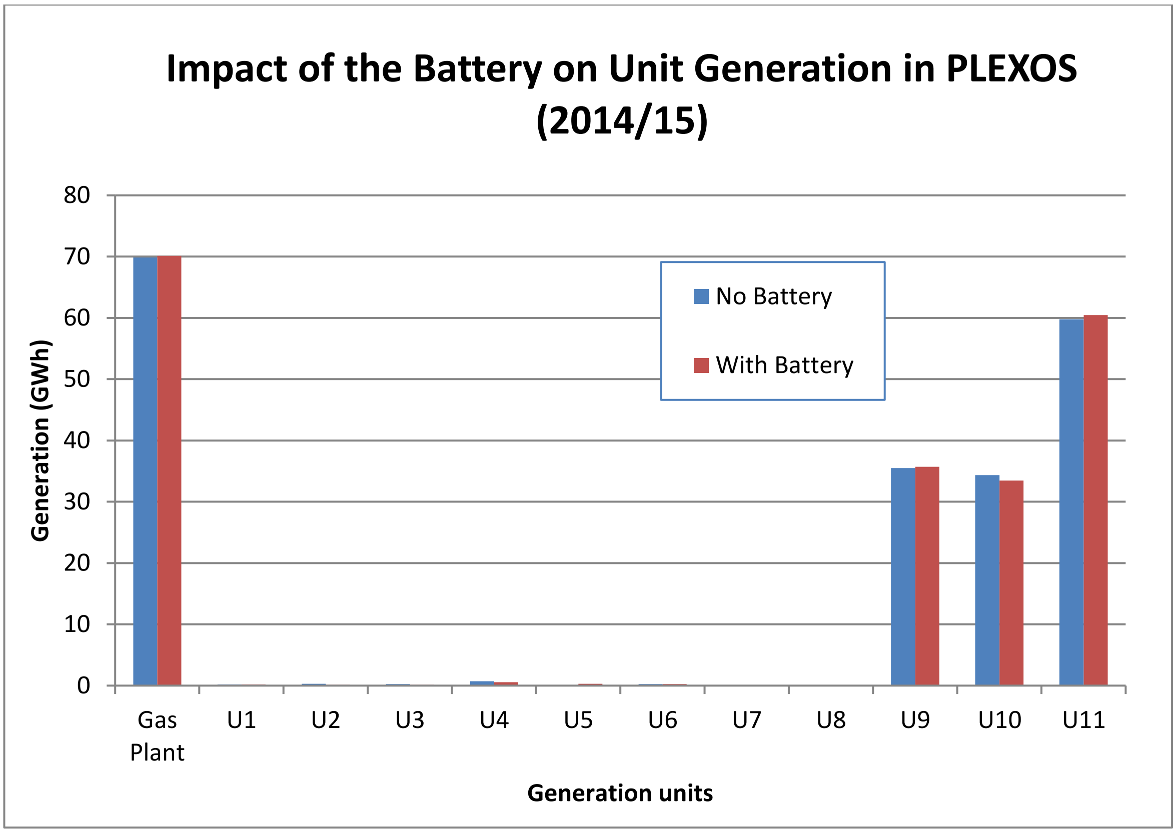

FIGURE 6.4: IMPACT OF THE BATTERY ON UNIT GENERATION IN PLEXOS

Figure 6.5 plots the activity of the battery in both the PLEXOS and UC/ED model results for the same day, 12th December. The UC/ED model, as already highlighted in Figure 6.3, is active in most time steps unlike PLEXOS which shows some charging early in the day followed but some discharge in the afternoon and evening. Again, a negative value indicates the battery is charging.

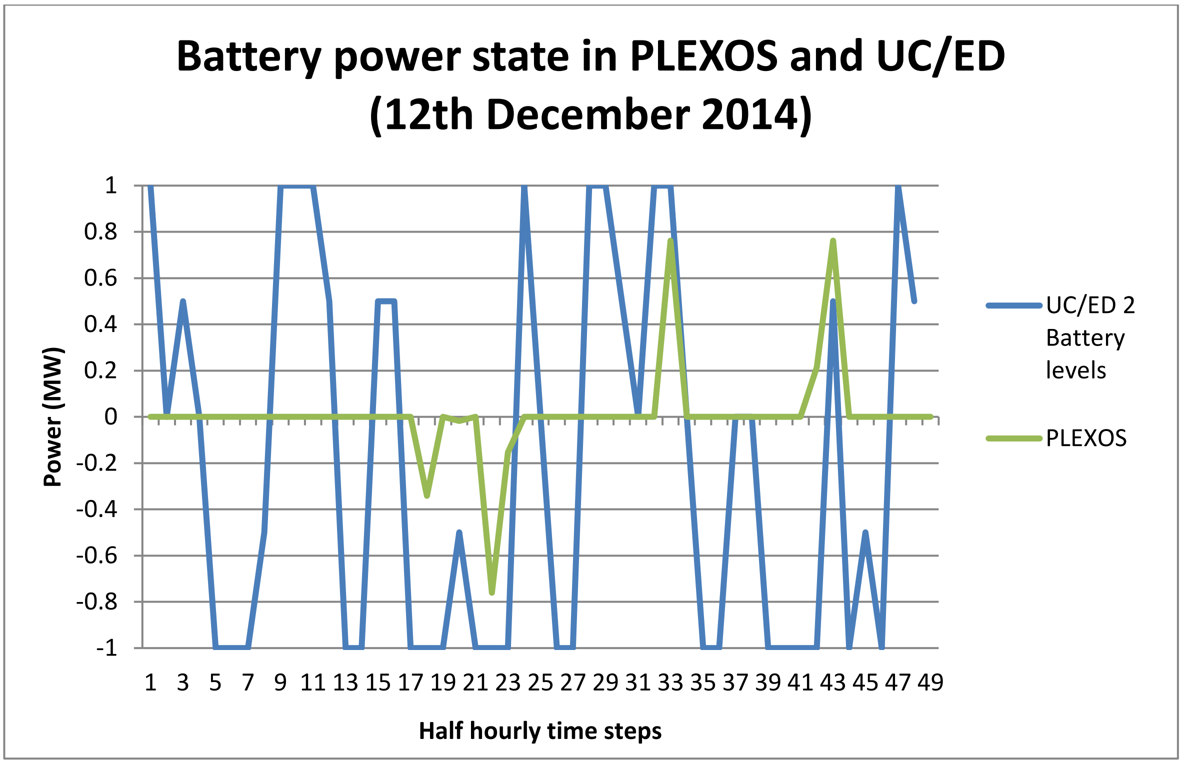

FIGURE 6.5: BATTERY POWER PROFILE ON 12TH DECEMBER IN PLEXOS AND UC/ED

The high activity levels in the UC/ED model are due to the absence of any operational constraints. However a supplementary difference could be because scheduling of the battery occurs prior to the dispatch calculation, which more accurately calculates the unit running costs and levels.

6.5 Impact of Battery Storage on Shetland

The impact a battery has on the future energy system can be determined from a number of factors, including: reduction of system running costs, the peak demand and resultant number of units required to meet demand, and renewable penetration levels.

The Time Step Balancing Model does not utilise the battery at all for the 2014/15 reference year although it shows how it can help increase renewable penetration with greater wind capacity levels. In these cases the total amount of fossil fuel generation decreases when a battery is added, thereby increasing the total utilisation of renewable generation. It does not have any impact on the peak fossil fuel generation required in the year.

The UC/ED model makes regular use of the battery and shows a small cost benefit by the presence of the battery. It also has no impact on the peak fossil fuel generation level required over the year.

The Time Step Balancing model provides insight as to how a battery can complement renewable generation. However it misses potential operational benefits such as more efficient dispatch of plant. The UC/ED model helps understand the impact on the dispatch of units and as a result the capacity required. However to derive a realistic charging profile further adaptations are required to include operational constraints which can better reflect the battery management strategy which is being modelled. Both models assume a central system and battery operator and do not account for a management strategy which aims to maximise revenues from the battery.

The Time Step Balancing model simulates scenarios quickly allowing for multiple scenarios to be run over the whole one year time horizon. The UC/ED has shown challenges in representing a battery in such a model type, in particular the extra complexity resulting in a full year being unmanageable to run in a single model run. Adaptations could be made to run a battery after the core UC/ED calculation to see the impact the battery can have on profile smoothing for example. This may result in a different solution as demonstrated by the study by Cebulla & Fichter (2017) which found that the utilisation of flexibility was higher when using mixed integer linear programming, such as in UC, compared to merit order linear programming.

6.6 Representing DSR

Storage heaters work by charging up in advance of the heat being required by end users in order to benefit from cheaper off peak electricity prices available in traditional economy7 style tariffs. Traditional storage heaters, whose consumption is included in the aggregate total electricity demand in the model versions to date, are scheduled through a radio tele-switching mechanism. Some households on Shetland have had smart electric storage heaters installed to replace their existing traditional storage heaters. The new smart electric thermal storage heaters have the ability to respond more dynamically to market signals and therefore charge at any time in the day where it is optimal to do so, providing heat demand is met. This quality makes them a more valuable source of flexible demand.

The model types are adapted to consider the extra flexibility that smart electric thermal storage heaters can provide. In order to represent this within the models, all the model types required the heat and power demands to be separated. This is because it is only the heat consumption which has the functionality to be flexible.

6.6.1 Modelling Heat & Power Demand

All models required the heat and power demands to be separate from one another to allow the heat demand from the storage heaters to be represented in a different way. The Investment Optimisation model requires the heat demand in its native aggregated time slice structure whereas the Time Step Balancing and UC/ED models require hourly and half hourly time series data respectively.

Heat demand at a resolution more detailed than daily is not readily available in GB (Sansom 2014), or in this case, Shetland. The only measured data from Shetland available for this study is total electricity consumption; therefore a proxy is required to estimate the breakdown of heat and power consumption. Once these consumption profiles have been determined the heat consumption then needs to be converted into actual heat demand.

In a system where there is gas demand, the gas consumption can be used as a proxy for heat and a linear regression demand model created using temperature amongst other variables to create a daily heat demand forecast. However, with no gas supply on Shetland this approach was not possible. Instead in this study a proxy heat demand profile is developed from the available datasets. Power consumption data is more readily available and for this study data from four substations collected as part of the Low Carbon Network Fund (LCNF) research project, Thames

Valley Vision, was used (Thames Valley Vision 2017). The power consumption data was scaled to match the Shetland data set by the daily peak level. It was assumed that traditional storage heater consumption occurs on Shetland between the hours of 00:00 and 05:00 only and in the months October to May inclusive. This means that outside of these hours the electricity consumption was entirely for power or fixed heat, but inside that range consumption was for power or for charging storage heaters. Therefore, the power consumption in the scaled Thames Valley Vision data was subtracted from the original Shetland total electricity consumption data to reveal the estimated consumption from the traditional storage heaters.

Only a single year of data was available for this analysis, the reference year 2014/15. If more data was available to split the consumption, econometric methods could forecast future consumption trends for heat and power individually, as with the aggregate demand calculated in the econometric model in Chapter 5.

The half hourly heat consumption profile from the traditional storage heaters is converted into a daily demand by adding together the consumption within a given day. The original half hourly profile only provides the current storage heater consumption and does not provide any indication as to the profile of the heating demand. This daily demand can then be layered onto a master heat demand profile to create a heat demand time series model. A master heat profile has been created, shown in Figure 6.6, informed by the method used by Sansom (2014). It displays the distribution of total daily demand across a single day. To create a realistic heat demand profile for Shetland, monitoring of homes using storage heaters and analysis of their comfort demands across different day types and times of the day is required. Frontier Economics (2015) noted in a recent report that only small samples of high resolution heat demand data exists from various research studies, which makes creating accurate heat demand profiles difficult. Additionally Boßmann & Staffell (2015) note that even those that do exist are not relevant for future demand trends, due to changes in technology and resulting behaviour.

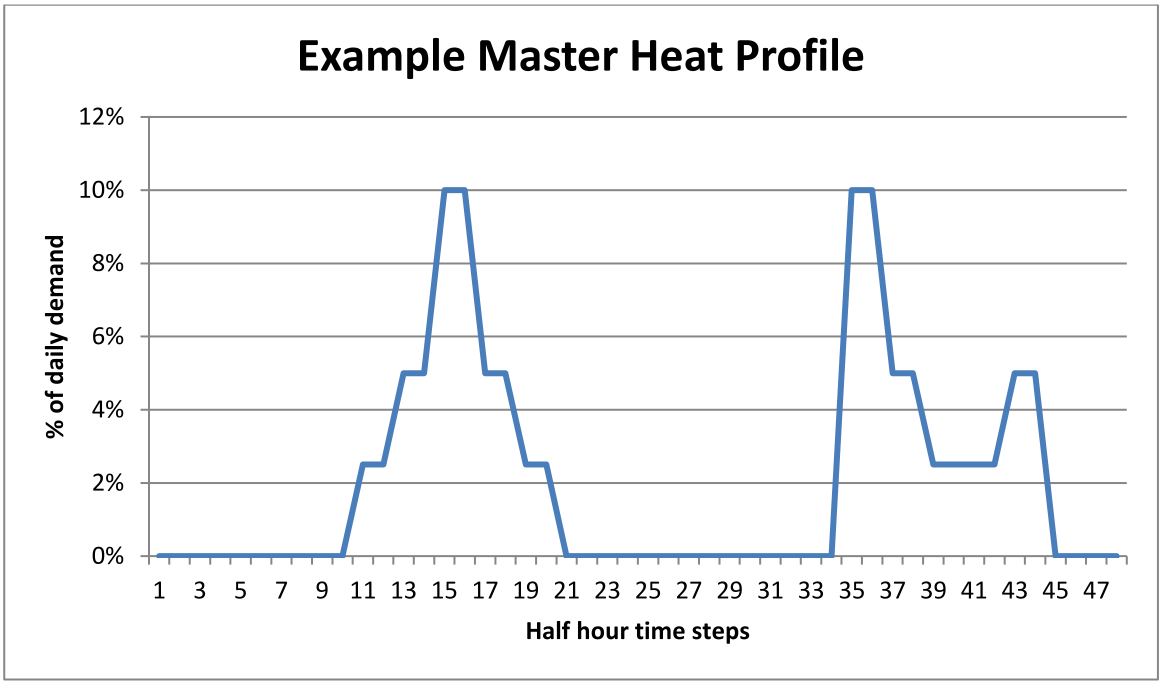

FIGURE 6.6: EXAMPLE MASTER HEAT PROFILE

Figure 6.7 illustrates how the newly separated power and heat demands compare to the total electricity demand used previously. It shows that the heat demand is only a small amount of the total demand, and that the total remains almost identical.

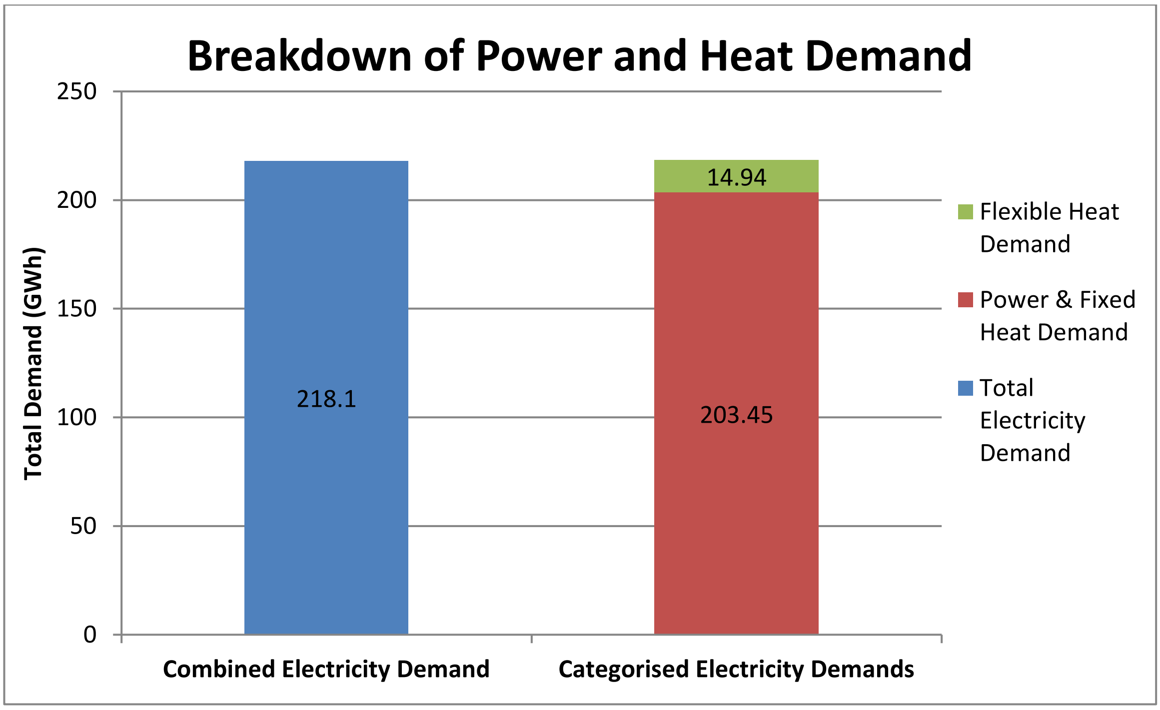

FIGURE 6.7: BREAKDOWN OF POWER AND HEAT DEMANDS

The total electricity used for heating is likely to be considerably higher than what has been captured in this storage heater consumption proxy. It is likely that a significant amount of electric heating consumption will come from storage heater boost functionalities, and from direct resistive heating appliances. However, this heat demand is a useful indication for the amount of electrical heating demand which can be flexible.

6.6.2 Investment Optimisation Model

To represent smart storage heaters an extra demand technology function has been introduced to enable the heat and power technologies to be distinguished. Figure 6.8 illustrates the model design with the adaptation for smart storage heaters. The 'T_Elec_Heat' represents the smart storage heater technology and 'T_Elec_Power', all the other electricity consuming technologies. Welsch et al (2012a) adapted the core OSeMOSYS code to allow for demand shifting and this functionality to delay or advance demand by a number of time slices is reproduced exactly in this study. The amount of the demand which can be flexibly met is defined in the model, in this case 100% of the 'Elec_Heat' demand is flexible. In this study the storage heaters have been modelled as demand which can be advanced by a time slice, from consuming in the winter day time bracket when the heat is required, to the winter night time bracket if that lowers the overall system cost, i.e. from utilising generation with a lower marginal cost, such as wind. This method is similar to the demand technologies met by night time charging in the MAKAL model (Loulou et al. 2004).

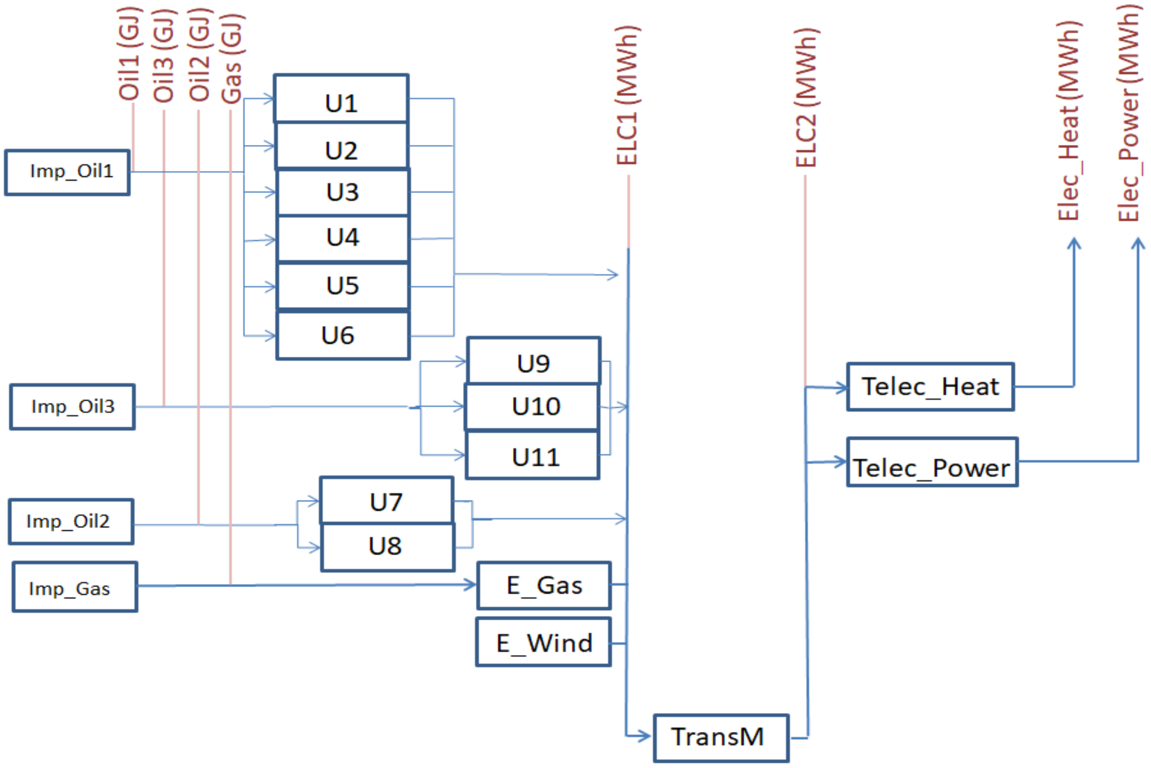

FIGURE 6.8: INVESTMENT OPTIMISATION MODEL WITH STORAGE HEATERS

The additional OSeMOSYS code, taken from the Welsch et al (2012b) study provides the option to include a cost associated with each time slice a demand is shifted. This cost can be a proxy for the inconvenience of shifting demand and covers the price a utility might pay a customer to provide flexibility, storage losses and any other additional costs as proposed by Welsch et al (2012a). However it does not include the storage loss in terms of energy, only the monetary value. In the case of a storage heater, energy is lost in the form of heat whilst it is storing energy, therefore the longer it is storing the energy, the greater the total energy requirement is. In this study no extra cost has been applied and therefore the system cost should be impacted only by a change in unit generation distribution. Table 6.8 documents the additional inputs required for the adaptation for smart storage heaters and the data source.

TABLE 6.8: ADDITIONAL INPUTS REQUIRED FOR SMART STORAGE HEATERS - INVESTMENT OPTIMISATION MODEL

Data Type	Reference
Total Power Demand (MWh) & proportion per time slice (%)	Created through proxy described in 6.4.1
Total Heat Demand (MWh) & proportion per time slice (%)	Created through proxy described in 6.4.1
Efficiency of the Storage Heater	Assumed 100%

Figure 6.9 plots the generation from each unit for the two scenarios, with traditional storage heaters and then with smart storage heaters for the reference year, 2014/15. It shows that the distribution remains broadly the same with traditional and smart storage heaters.

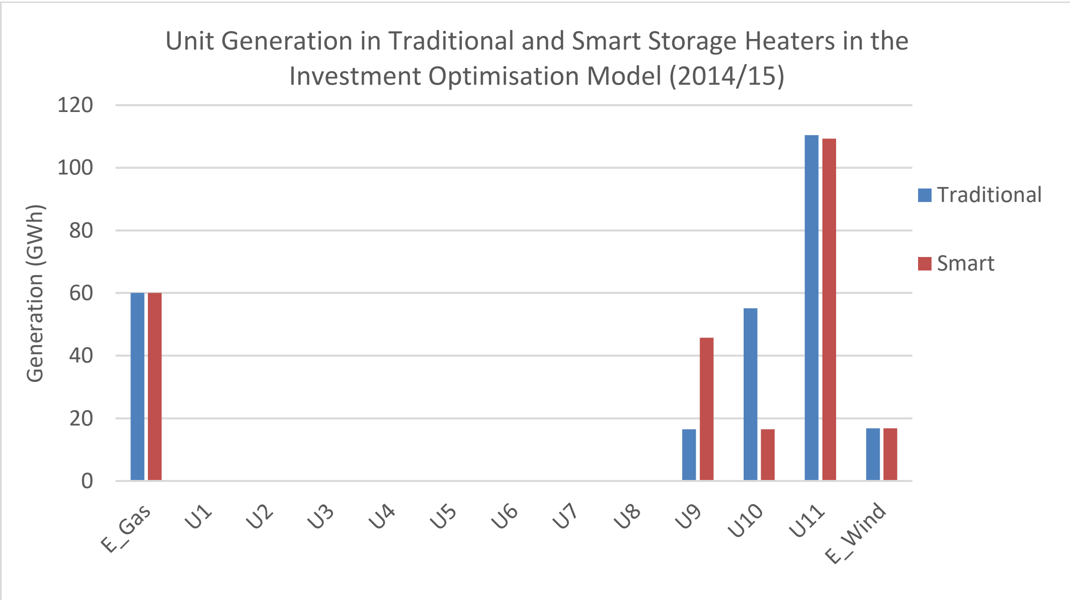

FIGURE 6.9: UNIT GENERATION IN TRADITIONAL AND SMART STORAGE HEATERS IN THE INVESTMENT OPTIMISATION MODEL

Figure 6.10, Figure 6.11 and **Error! Reference source not found.** show the distribution of generation across the seasonal time slices in three scenarios. In these figures the following shorthand is used: summer day, SD; summer nights, SN; winter day, WD; winter night, WN. Figure 6.10 shows the seasonal generation with traditional storage heaters, this is using the total electricity demand which has current storage heater demand embedded in the consumption data. Figure 6.11 shows the seasonal generation with smart storage heaters which has been implemented through the method discussed above, where the heat demand can be flexible.

Error! Reference source not found. assumes there are no storage heaters and that heat demand had to be met when required so in the winter day time slice.

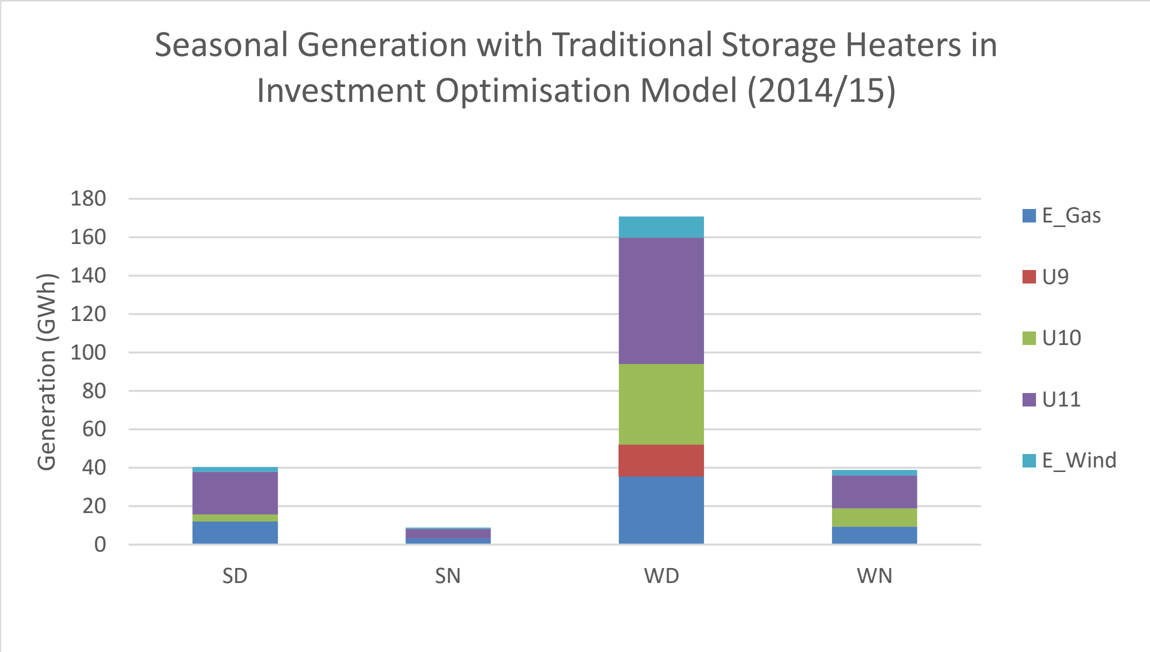

FIGURE 6.10: SEASONAL GENERATION WITH TRADITIONAL STORAGE HEATERS IN INVESTMENT OPTIMISATION MODEL

The smart storage heater and the traditional storage heater scenarios give the same result; the heat demand is met in the winter night time slice to be stored for the winter day when it is required.

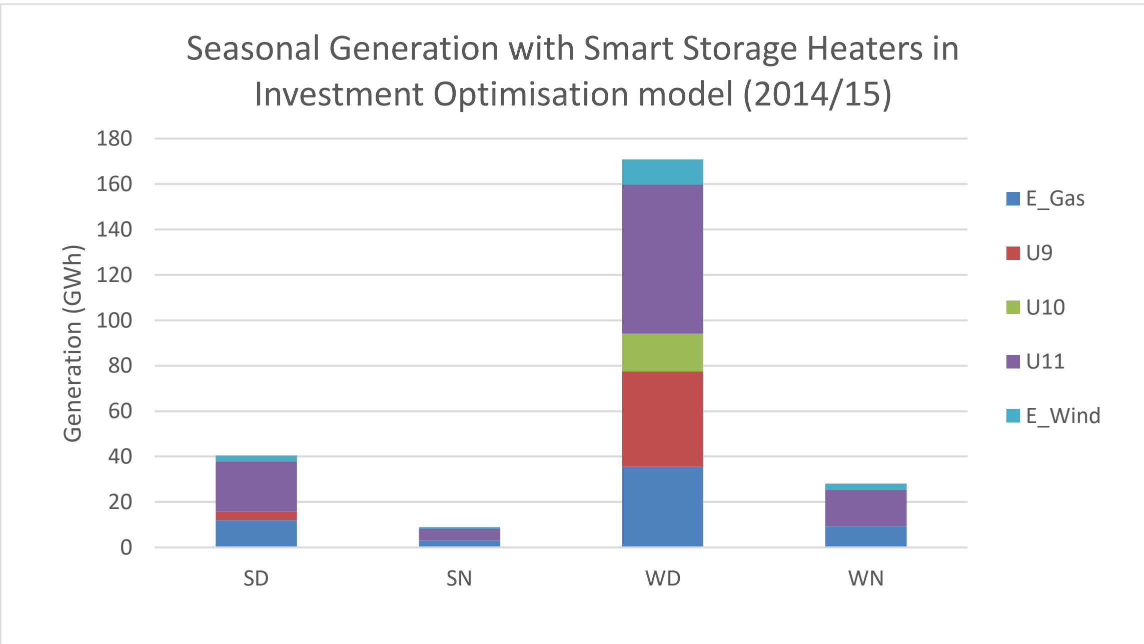

FIGURE 6.11: SEASONAL GENERATION WITH SMART STORAGE HEATERS IN INVESTMENT OPTIMISATION MODEL

The results also indicate that the cost of the system decreases by 3.5% with the addition of smart storage heaters, from £257.3M to £248.5M. This reflects both the operational and investment decisions which the model has taken. As discussed in Chapter 5, the solution seeks to build more wind as it is the cheapest generation source. Grid stability constraints need to be added to this model to ensure that this remains at a level which is operationally possible for Shetland.

6.6.3 Time Step Balancing Model

The storage heater technology is, from a modelling perspective, quite similar to that of a battery. It has similar constraints in terms of power flow and total capacity, and it aims to charge when there is excess supply arising from wind curtailment; however its capability to discharge electricity onto the system differs. The storage heater's discharge profile is fixed based on customers heat demand therefore the model requires power and heat demands as separate time series vectors. With a fixed discharge profile the model only has to calculate the optimal time to charge. This means it requires an element of foresight in order to charge in advance of when that demand occurs. It is therefore not possible to include using the native EnergyPLAN methodology which only has foresight of the previous time step. A daily optimisation algorithm has been created for this study and added to the Time Step Balancing model to add this capability. The optimisation function aims to optimise the charging of the battery in order to meet the fixed discharge profile and has visibility over a single day. This adaptation has added a hybrid function to this model; however it has not impacted on the core model method.

In this example the variable being minimised is the excess supply to ensure that this is fully utilised before requiring additional supply from fossil fuel plant. The constraints are that:

$$\sum_{t=0}^{t} S_{CHARGE} = \sum_{t=0}^{t} D_H \qquad (6.10)$$

$$S_{CHARGE}(t) \leq P_{HS}(t) \qquad (6.11)$$

The heat demand is met through optimising the charging schedule of the storage heating capacity across each day within the year. The resulting demand is met from fossil fuel plant on the system.

Table 6.9 shows that the added flexibility of the smart storage heaters has resulted in an increase in the total fossil fuel generation required over the year 2014/15 and in the peak fossil fuel generation.

TABLE 6.9: IMPACT OF SMART STORAGE HEATERS ON FOSSIL FUEL GENERATION IN TIME STEP BALANCING MODEL

	Total Fossil Fuel Generation (GWh)	**Peak Generation (MW)**
Traditional Storage Heater	201.3	42.6
Smart Storage Heater	201.0	53.4

Figure 6.12 plots the overall demand profile for the system with traditional and with smart storage heaters over a seven day period to enable a comparison of the shape. It demonstrated that the demand profile with the smart storage heaters follows the actual power and heat demand curve and does not find a more optimal charging profile for the smart storage heaters. This is illustrated by the high demand levels in the day time when both the power and heat demands are higher. The system with the traditional storage heaters charge the heaters in the night time hours resulting is a demand profile which is higher at night and lower in the day. This result is consistent with the model’s aim of reducing wind curtailment. With no wind to curtail there is no incentive for the smart storage heaters to store ahead of demand.

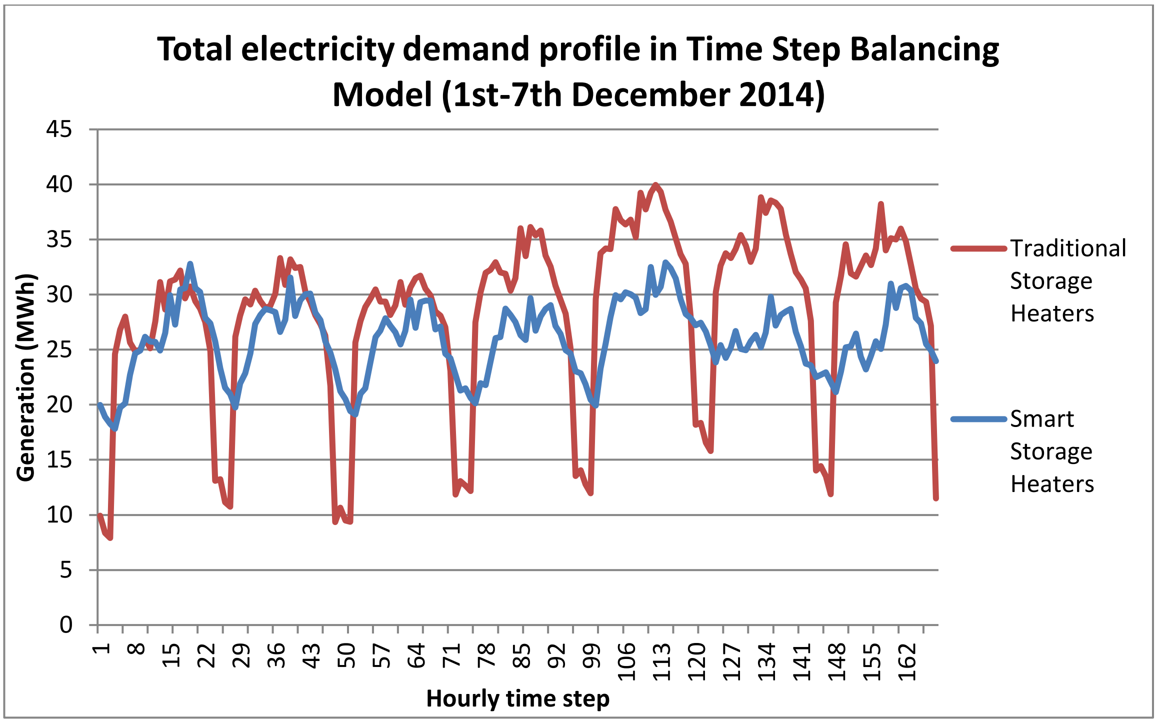

FIGURE 6.12: 7 DAY STORAGE HEATING CHARGING PROFILES WITH SMART STORAGE HEATER

As the operational cost is not included within the balancing calculation the levelling of demand to reduce peak generation is not incentivised. If the cost was calculated based on a merit order and individual units from the total fossil fuel required at each time step the costs of the system would have increased.

This result shows a less optimal operation of storage heaters than the traditional night time charging storage heaters due to the over simplistic balancing calculation used in this model. The inclusion of cost is essential to reflect the full potential of smart storage heaters to support the system. In order to better understand how smart storage heaters can help increase renewable penetration using the native model aim, the model can be run with multiple wind capacity scenarios, as illustrated in section 6.4.2 for the battery technology.

6.6.4 Unit Commitment/ Economic Dispatch

As with the battery, the storage heater charging profile is calculated in the UC part of the model using a method comparable to the Time Step Balancing Model. The total electricity demand is split into half hourly power demand and half hourly heat demand, using the method discussed in section 6.4.1. The heat demand is what has to be met by the storage heaters and therefore the storage heaters must have charged enough to meet the demand in a given time step. The model optimises the charge profile of the heater to reduce cost in order to meet this pre-defined heat demand. The user can specify the number of power levels the storage heater can take, as demonstrated in the battery method.

$$min_x(f^t x) \ subject \ to \begin{cases} x(t) \in Z \\ Gmax(u).x(t) \geq -(d_{POWER}(t) + r(t)) \\ Gmin(u).x(t) \geq d(t) \\ 0 \ \leq x(t) \leq 1 \\ E_{SH}(t) = \sum_{t=0}^{t} p_{SH}(t) - \sum_{t=0}^{t} d_{HEAT}(t) \\ p_{SH} \leq P_{SH} \end{cases} \qquad (6.12)$$

Where,

$$f = (C_{AV}(u) \,. x(t)) + C_{starts}(u) \qquad (5.5)$$

$d_{POWER} = Power \ demand \ (MW)$
$p_{SH} = Power \ state \ of \ storage \ heaters \ (MW)$
$d_{HEAT} = Heat \ demand \ (MW)$

The power demand and the storage heater charging profile is added together to create a total electricity demand for the power and optimal storage heater operation. The ED algorithm calculates the resulting generation from each unit scheduled in the UC solution to meet this combined demand.

$$d_{ED}(t) = d_P(t) - p_{SH}(t) \qquad (6.13)$$

Where,

$d_{ED} = Demand\ to\ be\ met\ in\ the\ ED\ calculation\ (MW)$

$d_P = Power\ Demand\ (MW)$

As with the battery this added significant computational requirements and therefore only seven days were run in a given scenario to compare the insights.

The number of power levels for the storage heaters was altered to understand the impact of this assumption and the level at which storage heaters would charge optimally. This was achieved by comparing the storage heater charging profile for a number of power level scenarios to see when the profile was no longer affected.

Figure 6.13 plots the smart storage heater profiles over a single day for a number of power level scenarios. It shows that when eight or more power levels are present the basic trend regarding when the storage heater charges remains relatively unchanged; however differences in the magnitude of the profile and the number of hours which they charge for remain. The charging power continues to change as the number of power levels increase, but as the peak charging level does not change from 16 to 32 levels and the variations are smaller, 32 levels was used for the remainder of the analysis. Again, a negative power value indicates the storage heater is charging.

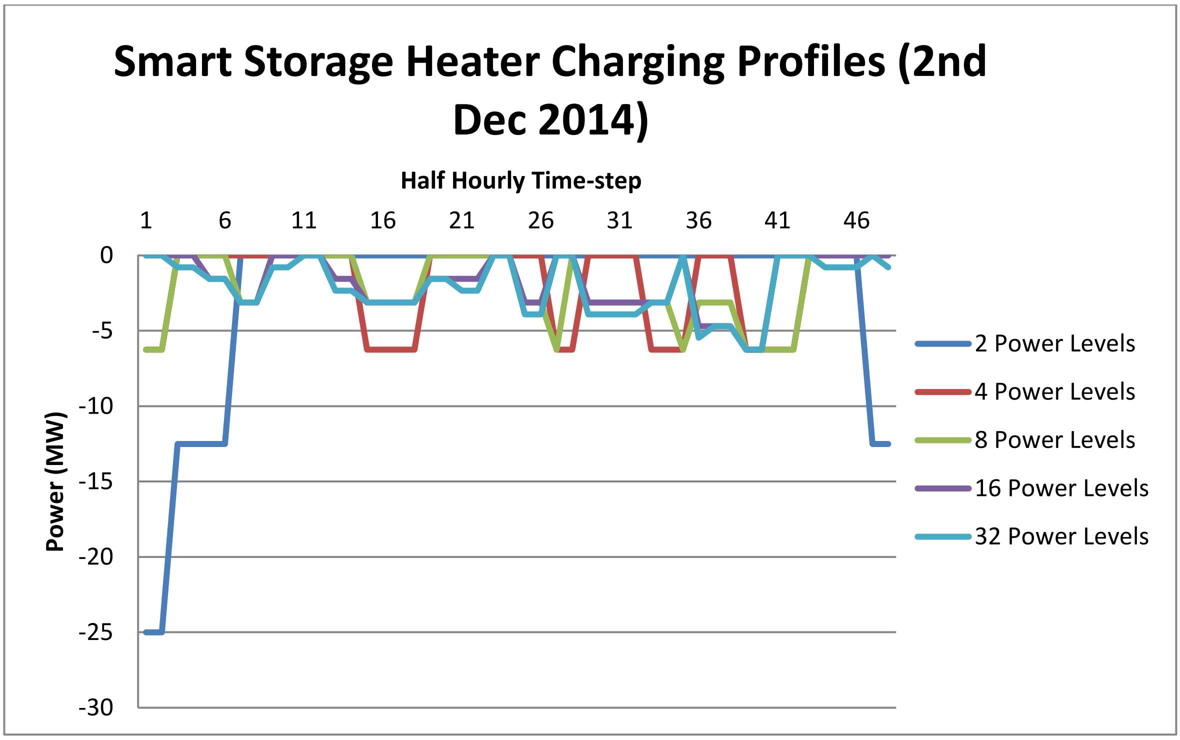

FIGURE 6.13: SMART STORAGE HEATER CHARGING PROFILES IN UC/ED

The 32 power level scenario was run over a seven day time horizon, from 1st to 7th December, and the impact of the additional flexibility of the storage heaters was analysed.

Table 6.10 shows that the smart storage heater capability has resulted in a decrease in the overall amount of fossil fuel generation required, and a decrease in the system cost in the seven day period. The peak fossil fuel generation level has decreased very slightly.

TABLE 6.10: IMPACT OF STORAGE HEATERS ON TOTAL AND PEAK GENERATION (1ST-7TH DECEMBER 2014)

	Fossil Fuel Generation (MWh)	Peak Generation (MW)	Cost (£M)
Traditional Storage Heaters	4351	33.6	1.20
Smart Storage Heaters	4143	33.5	1.15

Figure 6.14 shows the generation from each unit and how this changes when using traditional or smart storage heaters. It shows an overall reduction in the generation from the more expensive units U1 to U6, although there is some change in distribution between units. U6 is not used at all in the smart storage heater scenario highlighting the potential to reduce installed capacity. It also shows that some generation shifted between units U9 and U10 but as explained previously, these units have the same costs therefore are interchangeable and scheduled to optimise start-up costs.

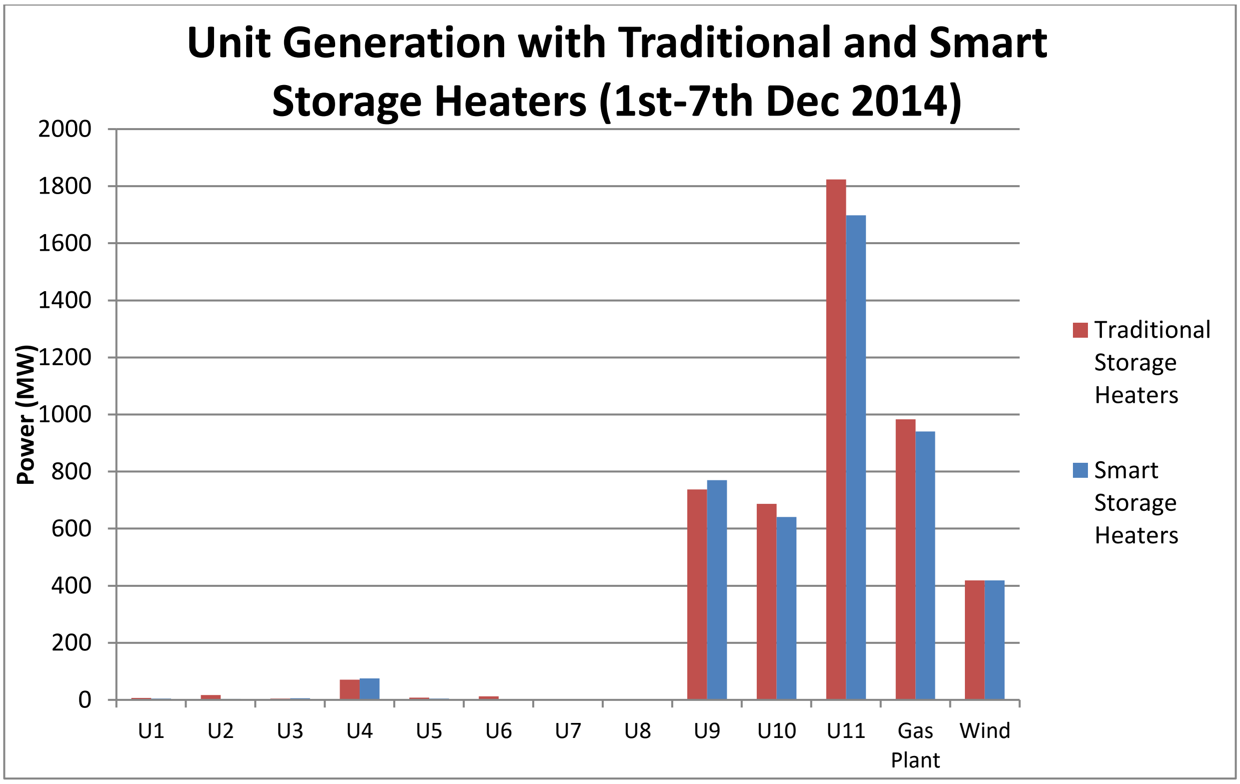

FIGURE 6.14: COMPARISON BETWEEN UNIT GENERATION WITH TRADITIONAL AND SMART STORAGE HEATERS IN UC/ED MODEL (1ST -7TH DECEMBER 2014)

COMPARISON WITH PLEXOS

The smart storage heater scenario was also run in PLEXOS to see the impact over a full year. PLEXOS is a commercial tool which does not allow users to change the source code, therefore an existing technology function is used as a proxy for the storage heaters. As it is a power system model there are many unit types and with different characteristics available to use. In this model, the pumped storage technology node has been chosen as a proxy for the storage heaters. The pumped storage unit is set up to charge from the main grid but to discharge, with a forced profile representing the heating demand, to a new heating grid. This allows a fixed heating demand to be incorporated through the fixed discharge profile but as heat not as electricity like a traditional pumped storage technology. Losses are accounted for with a user inputted heat discharge rate, proportional to the level of storage in the unit; however this loss can be used towards meeting demand when the discharging occurs at the same time.

Table 6.11 shows that in PLEXOS the fossil fuel generation required is reduced with the smart storage heaters. The peak generation does however increase slightly, as was illustrated in the UC/ED results.

TABLE 6.11: IMPACT OF SMART STORAGE HEATERS IN PLEXOS

	Total Fossil Fuel Generation (GWh)	**Peak Generation (MW)**
Traditional Storage Heaters	201.3	43.7
Smart Storage Heaters	194.2	43.9

The charging profile output was compared between the UC/ED and the PLEXOS model, illustrated in Figure 6.15 Figure 6.15: Comparison Between Smart Storage Heater Charging Profile in UC/ED and PLEXOS It shows that the charging profile follows a similar trend with the UC/ED results although PLEXOS chooses to charge earlier in the night time than the UC/ED.

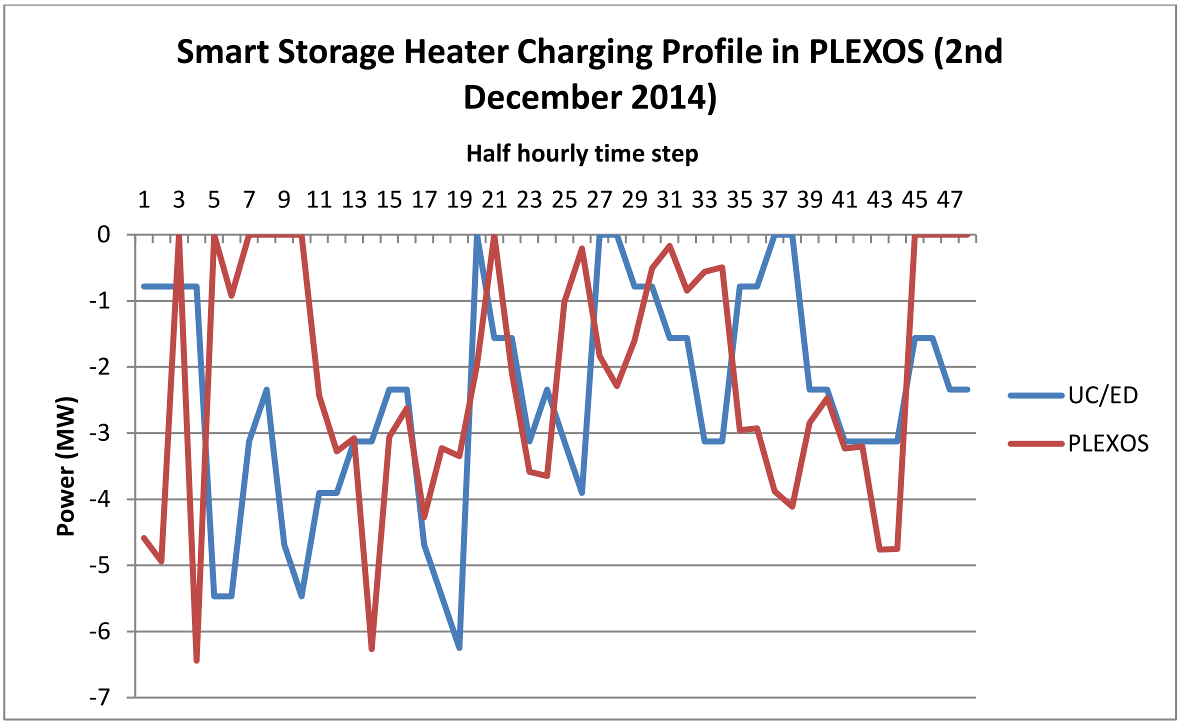

FIGURE 6.15: COMPARISON BETWEEN SMART STORAGE HEATER CHARGING PROFILE IN UC/ED AND PLEXOS

The main differences between the smart storage set up in PLEXOS compared to the UC/ED model built for this study are that heat losses are present in PLEXOS and that the storage heating profile is determined in the UC calculation in the UC/ED whereas it is understood they happen in the same calculation in the PLEXOS model.

6.7 Impact of Storage Heaters on Shetland

The model types consider storage heaters in two main ways. In the case of the Investment Optimisation model the storage heaters are treated as a flexible demand which can be shifted, whereas the UC/ED and Time Step Balancing model consider the storage heaters in the same way as a battery, with a fixed discharge profile.

The Investment Optimisation model found that the smart storage heaters are optimally charged in the night time slice as the traditional storage heaters currently do. As the time slices are aggregated the Investment Optimisation Model cannot identify how the smart and traditional storage heaters vary in their exact charging profile and how they could help manage the intermittency of wind and demand. It does provide an indication of the number of units required to run a system with this technology and that it can reduce the need for some more expensive units by reducing the winter day time demand. As demonstrated in Chapter 5, this model type may mask the need for peaking units.

The Time Step Balancing model outputs a solution for the smart storage heaters which is less optimal than the traditional night storage scenario. This is because it does not consider reducing peak demand or cost as a driver, only reducing wind curtailment. As there is no wind curtailment in the 2014/15 scenario, the heat demand is met by the storage heater at the time of demand and not stored at a more optimal time of day. Consideration of the economics of the system is required to provide a more optimal and realistic charging profile

In the seven day example run in the UC/ED model, the peak generation was also increased as a result of the flexible storage heaters. This suggests a cheaper operational schedule was to maximise the units which were scheduled whilst they were on, creating a larger overall peak in this scenario.

6.8 Discussion

The three energy models identified in this study, excluding the Econometric Demand Forecasting model, are examples of those used to look at system level problems, and therefore consider generation in more detail than demand. Despite this similarity, these models are all different in their design and adapted to model the smart storage heater in different ways.

The main difference preventing direct comparison between the models is the way the Investment Optimisation model uses average time slices to consider both demand and generation, including wind output. This can be seen to contribute to a significant reduction in accuracy as it only models typical days and cannot consider extremes on a more granular time level. For instance when modelling the storage heaters the model represents this by shifting between time slices, so from day to night. In reality there could be demand shifting occurring solely within the night hours which are too detailed for the Investment Optimisation model to recognise. This aggregation also means that it cannot consider chronology and therefore the state of charge and the heat losses of the storage heating technologies. This will become increasingly more of a problem as a greater number of flexible technologies are added to the electricity system. This model could be improved by adding in more time slices to account for the daily peaks and troughs in more detail.

The difference between the Time Step Balancing model and the UC/ED model is that the former minimises the objective function within an hour and has no foresight of future time steps, only the result of the previous time step, whereas the UC/ED has visibility across all time steps. This difference in approach was maintained for the addition of the battery, but for the smart storage heater an optimisation function was added which provided foresight across a single day. The time series nature of the Time Step Balancing Model and the UC/ED model means that there is potential for visibility of previous store states. This visibility is important when considering the actual operation of a storage technology and to see the impact of extremes, both of which are missed if modelled purely in an Investment Optimisation model.

The Time Step Balancing model and the UC/ED model are run at hourly and half hourly resolutions respectively. They could be run at a finer resolution to illustrate additional impacts, such as the operation of storage heaters as a result of plant characteristics which occur at a sub 30 minute resolution (Deane et al. 2014).

The Time Step Balancing Model has the advantage of very quick processing times which means that numerous scenarios can be run to help understand the impact of different variables to understand which can add value to the system. It also has the flexibility to make certain algorithms more complex depending on the focus of the model, such as the storage heating and battery algorithm developed for this model. Its main flaw is the lack of cost representation; however a version of EnergyPLAN is available which considers the economic drivers. This may help improve the model when considering the utilisation of flexible technologies and the consequence on the market. It also does not consider units in isolation, however an amendment to implement a post calculation merit order would provide a unit generation solution, although this would not be included in the core calculation. All models assume a central system and storage operator and do not account for a management strategy which aims to maximise revenues from the storage technology.

The UC/ED model was unable to run for the full 12 month reference year, 2014/15, due to the high model running times. This highlighted the added computation complexity required with the addition of both the battery and the storage heater. This insight backs up the claim in a report by CSE about the Government demand side capability, that complex programming tools are required to model DSR (Centre for Sustainable Energy 2014). This model type could be simplified by altering the battery operation to after the UC and ED solution has been calculated and then the potential impact of the battery analysed.

6.8.1 Real Demand Sensitivity

Another key challenge for the smart storage heater scenarios was the availability of heat demand data. With the current time slice resolution of the Investment Optimisation model it is unlikely to make a difference to the storage heater scheduling. However, in the Time Step Balancing and UC/ED models which require time series data an inaccurate demand data set could make a significant difference to the output.

Understanding the demand instead of the consumption is important when considering the potential to shift or reduce demand. Using the example of electric cars, the demand is when a customer wants to drive, both in terms of the distance and the time of the journey. The consumption however, is when that car is filled with fuel. Historically that has been when a customer has gone to a petrol station, but for electric cars this consumption pattern is expected to frequently occur at night. The filling up of car with petrol or electricity only needs to occur to ensure that future demand can be met, so understanding the demand provides the ability to calculate the potential charging times. For electric storage heaters the method is similar. The demand is determined by the temperature and time the customer wants a room, the consumption arises when the heaters are charged from the grid. The main difference between the heater and the car is that the heater is in a fixed position and therefore could theoretically be charged at any time, whereas the car must be plugged in to draw power.

Figure 6.6: Example Master Heat Profile illustrates the heat profile used for the Shetland case study. This was based on the output from a previous study and therefore is unlikely to be representative of the true aggregate heat profile for Shetland. To investigate the impact of this assumption on the model results, the models have been re-run twice using adjusted heat profiles. These profiles represent extreme cases; a flat profile where demand is evenly spread across all hours of the day and a spiked profile where all the demand is condensed to 08:00 - 09:00 and 18:00 – 19:00. This is illustrated in Figure 6.16. Whilst only two examples are considered here, there are other sensitivities which could be considered, for example the difference between days of the week and when in the day the peak occurs.

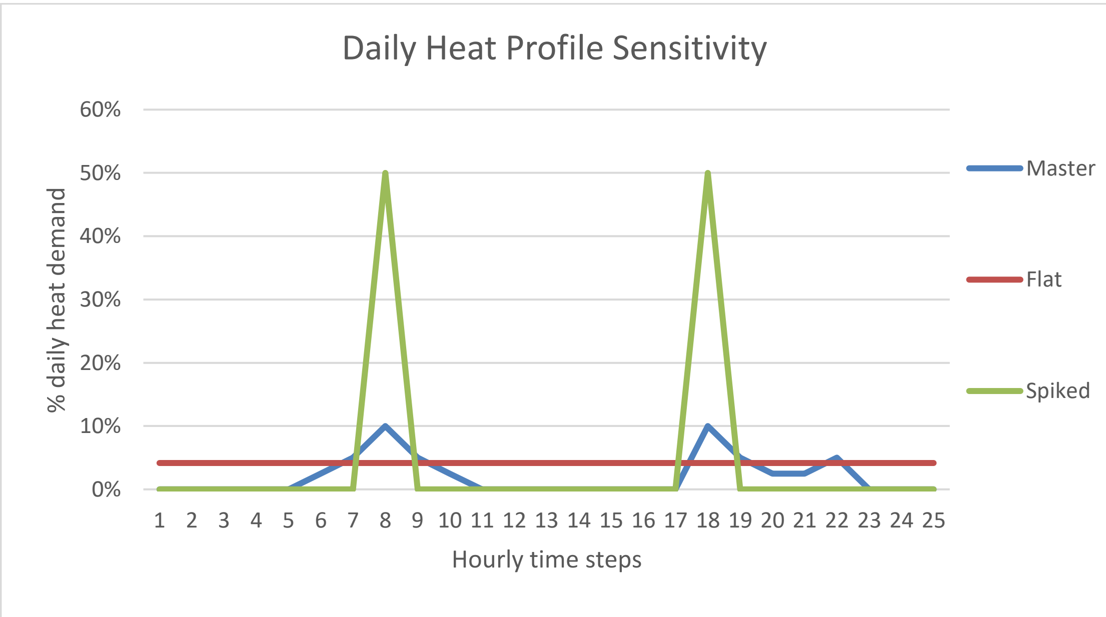

FIGURE 6.16: HEAT DEMAND PROFILES FOR SENSITIVITY ANALYSIS

In the instance of the Shetland case study the level of flexible heat demand is relatively low and therefore it is not expected that the cost and scheduling of generation will be very sensitive to the demand. Therefore the sensitivity analysis has also been run for all demand profiles, where the daily flexible heat demand is twice as high.

Of the three models analysed above only the Time Step Balancing tool and the UC/ED tool will be affected by the change in the daily profile as the Investment Optimisation tool does not consider such a high level of data resolution.

Figure 6.17 shows the impact that the different heat demand profile has on the generation output from each unit in the UC/ED model. The trend remains constant however there is some variation, particularly with the smaller units, however the generation is minimal from these. These results are just for a seven day period, therefore the impact across the year would have greater significance. The proportional difference across units as a result of having twice the level of heat demand was not significant across the profiles.

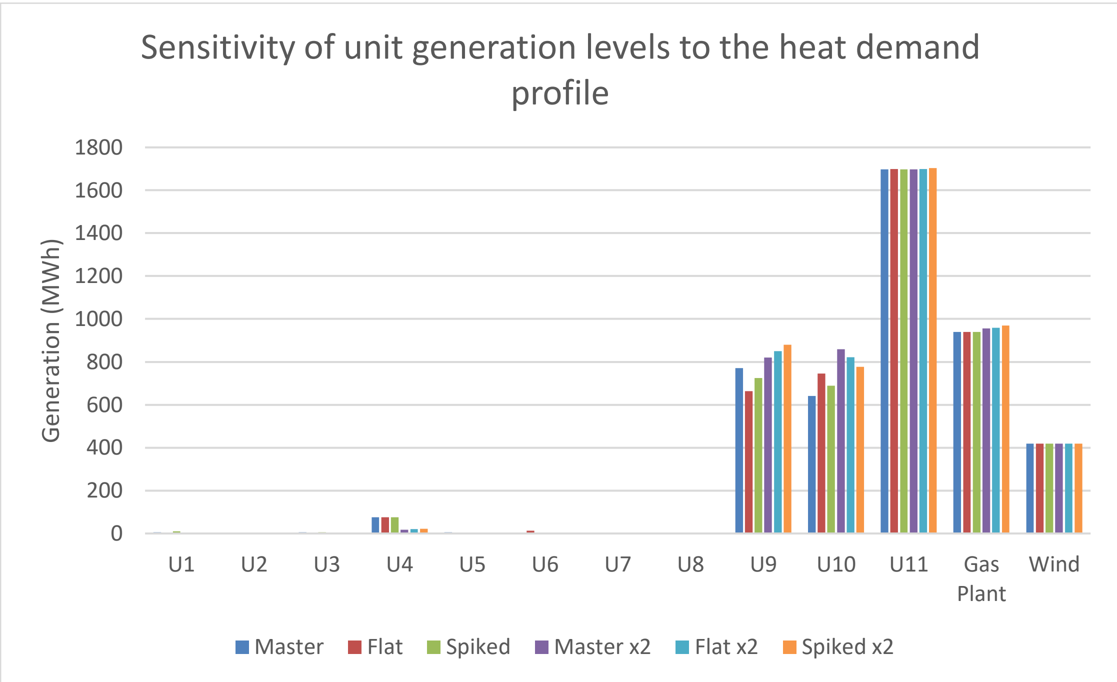

FIGURE 6.17: SENSITIVITY OF UNIT GENERATION IN UC/ED MODEL

What is not clear from the graph due the scale is that for the scenarios where the daily flexible heat demand remained the same, four of the units U1-U6 would be used, however for the scenarios with double the daily flexible heat demand, only U4 was scheduled and generating. This has an impact on the peak demand. Table 6.12 shows that in this seven day period the scenarios with increased demand have lower peak generation. The peak was also higher for the extreme scenarios than the master profile.

TABLE 6.12: SENSITIVITY OF PEAK GENERATION LEVEL IN UC/ED MODEL

Peak Power (MW)	Current demand	Double demand
Master	33.54	33.73
Flat	37.01	33.77
Spiked	37.05	33.77

As the Time Step Balancing tool only has one cost per plant type the change in generation levels did not impact on the total system cost model across the different scenarios. Table 6.13 shows that the peak generation varies considerably by profile. The flat profile provided a lower peak generation level than the master and the spiked in a larger peak generation level. The spiked demand shape also resulted in a very small level of wind being constrained off. The results show that the impact on the peak generation from increasing demand is not as significant as the shape. This is different to the trend seen in the UC/ED model, however the time period and the method are different between the models.

TABLE 6.13: SENSITIVITY OF PEAK GENERATION IN TIME STEP BALANCING TOOL

Peak Generation (MW)	Current demand	Double demand
Master	60.43	79.7
Flat	46.6	50.6
Spiked	82	82

The results from both models show that the impact of the demand profile does have an impact on units required to operate the system and the resulting dispatch and system cost, particularly when looking across a full year.

6.8.2 Suitability to Provide Insight to Thesis Questions

Table 6.14 illustrates the insight that each model type could provide to each of the industry questions following the adaptations. This can be compared with Table 5.13 in Chapter 5.

TABLE 6.14: IMPACT OF ADAPTATIONS TO PROVIDE INSIGHT TO INDUSTRY QUESTIONS

Key
Good representation
Some representation
Poor representation
Existing capabilities present which could be explored

Industry questions \ Model type	Investment Optimisation	Time Step Balancing	UC/ED	Econometric Demand Forecasting
What system benefits can electricity storage provide?	Poor representation	Good representation	Good representation	Poor representation
What effect will the increase in distributed level generation have on the system?	Poor representation	Poor representation	Poor representation	Poor representation
What is the effect of weather based renewables on the system	Poor representation	Good representation	Good representation	Poor representation
What is the future for heat going to look like and what impact will that have on the electricity system?	Some representation	Good representation	Good representation	Existing capabilities present which could be explored

The Time Step Balancing model and UC/ED models have been adapted to consider battery storage resulting in a much improved representation. The Time Step Balancing model has demonstrated its ability to consider the impact a battery could have on renewable penetration. However, it needs further adaptations to consider other battery operational strategies, such as the economic benefit. The UC/ED model has displayed the benefit a battery can have in improving the operational strategy of the generating units. It could be improved further with more constraints for example on the number of cycles it can achieve in a day.

The adaptations made in this chapter have not resulted in any additional benefit to understanding the effect of distributed generation or renewable generation. The three system models have all been adapted to consider smart electricity storage heating technology. The Investment Optimisation model is able to show the impact of electric heat demand which is shifted by a time slice. This model type can consider other fuel types therefore this attribute is not restricted to electric heating. The Time Step Balancing model and the UC/ED models have demonstrated their ability to consider electric heat storage but this is restricted to electric heating technologies. No adaptations have been made to the Econometric Demand Forecasting model, however the learnings from the creation of the heat demand proxy has illustrated potential benefit in creating individual models to forecast heat demand and power demand. This is likely to be restricted due to data availability issues.

6.9 Chapter Summary

This chapter has explored the capability of the identified model types to adapt to model the battery and the smart storage heaters present on Shetland. The adaptations resulted in an improved capability and understanding of how the model types can provide insight to the industry questions. This meets Objective 4 of this research which is to examine the strengths and weaknesses of the core model types.

Significant additional complexity was required to include both battery storage and the smart storage heaters in the energy system models. This complexity resulted in increased computing time, however the value in the creation of the model provided an increased understanding of the interactions and impact of these technologies, and the strengths and limitations of the output.

Two modelling capabilities were identified as important to consider the battery and smart storage heater technologies. These were:

i. A representation of chronology and visibility across time steps, which is recognised as important for any storage or flexible technology.

ii. The ability to separate the electricity demand for heat and power individually. This is essential in order to demonstrate the flexibility potential of the heat demand met by the smart storage heaters.

There is challenge present in calculating real demand. This is a direct result of poor data availability of the consumption from individual demands and user behaviour. This challenge was highlighted in the interviews undertaken in Chapter 4. In the absence of better data this could be improved through the use of building physics models. Increase data availability would allow for improvements to the Econometric Demand Forecasting model to consider versions which consider power only and heat only and without distributed generation.

The operational strategy considered was demonstrated in this chapter to be important when understanding the insight which can be drawn from these model types. Operational strategies such as reducing wind curtailment or reducing system cost can result in different outputs therefore the purpose of the scenario needs to be considered. The models in their current form also do not consider the operational strategies of the technology owner. They consider a system where there is a central dispatcher and not where there are numerous agents making decisions with the aim to maximise their profits. The Time Step Balancing model has the potential to be further adapted to change its operational strategy, as illustrated by the different versions of the EnergyPLAN tool which it is based on.

7 DISCUSSION

Through the multi-disciplinary analysis presented in this thesis, a number of findings have emerged to assist modellers and their users. This includes recognition of modelling limitations and best practice principles to aid improved modelling and better interpretation of modelling insights.

7.1 RESEARCH OBJECTIVES

Due to the multiple approaches used for each objective and how the insights feed into one another, as illustrated in Figure 1.1, a single chapter of work does not relate specifically to one research objective. For this reason they are not discussed one by one in this chapter and instead key themes are pulled out from the research. The objective(s) which each theme contributed to is highlighted within each section. However, to illustrate that all of the objectives have been met, a summary of the key findings is summarised below:

Objective 1: Identify the range of energy system models being used and the previous classification approaches being applied, with particular regard to models used in relation to UK energy policy.

Chapters 2 and 3 analysed both academic and government literature to understand the range of modelling techniques and tools that are used, what theoretical assumptions they make and if they fit into clear model classes. It found that there is no universal classification system as a result of the complex landscape of techniques and terminologies that are used. This is discussed in Section 7.2. Chapter 3 reviewed what model types government used and found considerable overlap between the academic and government studies. This fed into the creation of the core model classes used in Objective 3.

Objective 2: Explore how the identified models are being operationalised for UK energy policy development and the role which model outputs have played in informing recent energy policy decisions.

The model classes used by Government were explored in Chapter 3. Chapter 4 built on this by interviewing energy sector stakeholders to understand how modelling insight is used in the policy making process. These findings are outlined in Section 7.5.

Objective 3: Identify relevant core model types and generate representative versions for the case study of Shetland.

Four core model classes were identified: Investment Optimisation, Time Step Balancing, Unit Commitment/Economic Dispatch and Econometric models. Section 7.2 describes these model classes in more detail. Representative versions of each of these model classes were recreated for Shetland in Chapter 5.

Objective 4: Examine the strengths and weaknesses of each model type in responding to a range of identified business questions.

Insight for Objective 4 came from Chapters 5 and 6. Through building of the representative models in Chapter 5, the difference in attributes such as chronology and temporal resolution were identified. These are discussed in Sections 7.5 and 7.7. Chapter 5 also highlighted some of the data assumption challenges, most notably for heat demand. Finally, through adapting the models to analyse the impact of flexibility and storage, Chapter 6 reviewed the suitability of the models to provide insight to the business questions. This is discussed in Section 7.9.

Objective 5: Advise the industry partner of opportunities to improve energy system capability, through enhancement or improved interpretation of existing tools, or through adopting new tools.

This is addressed in Section 7.10 and brings together the findings, most notably from Chapter 4 and Chapter 6 and provides recommendations to industry on how to improve existing capability and enhance the value from modelling activities.

7.2 TAXONOMY OF MODELS

To meet objective 1, chapters 2 and 3 reviewed the existing range of energy system models being used and previous classification attempts. It found that there is no standard taxonomy of energy system models. The literature showed that classifying models into groups depending on their method and purpose has been attempted by a number of studies; however a consensus has not been achieved. There are no agreed classification groups or universally applied terminology which can be used to describe different model types. The increased effort to hybridise models has had significant influence in this confusion of terminology. Hybrid models are gaining prominence as increasing computational power allows for ever more complex models. This coincides with new challenges emerging which require modelling. This study has identified a number of core model types which are seen as influential in the policy making environment. The identification of these core models contributes towards objective 3, these model types are listed below:

i. Investment Optimisation
ii. Unit Commitment/ Economic Dispatch (UC/ED)
iii. Time Step Balancing
iv. Econometric Demand Forecasting

The term ‘optimisation’ has been identified as a descriptor term which is being over used. The optimisation descriptor might be used differently depending on who is using it, for example a mathematician is likely to use it to describe a type of algorithm, whereas a policymaker would use it to describe a common model type. This thesis has defined one of the most common model types for long term energy system modelling and policy making as ‘Investment Optimisation’ models. These models are often referred to as simply ‘optimisation models.’ This could lead to confusion as some models may include an optimisation algorithm within a small section of their model, whilst others could use the term optimisation more generically, such as EnergyPLAN which uses the term to mean finding the best solution.

7.3 Value of Simple Models

The increasing number of modelling tools with added functionality and combined techniques creates an ever more confusing environment for model users. Increased hybridisation may provide increased value through their sophisticated methods, but the increased complexity creates further opportunity for errors to be made in either application or interpretation.

A number of participants interviewed in Chapter 4 thought that simple models which were easily understood and well communicated could be of more value than complex models when used for policymaking. This thesis has run analysis using a variety of levels of complexity when gathering insights to meet objectives 3 and 4. From a Time Step Balancing tool with aggregated plant information and basic balancing, to a basic UC/ED model built in Matlab, which considers all the units separately and various operational constraints through to PLEXOS. PLEXOS is a proprietary tool which requires significantly more variables than the UC/ED model built for this study and which uses a methodology that is obscured from the user. Despite the extra complexity of PLEXOS, the UC/ED and PLEXOS model displayed the same overall results and general trend in the unit dispatch.

Even the UC/ED toy model was run with significant technological detail due to the small number of units and plant. If this were scaled up to GB this would quickly become complex and significantly increase the computational power required. Instead it is likely that clusters of units of similar sizes and fuels would be created to reduce the complexity as used by Cebulla & Fitcher (2017).

Participants in the interviews in Chapter 4 highlighted the amount of insight gained from undertaking the modelling process itself. If models are more simplistic then more stakeholders can use the models themselves as opposed to outsourcing models to dedicated modellers to undertake on their behalf. It also means that the model itself is better understood by those who use it which means more insight can be derived. Simplistic results which are easily understood offer greater value to more stakeholders than complex results with no clear meaning. This was found in this study when modelling the UC/ED compared to the PLEXOS model. Uncertainties in certain outputs in the UC/ED model could be understood and errors identified, whereas in the PLEXOS model it was less clear if there was an error in the result. When considering the battery results produced by the UC/ED model it was possible to analyse why the battery has been overused, and discover that was due to the lack of a constraint on the number of daily storage cycles. This analysis would not have been possible with PLEXOS derived results. Another example of the same limitation of more complex models is the recognition of the need for a peak demand proxy in the Investment Optimisation model.

Policy papers only outline final costs or other figures. Simple models may allow greater learnings and improved ability to transfer and communicate that knowledge to stakeholders through easier conversation, which increases transparency. However this does not negate the value of complex and detailed models. It suggests considering what is important for the question being modelled, and identifying what can be simplified without significant detriment to the outputs, to allow for easily communication, resulting in more value.

7.4 Transparency and Investor Confidence

Transparency was mentioned by a number of participants in the interview process in Chapter 4. It was thought that there should be a greater effort to increase the transparency of the models. This would lead to greater confidence for industry and investors who need a degree of insight into the future in order to make investment decisions. This presents an opportunity for simpler models to be created, which are understood more clearly by stakeholders which may help increase confidence.

If investors have greater confidence in the trajectory of the GB energy system they are more likely to make the longer term investments and deploy the technologies that Government need to deliver on their own long term strategies. An understanding of the degree to which models play a part in Government decisions and future strategy assist with gaining policy certainty. It was widely agreed by the participants interviewed that Government have the correct range of models; however their knowledge about specific models used and the modelling landscape is weak. This may be partly due to the communication of the modelling activities by Government. There was a significant difference in the number of models found referenced in impact assessments and policy papers, 26, when compared with the number BEIS quoted as being actively used, 72. It was also thought by some participants that models did not have a key role in determining the policy direction, specifically in the case of big political decisions like Hinkley Point C and CCS investment decisions. This all creates significant uncertainty for investors as well as a reluctance to work with policy makers on long term decisions unless they are suitably de-risked. Views from stakeholders in Chapter 4 alongside the Government model review provided an innovative multi-disciplinary approach to gathering insight on how models are operationalised in UK energy policy to meet objective 2.

7.5 Insights from Models

Different model types, despite using different methods, can often contribute similar overarching results or head line figures however they can each provide different insights to the problem.

The core differences between the models which impacted on variations in the model outputs and their insights were:

- Temporal representation, i.e. time slices or time series.

- Level of individual unit operational characteristics, such as efficiencies and start-up costs.

The UC/ED model and the Time Step Balancing tool gave very similar results in terms of the output required from the power plants and the wind generation. This is because they both used actual time series data of demand and wind output. By contrast the Investment Optimisation model gave different results to the other two for both the overall generations from fossil fuel plant and from wind. This was due to the temporal representation and the lack of visibility of intermittency. It is concerning that this simplification can result in such a different outcome, especially when this is a model widely used for policy and long term strategies. It is important that this limitation is recognised not just by the model user but by the recipients of model's output. This understating by industry and other stakeholders required to make investments and operational decisions as a result need to be able to have an open discussion about the direction of that policy. This model type can include a peak demand constraint to ensure enough capacity is installed which is an important parameter for this model type. This is important for a system which has large differences in the maximum and minimum demand within a year, which is the case on Shetland.

The UC/ED model provides good insight into the units generating and the operational costs due to its increased temporal resolution and foresight across time steps, which allow for increased plant operating constraints. The cost which is calculated will be more accurate due to the extra cost and efficiency parameters.

The Time Step Balancing model has the advantage that it can run simulations very quickly, allowing for many scenarios to be run to compare insights. This allows for a greater understanding of the potential impacts of different technologies or deployment levels on other parts of the system. Its structure allows for adaptations which are useful to test new novel technologies. It also has the greatest potential to vary the operational strategy of the system, for example by reducing wind curtailment and minimising cost. It should be noted that these do not always represent an accurate representation of the market reality. This is because it does not consider cost and consequently individual plant type constraints in its method. Plant dispatch could be added post process if this is required and the system cost calculated.

Running multiple scenarios and comparing their outputs will provide useful insights. Chapter 4 identified the best practice principles which are important when considering what insights can be taken from scenario modelling exercises. These are:

- There are multiple objectives to consider when looking at our future energy system design. Be aware that the cheapest scenarios may not be the answer. One scenario may be slightly more expensive but be politically and/or behaviourally easier and therefore more likely to achieve results.

- Be alert to uncertainties. All scenarios are just a single scenario and not a prediction, therefore care must be taken when using these as an input for further modelling.

- It can be useful to compare the common strands of various scenarios created by different stakeholders. These trajectories and alignment of views can be useful to provide a guide for industry, but be aware of the scenario creation methodology.

- Compare the ranges and understand where there are significant uncertainties.

Be aware that what is currently ‘trendy’ often skews scenarios (for example electric vehicles or hydrogen).These insights provide useful insight into the strengths and weaknesses of the different model types in objective 4 as well as considerations for the industry partner in objective 5.

7.6 Data Assumptions

Any modelling activity requires a number of assumptions to be made. Assumptions exist in the method assumption embedded in the model and in the data inputs provided to run the model.

Understanding the nature of these assumptions along with their potential impact is important, as is implementing mitigating actions.

Different model types require different data inputs. Cost is an example of an input which all models require with varying levels of detail. The UC/ED model requires detailed costs and fuel usage per unit, including no load and incremental fuel use whereas the Investment Optimisation model required cost in an aggregated single value. The Time Step Balancing model does not consider cost in its calculation, however an average cost can be calculated based on the output. Efficiency data inputs are often estimated as little data is publicly available due to its commercially sensitive nature. Efficiencies also come in different forms depending on the method, for example incremental efficiency in the UC/ED model compared with an overall efficiency in the others. To ensure consistency, it is important that these data inputs are harmonised if using more than one model type.

Chapter 4 demonstrated that data challenges exist throughout the system, particularly at the household and distribution levels. This was supported by the challenge which occurred in the case study modelling in determining a heat demand profile. More data collection and monitoring needs to occur at household levels to understand usage as this is going to be required more frequently as we look at DSR opportunities and electrification of other energy uses. Studies which have monitored usage need to be required to share this data in a timely manner.

Increased data monitoring and sharing to increase data availability could have a positive effect on stakeholder confidence. Participants raised concerns about how the outputs were being interpreted and communicated particularly when certain input assumptions were seen to be inaccurate. Further work could be undertaken to understand the effect and sensitivity of different data assumptions across model types. Analysis of the sensitivity of different assumptions and the resolution of time series data would increase the understanding of the value of simple models. The insight informing this was contributed to from both from the learnings of creating the representative models and developed further when considering the data required to meet the industry question around DSM in Chapter 6, and is a key finding of objective 4.

7.7 Chronology/Foresight

A key attribute identified for objective 4 as being important in modelling both the battery and the smart storage heaters was chronology and visibility across time steps. The attribute of chronology ensures that it does not charge above its capacity limit, which is important for both the battery and the smart storage heaters. The foresight is an essential extra quality when considering the smart storage heaters as the model needs to know how much it needs to store in order to feed the heat demand in that day.

Only the time series models (the Time Step Balancing model and the UC/ED model) can consider chronology. In their core version, only the UC/ED model had the ability to consider foresight, but that was limited to operational constraints. All models required an element of foresight to be added to consider the battery and/or the smart storage heater.

The investment Optimisation required an amendment to consider shifting between the winter day and winter night time slices. The UC/ED model enhanced the existing functionality further to extend foresight to the battery and smart storage heater. The Time Step Balancing model required the greatest amendment which was to introduce an optimisation algorithm as an add-on to the model which adds a hybrid quality to the model. It does not change the core process of the model but adds an additional stand-alone calculation.

The Investment Optimisation model treated the smart storage heaters as a variable demand which could be shifted between time slice, from night to day. The UC/ED and Time Step Balancing models instead include the battery as a two way generator which can be utilised to reduce cost or renewable curtailment depend on the operational strategy of the model. The UC/ED and Time Step Balancing models treat the smart storage heaters as a battery with a forced discharge profile to meet heat demand. This extra detail was possible due to the time series representation available in these two models. The Investment Optimisation model cannot account for any peaks in demand or variability of supply, and therefore only provides an indication of the time slice which provides the cheapest solution; this is the same across the whole season. The lack of temporal resolution meant that it was unable to compare the differences between traditional night time storage heaters and those which charge more dynamically in response to market signals. The battery was not represented in this study.

The Time Step Balancing model, with its objective to reduce any wind curtailment, provides a useful tool to analyse the potential technologies which could help increase the renewable capacity; however it was unable to consider real system operation. A cost element was required in order to see how the battery and storage heaters would actually operate in the system and the impact they would have on allowing more wind to connect to the system. The UC/ED model demonstrates the value which these flexible technologies can have in increasing the operational efficiency of the unit scheduling. However this model requires additional operational constraints to allow the battery to run subject to a realistic management strategy for Shetland.

The smart storage heaters modelled in Chapter 6 could be representative of other types of flexibility like electric vehicles and demand turndown. Flexible technologies exhibit varying qualities, however many of the insights determined for the smart storage heaters are likely to be useful for other technologies.

7.8 Real Demand

Energy system models tend to include more detail on electricity generation than electricity demand. This was further verified when trying to include heat demand into the models to allow for the representation of smart storage heaters.

In order to model the smart storage heaters the actual demand for the heat was required at a half hourly and hourly resolutions for the Time Step Balancing and the UC/ED models respectively. This is because these models required actual heat demand to be represented in the model as a fixed discharge time series for the heaters which can charge flexibly to reduce the cost. This demand was not an existing data source that was available for Shetland. The demand data set for Shetland contains the total electricity consumption, which includes that used for power and heat. Even if decoupled into two datasets the heat consumption would not reveal the heat demand, instead it illustrates when the storage heaters are currently charging based on the existing radio tele-switching arrangements.

A proxy had to be created for both de coupling the heat from power and to determine a heat demand profile for households in Shetland. The proxy used was a result of the best data available. Greater monitoring of energy demands would aid this and make the proxy creation a more robust technique. However when considering household energy uses there could be an important role for the insights of building level modelling to increase the accuracy. The significance of this model type did not become apparent until Chapter 6.

This problem does not just represent a challenge for storage heaters but also for electric vehicles and other smart demand shifting opportunities. Understanding the actual demand for individual appliances and activities is essential to recognise its flexibility potential. This is a key insight identified as part of objective 4 which feeds into the industry recommendations in objective 5.

7.9 Capability for Industry Questions

Industry questions were identified as part of an SSE stakeholder engagement process at the outset of this project as were analysed in detail in chapter 5 to contribute to objective 4. They outline some future system challenges that SSE believes will be important going forward. How the identified models are able to provide insight to those questions is discussed and any additional capabilities which are required are highlighted.

What system benefits can electricity storage provide?

Two attributes are important for a model to provide useful insight into the value of electricity storage, as demonstrated with the battery case study for Shetland. These are chronology and visibility across time steps. Chronology is only possible in a model which uses a time series approach. This is important to ensure that the model does not over charge a battery. Both the UC/ED and Time Step Balancing models are able to recognise the current battery charge state when calculating its solution for a given time step. Models which exhibit foresight over time steps can provide useful insights into the optimal charging profile of the store. Of these two models only the UC/ED model had visibility across the time horizon to identify and optimal charging profile for the battery. The Time Step Balancing model only had visibility of the time step being calculated. However the Time Step Balancing model does have the ability to quickly run multiple scenarios to address the capability of a battery under different management strategies, in the example modelled this was to increase the penetration of renewable generation in a system. Adaptations could be made to the battery operation strategy to for example reduce cost, although it does not consider unit costs in much detail just at an aggregate system level. When interpreting the insights from the various scenarios the differences to the market operation needs to be considered. However, the increased complexity of the UC/ED model type does mean that considerably more time and computation power is required to run multiple scenarios and over time horizons.

The Investment Optimisation model could be adapted further to include the impact of electricity storage across time slices. Its average time slice representation of time means that it is unable to understand the impact of a battery over a daily cycle, but it could illustrate some advantages of seasonal storage where a high resolution is not required.

What effect will the increase in distributed level generation have on the system?

Distributed generation is a recognised challenge. Participants in the interview process highlighted the poor data availability regarding installations. This question was not specifically addressed for Shetland however further work could be done to explore how econometric demand models could account for this in more detail.

What is the effect of weather based renewables on the system?

Renewable generation is treated differently in each type of model. Investment Optimisation models use average capacity factors per time slice which levels out the peaks and troughs within a time slice. The need for a proxy for peak demand was identified in order to ensure there is enough fossil fuel capacity to meet demand. This capability could be expanded to account for low renewable generation. Increased time slice resolution will aid representation of renewable generation however will not be able to consider the intermittency of renewable generation in as much detail as models which use a time series approach.

The time series models (the Time Step Balancing model and the UC/ED model) can run multiple scenarios to see how different renewable outputs will affect the need for fossil fuel plant, and the impact on renewable penetration, depending on the model aim.

What is the future for heat going to look like, and what impact will that have on the electricity system?

In the absence of sufficient data on current heat demand, understanding the future heat demand is problematic. Separate heat and power demand data sets are required to identify the impact of a reduction of increase of electricity for heat demand. This can be achieved by increased data monitoring and increased insights from building level models.

Adaptations to the models that consider the impact of electrical heat demand which can be stored have been achieved in this study. The Investment Optimisation model considered the day time heat demand to be shifted to the night if optimal to do so, whereas the other models considered the smart storage heaters as a battery with a fixed discharge profile which corresponded to the heat demand. The models demonstrates that smart electric thermal storage heaters have a positive system impact when compared to those which have a fixed night time charging profile or charge when demand is needed. However the Investment Optimisation model alone cannot consider the added flexibility a smart storage heater has compared to a smart storage heater under the day and night time slices implemented.

7.9.1 Industry Dissemination

SSE wanted to understand how an increased modelling capability and understanding of the landscape could facilitate better dialogue with policymakers and allow them to explore their future role in the energy system. Objective 5 aimed to address this need. This thesis has provided increased clarity on the tools being used by Government and has identified the core model types to increase the knowledge of the energy system modelling context. The improved insight will help increase understanding of the modelling outputs published by Government and allow further probing by stakeholders. When considering the industry questions illustrated above, the insights and modelling advice enable the confidence to undertake a modelling activity and a guide to which model types and attributes might be most appropriate.

It has also allowed SSE to gain a greater understanding of the perceptions of energy system modelling within its organisation, which was achieved through an extending the list of questions where were used in the interview process when speaking to SSE colleagues. Internal dissemination activities will allow this information and the insight in the core thesis, to be transferred.

7.10 Limitations of the Research

7.10.1 Shetland as a Case Study

Shetland was chosen for this project due to its scale and suitability for this project. However, the differences between Shetland and GB must be considered before applying the same conclusions when using these model types for a GB system question. The computational challenges have already been cited in this chapter, if using a more sophisticated software these models could be enhanced to include more units, however it is likely that even so clusters and aggregation would need to occur and not include GB power stations at their individual units. The system operator has ancillary service contracts for flexibility services, there is no difference between the distribution network and transmission system operator.

Geographical differences are also important and in GB are more complex in terms of within network complexities. This was not considered for Shetland but in a GB system the geographical operational constraints would be interesting to incorporate to understand the impact that the inclusion has on energy system model outputs.

7.10.2 Lack of Heat Demand Data

As explained in Chapter 6, actual heat demand and the amount of the electricity demand which is consumed for heat is not known. The impact of the uncertainty of the heat demand profile was investigated in the sensitivity analysis. It shows that for the system of Shetland and level of heat demand modelled, the effect of the heat demand shape has not had an impact on the core learnings, however does result in variability in unit dispatch levels and peak generation levels and should be considered when modelling flexible electricity demands.

7.10.3 Restricting the Government Review to DECC/BEIS Models

Chapter 3 only considered models referenced in DECC/BEIS impact assessment and policy papers to review the model types used to inform policy. It is acknowledged in Section 3.4 that this could have resulted in models used by other governmental organisations or industry actors which informed policy not captured. However, it is likely to be a useful indication of the types of models used.

7.11 Future work

Further areas of work have been identified which could provide further insights to these and similar problems. These are:

- The insight gained from the smart storage heater modelling can have applications for electric vehicles and other smart appliances which also rely on an understanding of an individual demand profile. Work to identify the real demand for other technologies will help improve our understanding of how flexible technologies can add value to the energy system.
- This research has discussed the positive impact of a time series approach compared to an average time slice approach. A deeper understanding of the impact of the resolution of these approaches could further increase the insight these model types can provide. A greater understanding of the sensitivity of certain data assumptions will help maximise value of the model whilst keeping it as simple as possible. This will also allow for stakeholders to conduct a cost benefit analysis of additional computational power to run complex models.
- Four model types were analysed in this research which were identified through the review of models in academia and Government in Chapter 3. Throughout the thesis it became clear that building physics models may also be important in providing insight to some of the industry questions when used in collaboration with other models. This could be explored in greater detail.

8 CONCLUSIONS

The complex nature and the range of different types of energy models used in Government make them difficult for industry to utilise. This thesis sought *'To investigate the role which different energy system model types play in informing Government energy policy and the consequent options for a UK energy company to inform its strategic business planning.'* The work has shown that the changing energy landscape will make this even more of a challenge moving forwards as new technologies are deployed which exhibit smart and flexible functionalities.

A wide range and number of modelling tools are being used by industry, government and academia to examine various aspects of the energy system. These tools apply a range of core methods, which are commonly described by a confusing variety of terms. Despite previous researchers' best endeavours to establish a clear taxonomy of models, no such standard framework has emerged or settled. The increasing use of hybrid modelling approaches is serving to further this confusion. This thesis has surveyed the use of energy system models within UK Government and identified a number of tools that have been used to inform recent policy decisions. Stakeholder interviews have revealed concerns about poor transparency in the design and use of many of these tools. Stakeholders expressed a lack of understanding of the tools being used and therefore had little confidence in the modelling being undertaken.

Although there is a recognisable role for detailed and complex models to inform policy decisions, there is also an opportunity for Government to make greater use of simple models with a clearer narrative. This will help the energy community to understand decision making and engage with this process. The resulting increase in collaboration between energy system stakeholders will provide greater confidence to stakeholders.

This study has demonstrated the value that simple models can have in providing insight. The development of the representative, simple models, explored as part of objective 3, allowed greater clarity of underlying method assumptions and input parameters which resulted in additional understandings about the potential interactions and impacts of different scenarios. Simple models can more easily allow for multiple runs to compare more scenarios and operational strategies and therefore are likely to provide useful insights for industry for certain modelling activities.

Four core model types were identified as being particularly influential in policy development and were selected for closer scrutiny. To explore the basis of each model type, simplified versions were constructed, either using open source tools, or developing code from first principles. The models were then applied to case study island of Shetland and assessed for their ability to provide insight to a set of industry questions, defined at the project outset. Adaptations were required to the core model structure in order to model the flexible technologies on Shetland. In general the adaptations increased the capability.

These model types have fundamental differences in their underlying logic and the problems that they were originally developed to solve; however their application has broadened and different model types are commonly applied to address certain problems. Alongside the different theoretical framing, the models display some significant differences in configuration, whether they can work with high temporal resolution time series or just average time slices, the level of generation unit detail and the flexibility to consider different operational strategies. The model classes are summarised below:

- Investment Optimisation models typically consider seasonal time slices and run over long time horizons. They have particular value for forecasting future plant mix based on an optimal system operation.
- Time Step Balancing models balance demand and supply within each hour using time series inputs. They provide value when considering renewable generation projects to understand what technologies can help increase renewable penetration. This model type can also be adapted to consider different operational strategies.

- Unit Commitment/Economic Dispatch use a detailed understanding of power plant operation and operating constraints and cost to simulate the optimum unit dispatch under different scenarios, typically at 30 minute resolution.
- Econometric Demand models forecast future demand based on past correlation between variables such as day types and weather. Then typically run at yearly to daily resolution.

More than one model could provide insight to each question, illustrating the usefulness of using multiple models to gain increased insight to a modelling problem. No one model has been identified as more useful to industry than another however their strengths and weaknesses need to be considered when choosing one or more to provide insight to a problem. As a result industry should skill up in areas which they do not currently have capability in order to have access to a few models which are well understood, to increase the value from their modelling activities.

Objective 4 explored the strengths and weaknesses of these different models. It identified that the impact of average time slices in the Investment Optimisation model was the increased time horizon it could run over. It is able to grasp the core trend of units required, however the number of hours required from each generation was less accurate and there was a risk that peaking plant requirements were not visible. Whilst this model type provided a useful long time view, it needs to be run alongside more detailed models to ensure important system interactions are accounted for if being used to inform investment decisions.

The Time Step Balancing tool provided the greatest flexibility to consider different operator strategies. Whilst in this study the only strategy considered by the Time Step Balancing model was to minimise wind curtailment, it is possible to further adapt this model to run scenarios such as minimising system cost and to account for likely storage operator behaviour. This model type can run scenarios over a short time period to allow greater insights from a range of scenarios. It is important however to recognise that this model is suited to exploration as opposed to illustrating actual market behaviour due to its poor representation of generating unit characteristics. This may be why it appears to be neglected from Government modelling activities.

Two attribute themes emerged from exploring the initial model capabilities. In order to explore the industry problem set effectively, adaptations were required that allowed the models to better represent energy flexibility solutions and to better reflect the difference between heat and electricity demand.

i. The inclusion of chronology and visibility across time steps is essential in order to understand the impact of flexibility solutions such as batteries or smart technologies.

ii. Representing the underlying heat and power demands separately was required to be able to model the smart storage heaters. Understanding the customer demand for different activities accurately is important to understand the full value that flexible technologies can provide to the system. This study illustrated the lack of quality data and knowledge available to create a reliable input.

In terms of objective 5, to advise industry partners of opportunities, this project recommends that industry, in collaboration with government, prioritises activities which will increase availability of data to better understand the behaviour of its customers. This will result in more valuable data which can help assess system benefit for a wide range of DSR technologies.

Understanding real demand is important to understand the implications for DSR. This challenge is generally recognised by stakeholders, but was not considered as much by industry stakeholders, as illustrated in the interview process. There is potential for the econometric model to further adapt and building physics models could provide a benefit when used alongside whole system models to provide robust demand input assumptions and scenarios.

Energy modelling has played a significant role in the shaping of energy policy and therefore the energy market. There is no doubt that use of energy models will continue to form strategy for setting energy policy, making it vital that the modelling methods and inputs are as robust as possible. Models need to continue to adapt to the changing landscape, such as to enable representation of flexible technologies, and to increase transparency to provide stakeholders with greater confidence in Government modelling approaches.

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APPENDICES

APPENDIX A: INTERVIEW QUESTIONS

The below questions are a guideline set of questions and areas that may be used in these semi structured interviews. The exact set of questions used will vary depending on the participant's expert area and their company.

Part 1: Setting the scene [find out about their role and organisation]

- Could you tell me a little more about your current role and background?
- In order for me to be able to pull common trends from this project which category does your organisation fit into? Government/ Academia/ Industry (utility or supply chain)/ Other stakeholder (inc consultancy, non-academic commentator)
- Which of the following descriptions applies to you? (It can be more than one.) Modeller/ model output user/ policy maker/ energy commentator/economist / other (please specify) (strategic)
- What policy decisions have most affected you/your organisation in your role?
- How do you/your organisation typically engage with Government policy makers?

Part 2: Case study (Heat Strategy/EMR/FITs) [How they engage with government and discussion of the strengths and weaknesses of the analysis and communication of in that example]

- In this instance, at what stage in the policy development process did you/your organisation become involved?
- Do you know what analysis was undertaken for this policy and what tools/methods were used?
- In this example do you believe the analysis being used was fit for purpose?
- Do you think the communication of the analysis/modelling was adequate?

Part 3: Existing model capability within your organisation

- Does your organisation undertake (or use) any in house energy system modelling or commission any from external sources?
- If in house what types of tools do you use and why?
    - o What skills do those model users have?
    - o How are the results normally used?
- If commission externally why/when do you chose this route?
    - o What sorts of tools do they use?
    - o How are the results used?
- What live issues are of interest to you and your organisation currently?

Part 4: Future modelling for policymaking [Continuation of above but more general]

- What tools do you think government are using?
    - o Are you able to compare these to the core model types I have here?
- Do you think that government are using the right range of tools?
    - o Do you consider these tools adequately validated?
- Where are the gaps in your opinion in government energy system modelling?
- What in your opinion would be the most useful piece of analysis or insight that government could share/do to aid informed policy making?
- If the models were available would you do your own analysis using them?
- Do you think energy system modelling plays an important part in a policy development?
- Do you think there are some policy areas where it is more important than others?

Appendix B: Participant Information Sheet

Participant Information Sheet

My name is Alice Gunn and I am an EngD researcher in the School of The Built Environment at the University of Reading.

I am carrying out a research project on 'The Impact of different Energy System Modelling Techniques on UK Energy Policy Design'. If you are willing to be interviewed you will be asked to participate in an interview of about 45 minutes, at a time and place of your choice.

During the interview I will ask you questions on your experience with the energy policy development process and in particular your views on the energy system modelling and analysis used. With your permission, I would like to record the interview and transcribe the section later. Copies of the transcript will be available on request and any changes which you ask for will be made. You can choose not to answer any questions and you are free to withdraw from the study at any time.

At every stage, your identity will remain confidential. Your name and all identifying information will be removed from the written transcript. My supervisor and I will be the only people who will have access to this data. The data will be kept securely and destroyed when the study has ended, which will be 3 years from the completion of the research (October 2020). The data will be used for academic purposes only.

Copies of any outputs, such as articles or presentation slides, will be available on request. If you have any further questions about the study, please feel free to contact me or my supervisor.
Alice Gunn – a.gunn@pgr.reading.ac.uk
Dr Phil Coker – p.j.coker@reading.ac.uk

This project has been subject to ethical review, according to the procedures specified by the University Research Ethics Committee, and has been given a favourable ethical opinion for conduct.

Alice Gunn

Signed:
Date: 22/09/2016

APPENDIX C: CONSENT FORM

Consent Form

1. I have read and had explained to me by Alice Gunn, the Information Sheet relating to this project and any questions have been answered to my satisfaction.
2. I understand that my participation is entirely voluntary and that I have the right to withdraw from the project any time, and that this will be without detriment.
3. I understand that my personal information will remain confidential to the researcher and her supervisor, Dr Phil Coker, at the University of Reading, unless my explicit consent is given.
4. I understand that my organisation will not be identified either directly or indirectly without my consent.
5. I agree to the arrangements described in the Information Sheet in so far as they relate to my participation.

Name:

Signature:

Date: