Title	Innovative approaches to developing deep decarbonisation strategies
Author(s)	Pye, Steve
Publication date	2019
Original citation	Pye, S. 2019. Innovative approaches to developing deep decarbonisation strategies. PhD Thesis, University College Cork.
Type of publication	Doctoral thesis
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Embargo information	Not applicable
Item downloaded from	http://hdl.handle.net/10468/9495

Ollscoil na hÉireann, Corcaigh

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Innovative approaches to developing deep decarbonisation strategies

Thesis presented by

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for the degree of

Doctor of Philosophy

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November 2019

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Declaration

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism.

Signature: 

Date: 21st November 2019

Acknowledgements

I would first like to thank my supervisors, Professor Brian O'Gallachoir and Dr Paul Deane, for encouraging me to undertake this PhD, and for providing me with guidance in my research. I have enjoyed the many helpful conversations, their hospitality in Cork, and benefitted hugely from their expertise. I would also like to thank other colleagues at UCC for their collaborative engagement, including James Glynn, Fionn Rogan, and Xiufeng (Jason) Yue.

Colleagues at UCL across a range of different research collaborations have contributed to the research described in this thesis. In particular, it has been a pleasure to work closely with Francis Li, exploring different qualitative and quantitative approaches on the ETI-funded project focused on uncertainty and decision-making. Other colleagues who helped develop ideas and collaborated include James Price, Christophe McGlade, Pei-Hao Li, and Ilkka Keppo.

I would also like to thank Professor Neil Strachan for encouraging me to undertake a PhD in the first place, and for providing support to allow me to take this research forward. Thanks also to Professor Mark Howells for hosting me as a researcher at KTH, Stockholm, in the summer of 2018, to meet the other requirements of this PhD.

Finally, I would like to thank my family, Mia, Tom and Will, for being hugely supportive during the process – and giving me time and space in our very busy lives to undertake this PhD.

Executive summary

After years of discussion by the international community as to how best to tackle the challenge of climate change, the Paris Agreement in 2015 both refocused attention on the necessary climate mitigation goals and saw a shift towards a more bottom-up, country-led approach to delivering on this agreed ambition.

It is in this context that the research presented in this thesis on *Innovative approaches to developing deep decarbonisation strategies* has been undertaken. Recognising that the energy system is the largest source of CO_2 emissions contributing to climate change, analytical approaches such as those using energy models, are needed to help decision makers navigate the different options to drive the energy system towards being low carbon and net-zero emitting in future years.

However, there is a question as to whether energy modelling, notably energy systems modelling, is fit-for-purpose or needs to further adapt and innovate. This concerns not only the functionality and credibility of the modelling tool, but also its application to the decarbonisation challenge, including the analytical process in which it sits.

This research focuses on innovation in modelling approaches in two key interlinked areas; i) characterising deep uncertainty of the transition across different domains, and ii) opening up the analytical process to greater scrutiny and participation. The interlinkage is that 'deep uncertainty', which both reflects a lack of agreement on model framing, structure, and assumptions, and what constitutes a desirable outcome, necessitates enhanced scrutiny and participation by a range of stakeholders.

To assess how innovative approaches to energy modelling can enhance decarbonisation analyses, this research focuses on a range of objectives. It first considers the strategic decarbonisation challenge that models need to inform, then explores how current practice can provide useful insights for decision makers, and finally assesses how approaches can be more innovative in moving practice towards stronger engagement, a broader understanding of uncertainty, and improved modelling methods. The linkages between these different research areas are shown in Figure ES1. Focusing on the use of energy system models, the research employs a range of quantitative and qualitative methods, reflecting the interdisciplinary nature of the research.

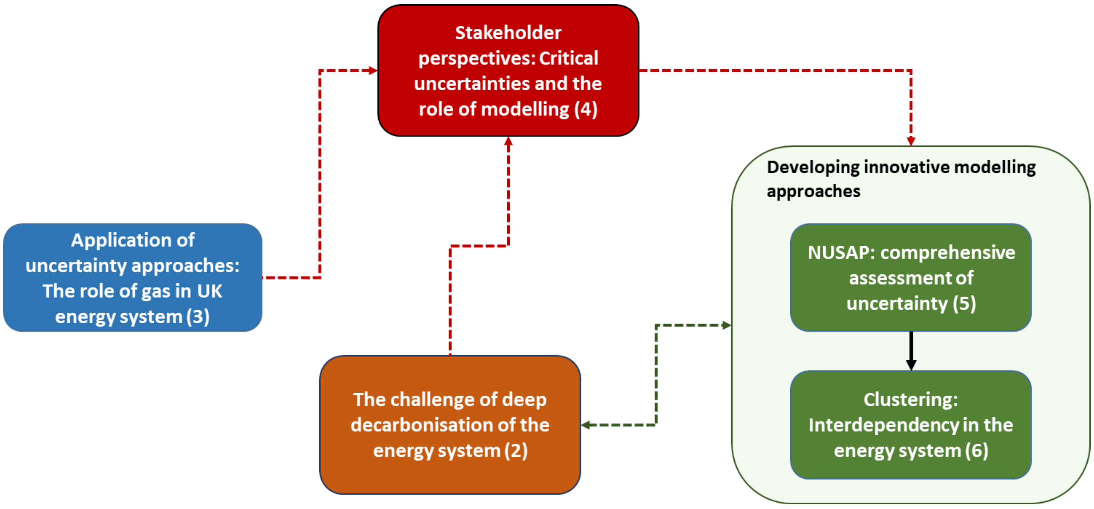

Figure ES1. The linkages across the research elements of this thesis. The bracketed numbers in the figure indicate the chapter number of the thesis.

The research starts (in Chapter 2) by highlighting the challenges arising from stronger climate policy ambition, notably the transition to a deeply decarbonised net-zero energy system. Modelling needs to be able to analyse the scale of the mitigation challenge, the critical options required, and the key uncertainties facing decision makers, including the level of national ambition, availability of key resources, technology deployment, and societal response. The research argues that the UK requires stronger ambition to ensure domestic mitigation efforts are consistent with global climate policy objectives, and that supporting modelling analyses should use an extended time horizon beyond 2050 to explore pathways to net-zero by the middle of the century and beyond.

Two current approaches to uncertainty assessment are then demonstrated, and applied to the UK policy question of the future role of natural gas in the energy system (Chapter 3). The case study underlines how the use of different approaches to modelling can be insightful, both to explore divergent energy futures under uncertainty, and provide decision makers with guidance on the development of an energy strategy.

Before exploring innovative modelling approaches to enhance the analysis of deep decarbonisation pathways, the research focuses on seeking the perspectives of stakeholders engaged in the debate on energy sector decarbonisation, again using the UK as a case study (Chapter 4). The research reveals a diversity of views on the most critical uncertainties, how they can be mitigated, and how the research community can develop approaches to better support strategic decision-making. While socio-political dimensions of uncertainty are discussed by experts almost as frequently as technological ones, there exists divergent perspectives on the role of government in the transition and whether or not there is a requirement for increased societal engagement. On improving modelling for decision support, the challenge highlighted is one where many uncertainties fall outside of the model boundary, and the focus remains on the narrow technological domain that models capture.

There is therefore the need for a new approach to uncertainty assessment that overcomes analytical limits to practice, is more flexible and adaptable, and which better integrates qualitative narratives with quantitative analysis. There is also a need for a more participatory approach to designing modelling exercises, which has the potential to produce analyses that capture broader uncertainty, wider expertise, and engender buy-in.

In response, innovative modelling approaches are considered. First, a method known as NUSAP (Numeral Unit Spread Assessment Pedigree) is developed and applied (Chapter 5). It recognises the shortcomings of quantitative-only approaches to uncertainty assessment and through structured stakeholder engagement, it seeks to identify qualitative dimensions of uncertainty, to compliment quantitative analysis. The elicitation process finds that statistically influential assumptions on quantitative model results often have a poor knowledge-based underpinning, and are subject to potential value-ladenness. This particularly applies to assumptions around carbon capture and storage (CCS) deployment and bioenergy resources, both of which are highly influential in driving model outcomes. The approach also highlights the increasing uncertainty in the longer term, and provides valid questions about the structural assumptions in the model.

This approach, grounded in post-normal science thinking, is important for capturing uncertainties outside of narrow techno-economic framing, whilst promoting meaningful engagement that recognises the many perspectives and multiple expert opinions on the plethora of issues considered in energy system decarbonisation analysis.

Second, the use of clustering analysis to understand the role of different technologies in the energy system is explored (Chapter 6). The approach considers interdependency, competition, and independence across different technologies and resources in the energy system. The key innovation is an approach to better understanding the linkages between different modelling solutions in a complex and uncertain energy system. The research finds that specific technologies, such as CCS, have a strong influence on the system evolution (and the relationships between options). It also suggests that other technologies are largely unaffected by what other technologies are deployed, suggesting robustness. Finally, it identifies that some technologies appear interdependent, meaning they are typically deployed together e.g. heat pumps and fabric retrofit, building electrification and storage. Conversely, a number of technologies are identified as in competition, and negatively correlated. This analysis provides useful information for decision makers on why different technologies emerge under a range of scenarios, and where their deployment is affected by the deployment of other technologies and the wider system configuration.

The nature of the challenge of deep decarbonisation means high levels of uncertainty due to the scale of transition, the rate of change required, and the multiple actors involved who have a stake in the process. Modelling must attempt to represent this uncertainty to allow decision makers to explore the range of possible pathways, in order to develop robust, adaptive strategies to contend with this. However, it is also important that modellers can provide insights into what are the most influential uncertainties. A decision maker might see a large ensemble of scenario pathways, reflecting the distribution of plausible outcomes, but have limited insight into what uncertainties matter the most. Techniques such as global sensitivity analysis and clustering analysis can provide insights into what drives different outcomes. In addition to the need to determine the influence of uncertainty in the model, there also needs to be a recognition of uncertainties not included in the model, usefully illustrated by the NUSAP exercise (chapter 5) and the expert interviews (chapter 4). If not, there is a danger that modellers convey a sense of having provided a comprehensive analysis of uncertainty simply through using a specific recognised quantitative approach.

Finally, the research suggests a need for more robust engagement with a diversity of stakeholders, to i) allow for stronger participation, engendering trust and buy-in through greater transparency, ii) to gain expertise particularly given the interdisciplinary nature of the decarbonisation challenge, and iii) to challenge and scrutinise the assumptions in the model, and the thinking of modelling analysts.

Thesis output

Journal papers (as per the order in the thesis):

Pye, S., Li, F. G., Price, J., & Fais, B. (2017). Achieving net-zero emissions through the reframing of UK national targets in the post-Paris Agreement era. *Nature Energy*, 2(3), 17024.

McGlade, C., Pye, S., Ekins, P., Bradshaw, M., & Watson, J. (2018). The future role of natural gas in the UK: A bridge to nowhere? *Energy Policy*, *113*, 454-465.

Li, F. G., & Pye, S. (2018). Uncertainty, politics, and technology: Expert perceptions on energy transitions in the United Kingdom. *Energy Research & Social Science*, 37, 122-132.

Pye, S., Li, F. G., Petersen, A., Broad, O., McDowall, W., Price, J., & Usher, W. (2018). Assessing qualitative and quantitative dimensions of uncertainty in energy modelling for policy support in the United Kingdom. *Energy Research & Social Science*, 46, 332-344.

Pye, S., Li, P. H., Keppo, I., & Gallachóir, B.Ó. (2019). Technology interdependency in the United Kingdom's low carbon energy transition. *Energy Strategy Reviews*, *24*, 314-330.

Conference papers and presentations:

Pye, S. (2016). Achieving net-zero emissions: reframing national targets in the post-Paris Agreement era. 1st June 2016. https://www.ucc.ie/en/iew2016/

Workshops and invited talks:

Pye, S. and Li, F.G. (2017). Energy Pathways under Deep Uncertainty: What do Decision Makers Really Think is Important? 30th March 2017. http://www.wholesem.ac.uk/wholesem-events-repository/energy-pathways-under-deep-uncertainty

Pye, S. and Li, F.G. (2017). Workshop on exploring qualitative uncertainty in UK decarbonisation pathways. 14th September 2017. http://www.wholesem.ac.uk/wholesem-news-publication/QUUKDP

Pye, S. (2017). What should the UK's climate targets be in the post-Paris Agreement era? 28th June 2017. http://www.wholesem.ac.uk/wholesem-events-repository/WhatshouldtheUKclimatetargetsbe

Units and abbreviations

ACA	Academic stakeholder group
AIMMS	Advanced Interactive Multidimensional Modelling System
BECCS	Bio-energy with Carbon Capture and Storage
BEIS	(UK) Department for Business, Energy and Industrial Strategy
CCC	(UK) Committee on Climate Change
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CLA	Clustering Analysis
CS	Civil Service stakeholder group
DDPP	Deep Decarbonisation Pathways Project
DECC	(UK) Department for Energy and Climate Change
ESME	Energy Systems Modelling Environment
ESOMs	Energy System Optimization Models
ETSAP	Energy Technology Systems Analysis Programme
GGR	Greenhouse Gas Removal
GHGs	Greenhouse Gases
GSA	Global Sensitivity Analysis
IAMs	Integrated Assessment Models
IEA	International Energy Agency
IGDT	Info-Gap Decision Theory
IND	Industry stakeholder group
IPCC	Intergovernmental Panel on Climate Change
LMDI	Logarithmic Mean Divisia Index
MCA	Monte Carlo Analysis
MGA	Modelling to Generate Alternatives
NDCs	Nationally Determined Contributions
NGO	Non-Governmental Organisation
NUSAP	Numerical Unit Spread Assessment Pedigree (approach)
OG	Other Government stakeholder group

PMCA	Probabilistic Monte Carlo Analysis
ScA	Scenario Analysis
SI	Stakeholder Involvement
SMR	Steam Methane Reforming
UKTM	UK TIMES model
UNFCCC	United Nations Framework Convention on Climate Change

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1. Introduction

1.1 Background to research

1.1.1 Modelling to support radical emission reductions

The publication in October 2018 of the Intergovernmental Panel on Climate Change (IPCC) Special Report on the impacts of global warming of 1.5 °C and related global greenhouse gas (GHG) emission pathways again reinforces the dramatic reductions required in global greenhouse gas emissions (Masson-Delmotte et al., 2018). For a 1.5°C warming limit relative to average pre-industrial temperatures, CO_2 emissions need to be around zero by the middle of the century (Rockström et al., 2017; Rogelj et al., 2018a, 2018b).

National requirements for emission reductions are based on self-determined pledges made by countries and other actors, such as cities and businesses, and as such are not allocated using a burden sharing approach but rather are bottom-up in nature. This reorientation of the United Nations Framework Convention on Climate Change (UNFCCC) approach to GHG mitigation was formalised in the Paris Agreement (United Nations, 2015a), requiring that initial pledges made in 2015 must be further strengthened, through a ratcheting process. A number of analyses have highlighted the importance of strengthened commitments if the goal of the Paris Agreement is to be met (Fawcett et al., 2015; Rogelj et al., 2016a).

The renewed focus on country-level action means that analytical modelling tools to support decision makers' choices of mitigation options are critical to help achieve meaningful reductions. The potential of modelling tools for guiding strategy development and the decision making process on radical emission reductions was demonstrated under the Deep Decarbonisation Pathways Project, or DDPP (Bataille et al., 2016; Pye and Bataille, 2016; Waisman et al., 2019). This proved an important scientific contribution to the underpinning for Article 4.19 of the Paris Agreement, which encourages parties to produce long-term low greenhouse gas emission development strategies. The 2050 Pathways Platform, an initiative established to assist stakeholders in meeting the objectives of Article 4.19, has published a guidance manual, in which analytical modelling tools form a crucial part (2050 Pathways Platform, 2017).

With energy sector emissions the single largest source of global GHG emissions, at over 60% of the total (Olivier et al., 2017), energy modelling tools have a particularly important role to play. The application of energy modelling to national-level assessments of decarbonisation policy is well developed (Capros et al., 2018; DDPP, 2015; Deane, 2013; Strachan et al., 2009). However, as countries start to grapple with the reality of policy implementation for more ambitious net-zero targets, there is a question as to whether energy modelling, notably energy systems modelling (DeCarolis et al., 2017), is fit-for-purpose or needs to further adapt and innovate. This concerns not only the functionality and credibility of the modelling tool, but also its application to the decarbonisation challenge, including the analytical process in which it sits.

1.1.2 The role of energy modelling in the UK decarbonisation debate

In the UK, energy system models have informed the decarbonisation debate since 2003 (DTI, 2003), providing insights into the types of energy system that could deliver deep emission reductions. These models typically represent the whole energy system, from primary energy production to the provision of end use energy services, such as heating and mobility. For the purposes of this thesis, the focus is on energy system optimisation models, such as the TIMES framework (Loulou et al., 2005), which use linear programming to explore cost-optimal system designs.

While their specific impact on policy decisions is difficult to determine, what is evident is that these models have been at the heart of the UK strategy debate. Some important contributions to the debate include insights that i) the transition to a low carbon economy is not cost-prohibitive (Strachan et al., 2009); ii) deep decarbonisation is technically feasible and there are multiple pathways but also some key technology options (Ekins et al., 2013; Pye et al., 2015a) ; iii) path dependency issues require that policy decisions undertaken now recognise longer term objectives (Pye et al., 2008); and iv) as a result, long term target ambition matters (Pye et al., 2017).

The extensive use of such models in the UK context is reflective of a number of factors; i) providing the ability to meet the new energy policy challenge of decarbonisation in the 2000s (Taylor et al., 2014); ii) incumbency advantage, based on existing capacity and funding (Strachan et al., 2016); iii) offering useful insights to stakeholders on feasibility and system wide interactions (McDowall et al., 2014); and iv) by functioning as a 'boundary object', both connecting and meeting the needs of different science and policy communities, and providing and supporting a shared understanding of the policy problem (Taylor et al., 2014).

However, there is a debate in the policy and modelling community concerning whether such models are fit for purpose (Pfenninger et al., 2014), and if they are, how they can be improved. A stocktake by (McDowall et al., 2014) elicited key stakeholder perspectives, many of whom were the users of such modelling, and determined a range of areas of improvement for the provision of more effective support to the energy strategy and policy formulation process.

1.1.3 The need for innovation in energy system modelling

Climate policy to enable the required emission reduction can be grouped into the category of "wicked" (Churchman, 1967; Rittel and Webber, 1973) or "post-normal" (Funtowicz and Ravetz, 1990) challenges. These are highly complex problems with no obviously "right" solutions, beset by deep uncertainties, owing to the scale of the required future transitions, both the current and long-term timescales for action, and the numerous and diverse stakeholders who have vested interest in the outcomes.

How should energy system modelling respond to this complex challenge? Whilst many developments could be considered to improve current practice, arguably it needs to innovate in two key interlinked areas; i) characterising deep uncertainty of the transition across different domains, and ii) opening up the analytical process to greater scrutiny and participation. By 'deep uncertainty', (Lempert, 2003) provides a helpful definition. It arises where decision makers don't know or can't agree on i) the appropriate models to describe the interactions among a system's variables, ii) the probability distributions to represent uncertainty about key variables and parameters in the models, and iii) how to value the desirability of alternative outcomes.

This definition shows how the issues concerning types of approaches to modelling uncertainty and the need to engage and involve stakeholders are strongly linked. This is also reflected in post-normal science thinking, with high levels of uncertainty making analytical outputs contested, and therefore requiring transparency of assumptions, and openness to scrutiny and critique of the analytical process and results (Funtowicz and Ravetz, 1993). Furthermore, opening up the process allows for broader expert engagement, and prospects for improved analysis, and wider buy-in and engagement by the stakeholder community. (Pfenninger et al., 2014) identify this as one of the key challenges for energy modelling under the heading 'uncertainty and transparency'. In their reflective paper on energy scenario modelling in the UK, (McDowall et al., 2014) elicit from stakeholders that analyses could be improved by greater focus on 'uncertainty, transparency and communication'.

A range of formal uncertainty methods have been used in energy modelling, including robust optimisation, stochastic programming and probabilistic Monte Carlo simulation (Haurie et al., 2012). A recent paper by (Yue et al., 2018) has reviewed the extent to which such approaches have been used in energy system modelling, finding that most analyses do not apply them. Criticism from within the community has highlighted that the systematic consideration of multiple sources of uncertainty (see Table 1.1) has been insufficient (Pye et al., 2015b, 2014; Usher and Strachan, 2012). Furthermore, many analyses have relied on expert judgement, without opening up the analytical approach to robust scrutiny and critique beyond that of the narrow energy modelling community.

With innovation in modelling practice, it should be possible to enhance analyses so that decision makers can take robust decisions under uncertainty based on analysis that has been subject to meaningful stakeholder engagement.

1.2 Aims and objectives

The aim of the thesis is to assess how innovative approaches to energy modelling can enhance decarbonisation analyses, by improving the assessment of uncertainty, and through meaningful engagement with stakeholders during the analytical process. To meet this aim, the following objectives were set (formulated as a set of research questions) –

i. What are the key challenges of rapid and deep decarbonisation for decision makers, and recognised areas of uncertainty? (Chapter 2)
ii. How can current uncertainty approaches be used to effectively explore the role of natural gas under decarbonisation? (Chapter 3)
iii. From the perspective of decision makers, are existing modelling approaches sufficient to meet the decarbonisation challenge? (Chapter 4)
iv. What innovative modelling approaches can help meet the challenge of robust uncertainty assessment and meaningful engagement? (Chapter 5)
v. What new approaches can be used to enhance the understanding of system interdependencies, to improve insights for and communication to decision makers? (Chapter 6)

In summary, objective i) sets out the strategic decarbonisation challenge that models need to inform. Objective ii) and iii) explore how current practice can provide useful insights for decision makers. Objectives iv) to vi) explore how approaches can be more innovative, in moving practice towards stronger engagement, a broader understanding of uncertainty, and improved modelling methods. The structure of the thesis in meeting these objectives is elaborated further in section 1.4, with a focus on, but not limited to, the UK experience of using energy system models for decarbonisation analyses.

1.3 Research methods

In addressing the overall aim and objectives of this thesis, a range of different approaches are used, reflecting the interdisciplinary nature of this research. First, energy system modelling is described, the basic approach at the core of this research. Second, different approaches to uncertainty assessment are presented, highlighting some of the key modelling approaches used here. Third, the qualitative research methods used, notably in chapters 4 and 5, are described.

1.3.1 Energy system modelling

Energy system models provide a quantitative-based representation of the whole or parts of the energy system, including the physical infrastructure requirements, the system operation, and in many cases, the investment and cost implications of meeting energy service demand. (Pfenninger et al., 2014) usefully categorise these model types into optimisation, simulation, power-sector and mixed method typologies.

In this thesis, the focus is on energy system optimization models (DeCarolis et al., 2017). These techno-economic models can be characterised as representing the energy system using a technology-explicit structure that, subject to a range of constraints (rules in equation form), meet the energy demand requirements of different sectors of the economy. Such models employ linear programming to explore optimal systems in future years, subject to user-defined constraints. As discussed earlier, their utility to policy makers includes determining cost-effective approaches to decarbonisation, being able to model multiple sensitivities, exploring trade-offs between sectors due to their integrated system framework, and providing explicit detail across options (required investment, installed capacity, final energy consumption, associated GHG emissions etc.).

They constitute one of the most widely used types of energy modelling approaches, with well-known frameworks including TIMES (Giannakidis et al., 2015), MESSAGE (Messner and Strubegger, 1995), OSeMOSYS (Howells et al., 2011), and ESME (Pye et al., 2015b). In this thesis, the UK energy system models, UK TIMES (UKTM) and the Energy System Modelling Environment (ESME) are used. UKTM analysis is featured in Chapters 2 and 3, while ESME modelling is presented in Chapters 3, 5 and 6. A more detailed overview of these two models is provided in Appendix B1.

1.3.2 Approaches to modelling uncertainty

(Walker et al., 2003) usefully propose an uncertainty matrix that captures three dimensions of uncertainty – location, level, and nature. ‘Location’ concerns where uncertainty reveals itself within the modelling process, be it the model structure, assumptions, or analytical process. ‘Level’ reflects ‘where uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance’, while ‘nature’ focuses on uncertainty arising due to imperfect knowledge (epistemic) or inherent variability (aleatory).

The uncertainty matrix, further refined by (Refsgaard et al., 2007) and established in guidance provided by the Netherlands Environmental Assessment Agency (PBL) (Petersen et al., 2013), is ‘a tool by which to get a systematic and graphical overview of the essential features of uncertainty in relation to the use of models in decision support activities.' In effect, understanding the features of uncertainty allows one to determine the type of modelling approaches to employ. In doing so, it forces the modeller to recognise the different sources of uncertainty across the modelling process, and the appropriate approaches given these sources and their levels of uncertainty.

Table 1.1 provides an uncertainty matrix of the different approaches used in this research. The rows concern sources of uncertainty across modelling studies. It includes –

- *Context and framing*. These are the boundaries of the system to be modelled, lying outside the particular focus of analysis – but crucial to the broader understanding of the problem.
- *Input uncertainty*. System data concerns information used to represent the existing system e.g. building stock, while driving forces are those changing the system e.g. scenario drivers.
- *Model structure*. The underlying formulation of relationships in the model, and linkages between different elements e.g. equations.
- *Model – technical*. Errors arising due to software implementation and bugs in model code, or hardware problems.
- *Model – parameters*. Related to uncertainty across parameters in the model.
- *Model outputs*. Uncertainty caused by all other sources propagated through the model and reflected in the results.

Types of uncertainty in the table columns reflect the level of uncertainty, from some understanding of uncertainty (statistical), to Knightian uncertainty (scenario) where probabilities cannot be assigned to any given outcome. Qualitative uncertainty is that which is not easily quantifiable, and relates to the quality or pedigree of model assumptions, and the values embedded in such assumptions. Recognised ignorance is fundamental uncertainty about the assumptions, including relationships in the model, and which may or may not be reducible (indeterminacy).

From the matrix, it is informative to note that as uncertainties become less understood, the use of non-model methods such as NUSAP (described below) becomes more important, as reliance on expert judgement is increasingly needed.

Table 1.1. Uncertainty matrix for approaches used in this research

Based on Table 5 in (Refsgaard et al., 2007)). Table abbreviations: ScA, scenario analysis; PMCA, Probabilistic Monte Carlo-based analysis; GSA, global sensitivity analysis; CLA, clustering analysis; NUSAP, Numeral Unit Spread Assessment Pedigree; SI, stakeholder involvement. Numbers in brackets denote the chapter of the thesis in which these approaches feature.

Sources (or location) of uncertainty		Types of uncertainty		
		Scenario uncertainty	Qualitative uncertainty	Recognised ignorance
Context	Natural (environmental), technological, economic, social, political	ScA (2,3,6); SI (4); CLA (6)	NUSAP (5)	NUSAP (5); SI (4)
Inputs	System data	GSA (5)	NUSAP (5)	NUSAP (5)
	Driving forces	ScA (2,3,6); SI (4); GSA (5)	NUSAP (5)	NUSAP (5); SI (4)
Model	Model structure	SI (4)	NUSAP (5)	NUSAP (5); SI (4)
	Parameters	ScA (2,3,6); SI (4); PMCA (3, 6); CLA (6); GSA (5)	NUSAP (5)	NUSAP (5); SI (4)
Model outputs		GSA (5)	NUSAP (5)	NUSAP (5)

Each of the approaches is briefly described below, with cross-references to the parts of the thesis where the approach is featured.

Scenario analysis (ScA)

Scenario analysis, featured in chapters 2, 3 and 6, is the use of modelling tools to consider alternative future energy systems that may evolve from the current system, to help inform and improve decisions that need to be taken given a future that remains uncertain or undecided (Hughes and Strachan, 2010). Decisions to be informed may include proactive (help shape future) and / or protective (robust against uncertainty) characteristics. Scenarios may also be focused on building consensus or facilitating debate. The scenario analyses featured in this thesis are predominantly of a normative (or anticipatory) nature, whereby they start by proposing a future state, often in terms of climate policy ambition, and then work backwards in time (or backcast) to assess how this future state could emerge.

Probabilistic analysis using Monte Carlo analysis (PMCA)

This is a method for generating many model simulations based on Monte Carlo (or similar) sampling across the probability distributions of multiple model input assumptions. This stochastic approach allows for the assessment of multiple uncertainties together, to explore the impact on model output variation. This is done by sampling probability distributions across model input parameters, and then running the model multiple times based on the sample. The application of this approach here is to scenario rather than statistical uncertainty, or Knightian uncertainty rather than Knightian risk (Knight, 1921). The resulting challenge of determining probability distributions over the long term means that in this research simplified distributions are used, such as uniform or triangular, informed by the literature and expert judgement (Pye et al., 2015b). This approach is used by the ESME model, and featured in chapters 3, 5 and 6. As shown in Chapter 5, it can be combined with global sensitivity analyses (GSA) techniques, described below.

Global sensitivity analyses (GSA)

Global sensitivity analyses seeks to assess how the distribution across model outputs can be apportioned to the sources of uncertainty in the model input (Saltelli et al., 2008), differing from uncertainty analysis, such as PMCA, which is concerned with quantifying uncertainty in the model output. The strength of this approach is that it provides insight into what the most important uncertainties are i.e. those that most influence the variation in model outputs. In Chapter 5, the GSA approach used is the Morris Method, and forms a key component of the NUSAP method.

Clustering analysis (CLA)

Clustering analysis, as featured in chapter 6, can be used to group scenarios metrics based on information in the dataset about those metrics and their relationships. Clustering algorithms, of which there are a number of types, group metrics that are similar to each other and different enough from metrics clustered in other groups. In this research, the approach is used to explore interdependency between technologies, by exploring whether certain technologies increase or decrease deployment simultaneously (interdependent), whether their deployment moves in opposite directions (compete) or whether their deployment appears to be independent from each other. The approach is combined with PMCA, which is used to simulate the multiple scenarios used in the clustering analysis.

Numeral Unit Spread Assessment Pedigree (NUSAP) approach

The NUSAP approach is featured in Chapter 5. It recognises that there are qualitative dimensions of uncertainty that usually lie outside of the model analysis framework. These include methodological (unreliability), epistemological (ignorance) and societal (social robustness) dimensions (Van Der Sluijs et al., 2005). The NUSAP framework provides a structured approach to exploring these qualitative dimensions, through stakeholder workshops, focusing on the 'pedigree' of model assumptions, and the potential value-ladenness. Combined with GSA, the implications of the assessment of model assumptions can be considered against the quantitative insights from the GSA, via a diagnostic diagram.

Stakeholder involvement (SI)

Stakeholder involvement is a crucial element of modelling studies that can be taken forward in multiple ways, and for a range of different reasons. In (Refsgaard et al., 2007), reasons include i) enabling articulation of concerns and to improve problem framing; ii) providing opportunity for imparting knowledge and solutions; and iii) facilitating active involvement in co-producing the analysis. In this research, chapter 4 describes the use of an interview approach to elicit perspectives of experts active in the UK energy strategy space. In chapter 5, part of the NUSAP approach is to run a structured workshop to elicit stakeholder perspectives on the pedigree of modelling assumptions. The involvement of stakeholders calls for the use of qualitative research methods that are described in the respective chapters, and briefly summarised below.

1.3.3 Qualitative research methods

A key part of this research has been stakeholder engagement, which requires a move away from quantitative modelling-only approaches, to the use of qualitative research methods. In chapter 4, semi-structured interviews are used to elicit perspectives on critical uncertainties related to decarbonising the energy system, and on the use of models for supporting decision making. These interviews featured a limited number of open-ended questions, intended to elicit views and opinions from the participants (Creswell, 2014). This approach was chosen based on much of the reasoning set out in (Aberbach and Rockman, 2002), primarily because it was not clear what range of issues the stakeholder group would cover, with a key objective of the research to reveal them without biasing responses through question framing. The guidelines for the interview are provided in section 4.2 of chapter 4. Expert selection for interviews was based on purposive selection, as per other similar studies (Cox, 2016; Gillard, 2016) and enhanced through snowball sampling (Atkinson and Flint, 2001). The interview responses were subsequently coded, based on established approaches in the literature, as detailed in section 4.2.

For the NUSAP workshop, this followed established practice. (Van der Sluijs et al., 2002) proved particularly useful in establishing how the workshop should be run, as did direct communication with NUSAP experts involved in previous assessments. Full details of the approach are provided in chapter 5, with additional information on the workshop, and associated materials, in Appendix C2.

1.4 Thesis in brief

In addition to this introductory chapter and the concluding chapter (7), the body of the thesis consists of five chapters, which have all been published in peer reviewed scientific journals. Figure 1.1 provides an illustration of the flow of the thesis, as described here, and the linkages between the individual chapters.

Chapter 2 (Pye et al., 2017) highlights the new challenges arising for target setting from the Paris Agreement and the recent report from the IPCC on the climate impacts of 1.5°C (IPCC, 2018). Using the UK as an example, this research assesses the large-scale challenges of the transition to a deeply decarbonised net-zero energy system. Using energy systems modelling, it highlights the scale of the mitigation challenge, the critical options required, and the key uncertainties facing decision makers, including the level of national ambition, availability of key resources, technology deployment, and societal response. Given the push towards stronger ambition, the chapter argues the need for longer term targets that may extend beyond 2050, to avoid lock-in and to ensure the sufficiency of near-to-medium term action. It also underlines the challenges to energy system modelling of being able to usefully inform the debate on long-term strategy. Chapter 2 sets the context for the rest of the thesis, hence its central position in Figure 1.1.

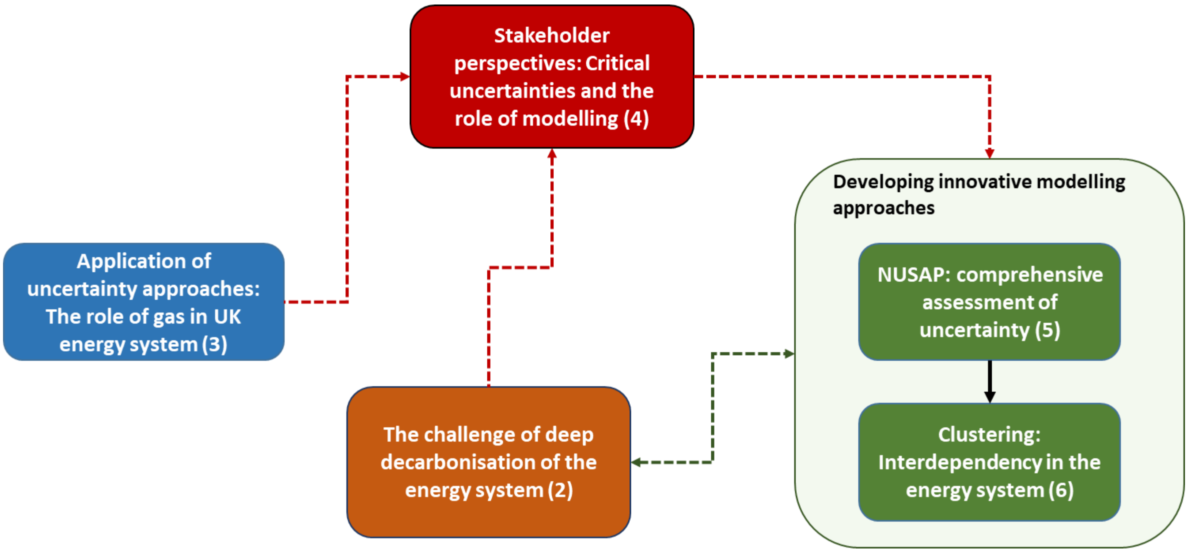

Figure 1.1. The linkages across the thesis chapters
The bracketed numbers in the above figure indicate the chapter number of the thesis.

Chapter 3 (McGlade et al., 2018) applies two approaches for uncertainty assessment, to the contentious issue of the role of natural gas in a decarbonising UK energy system. Using both scenario and Monte Carlo-based probabilistic approaches, the analysis provides a useful example of how multiple approaches to modelling can help explore divergent energy futures under uncertainty, and provide helpful insights to decision makers on the development of the domestic energy strategy.

The question this thesis considers is whether the current approaches, as employed in the previous chapters, are sufficient given the challenges of decarbonisation. Chapter 4 (Li and Pye, 2018) therefore seeks the perspectives of stakeholders engaged in the debate on energy sector decarbonisation in the UK. Using a qualitative research approach (semi-structured interviews), perspectives are elicited on the key issues and uncertainties that need to be considered in strategy formulation, and the ability of current analytical approaches to meet the requirements for decision support. This wide-ranging interview exercise adds an important new element to developing energy modelling approaches that are fit for purpose. Without this step, it is not possible to easily determine what decision makers consider to be key issues in formulating a strategy, and the type of decision support that is required.

The remaining chapters of the thesis respond in part to the challenges set by the stakeholders in chapter 4, recognising that specific aspects of energy modelling practice need to be developed. Chapter 5 (Pye et al., 2018) identifies shortcomings in the quantitative-only approach to uncertainty assessment. It applies an approach to capture the qualitative dimensions of uncertainty inherent in the use of models, using a structured elicitation approach called NUSAP. This expands the toolbox for uncertainty assessment and pulls in dimensions of uncertainty often overlooked.

Finally, chapter 6 (Pye et al., 2019) introduces the application of clustering analysis to understand, given the range of uncertainties, the role of different technologies in the energy system. It considers interdependency, competition, and independence across different technologies and resources in the energy system. The key innovation is an approach to better understand the dependencies between different modelling solutions in a complex energy system.

1.5 Role in collaborations

This thesis comprises my own work and was written by me, but involved collaboration at many junctures. All chapters have been published in scientific journals. Professor Brian Ó Gallachóir, my supervisor, has advised on all aspects of this thesis.

Research described in Chapter 2 was led, designed and undertaken by me but with inputs from colleagues at the UCL Energy Institute. Notably, Birgit Fais assisted in the model set-up, while Francis Li and James Price helped further refine the research design. All colleagues contributed to writing the journal article.

Chapter 3 was led by Christophe McGlade from UCL. My main contribution as second author was in the design of the research approach, and undertaking the probabilistic analysis using the ESME model. I was also heavily involved in writing the journal paper.

The research project underpinning Chapter 4 was led by me, with joint authorship of the paper with Francis Li from UCL. Both authors jointly developed the research approach, and undertook the stakeholder interviews. I undertook the analysis of the interview transcripts, and wrote up the findings. The final paper was written by both authors.

The research project underpinning chapter 5 was led by me, as was the resulting paper. I developed the research design, led the workshop activity, undertook the analysis of the workshop results, with important contributions from my co-author Francis Li. I undertook the quantitative modelling, with contributions on the global sensitivity analysis from James Price (UCL) and Will Usher (Oxford University). All other listed authors assisted with the workshop facilitation and finalisation of the journal paper.

The research described in chapter 6 was led and undertaken by myself, with input on the research design from colleagues Pei-Hao Li and Ilkka Keppo. Pei-Hao Li also assisted in the development of the clustering analysis routines. I led the analysis of the results, and the writing of the journal paper, with input from the other listed authors.

2. Achieving net-zero emissions through the reframing of UK national targets in the post-Paris Agreement era

Abstract

The Paris Agreement provides an international framework aimed at limiting average global temperature rise to well below 2°C, implemented through actions determined at the national level. As the Agreement necessitates a 'net-zero' emissions energy system at some point prior to 2100 depending on the interpretation of the ambition level, decarbonisation analyses in support of national climate policy should consider the post-2050 period. Focusing solely on mitigation objectives for 2030 or 2050 could lead to blindsiding of the challenge, inadequate ambition in the near term, and poor investment choices in energy infrastructure. Here, using the UK as an example, it is shown that even an ambitious climate policy is likely to fall short of the challenge of net-zero, and that analysis of the post-2050 period is therefore critical. The research finds that the analysis of detailed, longer term national pathways which achieve net-zero emissions is important for future reassessment of ambition under Nationally Determined Contributions (NDCs).

Keywords

Net-zero emissions; energy systems; long term climate targets; carbon budgets

2.1 Introduction

Global ambition to limit anthropogenic warming to 2°C requires a radical transformation of the energy system to one that produces 'net-zero' greenhouse gas (GHG) emissions before 2100 (IPCC, 2014). For a 1.5°C limit, action has to be even more rapid, with net-zero emissions achieved much earlier (Rogelj et al., 2015a). The goal of net-zero GHG emissions is expressed in the Paris Agreement as a system that achieves 'a balance between anthropogenic emissions by sources and removals by sinks' (United Nations, 2015a). In this chapter, net-zero is defined as 'reducing net CO_2 emissions from energy and industrial processes, after accounting for CCS, to zero' (Rogelj et al., 2015b). However, analyses of current pledges by individual countries, Nationally Determined Contributions (NDCs), estimate that such action will result in warming of between 2.9 and 3.4°C (based on a 66% probability) (Rogelj et al., 2016a). This reveals a fundamental disjuncture between the aspiration for an equitable global transition to a net-zero future and the national policy planning being carried out. This disjuncture will only be addressed by countries fully exploring the ambition levels in the Agreement, and a subsequent ratcheting up of mitigation action. To date, however, government-backed national studies exploring net-zero transitions are limited to Bhutan (Ea Energy Analyses and

COWI, 2012), Costa Rica (Pratt et al., 2010), Ethiopia (Environmental Protection Agency, 2011), Norway (Norwegian Environment Agency, 2014), and Sweden (Swedish Environmental Protection Agency, 2012), while no NDCs have assessed emissions reductions targets in the post-2050 period.

Furthermore, longer term planning horizons are needed to understand path dependencies (O'Neill et al., 2010). Energy system investments are often into capital intensive assets with long lifetimes, raising the risk of technological 'lock-in' (Riahi et al., 2015) to system configurations that will meet 2030 or 2050 targets but which are unsuitable for achieving net-zero positions thereafter. However, most NDCs only consider 2025 or 2030 as their target time horizon. The Paris Agreement encourages this reframing of NDCs; firstly, promoting a longer term perspective, with Article 4.19 stating that 'Parties should strive to formulate and communicate long term low greenhouse gas emission development strategies'.[1] Secondly, the pledge and review approach will allow countries to periodically re-assess the strength of their ambition. Critical also to this reframing is the recognition that countries have divergent priorities and circumstances (DDPP, 2015), as per the principle of 'common but differentiated responsibilities and respective capabilities' (United Nations, 2015a).

Using the example of the UK, the implications of 2°C-compliant carbon budgets on the national energy system are explored under a range of critical uncertainties, using the energy system model UKTM.[2] The most stringent budget, named 590 Equity and constituting ambition 'well below 2°C', results in a net-zero system before 2050, and requires stronger mitigation efforts than those currently envisaged by UK policy. The central budget cases chosen (590 Inertia / 1240 Equity) result in net-zero emissions by 2070, and again requires higher ambition than under current UK climate legislation. In conclusion, the strategic national energy system planning, even in the short term, requires analysis with a post-2050 time horizon that appropriately reflects global climate ambition. Furthermore, such analyses need to capture policy-relevant uncertainties, which in the case of the UK include future bioenergy availability, CCS deployment, and consumer response, including societal acceptance of increasing mitigation costs.

2.2 Critical uncertainties under a net-zero emission transition

In exploring stronger ambition over the longer term, there are a range of key uncertainties that energy transitions must explore, to understand implications for technical, economic and socio-

[1] Long-term implies to 2050.

[2] This analysis was produced in 2015/16, prior to the publication in 2018 of the IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways (SR1.5) (Masson-Delmotte et al., 2018). Hence, it focussed on the 2°C budget range, based on information from IPCC's Assessment Report 5 (AR5). The lower end of the budget range used in this analysis corresponds to that consistent with a 1.5°C (50% probability) budget in SR1.5.

political feasibility. Four that are critical to consider in country-scale analyses include; i) the global carbon budget and its allocation; ii) commercial availability of key energy system technologies; iii) bioenergy resource, including its use for generating 'negative' emissions; and iv) demand levels for energy services. Their criticality is discussed below, with additional detail, including on the uncertainty ranges used, provided in Appendix A1.

Concerning i), a key finding to emerge from climate modelling in the last decade is the near-linear relationship between cumulative CO_2 emissions since preindustrial times and the rise in global mean surface temperature over that same period (Allen et al., 2009; Meinshausen et al., 2009). The simplicity of this relationship has proven particularly attractive at the science-policy interface where a selected global warming threshold and probability of achieving said limit can be distilled into a global CO_2 emissions budget. In the latest review of carbon budget estimates, (Rogelj et al., 2016b) recommend the use of a CO_2 budget range of 590-1240 Gt (from 2015 onwards) from the IPCC AR5 Synthesis Report (IPCC, 2014), commensurate with limiting warming to 2°C with at least a 66% chance. The sizeable budget range is largely driven by uncertainty in future non-CO_2 GHG emissions.

Furthermore, national level studies require an approach to share out a global emissions budget. An extensive literature exists that considers allocation of climate mitigation from different perspectives (Füssel, 2010; Höhne et al., 2014; Ringius et al., 2002; Robiou Du Pont et al., 2017). A recent approach is that proposed by (Raupach et al., 2014), also used in (Peters et al., 2015), which applies effort sharing principles of equity (per capita basis) and inertia (current total emissions basis, also known as grandfathering) to carbon budgets. For a developed country such as the UK, equity leads to the allocation of a much more stringent, lower budget, compared to what would be achieved under inertia, based on current emissions. Within this allocation framework it is implicitly assumed that other countries are also pushing toward commensurate levels of ambition. The implementation of these budgets is further described in the methods section (2.5) and Appendix A1.

For ii), both nuclear power and the use of fossil fuels with large-scale carbon capture and sequestration (CCS) technology are often shown to play key roles in decarbonisation scenarios (Clarke et al., 2014). However, their effective deployment is beset by multiple uncertainties, relating to technical feasibility, commercialisation, and public acceptability (Bruckner et al., 2014). The attraction of CCS lies mainly in the potential for delaying the shift away from fossil fuel use, reducing overall transition costs. However, there has been limited progress in moving to commercial-scale deployment, with few projects having implemented the full CCS chain at scale (Leung et al., 2014). Nuclear power also appears as a cost effective option in energy modelling exercises, but faces significant uncertainties. Plants are complex to build and highly capital intensive, with a history of cost escalations and public resistance to deployment (Corner et al., 2011; Grübler, 2010).

Concerning uncertainty iii), even in strongly decarbonised futures, residual emissions from hard-to-address sectors may require a negative emissions strategy to achieve a net-zero emissions position. 87% of global IPCC AR5 scenarios with a 66% chance of staying below 2°C deploy negative emissions technologies, with bioenergy CCS (BECCS) technology being most prevalent (Fuss et al., 2014). However, the practicality of negative emissions strategies remains contested (Smith et al., 2015). Additionally, future bioenergy resources are likely to be constrained by biophysical and socio-economic factors, with a wide range of estimates reflecting uncertainties around food security and diets, land use dynamics, and water use (Slade et al., 2014).

Finally, concerning iv), uncertainty of future demands for energy services such as mobility, heating and lighting are important drivers of CO_2 emission levels. Reducing such demands can be achieved via a range of mechanisms, including pricing, regulation, and information provision to influence consumer choices. A number of modelling assessments have underlined the role of price-induced demand reductions in energy services, particularly in sectors where mitigation options are limited. However, the role and impact of such a mechanism is also highly uncertain, in large part due to a limited empirical basis (Pye et al., 2014).

2.3 Methods

Implications of a net-zero transition for the UK, subject to the above uncertainties, are modelled under the 2°C (66%) emission budget range (from 2015) of 590–1,240 $GtCO_2$, with the allocation of the global budget to the UK explored on equity and inertia principles. The UK is widely regarded as being amongst the group of advanced economies which have the most ambitious goals, legislating for a legally binding 2050 GHG target (HM Government, 2008) that has, in recent years, appeared to engender broad cross-party political support (Lockwood, 2013). Additionally, the setting of climate targets in the UK has been informed by an evidence based process using multiple model-based analyses (Anandarajah et al., 2009; Usher and Strachan, 2010). This case study therefore explores whether a post-2050 net-zero target could necessitate a rethink of the current policy architecture, ambition level, and approach to modelling.

The modelling analysis results in four sets of model outputs, based on the combination of global budget and allocation principle e.g. 590 Equity. The 1240 Equity and 590 Inertia cases have very similar results for the UK, given their almost identical budgets. These budget cases are compared to the UK's current policy framework (Policy case), for which it is assumed that the 2050 level of decarbonisation is maintained to 2100. Combinations of the uncertainties described above (16 in total) are explored for each budget case (Table 2.1, and Appendix A1). In addition, a further budget case, 915 Blend, was also investigated and is described in Appendix A2.

Table 2.1. Model scenario dimensions for UKTM analysis
The number of scenarios for the 590 budget cases is 32, based on the following: (allocation approaches x2) x (input uncertainties (2x2x2x2)) = 32

Global budget ($GtCO_2$)	Allocation approach	Input uncertainty	Uncertainty level	No. of scenarios
590	Equity Inertia	Biomass availability CCS uptake Nuclear uptake Demand response	High Low	32
1240	Equity Inertia	Biomass availability CCS uptake Nuclear uptake Demand response	High Low	32
915	Blend	Biomass availability CCS uptake Nuclear uptake Demand response	High Low	16
	UK policy	Biomass availability CCS uptake Nuclear uptake Demand response	High Low	16

The UKTM model

For the analysis, the UK integrated energy system model, UKTM, is used (Pye et al., 2015a). This model has been developed at the UCL Energy Institute over the last few years as a successor to the UK MARKAL model (Kannan et al., 2007). UK MARKAL was a major analytical framework used to underpin UK energy policy making and legislation from 2003 to 2013 (Anandarajah et al., 2009; CCC, 2008; HM Government, 2011). A version of UKTM is now being utilised by the UK Department of Business, Energy and Industrial Strategy (formerly the UK Department of Energy and Climate Change) to inform their climate policy analysis, including the 5th Carbon Budget (CCC, 2015a).

UKTM represents the technology and fuel choices across different energy-using sectors under decarbonisation objectives. These choices are made based on what is economically-optimal, subject to numerous constraints that reflect system characteristics. These include balancing of supply and demand across multiple diurnal and seasonal time periods, limits on technology build rates, and representation of available resources. A key strength of this approach is that it permits trade-offs between actions in one sector versus another, and allows for full emissions accounting. The model is divided into three supply (resources and trade; processing and infrastructure; and electricity generation) and five demand sectors (residential, services, industry, transport and agriculture). All sectors are calibrated to UK energy balances in the base year, 2010 (DECC, 2011a), for which the existing stock of energy technologies and their characteristics are taken into account.

The large variety of future supply and demand technologies are represented by techno-economic parameters such as the capacity factor, energy efficiency, lifetime, capital costs, O&M costs etc. For most technologies or technology groups, growth constraints between 5 to 15% per year are fixed to ensure realistic future technology deployment rates. With respect to future technology costs, exogenous learning rates are applied, especially in the case of less mature electricity and hydrogen technologies, assuming that the UK is a price taker for globally developing technologies. A global discount rate of 3.5% p.a. for the first 30 years and 3% afterwards is used based on Government guidance on economic appraisal (HM Treasury, 2011). In addition, sector-specific discount rates are included to reflect the varying private costs of capital by sector (10% for all energy supply sectors, industry, agriculture and service sectors, 7% for transport, and 5% for the residential sector (Usher and Strachan, 2010)).

While UKTM has flexible time periods, and can be run for any time horizon up to 2100, the analysis uses two single-year time periods representing 2011 and 2012 and there-after five year periods from 2015 up to 2100. To represent changes in demand across seasons and hours of the day, it features a time resolution of 16 time-slices (four seasons and four intra-day time-slices). This allows for some representation of peak demand, system security via a peak reserve margin, and therefore key requirements for power system operation. In addition to representing energy flows, UKTM models both energy and non-energy related CO_2, CH_4, N_2O and HFC emissions, although non-CO_2 GHGs have not been explicitly considered in this analysis.

Table 2.2. UKTM sector descriptions

Sector	Description
Resources and trade (UPS)	Includes potentials and cost parameters for domestic resources and traded energy products. Fossil fuel prices are sourced from DECC projections (DECC, 2014a), while the assumptions on bioenegy potentials are aligned with the CCC's Bioenergy Review (CCC, 2011a).
Energy processing (PRC)	Covers all energy conversion processes apart from electricity generation, including oil refineries, coal processing, gas networks, hydrogen production, bioenergy processing as well as carbon capture and storage (CCS) infrastructure.
Power generation (ELC)	Represents a large variety of current and future electricity generation technologies as well as storage technologies, the transmission grid and interconnectors to continental Europe and Ireland. The technology assumptions are mostly aligned with DECC's Dynamic Dispatch Model (DDM (DECC, 2012)).
Residential (RES)	Domestic housing is divided into existing and new buildings with existing buildings being further differentiated along the categories of flats/houses and cavity-walls/solid-walls. In addition to a large portfolio of heating technologies for the two main energy service demands of space heating and hot water, other services like lighting, cooking and different electric appliances are represented. The technology data is mainly aligned with the National Household Model (NHM).
Services (SER)	As per the residential structure, but with the building stock divided into low- and high-consumption non-domestic buildings. The technology data is mainly aligned with the National Household Model (NHM).
Industry (IND)	Divided into 8 subsectors of which the most energy-intensive (iron & steel, cement, paper and parts of the chemicals industry) are modelled in a detailed process-oriented manner (Griffin et al., 2013), while the remainder are represented by generic processes delivering the different energy services demands. Data are aligned with DECC assumptions (Fais et al., 2016b).
Transport (TRA)	Nine distinct transport modes are included (cars, buses, 2-wheelers, light goods vehicles, heavy goods vehicles, passenger rail, freight rail, aviation and shipping). Technology parameters for road transport are mainly sourced from work by (Ricardo-AEA, 2012).
Agricultural and land use (AGR)	Represents, in addition to processes for the comparatively small fuel consumption for energy services, land use and agricultural emissions as well as several mitigation options for these emissions based on work by (Defra, 2015).

Future modelling of net-zero pathways will require additional consideration to be given to new options for mitigation, with a focus on residual emissions in industry and transportation, additional carbon dioxide removal (CDR) technologies (e.g. Direct air capture, afforestation), and a strong focus on the demand side opportunities, to avoid, shift and reduce demand, as per (Creutzig et al., 2018).

Sensitivity analysis approach

The scenario sensitivity analysis focuses on the key set of identified system uncertainties – carbon budget level, CCS deployment, role of nuclear, bioenergy resource level, resulting in 64 model runs (Table 2.1 and Figure A1.1, Appendix A1). For comparison, an illustrative UK policy case has also been modelled under the same uncertainty dimensions (16 model runs), based on the current policy framework but with 2050 ambition extended to 2100.

The global carbon budget range for 2°C (66% probability) is taken from the IPCC AR5 assessment. The low and high end of the budget range, 590-1240 $GtCO_2$, are used in the modelling. This is similar to the 1.5°C (33% probability) budget range (IPCC, 2014). The 1.5°C (50% probability) budget range was not analysed due to its stringency (Figure A1.2, Appendix A1). To allocate a share of the global budget to the UK, two approaches are used (Raupach et al., 2014) – i) equity, where allocation is on an equal per-capita basis, giving the UK a 0.8% share of the budget, and ii) inertia, determined by its 2010 share of global emissions, giving the UK a 1.5% allocation. These provide both a high and low allocation stringency respectively, and in combination with the global budget range, result in a wide spread of UK budgets for analysis, compliant with the 2°C climate objective. An additional sensitivity 915 Blend provides a central case for comparison, and is described further in Appendix A2.

The budget is implemented between 2015-2100, leaving the model free to determine the timing of emissions, and the point at which net-zero is reached. To illustrate the requirement of the Paris Agreement requiring developed countries to achieve net-zero faster than other nations, a constraint that net-zero must be achieved at least by 2080 is introduced. The modelling approach does not however permit net negative accounting. This is so that negative emission technologies are deployed sparingly in order to deal with hard to mitigate sectors rather than at a larger scale to provide system wide flexibility and reduce the need for near term action (see Appendix A2).

CO_2 offsets are not permitted, meaning that the UK has to ensure all reductions are accounted for domestically. This is broadly consistent with the UK's current approach, and the guidance provided by the statutory UK climate advisors, the Committee on Climate Change (CCC, 2015a). While offsetting could provide a degree of flexibility in the transition, it is assumed that other countries will also be aiming for net-zero, and therefore will have limited scope for supplying offsets, with those available likely to be at high market prices.

Uncertainty regarding the role of nuclear power and CCS technology is reflected in divergent high and low cases. The high case uses constraints that are in line with current UK government assumptions. Nuclear energy can contribute a maximum of 33 GW to electricity system capacity, while CCS technologies in electricity generation, industrial CCS and hydrogen production are commercially available from 2030 onwards, with permitted annual growth at 5-10%. In the low case, the nuclear capacity is capped at 15 GW (close to the currently installed 11 GW), reflecting constraints on financing and public acceptance. In the low case for CCS, commercial availability is delayed to 2040 and the growth constraint tightened, from 10% to 5% per year.

For the UK, bioenergy resources have been shown to be the most critical uncertainty for meeting decarbonisation goals cost-effectively (Pye et al., 2015b). A high and low case have been formulated based on published bioenergy scenarios (Appendix A1). The high case reflects extending land use for bioenergy, allowing bioenergy to grow to four times the current level, while the low case reflects constraints on land use and restrictions on imports.

Demand reduction resulting from changes in the price of energy services completes the scenario sensitivity set. Providing a crucial policy mitigation option in those sectors where technology-based solutions are costly, limited or exhausted, reductions in demand are accounted for as welfare losses, allowing for a system cost trade-off with supply-side options. Low and high own-price elasticity assumptions have been used for the sensitivity range (Pye et al., 2014). The absolute limits of demand reduction have been set at 15% per annum in the low case and 40% per annum in the high case, versus an inelastic counterfactual for each. Reductions in demand resulting from non-price factors, such as societal change, are not represented.

2.4 Results: CO_2 pathways and budget feasibility

The analysis shows that achieving a 2°C compatible net-zero position in both Equity cases requires stronger action before 2050 than is achieved under the current UK policy case. In Figure 2.1, cumulative emissions to 2050 under the 590 and 1240 Equity cases are at 33% and 64% respectively of the Policy case total. In the 590 Equity case, extremely high average annual reductions of 9% per annum to 2030 are required to remain within the carbon budget, resulting in net-zero emissions by 2045. This compares to 4% per annum under 1240 Equity, which reaches net-zero emissions after 2050 but by 2070. CO_2 emissions have been reducing on average by 1% per annum since 1990, underlining the necessary but unprecedented increase in mitigation efforts.[3]

[3] DECC (2016). Final UK greenhouse gas emissions national statistics 1990-2014. https://www.gov.uk/government/collections/final-uk-greenhouse-gas-emissions-national-statistics

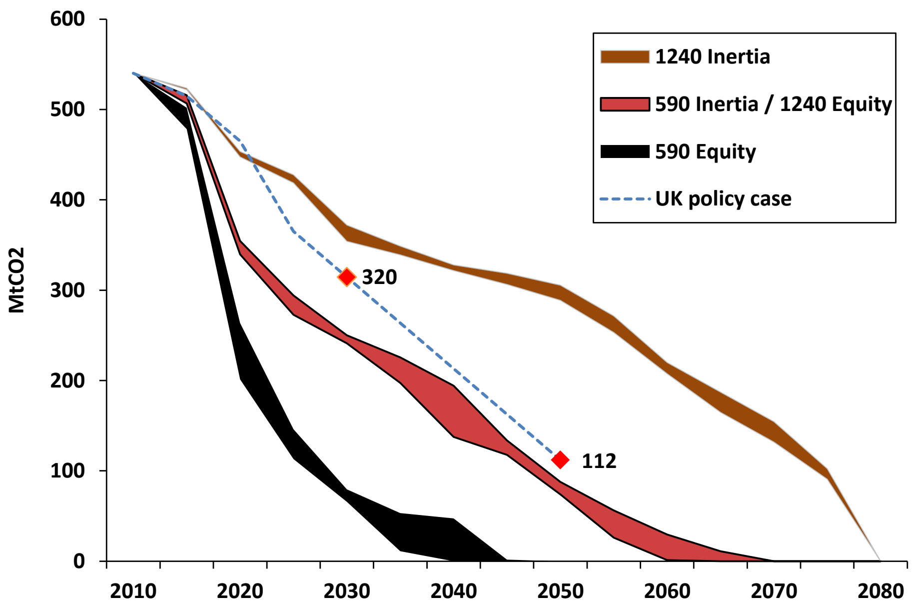

Figure 2.1. Net CO_2 emissions from the energy system under the 2 °C (66% probability) carbon budget range based on *Equity* and *Inertia* allocations.

The emission trajectories represent the full range for all feasible runs, which are those that did not include the backstop mechanism. Note that 590 Inertia has the same UK budget as 1240 Equity, and these are therefore presented as a single trajectory. In the policy reduction trajectory, the red markers show CO2 emissions indicative of the UK Government's 5th carbon budget (2030) and the Climate Change Act 2008 (2050).

The 590 Equity case, however, is at the limits of feasibility. 70% of the runs for this case deploy a 'backstop' mitigation mechanism by 2050, priced at £10,000 /tCO_2 (Figure A2.2, Appendix A2).[4] Deployment of the backstop effectively means that the model has failed to find a solution. In the 590 Equity case, the use of the backstop mechanism results from limits on the model's ability to rapidly deploy low carbon technologies in the near-term. Deployment rates are restricted due to physical build rate constraints, a lack of commercial availability or underdeveloped supply chain capacity. In the other budget cases, infeasibilities are found only in those model runs that assume low bioenergy resource potential, meaning insufficient negative emissions can be generated to offset residual emissions in the post-2050 period, with resulting net emissions of 40-45 $MtCO_2$ (Appendix A2). None of the model runs deploying the backstop mechanism are included in Figure 2.1, or in subsequent results presented below.

Emission reduction options under transition pathways

The mitigation options under different transition pathways are strongly influenced by the uncertainties described earlier. The results demonstrate that staying within budget levels without CCS is extremely challenging, underlining the critical nature of this technology. Figure 2.2 shows the relative importance of CCS in each scenario, illustrating the cumulative level of emissions captured

[4] The backstop mechanism is not a proxy for a specific technology or group of technologies, but a mechanism for allowing non-feasible model solutions to enable further analysis.

and sequestered relative to the overall budget in each case. Median cumulative emissions captured and stored (8.9 $GtCO_2$) are equal to the total carbon budget level in the 1240 Equity case, and almost three times the more stringent budget level in the 590 Equity case (11.2 $GtCO_2$) (Figure 2.2).

The importance of BECCS to the system is particularly evident, representing 62-67% of the CO_2 captured across all cases, and accounting for approximately 85% of the total bioenergy used. BECCS deployment is seen as key for addressing residual emissions from hard-to-address sectors, such as international transport, that lack alternative mitigation options (this is discussed in more detail below). Crucially, the results show that the Equity cases see much higher median CCS deployment relative to the Policy case, both prior to and post-2050 (Figure A2.4, Appendix A2).

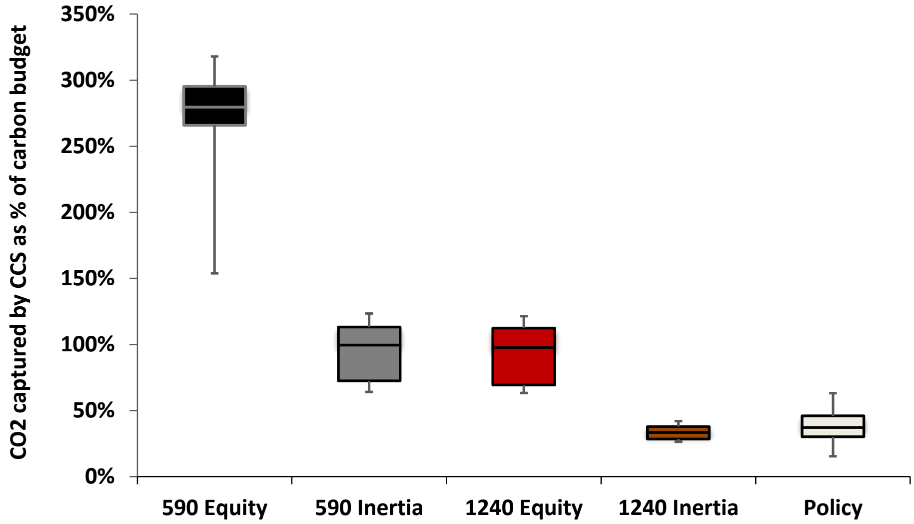

Figure 2.2. Cumulative CO_2 emissions captured and stored between 2025-2100 as a percentage of the overall carbon budget.
A value of over 100% indicates that CCS is used to sequester a level of CO_2 at least equivalent to the carbon budget. The lower and upper extent of the boxes show the 25th to 75th percentile range, respectively, which is separated by the median level. The whiskers show the minimum and maximum of the plotted data.

Figure 2.3 compares oil consumption, electricity generation, and welfare losses for key scenarios. The broad picture that emerges from Figure 2.3 is one where net-zero ambition results in higher rates and increased absolute deployment of mitigation measures in the Equity cases, as compared to the Policy case. Oil consumption declines more rapidly, falling to 20% and 40% of current levels by 2030 in the 590 and 1240 case respectively (Figure 2.3a and Figure 2.3b). A 'floor' level of 500 PJ of oil consumption is seen in all cases post-2070 primarily as a result of international transport having few technological alternatives to fossil-fuels (Figure A2.3, Appendix A2). A lower floor level resulting from lower transport demand or a switch to alternative fuels, would reduce the residual emissions in a net-zero system, and the corresponding need for CCS and BECCS deployment.

High growth in electricity generation, and the rapid reduction in its carbon intensity, reflects the importance of electrification in pre-2050 decarbonisation pathways (Figure 2.3d- f). The particularly steep growth in generation under the 590 Equity case (Figure 2.3d) is largely met by onshore and offshore wind, growing at the assumed maximum build rates of at least 3 GW per annum. The subsequent decline in system size post-2030 reflects other low carbon technologies outside of power generation playing a stronger role, as they become more cost-effective in future years. In both Equity cases (Figure 2.3d and Figure 2.3e), the average investment rate is higher than that observed in the Policy case, while existing fossil capacity is utilised at very low rates after 2020, as highlighted by the reduction in carbon intensity.

Finally, consumer surplus losses represent the reduction in energy service demands resulting from high carbon prices, represented as reductions in economic welfare (Figure 2.3g- i). That is, higher prices for delivering energy services are inducing demand reductions, for example in the provision of private car mobility, aviation demand, or excess heating and lighting. Under the 590 Equity case in particular (3g), the importance of this mitigation option for the transition in the near term is obvious, as it can be affected rapidly without large-scale investment or infrastructure build. These losses plateau post-2050, as supply-side solutions become more cost-effective, and can be scaled. Again, with the exception of the 1240 Inertia case (Figure 2.3i), levels of demand response are higher than observed in the Policy case.

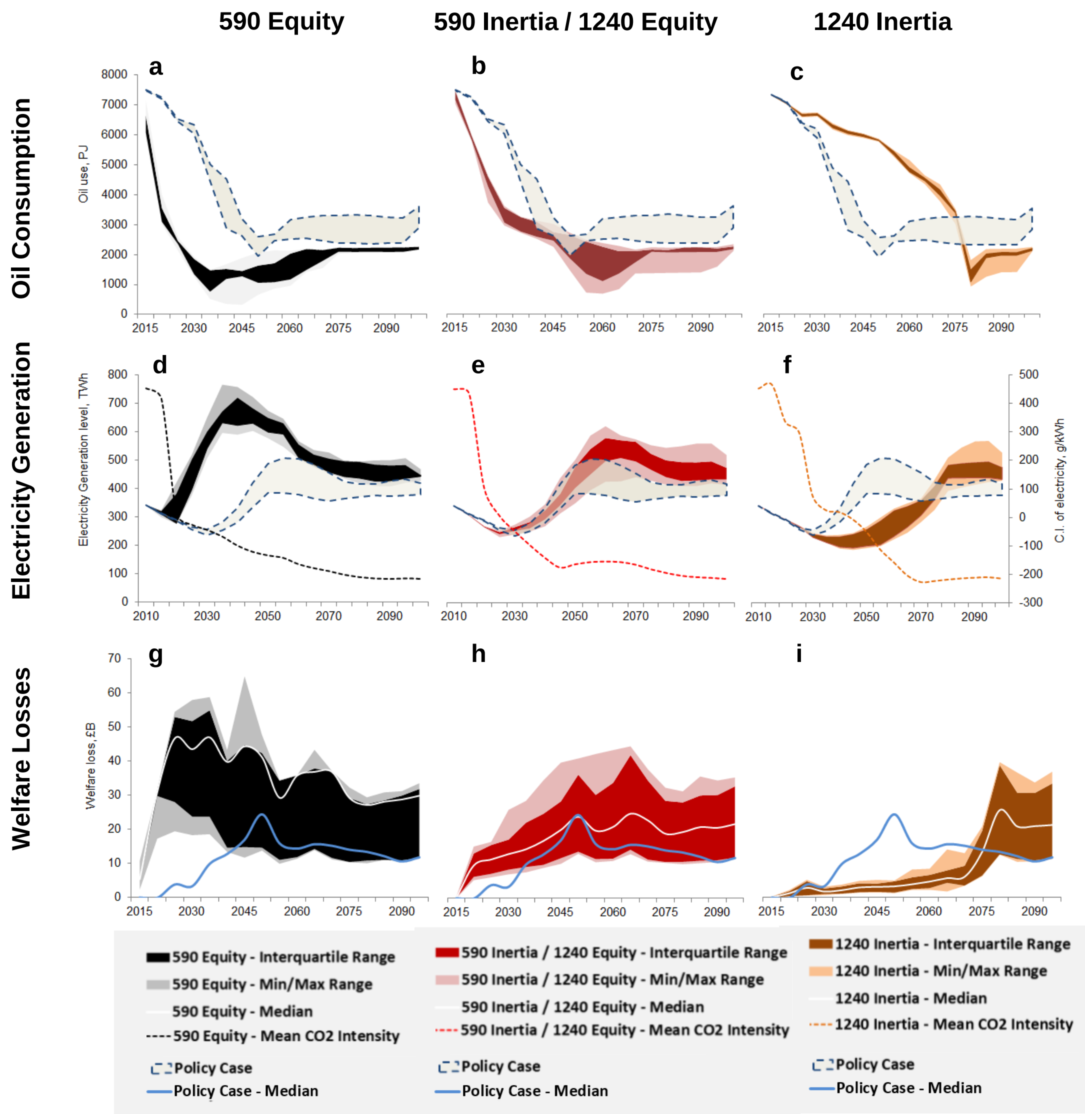

Figure 2.3. Selected decarbonisation transition indicators.

From left to right, the columns represent the cases 590 Equity, 1240 Equity / 590 Inertia and 1240 Inertia. In each plot, the darker shade shows the 25th to 75th percentile range (interquartile range) while the lighter shade gives the minimum and maximum extent. a –c. Oil consumption indicating a shift away from fossil fuels: **The budget range is compared to the Policy case, shown by the grey** dashed area; d-f. Electricity generation representing electrification as a key low carbon pathway: **The budget range is compared to the Policy case, shown by the grey** dashed area. The dashed trend line shows mean carbon intensity of electricity of the budget case, against the secondary vertical axis; g-i. Consumer surplus losses representing demand reduction in energy services: **The white trend line represents the** budget case median while that for the Policy case is shown by the blue trend line.

Economic implications

Over the period 2020-2040, the costs of the system re-orientation under the 590 Equity case are between 20-30% higher than the Policy case, reaching an additional £100 billion in 2030. Achieving this would need a massive increase in investment flows into the energy sector, and a policy package that could put the relevant market and regulatory-based incentives in place. To put this in context, the UK plans to spend £100 billion annually on all infrastructure by 2020-21, with an estimated share of 60% on energy infrastructure (Infrastructure and Projects Authority, 2016). The marginal costs of achieving these reductions reflect the policy challenge, with a 2030 marginal abatement cost of CO_2 at around £1800 /tCO_2 (Figure A3.1, Appendix A3). The annual cost increase over the same period for 1240 Equity is 2-3% (or £10 billion in 2030), which, as seen across the other metrics, also implies a strengthening of action versus the Policy case.

By 2050, investment levels are broadly similar across all cases (£260-275 billion), with the Equity cases and 590 Inertia seeing marginal costs in the range of £400-550/tCO_2, falling by 2080 as low carbon technologies reduce in cost (Figure A3.1, Appendix A3). The costs of the transition are of course strongly dependent on the modelled uncertainties. The bioenergy resource potential has the largest impact on costs, with only the high resource cases providing model-feasible solutions across all budget cases. For the other three modelled uncertainties, the impact on costs is highest from restricting CCS availability, followed by the level of demand reduction possible and then the level of nuclear deployment achieved, as illustrated by the 1240 Equity case (Figure A3.2, Appendix A3).

2.5 Discussion

The analysis shows that pre-2050, national mitigation efforts needed to stay within Equity-based budgets (and 590 Inertia) are likely to be underestimated without a longer term perspective on the necessary emission reductions. Both Equity cases require higher rates of decarbonisation than those projected under the current UK policy framework, which at the time of publication was based around achieving ambitious (but not net-zero) decarbonisation targets by 2050.[5] An important implication of this is that, given the relationship between cumulative CO_2 emissions and surface temperature rise, pre-2050 emission reduction targets should be informed by the overall long term objective of limiting warming to well below 2°C. If not, there is a real risk that insufficient action is taken out to mid-century to affect a transition that stays within the available carbon budget implied by the Paris Agreement's headline goals.

It is observed that the current UK policy framework locks-in a strategy that underestimates the levels of low carbon technology deployment required to meet an Equity-based carbon budget. Specifically, the role of commercially-deployed CCS appears critical. The feasibility of scaling this type of technology depends on demonstrating its commercial viability. Therefore, the UK government's decision to scrap its CCS demonstration programme in 2015 for the second time in 5 years appears short-sighted (Energy and Climate Change Committee, 2016). Secondly, a quicker phase out of fossil-based generation, and higher deployment of wind and nuclear power is required in the power sector. Thirdly, there is a need for more rapid and earlier reductions in emissions from the transport

[5] In 2019, the UK legislated for a net-zero GHG emission target in 2050 based on the advice of the (CCC, 2019).

and building sectors. In short, the results put into sharp focus the need for a more ambitious policy package if Equity-based budget cases are to be achieved.

Our analysis suggests that under the Equity allocation approach, the UK's legislated targets would need to be strengthened to include a net-zero target no later than 2070, thereby providing a clear policy direction (Geden, 2016), and to be founded on a carbon budget with at least a 66% probability of staying below 2 °C. This conclusion broadly holds for the budget case 915 Blend as described in the Appendix A2 (see Figure A2.1), which takes the central value from the global budget range and uses the hybrid allocation approach, Blend, from (Raupach et al., 2014). For a developed country such as the UK, a net-zero target in line with the ambition level expected under the Paris Agreement would form a useful basis for evaluating the sufficiency of pre-2050 actions.

The question remains how far below a 2 °C-type budget countries can push? One could argue that the findings for the 590 Equity case gives some indication of the actions required to meet a 1.5 °C carbon budget, although the former is still somewhat higher. The analysis for the UK shows that, barring an unprecedented fall in demand for energy or radical breakthroughs in sequestration technologies, realising a net-zero energy system prior to 2050 appears improbable (using the cumulative budgets assumed). At the very best, this would require radical and immediate action across all sectors and a rapid shift away from fossil fuels, both of which are happening but at comparatively sedentary rates (CCC, 2015a). While such a target could be considered politically infeasible, this type of analysis helps bridge the gap between the international political rhetoric of what is desirable and an evidence-based national level assessment of what could be achieved. This analysis provides an insight into just how challenging the required action is and helps expand the evidence base, which in the UK context, is recognised to be lacking to date (CCC, 2016a).

The broader findings here are wholly relevant for decision makers across the developed world in the post-Paris Agreement era. As countries are encouraged to revisit the ambition in their NDCs, the end goal of net-zero GHG emissions can be used to guide both near and longer term strategy. The longer term objective will be feasible only with the necessary action in the short term while the carbon budget still exists within which to manoeuvre. Crucially, therefore, national climate policy analyses will need to extend their time horizons, explore stronger ambition, and effectively assess the uncertainties that are most relevant to their national circumstances.

3. The future role of natural gas in the UK: a bridge to nowhere?

Abstract

The UK has ambitious, statutory long-term climate targets that will require deep decarbonisation of its energy system. One key question facing policymakers is the role of natural gas during both the transition towards, and in the achievement of, a future low-carbon energy system. Here the range of possible futures for the UK is assessed, concluding that natural gas is unlikely to act as a cost-effective 'bridge' to a decarbonised UK energy system. There is also limited scope for gas in power generation after 2030 if the UK is to meet its emission reduction targets, in the absence of carbon capture and storage (CCS). In such a case, gas use in 2050 is estimated at only 10% of its 2010 level. It also follows that a 'second dash for gas' while providing short-term gains in reducing emissions, is unlikely to be the most cost-effective way to reduce emissions, and could result in stranded assets and compromise the UK's decarbonisation ambitions. However, with significant CCS deployment by 2050, natural gas could remain at 50-60% of the 2010 level, primarily in the industrial (including hydrogen production) and power generation sectors.

Keywords

Natural gas; gas as a bridge; decarbonisation; climate policy; energy systems

3.1 Introduction

Natural gas has the lowest combustion carbon intensity of the three major fossil fuels (see e.g. IPCC (2006)). However, it has been shown that increases in the consumption of natural gas are not sufficient for reducing global greenhouse gas emissions since this would potentially substitute for both higher-carbon fossil fuels, e.g. coal or oil, as well as for lower-carbon or zero-carbon energy sources, such as renewables (McJeon et al., 2014). (McGlade et al., 2014) and (McGlade and Ekins, 2015) examined possible futures for fossil fuels, with a particular focus on the 'bridging' role that natural gas may be able to play during a transition to a global low-carbon energy system. This research found that there is a good potential for gas to act as a transition fuel to a low-carbon future up to 2035 on a global level, but only under certain conditions.

However, a key caveat to the positive conclusion that natural gas can play a 'bridging' role globally is that its potential varies significantly between different regions. Therefore, while some national-level studies have demonstrated that increases in natural gas consumption, in combination with certain emissions-reduction policies, can help reduce overall greenhouse gas emissions in the United States (Brandt et al., 2014; Moniz et al., 2010), it does not follow that this is the case in all countries and regions around the world. It is also noteworthy that the International Energy Agency's 'Golden Age of Gas' scenario that explored a future with more natural gas in the global energy system resulted in projected emissions on a trajectory consistent with a temperature rise of 3.7°C (IEA, 2011), well above the internationally-agreed threshold of below 2°C (United Nations, 2015a).

One crucial factor affecting the decarbonisation potential of natural gas is the level of fugitive methane emissions that occur during its production, transportation and distribution. This has been an ongoing source of controversy since the first paper on the subject by (Howarth, 2014; Howarth et al., 2011) suggested that such emissions from shale gas extraction were so high that they counteracted all benefits of switching from coal to gas, although multiple papers subsequently contested these findings (Cathles et al., 2012; Levi, 2013; O'Sullivan and Paltsev, 2012). Nevertheless, it is important to recognise that the UK's long-term decarbonisation objectives include only 'territorial emissions', or emissions generated within the country. Any fugitive methane from natural gas produced by the UK is included within its territorial emissions but imported gas is effectively 'carbon-neutral' from an upstream emissions perspective (the UK imported 45% of its gas in 2014). An increase in domestic gas production, such as from its putative shale gas resource (Andrews, 2013) might have lower life-cycle emissions than other sources of imports, such as Liquefied Natural Gas (LNG) (MacKay and Stone, 2013). But it is important to recognise that any fugitive emissions from domestic production would augment the UK's territorial emissions, potentially making it harder to achieve the UK's domestic decarbonisation objectives.

In the UK, natural gas accounted for 34 % of total primary energy consumption in 2015; of that 30% was used in the generation of electricity and heat by power stations; 37 % by households, mainly in heating buildings, and the remainder by industry and other users (BEIS, 2016). Climate change policies are a key dynamic that will affect future levels of gas consumption but (Bradshaw et al., 2014) also highlighted the myriad of technological, economic, and policy factors that will affect gas consumption in the UK and put these into a global context. The range of uncertainties around these factors means that how large natural gas consumption might be and what role it might play in the future, in the UK and elsewhere, depends on the assumptions about these factors and therefore remains an open question. This is illustrated in the UK context by the recent Future Energy Scenarios, developed by the national gas system operator (National Grid, 2016). They imply a lower consumption by 2030 under all cases, even those that do not meet the UK climate ambition, with a stronger reduction under the Gone Green scenario of around 25%. However, they also point to substantial quantities of gas still being required in the 2030s.

The energy system models UKTM (Daly et al., 2015) and ESME (Heaton, 2014; Pye et al., 2015b) are used to examine changes in the role of gas in the UK under a range of future energy scenarios. Two alternative models are used here for different reasons. First, the two models are better suited to constructing different types of scenarios. ESME is designed and set-up for the exploration of a large number of simulations, based on a wide set of parametric uncertainties. This allows for an enhanced assessment of the range of possible pathways, and a more systematic assessment of under what conditions different pathways emerge for natural gas. This would have been more difficult in UKTM, which is a more complex model, with a more detailed representation of the energy system, and is not set-up to run 100-plus simulations. UKTM includes a resource-upstream sector, with a more detailed characterisation of domestic gas production, processing and distribution, and imports. In addition to CO_2, it also accounts for non-CO_2 GHG emissions across the energy system, important given the methane emissions associated with gas production and distribution. Finally, end use sectors which use gas, the CCS system, and hydrogen production all have enhanced detail compared to ESME. Secondly, the set-up and assumptions within these models vary, meaning that drawing firm conclusions based only on a single model is avoided.

In discussing the central question of this chapter, whether or not gas can act as a 'bridge' fuel, there are two conditions that need to be fulfilled. In a scenario that is consistent with maximum 2°C temperature average global warming, gas consumption should increase either absolutely from 2010 or relative to another scenario that does not meet this temperature constraint. More specifically:

- Natural gas acts a 'relative' bridge in a region (or globally) when total consumption is greater in some period in a scenario consistent with at 2°C temperature rise*, relative to* a scenario that contains no GHG emissions reduction policies.
- Natural gas acts as an 'absolute' bridge in a region (or globally) when total consumption rises above *current* levels over some period until it reaches a peak and subsequently enters a permanent or terminal decline.

The remainder of this chapter is organized as follows; section 3.2 describes the modelling approach and the scenario framing. Section 3.3 follows with a presentation of the results from both models. Section 3.4 develops the discussion around the modelling insights, before drawing some key conclusions around the future role of gas in the UK.

3.2 Modelling approach and scenarios constructed

This section gives a brief overview of the two energy system models that have been used for the analysis – UKTM and ESME – and the scenarios that will be implemented with each. These models have some features in common – within physical and technical constraints, they optimise energy system development over time (minimising energy system cost or maximising a measure of social welfare) by assuming rational decision making by a central policy planner who has perfect information about the future. While the model frameworks necessarily provide a proxy representation of the actual energy system and its evolution, they nevertheless provide important insights about how energy systems could change in response to drivers such as fuel prices and emissions limits – and some of the trade-offs and choices that could be important. A detailed description of the two models used in this paper is provided in Appendix B1.

3.2.1 Energy system models

ESME is a fully integrated, regionally disaggregated model of the UK energy system, used to determine the role of different low carbon technologies for achieving the mid- to long-term climate mitigation goals set in UK legislation. The model has been used extensively for informing government and industry strategies (CCC, 2013, 2010; DECC, 2011b), and underpins a range of research papers on different aspects of energy system decarbonisation (McGlade et al., 2018; Pye et al., 2015b, 2014; Pye and Daly, 2015). Built in the AIMMS environment, the model uses linear programming to assess cost-optimal technology portfolios. It covers the key sectors of the UK energy system, including power generation, industry, buildings, transport and other conversion sectors e.g. biofuel production, and hydrogen production.

A set of energy service demands that capture requirements for industrial and building heating, electricity supply and mobility needs are provided as exogenous inputs, and largely reflect Government projections. The model then endogenously determines how to meet these demands in a cost-optimal manner, through investment in end use technologies (including energy efficiency measures), and in production and supply options to provide for different energy forms. Primary resource supply is characterised by commodity price and resource availability, with no distinction between imports and domestic indigenous production (except for biomass), and no explicit representation of resource and upstream sectors (although these are accounted for implicitly through the energy balances, prices and other statistics used as inputs). For emissions accounting, the model accounts for CO_2 but not other greenhouse gases (GHGs), such as methane (CH_4) and nitrous oxide (N_2O). Therefore, the CO_2 emissions constraints applied in the model that are used to understand the implications of the UK's GHG emission reduction plans make an exogenous assumption about the level of non-CO_2 GHG levels in future years, taking account of expected abatement, and are adjusted accordingly. In this version of the model, a total constraint of 160

$MtCO_2e$ is assumed, based on an assumed non-CO_2 GHG level of 55 $MtCO_2e$ (CCC, 2010), allowing for of CO_2 emissions of 105 Mt in 2050.

Uncertainty around cost and performance of different technologies and resource prices is captured via a probabilistic approach, using Monte Carlo sampling techniques. Gas extraction, production and distribution, and the associated emissions from this sector, are not represented explicitly, nor is there a distinction between domestic and imported gas resources. Further information is provided in Appendix B1. The limited representation of domestic gas production and distribution, and associated CH_4 emissions, means that the methane emissions penalty that would be incurred under stringent climate policy is not accounted for.

The UK TIMES energy system model (UKTM) was introduced in chapter 2 (section 2.3). It is distinctive from the ESME model, to include the accounting of all GHGs associated with the energy system, including CH_4 emissions from domestic production and distribution of natural gas. For gas and other energy commodity imports, only emissions at the point of use are accounted, as per the territorial or production basis for inventory accounting. This means CH_4 emissions from upstream production and transportation outside of the UK are not considered.

3.2.2 Scenarios constructed

ESME is well suited to exploring the effects of uncertainty on future energy and emissions pathways. Its strength is exploited here to explore the effects of uncertainty in technology investment costs in the power and transport sectors, fuel costs and resource potential (e.g. biomass imports), on future levels of gas consumption in the UK under different emissions assumptions. In the context of these uncertainties, recognising that there are others we have not included, we explore three specific scenarios that have been shown previously to have a large effect on the levels of gas consumed. These three scenarios are:

(i) A reference case which is required to meet the 4th carbon budget (a 50% reduction on 1990 emission levels by 2025) but with no other explicit requirements to reduce greenhouse gas (GHG) or CO_2 emissions thereafter;

(ii) An 80% GHG emissions reduction by 2050 case in which CCS is permitted; and

(iii) An 80% GHG emissions reduction by 2050 case in which CCS is not permitted.

A detailed description of the uncertainties explored is provided in (Pye et al., 2015b) and summarised in Table 3.1 below. A Monte-Carlo simulation process is used to explore these uncertainties with 250 runs implemented for each of the above three scenarios.

Table 3.1. Areas of uncertainty explored in ESME runs

Parameter	Sector	Approximate range of uncertainty
Investment costs	Power generation	Increases with novelty of technology from ±20% for mature technologies to ±70% central estimate for novel technologies
	Road transport	Increases with novelty of technology from ±10% for mature technologies to between +60% and -20% central estimate for novel technologies
	Heat pumps & district heating	±30% central estimate
Annual build rates	Power generation	±50% central estimate
Resources	Biomass availability	+150% & -50% central estimate
	Prices	Around ±40% central estimate for gas and coal Around +150% and -50% central estimate for oil

UKTM has a more detailed representation of the UK energy sector than ESME. It is therefore more complex, and represents certain features of the energy system better, including resource and upstream sectors, GHG emissions including CH_4, and range of technologies in end use sectors. This more detailed representation means that there is a consequent trade-off with the time to run a specific scenario. As a result, it is used to explore five better-defined but discrete scenarios. These scenarios are described in detail in Appendix B2, and some of the key assumptions that vary across each of the above scenarios are set out in Table 3.2.

The first, called **Abandon** assumes that climate change policy is downgraded in importance during the late 2010s, meaning that limits on emissions beyond the 3rd carbon budget (2018-22) are not implemented. Due to a lack of emphasis internationally on moving away from fossil fuels, and consequently higher overall demand, the price of fossil fuels is relatively high in this scenario. The second, **Insular,** scenario also assumes that climate change policy is downgraded in importance during the late 2010s. Following the recent decision to leave the EU, this scenario models a shifts towards a more inward looking energy policy with, for example, much less electricity connection to the European continent. Strict limits are placed on imports in favour of domestic fossil fuel (including new coal and shale gas) and renewable resources, and prices of fossil fuels are relatively high as a result.

The **Affordable** scenario continues with commitment to climate change targets well into the 2020s. However, since the world is not acting sufficiently quickly to reduce emissions, this commitment starts to falter. Policies to support the deployment of renewables are progressively scaled back as is policy support for nuclear and CCS. In the **Maintain** scenario, the UK continues its commitment to the long-term climate change targets (i.e. 80% GHG emissions reduction by 2050). This drives down the costs of many low-carbon technologies and energy efficiency measures, including CCS which is successfully commercialised and ‘rolled out’ (after 2025) alongside other low carbon technologies. Since the world shifts away from carbon-intensive fuels, fossil fuel prices remain relatively low.

The **Maintain (tech fail)** scenario is similar to Maintain, but there is a failure of efforts to commercialise CCS technologies. More emphasis is therefore placed on other forms of mitigation to meet UK targets such as renewables, nuclear power and energy efficiency.

These latter two scenarios are also required to keep within a cumulative level of emissions between 2028 (the end of the 4th carbon budget period) and 2050. This ensures that there is a steady progression towards the 2050 target and is used as a proxy for future carbon budgets to be set by the Committee on Climate Change. Since the analysis undertaken in this chapter, the proposed level of the 5th carbon budget, for the period 2028-2032 has been agreed, setting reductions (including international shipping) at 57% below 1990 levels (CCC, 2015a). Both of these scenarios see reductions in this budget period at levels slightly lower than this level, but nevertheless are broadly comparable with the 5th carbon budget.

Table 3.2. Core assumptions varied across the UKTM scenarios.
Under required emissions reduction, ‘Carbon Budgets’ refer to the 5 year periods across which average emission reductions have to be achieved, and which get progressively more ambitious over time to ensure the UK is on track to meet the long term 2050 reduction ambition. The latest agreed 5th Carbon Budget period will run between 2028-2032, and is near achieved in both Maintain scenarios.

Scenario Name	Required GHG emissions reduction	Technology availability	Fossil fuel prices	Import dependency
Abandon	35% reduction by 2020 (meets 3rd Carbon Budget only)	No new coal Nuclear delay	High	Outcome of the model
Insular	35% reduction by 2020 (meets 3rd Carbon Budget only)	Max interconnector 4 GW	High	Max 30% primary energy in 2020, falling to 5% by 2030
Affordable	50% reduction by 2025 (meets 4th Carbon Budget only) 60% reduction by 2050	Slow renewables deployment Delay in new nuclear Delay in CCS	Low	Outcome of the model
Maintain	80% reduction by 2050 (meet all legislated Carbon Budgets, and 2050 target)	No new coal	Central	Outcome of the model
Maintain (tech failure)	80% reduction by 2050 (meet all legislated Carbon Budgets, and 2050 target)	No new coal No CCS	Central	Outcome of the model

3.3 Results

3.3.1 ESME results

Gas consumption in the three core ESME scenarios is presented in Figure 3.1 which shows the implications of the uncertainties set out in Table 3.1. The maximum and minimum of these uncertainty ranges describe the 10th to 90th percentiles of consumption from the 250 runs in each time period i.e. the bottom of the range is defined by consumption in the 25th lowest run and the top by consumption in the 225th lowest (or 25th highest) run.

Median gas consumption in the reference case (that meets the 4th carbon budget) initially falls out to 2020 before rising rapidly between 2030 and 2040 and finishing at 4,250 PJ (115 Bcm), a 10% increase on 2010 levels. The uncertainty spread also grows over time from around 25% of the median value[6] in 2030 to over 60% by 2050.

[6] This is calculated by taking the difference between the high and low values and dividing by the median.

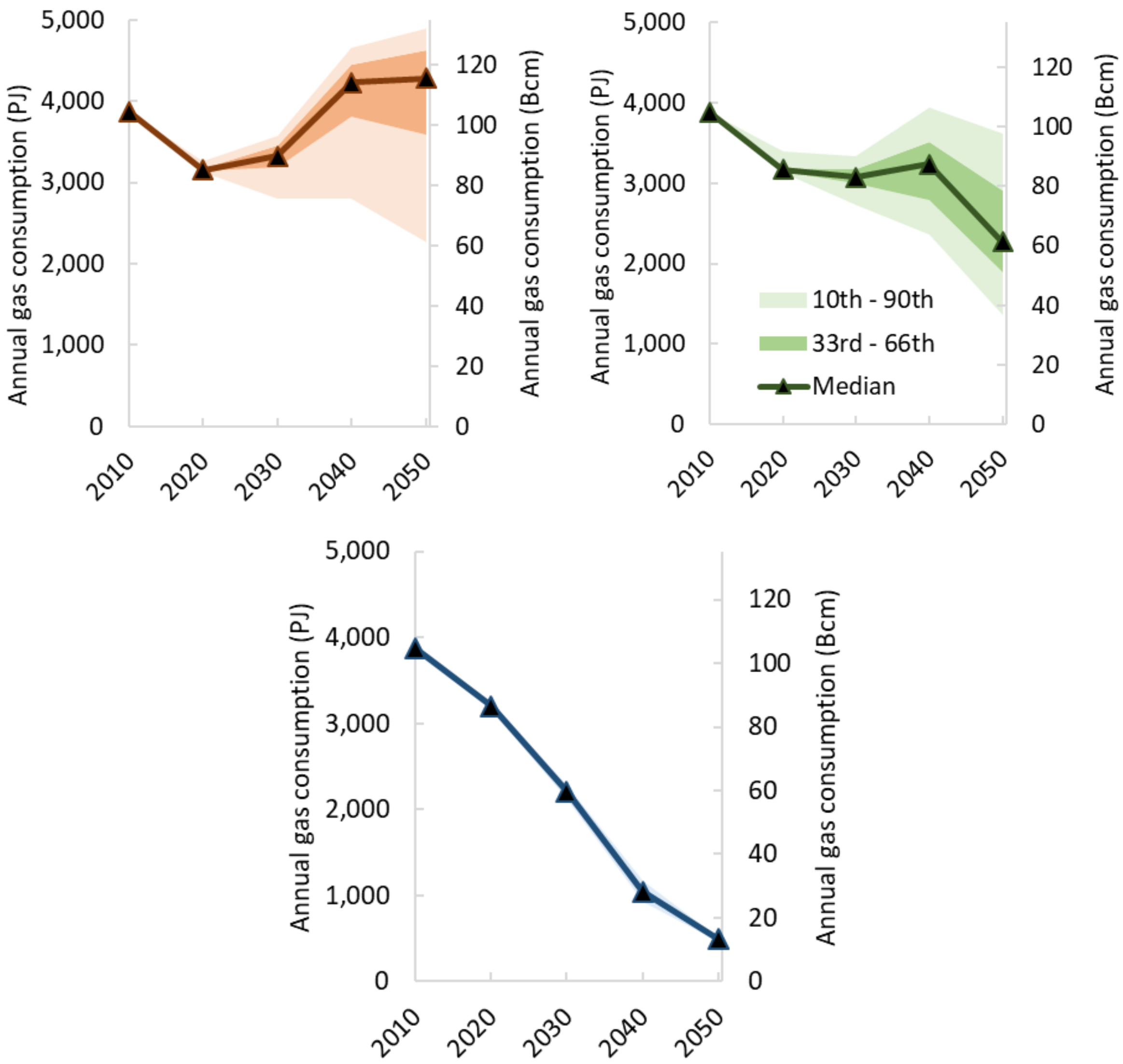

Figure 3.1. UK gas consumption in the three core ESME scenarios
Top left: Reference case where only the climate ambition set out in the 4th Carbon Budget (2023-2027) is met. Top right: 80% reduction case meeting the UK legislated Carbon Budgets and 2050 target with CCS technologies available for deployment. Bottom: 80% reduction case but without CCS deployment. In all plots, the number of simulations run is 250. The light shaded areas represent the 10th to 90th percentile ranges, dark shaded areas the 33rd to 66th percentile ranges, and solid lines the medians. The left hand axis has units in PJ, and the right hand axis in Bcm.

Figure 3.2 (left panel) gives the relationship between gas consumption in the Reference scenario and gas prices in 2050 and it can be seen that consumption does not increase much above 4,900 PJ (130 Bcm) regardless of the assumed gas price level. This ‘saturation level’ occurs because most (>90%) of electricity generation is met by gas, which also provides 65% of household fuel (this could be 5 to 10% higher if there was no penetration of district heating), and all Heavy Goods Vehicles (HGVs) are converted to run on natural gas. As a result, there is little additional market share that gas can gain.

In the 80% reduction case with CCS, the median consumption initially falls but is then largely flat to 2040 at just over 3100 PJ (around 85 Bcm) before exhibiting a large drop in the final period and thus ending up 40% below 2010 levels. The uncertainty spread up to 2030 is similar to that in the reference case but thereafter it grows rapidly to over 100% by 2050. This rapid growth in uncertainty can be explained by the larger range of new technology options that are available to the model in latter periods (such as conversion to hydrogen, use with CCS in the power sector), but the wide spread in the costs and rates at which these can be built. The changing manner in which gas is used out to 2050 is explored in more detail in the discrete UKTM scenarios below.

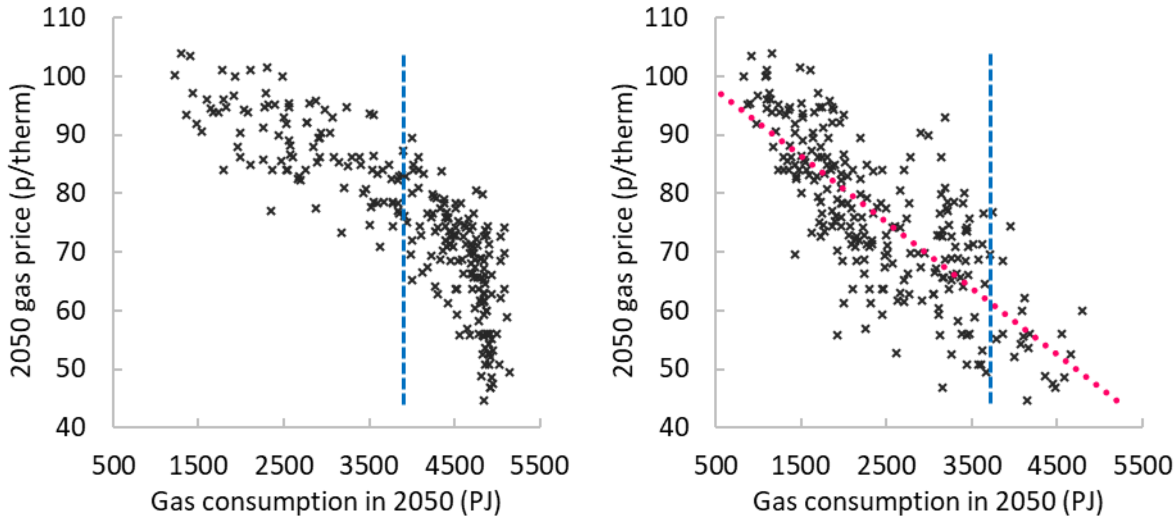

Figure 3.2. Relationship between consumption and gas prices in 2050 in the reference (left) and 80% reduction with CCS cases (right).
These figures include all 250 projections, with a linear line of best fit (pink line) plotted for the 80% reduction case (right panel). The blue line indicates the gas consumption level in 2010.

Comparing the median of the two scenarios it is again apparent that after 2020, consumption is always lower in the 80% reduction case than in the reference case. Despite the small rise over 2030-2040 in the 'with-CCS' scenario (a period in which CCS can start to be deployed at scale), the predominant downward trend of the median throughout the modelling period suggests that the ESME model finds little potential for gas to act as a bridge in the UK in an optimal trajectory towards a low-carbon energy system.

Nevertheless, it can also be seen that there is significant overlap between the uncertainty distributions for these two scenarios. Consumption in some of pathways towards the upper end of the distribution in the 80% reduction case with CCS is not significantly lower than 2010 levels. In general, these occur whenever gas prices are low and the technology options (e.g. hydrogen production or industrial use w/CCS) that can utilise gas as an input have favourable cost and build rate assumptions. Figure 3.2 (right panel) indicates that future gas levels in the 80% reduction case are closely (albeit not perfectly) correlated to assumed gas prices. If gas prices remain low (below around 60p/therm out to 2050), and there is sufficient technological innovation, including implementation of CCS, it could be possible for gas consumption in 2050 to be at similar levels to those in 2010 whilst still meeting the UK's emission reduction goals.

Finally, gas consumption for the 80% reduction case without CCS exhibits a sharp decline over the modelling period, and reaches less than 500 PJ (15 Bcm) by 2050. There is also almost no uncertainty spread for natural gas use despite utilising the same range of uncertainties that were explored in the previous two scenarios. This demonstrates that if CCS is not available, these uncertainties have next to no effect on the level of gas consumption, even when low cost. Of course, the uncertainties in the modelling do impact on a range of metrics that characterise other sectors of the energy system. Reaching the UK's emission reduction goals without CCS requires that, despite uncertainties over resource prices, power and end-use sector build rates and investment costs, gas must be steadily phased out over the next 35 years and thus be almost entirely removed from the UK energy system by 2050.

This is not only because gas cannot itself be used with CCS in this scenario, which clearly restricts its use when CO_2 emissions reductions are required, but also because decarbonisation of all secondary and end-use sectors is much harder to achieve without the use of CCS. Sectors that may continue to rely upon unabated gas consumption in the 80% reduction case with CCS therefore have to work additionally hard to reduce emissions. Gas is no longer useful as these sectors must shift to other low or zero carbon sources.

3.3.2 UKTM results

The detail of the differences in the use of gas over time and between scenarios can be best examined using the discrete runs implemented in UKTM. In this section, the focus is initially on the three scenarios that miss the long-term 80% reduction goal, next turning to those that meet this goal, and then finally comparing these to examine the extent to which gas can act as a bridging fuel.

Scenarios that miss emissions reduction goals

Figure 3.3 and Figure 3.4 present the changes in primary energy consumption and sectoral changes in gas consumption in the **Abandon, Insular,** and **Affordable** scenarios in 2030 and 2050. These are the scenarios not required to reduce emissions by 80% by 2050. Primary energy consumption in all scenarios in 2030 is at least 22% lower than in 2010, although it then stays relatively constant in each scenario thereafter.

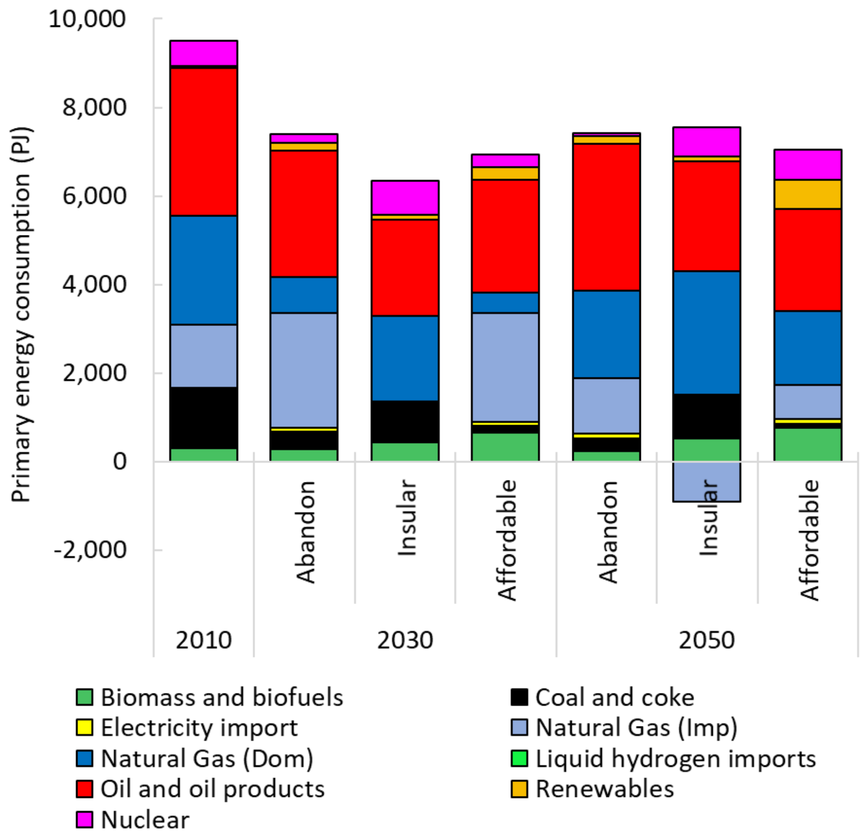

Figure 3.3. Primary energy consumption (PJ) in UKTM scenarios failing to meet 2050 carbon targets. Scenarios not meeting 2050 targets include abandon, insular, and affordable. Natural gas is split into domestic production (Dom) and net imports (Imp). Negative net imports under Insular in 2050 can be interpreted as exports.

Abandon exhibits the smallest drop to 2030 in overall primary energy consumption, much of which is due to a reduction in coal consumption. Abandon also has the smallest change in the level of gas consumption and in the way it is consumed. Despite dropping by nearly 20% between 2010 and 2015, gas consumption after 2015 remains broadly constant. There is a reduction in use in centralised gas generation over time, but this loss is compensated for by an increase in the use of combined heat and power (CHP) units in both the residential and industrial sectors. As a result, gas use in the residential sector actually increases steadily from 2015 onwards, the only scenario in which this occurs.

In 2030 primary energy consumption in **Affordable** is relatively similar to that in **Abandon** with slightly less coal consumption and higher levels of renewables and nuclear, but these differences are small. Both cases show a strong push towards imported gas in the 2030s, and then a large share towards domestic in the longer term, due to some exploitation of shale (as imported prices make this resource viable). The largest difference is in gas consumption, which exhibits a steadier decrease over time despite the availability of cheap gas. As the need for a 60% reduction in emissions by 2050 is most cost-effectively met by the decarbonisation of electricity, existing gas generation capacity is retired and is not replaced. Consequently, between 2030 and 2050 gas use in centralised generation exhibits the largest drop seen in any sector. In the residential sector there is a 1%/year average decline in gas use made possible initially through efficiency measures and latterly by a small degree of electrification of heat.

Insular displays the largest changes of the three scenarios in both 2030 and 2050. Given the need to rely predominantly on domestic sources of energy production, there is a much greater (and rapid) uptake in efficiency measures. Primary energy consumption is therefore 15% lower than in **Abandon** in 2030. Coal consumption is also significantly different, and this is the only scenario in which coal maintains its current share of primary energy consumption of around 15% throughout the model horizon; in all other scenarios, coal drops to less than 5% by 2030 (and less than 2% in the **Maintain** scenarios discussed in the next section). Between 2010 and 2030 total domestically produced gas use falls by 50%, with gas entirely removed from the electricity sector, and residential sector consumption dropping by nearly 30%. After 2030, annual consumption stagnates at around 2000 PJ (55 Bcm) with all sectors continuing to maintain their levels of consumption. A small level of exports can be observed in 2050, as shale production increases.

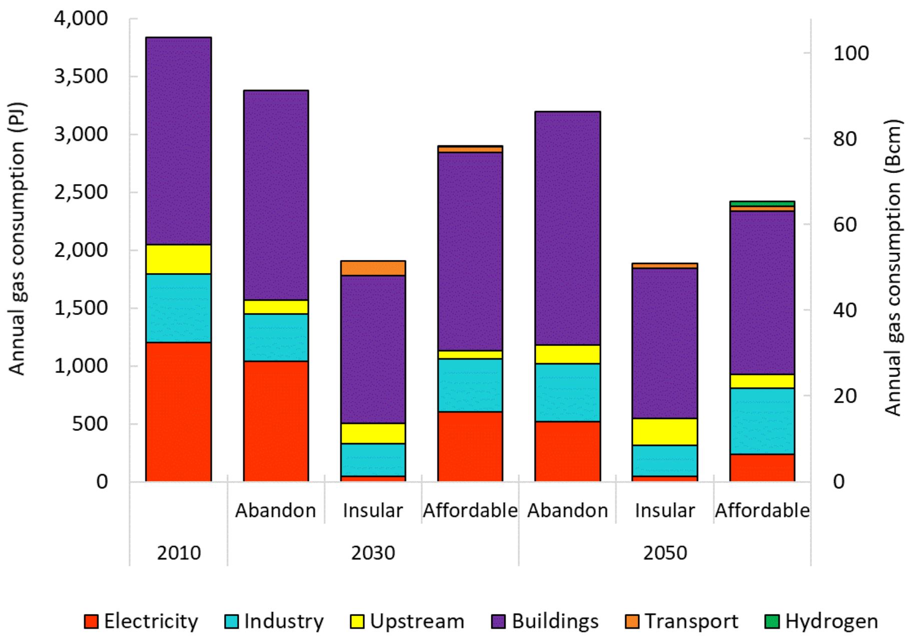

Figure 3.4. Sectoral gas use in UKTM scenarios failing to meet 2050 carbon targets.
Scenarios not meeting 2050 targets include abandon, insular, and affordable. The left hand axis has units in PJ, and the right hand axis in Bcm.

Focus on 80% GHG reduction targets

Figure 3.5 and Figure 3.6 next display primary energy consumption and sectoral gas consumption in the two core scenarios that meet the UK’s long-term emission reduction targets. Over the medium-term differences in energy consumption between these two scenarios and between the scenarios described above do not appear too large. For example, primary energy consumption in 2030 in both scenarios is 27% below 2010 levels, broadly similar to the reduction in **Affordable** and at a greater level than was seen in **Insular**. It is unsurprising that **Maintain** and **Maintain (tech fail)** are comparable in 2030 because the only difference between them, carbon capture and storage, is assumed only to become available in **Maintain** in 2025. Coal is effectively eliminated in both scenarios, but with a small fraction remaining in energy-intensive industries. In 2050, the reduction in primary energy in Maintain (tech fail) is lower than in most other scenarios (which see a rise between 2030 and 2050) due to the large decrease in natural gas consumption (as described below).

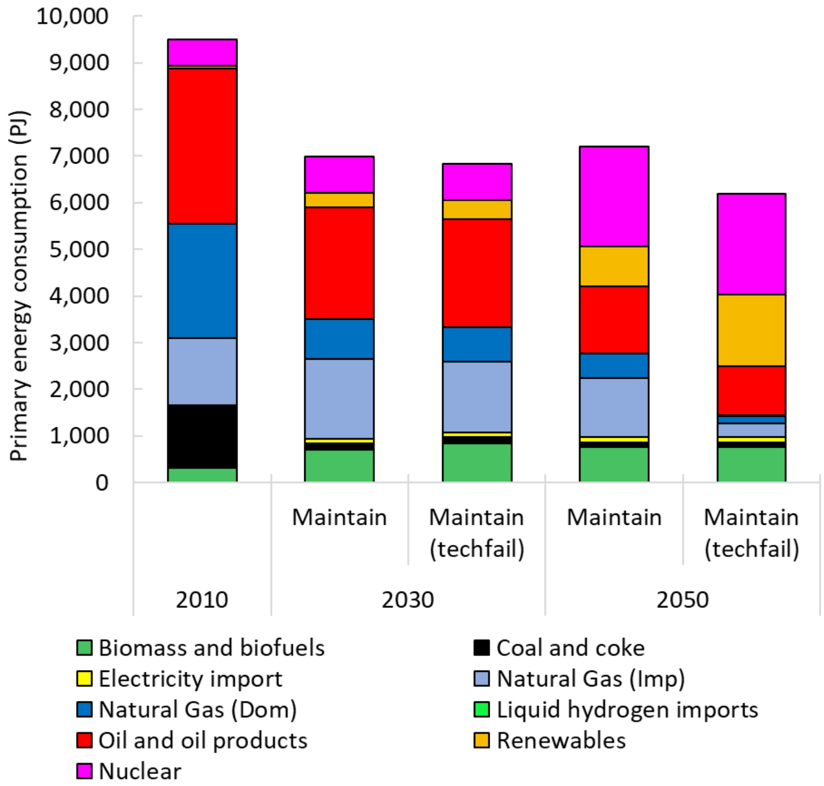

Figure 3.5. Primary energy consumption in UKTM scenarios that meet the UK's 2050 carbon targets. Scenarios meeting 2050 targets include maintain and maintain (tech fail). Natural gas is split into domestic production (Dom) and net imports (Imp).

Turning to gas consumption (in Figure 3.6), which is increasingly met by imports due to higher production costs in the UK, between 2010 and 2030 60% of the drop seen in both scenarios results from falls in the electricity sector, with smaller reductions in industry (accounting for 15% of the total drop) and residential (20%). There is, however, significant construction of new CCGT capacity throughout the 2020s (7.5 GW in **Maintain (tech fail),** 10 GW in **Maintain**)**,** although less than the 22 GW installed in **Affordable**. Despite this new plant, and the loss of close to 200 PJ (55 TWh) of electricity from coal plants, levels of generation from gas (and gas consumption) remain broadly flat in both **Maintain** scenarios. While it is therefore cost-effective to construct some new efficient CCGT plants, this mainly serves to replace existing coal and CCGT plant. Coal-to-efficiency and coal-to-renewables is found to be a more cost-effective solution than coal-to-gas substitution. Since **Affordable**, which fails to meet the long-term 80% reduction target, has a much greater level of coal-to-gas switching, this highlights a potential risk of relying predominantly on coal-to-gas switching in the power sector to meet the 2025 emissions reductions.

A small increase in the use of gas in transport can also be seen in both **Maintain** scenarios in the medium term, reaching a maximum of 100 PJ in **Maintain** and 170 PJ in **Maintain (tech fail)**. In both cases there is some uptake of CNG in Light (LGV) and Heavy Goods Vehicles (HGV). In both of these scenarios, this growth in CNG occurs while the technology market for hydrogen matures and by 2050 in both scenarios, all HGV service demands are satisfied by hydrogen. Possible alternatives for the road freight sector include biofuels and electric vehicles. However, electrification of freight at scale was not an option due to battery size and range issues (although recent developments in the market mean this assumption should be questioned). On biofuels, bioenergy tends to be allocated for use in industrial and electricity sectors, particularly in combination with CCS[7]; therefore, this leaves a limited supply for domestic biofuel production.

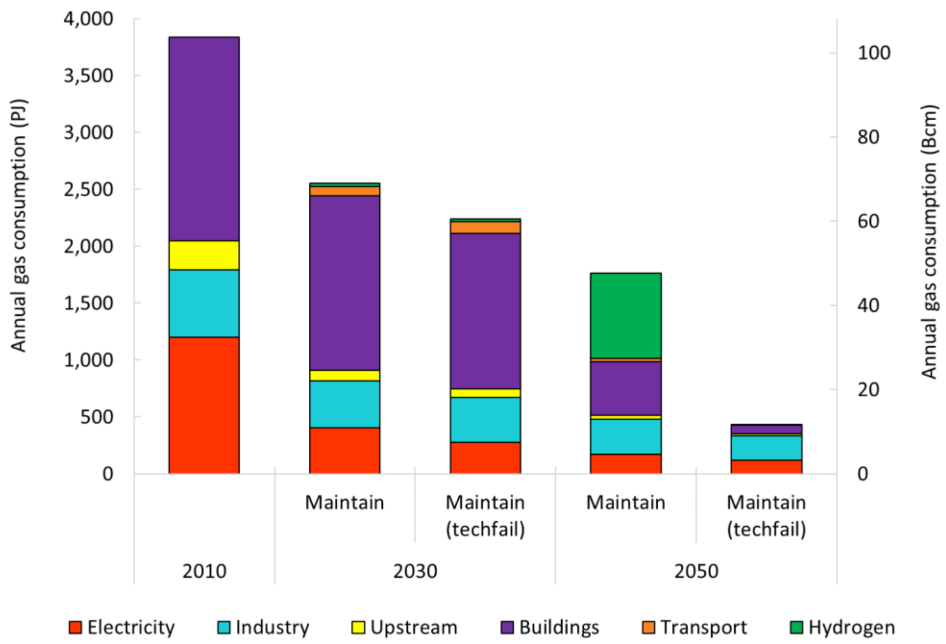

Figure 3.6. Sectoral natural gas use in UKTM scenarios that meet the UK's 2050 carbon targets.
Scenarios meeting 2050 targets include maintain and maintain (tech fail). The left hand axis has units in PJ, and the right hand axis in Bcm.

[7] Often referred to as BECCS (bioenergy with CCS). The system gets an emissions credit or negative emission for each unit of CO_2 captured from bioenergy, due to the CO_2 naturally stored in bioenergy during its growth phase.

Over the long-term to 2050, there are much starker differences both between these two scenarios and with the scenarios described above. Similar to what was seen in the ESME scenarios (Figure 3.1), it is clear that without CCS, gas is again almost entirely removed from the UK energy system. What remains in **Maintain (tech fail)** is predominantly used in industry (most of which is as a petrochemical feedstock or in non-energy uses) and as back up to the intermittency of renewables in the power sector (installed gas capacity is used at less than 5% load factor). Overall consumption is less than 450 PJ (12 Bcm), a 90% reduction on 2010 levels. It is no longer used for hydrogen production, as SMR technologies using gas are only deployed when CCS is available. Hydrogen production shifts towards electrolysis-based technologies.

In **Maintain,** there is a significant decrease in residential sector consumption, as this sector increasingly electrifies with heat pump technologies, and increases district heating coverage. However, this loss is largely compensated for by the growth of an entirely new industry, namely the steam methane reforming (SMR) of natural gas to produce hydrogen. Crucially, this SMR is carried out in combination with CCS so that the overall level of emissions that occurs is vastly reduced. Hydrogen in this context provides a useful vector for decarbonising decentralised service demands, predominantly transport (as discussed above) and industry, in approximately equal proportions. This technology is entirely absent in all other scenarios examined, demonstrating the necessity of both emission reduction goals, and the availability of CCS if gas for hydrogen production is to have any role in the future UK energy system.

There again continues to be some use of gas in the electricity sector, both as back up to renewable intermittency and as centralised CCS plant, although with only 2 GW of gas CCS capacity installed in the final period, this latter role is marginal. There is also continued reliance (around 300 PJ or 8 Bcm) on gas in industry, although as above, the majority of this is as use as a feedstock for petrochemicals and in non-energy uses. The emergence of hydrogen in the industry sector in latter periods impinges on the use of gas, as well the use of biomass, which is more usefully deployed elsewhere.

Gas use in the residential and service sectors (Buildings in Figure 3.6) exhibits a rapid decline between 2030 and 2050 in this scenario. It is only after 2035, as the 80% target becomes increasingly difficult to meet, that the majority of changes occur in the use of gas in buildings. This delayed action in respect of buildings poses challenges for emissions reduction policies. Continued use of gas is a very cost-effective way to provide heating in buildings, not least because all the necessary infrastructure has already been deployed over the past number of decades. Shifting to an alternative energy source, such as widespread electrification, is likely to require very large investment in infrastructure (strengthening of the distribution system), improved system balancing (to deal with a much larger peak demand), new technologies across households, and the development of new markets. It is apparent that alternatives are cost- effective only at higher CO_2 prices (i.e. when the reduction targets are increasingly stringent) and so only start to be adopted at a significant scale after 2035. Replacing nearly all of the gas used in buildings with alternatives, including with district heating but more significantly heat pumps, within a 15-year period is in reality extremely ambitious,[8] and would require significant development of infrastructure and market capacity beforehand to achieve. In reality, it is likely that the transition away from the consumption of gas in buildings will need to be underway in the mid-2020s. Key strategic decisions will need to be made concerning residential heating, as Government, the network operator, and utilities, in consultation with consumers, work through the different options, which also include serious consideration of hydrogen supply to buildings, which would allow for the existing gas pipeline infrastructure to be maintained (CCC, 2016b).

Gas as a bridge

The above UKTM results can be used to address the question as to whether or not gas can act as a bridging fuel towards a low-carbon UK energy system (Figure 3.7). Despite a small rise (<3%) in Maintain between 2015 and 2020, and a very slightly higher level of consumption (<4%) in the 2020s in Maintain compared with Abandon, gas consumption is lower in Maintain in all subsequent periods and falls continuously from 2020.

Looking back to the requirements to classify gas as a bridge set out earlier, it is apparent that gas acts as both a relative and absolute bridge only over the period 2015-20. Thereafter it soon falls below the level of gas consumption in both **Abandon** and in 2010. However, given that the absolute and relative increases in consumption between 2015 and 2020 are so slight, and since ESME did not exhibit any similar such increases, it can be concluded that, on the definitions of the term, there is practically no potential for gas to act as a bridge to a low-carbon economy in the UK.

[8] For comparison, the natural gas appliance replacement programme required for moving from town gas to natural gas took around 11 years (1967-77).

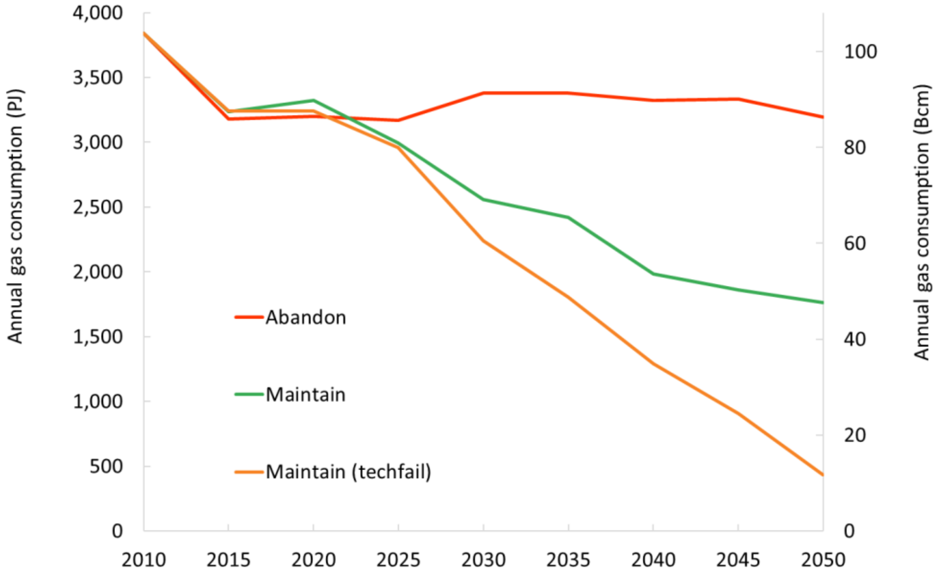

Figure 3.7. Gas consumption over time in Abandon, Maintain, and Maintain (tech fail).
The left hand axis has units in PJ, and the right hand axis in Bcm.

There is, nevertheless, some small potential for gas to act as a bridge fuel in specific niche sectors. For example, as noted above, in both **Maintain** and **Maintain (tech fail)** there is some uptake of CNG in LGVs and HGVs. This is also seen in **Affordable** but not in either of the other two non-80% reduction scenarios. At its peak, nearly 35% of HGVs are CNG in **Maintain** and nearly 60% in **Maintain (tech fail).** Since consumption of gas in freight transport grows in both **Maintain** scenarios out to 2040, compared with both 2010 and **Abandon**, it could therefore be reasonable to argue that natural gas can act as a bridge in the freight sector.

Table 3.3. Summary of scenario results

Scenario Name	GHG emission reductions (rel. to 1990)		Gas consumption level, PJ (% relative to 2010)		Key observations
	2030	2050	2030	2050	
Abandon	-35%	-33%	3,407 (88%)	3,223 (83%)	Limited reductions due to lack of either climate or security concerns. No increases due to higher gas price assumptions.
Insular	-46%	-43%	1,924 (50%)	1,900 (49%)	Rapid reduction in gas use by 2030 driven by energy security concerns, with a strong shift towards domestic gas, including shale in the longer term.
Affordable	-50%	-60%	2,920 (75%)	2,442 (63%)	Stronger reductions than abandon due to higher climate ambition. Post 2030, more limited decline as climate ambition fails to strengthen.
Maintain	-53%	-80%	2,579 (67%)	1,779 (46%)	Strong reductions by 2030 driven by climate ambition. These continue to 2050 although considerable gas remains in system due to CCS.
Maintain (tech failure)	-53%	-80%	2,262 (58%)	439 (11%)	Large reductions by 2050 in the absence of CCS, and under stringent climate policy.

3.4 Discussion and conclusions

Both the ESME modelling and the UKTM Maintain and Maintain (tech fail) scenarios make it clear that meeting the 2050 target will constrain the role for natural gas in the UK's energy system in the 2020s and beyond. The nature of that role is dependent on other developments in the wider energy system—such as new nuclear, the rate of energy efficiency improvement, demand reduction and the scale of renewable energy—and the availability of key technologies. The ESME results make clear the significance of CCS to keeping gas in the power generation mix and certain sectors of industry. Without CCS gas must be steadily phased out over the next 35 years and almost entirely removed by 2050. This represents a major challenge in relation to the decarbonisation of domestic heat and undermines the economic logic of investing in new CCGT capacity.

The Maintain and Maintain (tech fail) scenarios see a significant drop in the role of gas in the electricity sector (60%) and smaller drops in industry and the residential sector in the 2020s. In the electricity sector, the observed fall in coal generation is more cost-effectively replaced by increased end use sector efficiency and strong growth of renewables in the generation mix. It is only in the 2030s and beyond that the two scenarios differ significantly. The absence of CCS in Maintain (tech fail) —in keeping with the ESME results—means that gas must eventually be almost entirely removed from the energy system. What remains is used by industry and sparingly as back-up to renewable intermittency. Interestingly, the Maintain scenario keeps a significant amount of gas with CCS in the mix by finding a new role for it in the production of hydrogen. In the Maintain scenario, in addition to gas being used as a back-up for intermittency in the power sector, the availability of CCS permits some centralised CCS plant, and gas is used as a feedstock in industry. This scenario suggests that under certain conditions a significant amount of gas consumption (40-50 Bcm, or 50% of current levels) can still be compatible with the 2050 target.

Our analysis makes clear that determining the future role for gas in the UK is not a straightforward matter. A simple decision to shut down all coal-fired power generation by 2025 and build a new fleet of CCGT gas-fired power stations could be problematic as it could 'lock in' a significant amount of gas-fired capacity that would only be able to operate at very low load factors in the 2030s and beyond, unless retrofitted with CCS. It is questionable whether or not investors could be persuaded to build this capacity without very strong policy incentives, if load factors were even lower than they are now. Incentivising them to do so—for example via a capacity market—might not be the most cost-efficient solution. Those resources (the cost of which would ultimately end up on consumer bills) might be better used by replacing that lost coal capacity with additional energy efficiency and demand reduction measures and/or additional low carbon generation capacity. The analysis also makes clear the centrality of CCS to retaining gas in the power generation mix and certain sectors of industry. Without CCS, demand falls dramatically in the 2030s and beyond, making it even harder to justify investing in new gas-fired power generation.

Two final notes of caution: First, timing is everything. Delays in commissioning a new fleet of nuclear power stations and/or a slow-down in the deployment of renewable forms of energy—particularly in a context of no coal-fired generation after 2025—may increase the future role of gas to levels that are not compatible with the existing carbon budgets, particularly in the absence of CCS. Thus, what happens in the 2020s is critical in determining the path of the UK's energy system in the 2030s and beyond. It is important to avoid a high carbon 'lock in' that would either cause carbon targets to be missed, or leave significant amounts of infrastructure stranded due to a costly and rapid drive to a lower carbon system in the 2040s. Second, the scenarios show that the UK debate should not be reduced to a choice between a future with gas and a future without it. The Maintain scenario demonstrates that a significant amount of natural gas can still be consumed beyond 2030—though natural gas plays a different role than it does today. The real challenge is managing a 'soft landing' for the gas-fired power generation sector that keeps sufficient capacity on the mix as its role changes. In addition, alternatives to the use of gas outside the power sector, particularly in heating homes, need to be explored urgently. It is not clear that current policies will achieve this, which highlights the lack of a clear vision of the future role for gas in the UK's low carbon energy system.

The take-home message is clear. If all coal-fired power generation is to be removed by 2025, and the opportunity for CCS is delayed by Government inaction or lack of global progress on commercialisation, then policy makers must think very carefully about how best to replace that capacity. A 'second dash for gas' may provide some short term gains in reducing emissions. However, the modelling suggests that this is not be the most cost-effective way to reduce emissions and, in the absence of CCS technologies, it may well compromise the UK's decarbonisation ambitions.

Finally, for other countries, gas may provide a stronger transition role, particularly in those systems in which coal dominates, and where solutions are being sought to reduce CO_2 emissions and tackle air pollution (McGlade et al., 2014). However, even in such countries, careful consideration will need to be given to the longer term outlook for gas, such as outlined here for the UK, since significant gas infrastructure investment is likely to be required to push coal effectively out of the energy mix. These investments could be left stranded under decarbonisation pathways towards net-zero emissions, in which coal-to-gas switching is not compatible in the longer term.

In the context of the UNFCCC process, such issues are particularly pertinent, as countries revisit and strengthen their Nationally Determined Contributions, and start to develop their long term low GHG emission development Strategies.[9] The role of natural gas in the future, and decisions concerning investment in new infrastructure will need to be carefully considered to avoid lock-in, given the level of ambition required under the Paris Agreement. International cooperation on the development of CCS systems will be critical to reduce uncertainty and allow for consideration of natural gas continuing to play a significant role in the energy system in the 2040s and 2050s.

[9] In accordance with Article 4, paragraph 19 of the Paris Agreement, http://unfccc.int/focus/long-term_strategies/items/9971.php

4. Uncertainty, politics, and technology: Expert perceptions on energy transitions in the United Kingdom

Abstract

Energy policy is beset by deep uncertainties, owing to the scale of future transitions, the long-term timescales for action, and numerous stakeholders. This chapter provides insights from semi-structured interviews with 31 UK experts from government, industry, academia, and civil society. Participants were asked for their views on the major uncertainties surrounding the ability of the UK to meet its 2050 climate targets. The research reveals a range of views on the most critical uncertainties, how they can be mitigated, and how the research community can develop approaches to better support strategic decision-making. The study finds that the socio-political dimensions of uncertainty are discussed by experts almost as frequently as technological ones, but that there exist divergent perspectives on the role of government in the transition and whether or not there is a requirement for increased societal engagement. Finally, the study finds that decision-makers require a new approach to uncertainty assessment that overcomes analytical limits to existing practice, is more flexible and adaptable, and which better integrates qualitative narratives with quantitative analysis. Policy design must escape from 'caged' thinking concerning what can or cannot be included in models, and therefore what types of uncertainties can or cannot be explored.

Keywords

Climate policy; energy policy; uncertainty analysis; decision-making

4.1 Introduction

4.1.1 Energy and climate policy in the UK

The landmark climate agreement achieved in Paris in December 2015 sets a course towards global carbon neutrality during the second half of the 21st century (United Nations, 2015a). The IPCC's special report on 1.5°C has recently indicated that this needs to be achieved much sooner to limit average warming to 1.5°C. But while the target destination is known, the trajectories of individual countries across the century and the scale and speed of the transitions that can be achieved remain uncertain (e.g. (Pye et al., 2017; Rogelj et al., 2016a)). Within this global context the UK is currently one of the few advanced economies to have a legally binding emissions reduction target under domestic legislation that extends to mid-century (HM Government, 2008), with carbon budgets providing mid-term milestones to ensure progress (CCC, 2015b, 2010, 2008). This level of ambition, combined with the path dependent nature of long term technological change, makes the UK an interesting case study of a developed country seeking to trigger an energy transition by making decisions today under future conditions of uncertainty.

The energy system landscape in the UK has experienced a radical transition since the late 1970s, transforming from a state-directed, coal-dominated and export-focused energy system, to one that is market-led, gas-heavy and import-dependent (Pearson and Watson, 2012). The modern energy system has evolved since that period in significant ways, but still shares several legacy components from the old regime. For example, energy production remains heavily centralised and carbon-intensive. Despite major changes over the past 40 years, the stage is set for an even more fundamental transition in the coming decades. While the emerging contours of this new energy system paradigm remain difficult to define, it is clear that the need to eliminate carbon pollution could imply a total reimagining of the way that energy is produced, distributed and used. As well as the engineering systems themselves, energy system institutions and their governance could also be radically transformed, and indeed this might even be an essential prerequisite for such rapid technological change to occur (Foxon, 2011).

4.1.2 Decision-making under deep uncertainty

Climate policy is often grouped into the category of "wicked" (Churchman, 1967; Rittel and Webber, 1973) or "post-normal" (Funtowicz and Ravetz, 1990) challenges. That is to say, high complexity problems with no obviously "right" solutions. The literature on uncertainty analysis provides several useful definitions that can provide a platform for discussion, distinguishing between varying degrees of ignorance about the future. For example, seminal work by (Knight, 1921) makes the classic distinction between ignorance that can be reliably quantified (Knightian risk) and ignorance that is unquantifiable (Knightian uncertainty). The writings of (Wynne, 1992), (Stirling, 2007, 1999), (Funtowicz and Ravetz, 1990), and (Taleb, 2009, 2007), are all examples which elaborate further on the basic distinctions made by Knight between calculable and incalculable unknowns. Other work distinguishes between epistemic uncertainties that can be reduced through improved knowledge and aleatoric uncertainties that can effectively never be eliminated due to the intrinsic randomness of a phenomenon (Hallegatte et al., 2012).

(Lempert, 2003) define "deep uncertainty" as a condition where there is a lack of knowledge or agreement between parties on:

- conceptual models that describe relationships between driving forces
- the probability distributions of uncertainty across variables or parameters
- the value or desirability of different outcomes.

Deep uncertainty in complex systems can exert a particularly powerful paralysing effect on decision-making within institutions that are accustomed to dealing with challenges under a "predict-then-act" paradigm (Lempert, 2003), because the prediction stage of the process is impossible or only possible by making value-laden assumptions that are violently contested by key stakeholders (Funtowicz and Ravetz, 1993). Effective decision-making under such conditions requires extensive peer engagement in addition to the use of quantitative analysis methods.

4.1.3 Challenges for the status quo

Long term strategic assessment for the UK energy transition has largely been informed to date by quantitative analysis using computational models (e.g. (Ekins et al., 2013; Strachan et al., 2009; Taylor et al., 2014)). Their success in the policy domain can be explained by two factors; firstly, by being positioned to allow for consideration of new goals and configurations for the energy system as UK energy policy is re-orientated to face the decarbonisation challenge, and secondly, by functioning as a 'boundary object', both connecting and meeting the needs of different science and policy communities, and providing and supporting a shared understanding of the policy problem (Taylor et al., 2014). Model-based analyses have provided policymakers with a view on the overall affordability of the energy transition (Strachan et al., 2009), sketched out multiple potential transition pathways towards the normative target (Li et al., 2016), and demonstrated the path-dependent nature of energy system choices (Usher and Strachan, 2012).

After a strong paradigm shift towards recognising climate objectives in energy governance between 2000-2010 (Kern et al., 2014), the UK's position became progressively weakened in the period 2010-2015 during the prolonged economic recession. A number of high-profile policy reversals, for example, on domestic energy efficiency (NAO, 2016) and Carbon Capture and Storage development (NAO, 2017), have brought into sharp focus the challenge of moving from merely setting targets towards actual implementation and delivery (Kuzemko, 2015). At the time of writing, no new policies have been announced for over 12 months since the publication of the Fifth Carbon budget. The government's independent climate advisory body, the Committee on Climate Change, has identified a massive "policy gap" between long term targets and near term policies, and highlighted the current lack of a clear process "to turn proposals into action" (CCC, 2017). The mix of political dynamics, consumer expectations, and environmental targets found in energy policy makes for a complex picture, and a future transition fraught with uncertainty (Lawrence, 2016; Li, 2017). The risk remains that progress towards a low carbon future will stall unless successive future governments can continue to overcome socio-political inertia (Lockwood, 2013). A critique of the status quo contends that the current policy regime has become complex, entangled, and incoherent, "half-planned, half market-based, but with the disadvantages of each approach" (Keay, 2016). The scientific community has a crucial role to play in helping to close the current "gap between targets and implementation" (Gillard, 2016), through advising policymakers on how to evaluate the complex trade-offs between different options, and on how to make more effective decisions under uncertainty.

4.1.4 Aims and objectives

The urgent requirement for decarbonisation of the energy system (Pye et al., 2017) means that UK policymakers cannot afford to be paralysed in the face of the many uncertainties that pervade the policy landscape. A critical evaluation of existing practices for decision-support is required. This chapter seeks to broaden engagement with experts to determine the range of perspectives across the following three questions:

- What do decision-makers perceive as being the critical uncertainties relating to the UK's future transition to a low carbon economy?
- How do decision-makers think that the critical uncertainties can be mitigated? and;
- What improvements can be made in the area of decision support for strategic planning and policy design?

This type and level of explicit engagement with key stakeholders is an underutilised approach in the quantitative analysis community around energy and climate policy in the UK and is envisaged as a first step in reconceptualising the decision support process (Strachan et al., 2016). Section 4.2 of the chapter sets out the analytical approach, based on exploratory interviews with selected stakeholders. Section 4.3 presents the key insights from the interviews. Section 4.4 provides a discussion on the results of the study and Section 4.5 draws out the key conclusions.

4.2 Methodology

4.2.1 Interview approach

Interviews were conducted over a 4-month period between October 2016 and January 2017. To address the research questions, in-depth, face-to-face interviews were employed. These interviews featured a limited number of open-ended questions, intended to elicit views and opinions from the participants (Creswell, 2014). This style of exploratory, semi-structured interview was chosen based on much of the reasoning set out in (Aberbach and Rockman, 2002). Primarily, it was unclear what range of issues the stakeholder group would cover, with a key objective of the research to reveal them without biasing responses through question framing. A set of tightly focused, pre-determined issues for discussion with relatively closed questions would therefore not have been appropriate. It was judged that the experts engaged with would be more receptive to a relatively open-ended interview style, within which they could more fully expound their perspectives on the subject in question.

This exploratory approach, using the interview guidelines in Table 4.1, resulted in interviews that were more conversational compared with those using more structured approaches (Aberbach and Rockman, 2002). Discussions proved to be highly interactive in nature, allowing for further probing on the key issues (via sub-questions), thereby generating new information. As a result, interviews were undertaken face-to-face wherever possible (only 3 out of the 31 experts involved were interviewed remotely via teleconferencing).

Table 4.1. Characteristics of interview approach (adapted from (Legard et al., 2003))

Characteristics of approach	Description
Combining structure with flexibility	Structure around themes and questions to explore, with flexibility allowing for the interviewee to cover specific topics of choice, and for responses to be probed further. This was critical, to prevent any 'leading' of the interviewee or biasing of responses.
Interactivity	While the topics were interviewee led, the material is generated by the interaction between the researcher and interviewee. However, this interactivity sees the researcher remaining neutral, and not expressing opinions.
Probing	Used to achieve depth of answer in terms of 'penetration, exploration and explanation.' This is reflected in the interview questions used, including both content mapping and content mining questions.
Generative	The interview is generative of new knowledge or thoughts, based on the interaction with the interviewee. In the approach, this was done to ask about further issues related to a topic the interviewee had already been discussing, to avoid introducing bias.
Face-to-face interaction	Given the above characteristics, it is crucial that these interviews are conducted face-to-face. This was the case for all interviewees, except one participant that was interviewed via skype, and two participants by phone.

4.2.2 Selection of experts

All interview participants, listed in the acknowledgements section of the paper, have previously held, or currently hold, positions as key stakeholders in the development of UK energy strategy and policy, and can be regarded as subject matter experts. By stakeholder, these are people directly involved in the strategy development process, influence this process via their own organisation's research, or exert influence through being a key consultee to the process. Further reflection on the final composition of the interview sample is provided in Section 4.4.

Similar to other approaches to interview selection found in energy policy research (e.g. (Cox, 2016; Gillard, 2016)), the interview group was constructed based on purposive selection, identifying the expert community involved in energy and climate strategy development. This was enhanced through snowball sampling (Atkinson and Flint, 2001), with an explicit question to interviewees asking for suggestions for other experts to interview. 31 interviewees participated in total. While there is no correct sample size for such a study (Baker and Edwards, 2012), the stakeholder group is sufficiently representative of the organisations that make up the UK energy and climate policy community at large. The breakdown of the interviewees by organisation type is shown in Table 4.2. Over half of the sample originate from a public policy background, while the other 48% can be considered influential voices in the field or thought leaders who indirectly influence decision-making. The unequal distribution of groups e.g. industry (13%) vs civil service (29%) is acknowledged as potentially changing the emphasis of perspectives in the results, although given that this is about stakeholders involved in UK energy strategy, it is not surprising that the sample is skewed towards government stakeholders. In terms of their own self-described disciplinary backgrounds, the sample are split fairly equally between economics (33%), social and / or political science (38%) and engineering (29%).

Table 4.2. Classification of interviewees

Interview group	Interview group description	Share of sample (of 30)
Civil service (CS)	Senior officials formally employed in the UK civil service, involved in the development of energy and climate change strategy	29%
Other government (OG)	Senior officials from UK Government agencies, and senior advisors, either scientific or political, on climate and energy issues. These are not direct civil service employees but have a strong influence on government strategy through direct advice that they provide.	23%
NGO research (NGO)	Senior advisers and knowledge brokers involved in climate change and energy campaigning and research	19%
Industry (IND)	Senior staff from advisory consultancies and industry focused on energy issues	13%
Academia (ACA)	Senior academics (professors) engaged in climate and energy research	16%

4.2.3 Interview design

Table 4.3 lists the core questions forming the interview. The questions posed sought to address the key research objectives. Question (1) provides an understanding of the background of the interviewees, both in respect of their academic discipline and professional expertise (see Table 4.2). Question (2) is a mapping question that forms the primary framing for the whole interview, by determining what experts consider the critical issues for meeting the UK's decarbonisation goals. The question were framed around the UK's 2050 climate policy objectives (HM Government, 2008), but interviewees were also reminded that interim targets (carbon budgets) are relevant due to the path dependent nature of future low carbon transition. Question (3) was used to generate discussion regarding which issues are perceived to be the most problematic for decision-making, given their uncertainty. This is because there is an important distinction to be made from a decision analysis perspective between issues that are critical, but not necessarily uncertain (and therefore relatively straightforward to resolve), and those that are both critical and highly uncertain (consequently posing a greater challenge). In Section 4.3 (Results), participant responses to both Question (2) and Question (3) are considered together, because in practice it was found that interviewees tended to discuss both issues simultaneously.

Table 4.3. Interview questions

No.	Question
1	Can you tell us about your background and your expertise?
2	What factors do you think are the most critical in terms of their impact on the UK's ability to meet the 2050 decarbonisation target?
3	What do you think the level of uncertainty is regarding our current knowledge of each factor?
4	To what extent do you think that decision-makers can mitigate these uncertainties?
5	How can models be improved for decision-making support?

Question (4) allows for elicitation of views on how and if decision-makers can mitigate the uncertainties revealed in the discussion of Questions (2) and (3). The term "mitigation" is used here in the sense that it appears in the literature on decision making under uncertainty, i.e. "constructing strategies that will minimize or mitigate the effects of surprise" (Lempert et al., 2002). Finally, Question (5) directly asks how the current toolset for decision analysis could be improved in view of the earlier interview questions. This is important as the activities under this research programme will subsequently shift to a focus on developing improved methods for supporting decision-making on energy and climate policy.

4.2.4 Coding of interviews

The coding process for this study was challenging, given the semi-structured interview approach and open nature of the questions (Aberbach and Rockman, 2002). We critically reflect on this further in Section 4.4. Following established practices in the literature (Burnard et al., 2008; Creswell, 2014; Tesch, 1990), transcripts were coded manually in order to identify the main emerging themes from the interviews and to assess where they reflected agreement or contention. The coding process required reading through the transcripts by both authors, with one author first categorising responses for each of the key questions, followed by the other author reviewing the categorisation, and reviewing specific interview responses that could be considered ambiguous in the first review. Finally, both authors agreed on the final set of themes under which to categorise interview responses. These themes are presented in detail in the next Section. While the broad categories were straightforward to define, the interconnected nature of energy policy led to some challenges in categorising certain sub-themes. This is reflected on in more detail under Section 4.4.

4.3 Key insights from expert interviews

4.3.1 Mapping of uncertainties

Figure 4.1 shows which themes emerged from Questions (2) and (3), categorised under five categories, namely technology, policy, society, economics, and global dimensions. The visualisation reflects the percentage of interviewees that discussed a given theme, and the number and range of themes that emerged during the discussion, providing an initial view of what the interview sample collectively considered to be the most critical elements in the context of decarbonisation goals. It can be seen that the three most salient thematic areas to emerge from discussion, with similar shares of participants responding, were *politics* (**P**), *society* (**S**) and *technology* (**T**).

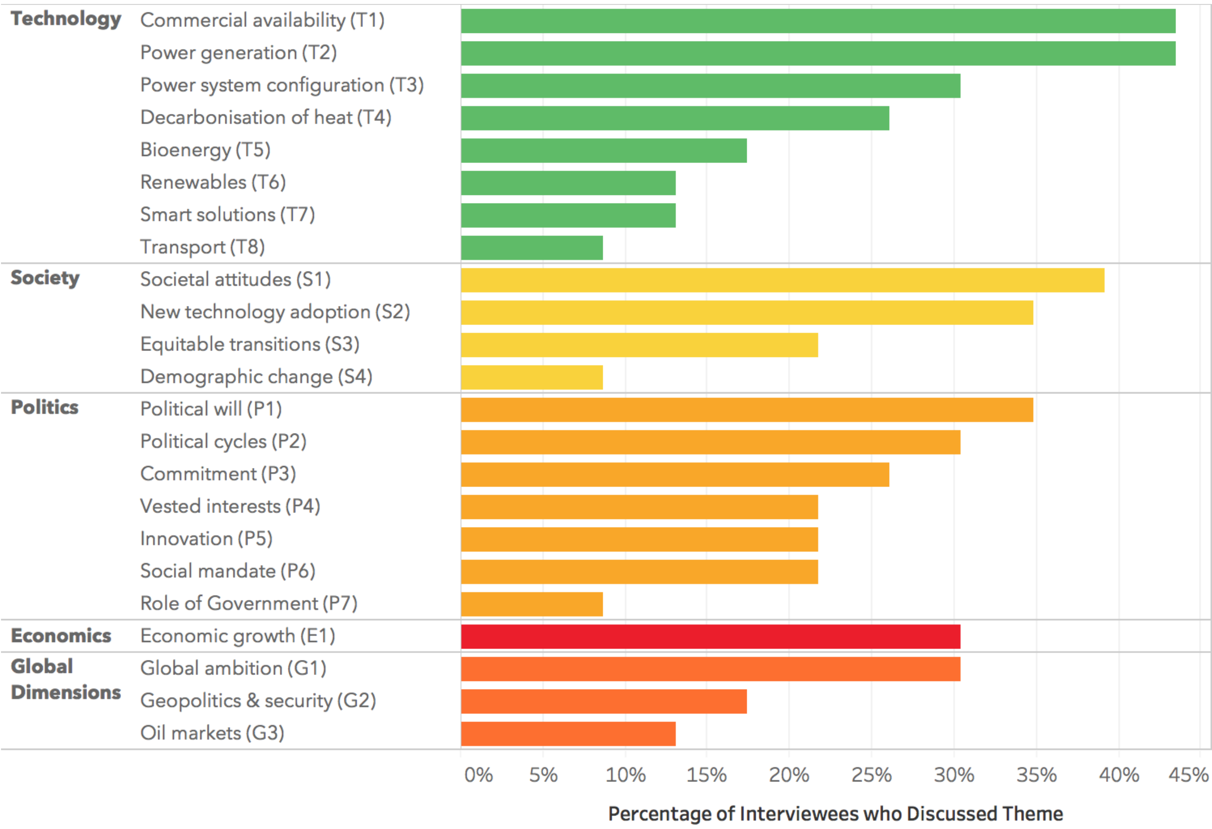

Figure 4.1. Mapping of critical factors: share of interviewees (%) discussing each theme by category[10]

Technology factors

New and innovative low carbon technologies will be crucial to decarbonising the energy system. The most discussed uncertainty concerned the *commercial availability* (**T1**) of key technologies. The **CS** group tended to view the UK as being likely to occupy a passive, price-taking role in the future global innovation system, relying on international investments in research and development (R&D) to bring

[10] In the Technology category, 'power generation' includes a range of low carbon generation types, including renewables, CCS and nuclear.

technologies to full commercial readiness. This "wait-and-see" strategy arguably has the effect of increasing uncertainties as it orients policy towards anticipating technology cost reductions, and the outturn deployment rates, rather than driving them, and also may miss the opportunity to establish new export industries. The example of the rapid fall in solar photovoltaic module costs over the last decade was often referred to in discussion.

The second and third most discussed technological uncertainties related to *power generation* (**T2**) and the future *power system configuration* (**T3**). Many experts, across all organisation types, highlighted uncertainties relating to the future availability of Carbon Capture and Storage (CCS). Contributing factors included the lack of policy support in the UK, a lack of progress on commercial deployment internationally, and continued questions around both the technical feasibility of the technology at-scale and unresolved liability issues around the long-term storage of liquid CO_2. Uncertainties related to new nuclear power deployment also featured heavily in discussion, with some experts even expressing doubts about the UK's ability to replace, let alone expand, its existing reactor fleet. Experts across most groups highlighted the criticality of the uncertainties surrounding the future *power system configuration* (**T3**), including the potential for novel distributed control and ownership structures to emerge.

Finally, significant *decarbonisation of heat* (**T4**) will be required as part of any future UK transition towards a low carbon energy system. This was widely recognised by participants from all groups as being particularly hard to address and featured in around a quarter of all discussions. Large uncertainties persist in this area. The UK population overwhelmingly prefers gas heating when compared with low-carbon alternatives (Ipsos MORI and EST, 2013), and there are presently no low-carbon alternatives to domestic gas boiler heating which offer comparable energy services at a similar or lower costs (Chaudry et al., 2015). As a result, there are few options for rapid changes to the heat sector that do not involve state intervention. However, as a number of **NGO** experts noted, this does not align with the current political narrative of economic opportunity and could be considered the antithesis of policy making that aims to offer choices to consumers through market-driven frameworks.

Political factors

Progress towards energy system decarbonisation is strongly influenced by political decision-making, including the framing and setting of the targets themselves. It is therefore not a surprise that themes under this category featured in many of the interview discussions. These included *political will* (**P1**), which many respondents noted was determined by short term *political cycles* (**P2**), the influence of *vested interests* (**P4**) and existence (or lack) of a perceived *social mandate* (**P6**) to act. Such issues were entirely raised by non-governmental participants, particularly from the Non-Governmental Organisation (**NGO**) and Academia (**ACA**) groups, most of whom stated this as one of their critical uncertainties.

Expanding their views on the effect of the UK's 5 year *political cycles* (**P2**), several experts commented that changes in government often affected the salience of climate policy at any given time, sometimes leading to short term thinking. This had a knock-on effect of creating uncertainty for investors due to frequent changes in policy approach and substance, making strategic decisions about large infrastructure projects with long lead times more challenging. As one expert stated, the political imperative for re-election can also lead to an increased focus on issues of industrial competitiveness and keeping costs down for consumers as elections loom, sometimes to the detriment of policy actions needed for longer term climate mitigation.

On *vested interests* (**P4**), two specific issues emerged from the **NGO** and **ACA** stakeholder groups; first, the difficulty (and inertia) in the transition arising from the presence of strong incumbents in the energy sector, and second, the disproportionate influence (relative to their economic contribution) of specific industrial lobbies. On the theme of *social mandate* (**P6**), several experts noted that the UK Government might find it harder to push towards challenging climate targets under societal conditions that they viewed as becoming increasingly polarised and fragmented. Uncertainty was also discussed in the context of nearly all future energy transitions being likely to increase the cost burden for consumers. The theme of the government's *social mandate* (**P6**) is obviously strongly linked to broader societal factors.

Societal factors

A critical uncertainty concerns the role of broader society in the transition, in terms of attitudes and participation. Broader *societal attitudes* (S1), which, as noted above, are strongly linked to the theme of the government's *social mandate* (P6), was the most discussed societal theme. This category captures responses that reflect on the importance of the transition challenge to society. All stakeholder groups raised this as a critical uncertainty, expanding their thinking along two main avenues of discussion:

- A lack of understanding about society's willingness to "own" the energy and climate challenge and shoulder increasing costs associated with future transitions. This may reflect the limited extent to which broader social engagement on energy and climate issues has been undertaken in the UK; and
- Uncertainty about the ability of the UK Government and other actors to influence the broader society's sense of collective responsibility towards achieving the challenge. Experts

questioned whether an increased social buy-in could be achieved by orientating the transition to align with the social agenda and lifestyle aspirations of different groups.

The second most discussed societal theme concerned consumer adoption of new technology (**S2**). Highlighted by a large number of respondents, primarily from the Civil Service (**CS**) and Other Government (**OG**) groups, its criticality relates to the need for rapid deployment of low carbon technologies if the UK's 2050 targets are to be met. Large uncertainties are evident again in this area due to the lack of understanding of whether consumers will want to adopt low carbon technologies, motivated by technology utility or a sense of ownership of the climate issue, and how they might interact with such technologies in the future energy system. A number of participants posed the question as to whether technological change that may not necessarily be "climate targeted", such as the increased adoption of information technology, could reduce emissions as a secondary or third order effect.

Participants from the **NGO** and **ACA** groups consistently raised the issue of *equitable transitions* (**S3**), which was the third most common discussion point within this category. This links again to broader ownership of the issue; if a large cross-section of society buys-in to the need for an energy transition and considers a given strategy for meeting climate targets to be fair, then support is more likely to follow. The difficulty in ensuring *equitable transitions* (**S3**) was also discussed, with the discourse on transitions noted as being heavily skewed towards future costs rather than future benefits.

Economic factors

While economic themes were generally discussed to a much lesser extent compared to the political, societal and technological areas, *economic growth* (**E1**) was noted by a range of interviewees from across stakeholder groups as an important uncertainty. Experts were unsure whether it was appropriate to assume that the UK would continue to maintain an economic growth rate aligned with long-term historical trends (e.g. around 2% annually (OBR, 2012)), or whether it was more prudent to plan for a sustained period of lower growth or future conditions of secular stagnation. A number of participants expressed their view that a growing economy would enable a more proactive climate policy agenda, due to larger Government budgets and stronger societal welfare leading to higher levels of investment across the different sectors, while the reverse might be true under a contracting economy. Some respondents in the **ACA** group highlighted the incompatibility of unconstrained economic growth with achieving global climate policy objectives (e.g. see (Jackson, 2009)), but noted that large uncertainties remain as to how best to transition away from this socio-economic model.

Global factors

The action of other countries in reducing emissions has the potential to be a source of uncertainty for UK climate policy, both in terms of driving the political agenda, and for delivering technological innovation. Experts who spoke at length on this subject came mainly from the **ACA**, **CS**, and **OG** groups. Interviewees noted that changes to the level of *global ambition* (**G1**) to mitigate anthropogenic warming could affect the UK position. Most however suggested that UK would be unlikely to readjust its ambition downwards towards weaker targets because of existing policy commitments that are written into domestic law. They did not, however, rule out the potential for the stringency of domestic targets to be increased further depending on overall global action levels.

4.3.2 Mitigation of uncertainty

Interviewees were also asked for their opinion (Question 4) on how decision-makers might best mitigate the above uncertainties discussed in Section 4.3.1. Two broad categories of mitigation actions were elicited; (1) the *credibility of political commitment*; and (2) *engendering social engagement*. A visualisation of the key themes in each category is presented in Figure 4.2.

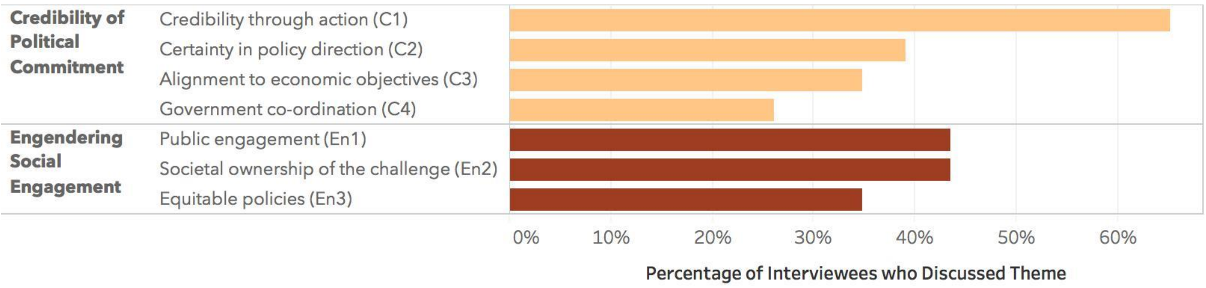

Figure 4.2. Mapping of uncertainty mitigation: share of interviewees (%) discussing each theme

Mitigating political uncertainties

While it is evident that the UK has set a strategic direction to follow to 2050, many experts from outside the **CS** group highlighted the need for the UK Government to push further in demonstrating its ambition. Experts acknowledged the importance of flexibility, noting that individual policies may outlive their effectiveness, and that the policy environment may continue to evolve in unforeseen ways; for example, regarding technologies or social priorities. However, many expressed a requirement for additional *certainty in policy direction* (**C2**) to allay fears that the UK will abandon or water-down its long term decarbonisation ambition.

The most frequently discussed suggestion for demonstrating Government commitment to achieving climate targets was to make direct investments at a level commensurate with the scale of the challenge, thereby gaining *credibility through action* (**C1**). Many participants suggested that a crucial role for Government was one of de-risking investments and facilitating learning-by-doing through direct investment in demonstration programmes, as reflected in the literature on innovation policy (Mazzucato, 2015). In many cases, it was suggested that this has to be done anyway, to explore and demonstrate the viability of untested systems and technologies. It was suggested that this approach may be particularly critical for technologies that rely on large connected infrastructures, are near commercialisation, or which do not have clear market incentives, with CCS being an obvious example. Several experts in the **NGO** and Industry (**IND**) groups opined that the UK Government appears to be particularly averse to investing in technology demonstration projects because of the perceived risk of failure and the resulting potential for unfavourable media coverage. However, they highlighted that a degree of failure, as a means of discovering which technologies will not work, should be viewed as a critical part of the innovation process.

A third suggestion for demonstrating a clear policy direction towards achieving ambitious climate targets (mentioned by multiple groups) was to improve *government co-ordination* (**C4**) and better align departmental objectives with the decarbonisation challenge. Finally, a number of experts from the **NGO** and **CS** groups advocated the *strategic alignment* [of climate and energy policy] *to economic objectives* (**C3**). While the interviews took place before the publication of the Government's latest industrial strategy document (HM Government, 2017), the participants noted the opportunity to align domestic efforts on emissions reduction with the development of export industries in which the UK has some existing advantages, namely low emission vehicles, offshore wind, and "smart" grid technology. Experts opined that this could be linked to broader social and economic goals, like rebalancing the UK economy, with more investment in manufacturing industries in regions outside of the dominant South East of the country.

Mitigating societal uncertainties

The interview process revealed divergent opinions on social engagement, the role of the state, and the balance of responsibility between government and the rest of society in enabling the energy transition. Several experts in the **CS** and **ACA** groups suggested the need for a broader *societal ownership of the challenge* (**En2**), noting that Government's role is inherently limited, and that it cannot prescribe all solutions. On the other hand, many experts, all from outside the **CS** group, opined that the ultimate responsibility for meeting the challenge lies with the Government. These individuals highlighted the importance of Government intervention not only to address existing market failures but also to play a role in kick-starting the necessary entrepreneurship and innovation activities, a perspective that is also found in the literature on innovation policy (Acemoglu et al., 2012; Mazzucato, 2015).

Public engagement (**En1**) was highlighted by almost half of the interviewed experts (across all groups) as a key means of mitigating societal uncertainties. Energy consumers have historically been conditioned to be largely passive players in the wider system, rather than active participants. As a result, few citizens devote much attention to energy and climate policy. Research finds that emphasizing collective, rather than personal responsibility for climate change actually increases pro-climate behaviour (Obradovich and Guenther, 2016) and that ambitious energy policies cannot be effectively pursued without two-way dialogue between the scientific community and the public via a national citizen engagement processes (Corner et al., 2014; Pidgeon et al., 2014). The **CS** group emphasised engagement with consumers by primarily economic means, through making low carbon alternatives to fossil fuel technologies more economically attractive. The **CS** group also generally advised against a future reliance on strategies that were premised on large-scale behaviour change. Other experts discussed a more interventionist role for government in shaping attitudes, and suggested that greater engagement could be fostered via recognising the co-impacts of solutions, such as improving human health through a reduction in air pollution, rather than a singular focus on climate change mitigation as the main issue (Lott et al., 2017).

There was also an emphasis by a range of experts, mainly from the **NGO** group, on the need to demonstrate *equitable policies* (**En3**) for the transition as a means of gaining broader public acceptance. Participants opined that government may need to explicitly acknowledge that there will be future winners and losers (Li et al., 2016), and tailor policies towards mitigating the impacts on losers e.g. through avoiding regressive measures. A suggestion common to interviewees from the **NGO** group was that future strategy should be tied into the political narrative of a UK that “works for everyone”, and could help to address the issue of regional economic disparities. The political economy literature shows that policies that engender trust from the electorate are both critical and frequently underappreciated by policymakers (Greenberg, 2014; Newell and Mulvaney, 2013).

4.3.3 Developing the analytical support for decision-making

The final part of the interview, Question (5) asked participants to consider, given the context of the previous questions, how can models be improved for decision-maker support? A visual thematic map of the discussions is presented in Figure 4.3, with the four most salient themes being that (1) there are *analytical limits to existing practice*, (2) that there needs to be a new emphasis on *opening up the uncertainty space being considered*, (3) that models need to be placed within broader *strategy development* frameworks, and (4) that there is a huge challenge related to *communicating uncertainty* to decision-makers.

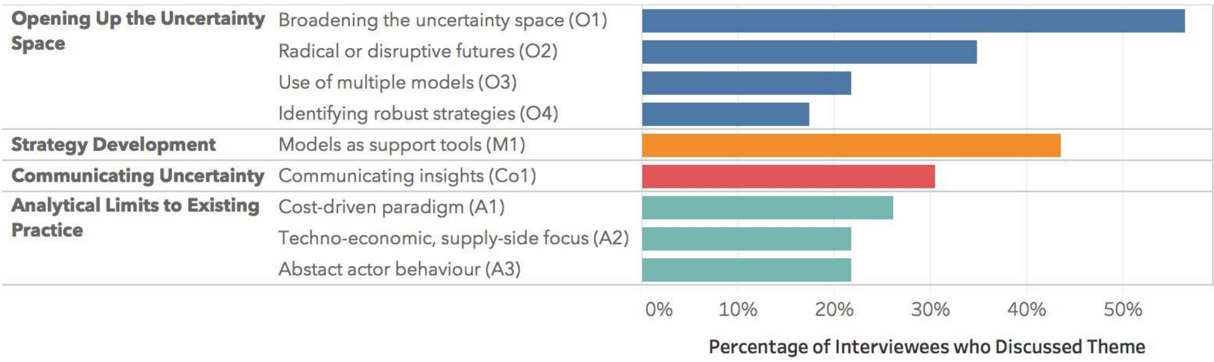

Figure 4.3. Mapping of decision analysis limitations: share of interviewees (%) discussing themes

Analytical limits to existing practice

There was much discussion amongst participants from a diverse range of groups regarding some of the limitations of existing model practice. First, in contrast to many other countries, the dominant paradigm for quantitative analysis in support of energy and climate policy in the UK is to use bottom-up techno-economic energy system optimisation models (ESOMs), such as UKTM-UCL (Fais et al., 2016b) or ESME (Pye et al., 2014). These place a *cost-driven paradigm* (A1) at the heart of the analytical approach, which condenses the diverse behaviours and motivations of different actors into a notional “utility maximising consumer” from neoclassical economic theory. Several interview participants expressed the view that directly incurred costs were not necessarily the only valid metric upon which to base decision-making (noting earlier discussions concerning the influence of lifestyle and behavioural norms on the uptake of products), and a well-known limitation of ESOM models is that small variations in costs can sometimes lead to a diverse range of solutions (DeCarolis et al., 2016; Li and Trutnevyte, 2017).

Multiple participants from the **IND**, **NGO**, and **ACA** groups discussed how investment decisions are often based on a range of non-cost factors, such as the track record for similar projects and the degree of trust placed in institutions, technologies or processes. These were noted as critically influential in guiding decision-making but not always straightforward to include in formal modelling, where there is often a reliance on *abstract actor behaviour* (A3). Interviewees also noted that the types of models most frequently used for decision support in their experience tend to have a strong *techno-economic, supply side focus* (A2). That is to say, they predominantly represent options for climate mitigation that rely on the development of new energy supply technologies, rather than options linked to changes in demand (i.e. behaviour and lifestyles, see (Creutzig et al., 2016)), and often abstract away or ignore societal and political factors. This approach leaves the core drivers of energy system change outside of the modelled system boundary. As a result, while the demand side of the energy system is often acknowledged as being important, it is often inadequately explored in policy design because its future variability is not well-captured in models.

Opening up the uncertainty space

The most discussed theme was improving the value of models for decision-making through *broadening the uncertainty space* (**O1**) considered by quantitative model analysis, particularly given that real world outcomes are often later shown to occur outside of the ranges estimated by models (McDowall et al., 2014). A number of explanations were given as to why it has become typical practice in the policy analysis community to use relatively narrow ranges for uncertain parameters. These included a need for numbers to be perceived as "credible", with the result that a consensus view is reinforced, and the institutional requirement or desire to align with "off-the-shelf" assumptions by other organisations e.g. government GDP forecasts, or International Energy Agency (IEA) cost data.

A number of experts commented that existing modelling approaches often overlooked the potential for outliers and "wildcard" events, and that exploring more *radical or disruptive futures* (**O2**) could provide useful alternative perspectives on the strategy being developed. This links to two emerging themes from the interviews; the importance of having a diverse spectrum of models and scenarios to provide a more expansive picture i.e. to use *multiple models* (**O3**), and second, the desirability of *identifying robust strategies* (**O4**) under uncertainty. This latter point was highlighted by the **CS** group in particular, who reflected on a need in government to identify and test strategic options that are "low-regret".

Models within broader strategy development frameworks

The second most discussed theme concerned the use of *models as support tools* (**M1**), within broader strategy development frameworks. Almost half of all participants advocated an approach where models would be used to support qualitative narratives by providing the quantitative underpinning to explore radically divergent futures, thus better enabling consideration of societal and political uncertainties in the decision process. Experts from the **CS**, **OG** and **IND** groups commented that there was a need for, and a move towards, future strategy development activities that can be characterised as being more "model-informed", rather than being "model-led".

Communicating uncertainty to decision-makers

Experts reflected on the challenge of *communicating insights* (**Co1**) on uncertainty to decision-makers. Often, single point estimates are used to describe key parameters, with limited reflection of the variance part of the analysis despite the fact that this approach essentially throws away a huge amount of useful information (Morgan, 2014). Several interview participants relayed experiences where decision-makers had questioned the plausibility of analysis that deviated from expected outcomes, and described their efforts to maintain trust and credibility in the modelling process as a result. Readers may wish to refer to a nuanced assessment of the trade-offs between salience, legitimacy and credibility in the science-policy process by (Sarkki et al., 2014).

Interview participants were divided regarding whether it was the responsibility of modellers to provide insights to policy makers in a fashion that facilitated straightforward, streamlined decisions, or whether politicians should make greater efforts to understand the more nuanced conclusions from complex scientific research. The scientific literature is surprisingly definitive on this subject. Seminal publications by both (Stirling, 2010a) and (Morgan, 2015) argue forcefully against the "dumbing down" of scientific insights into simple binary choices and call for politicians to accept greater responsibility for taking decisions despite the presence of irreducible uncertainties. Stirling also calls for a more plural approach to scientific enquiry that does not presume consensus around a particular asserted set of priorities and value judgements (Stirling, 2010b).

4.4 Discussion

4.4.1 Critical Uncertainties

What do decision-makers perceive as being the critical uncertainties relating to the UK's future transition to a low carbon economy?

As discussed in Section 4.3, interview participants expressed a broad range of perspectives, with no single area emerging as overwhelmingly dominant. This work however, empirically confirms an increasing awareness of the broader linkages between society, technology, economics and politics in the UK energy policy community, with socio-political challenges mentioned almost as frequently as technological ones. Many of the most critical issues, such as the role of government in driving the future transition, and where the balance of responsibility lies between society and government, were acknowledged as being difficult to capture with quantitative models alone (discussed further below in Section 4.4.3).

4.4.2 Mitigation of Uncertainty

How do decision-makers think that the critical uncertainties can be mitigated?

The interviews reveal differing perspectives between the groups that work within government and those that do not. It is notable for example, that many non-government participants (**NGO**, **IND**, **ACA** groups) advocated strongly for greater political commitment to decarbonisation (including the allocation of financial resources), while those in Government (the **CS**, **OG** groups) did not. Another point of divergence was participants' perspectives on how to best engage with the wider society on energy and climate policy issues. Interviewees from Government groups tended to approach the issue of societal engagement cautiously, emphasising economic factors and expressing doubts over whether “consumer behaviour” was something that the State could or should seek to influence. Many non-government participants, on the other hand, called for a much broader societal dialogue on energy policy and saw an opportunity for government to shape societal attitudes.

4.4.3 Decision Support

What improvements can be made in the area of decision support for strategic planning and policy design?

One of the strongest themes to emerge from the interview process was a call for analysis that takes into account a broader perspective on uncertainties, both those that can be easily put into existing quantitative models and those that cannot. While participants recognised the value of existing quantitative models, it was suggested that future analysis would benefit from being developed alongside rich narratives that could address the uncertainties that are difficult to capture in models through scenario framing. This implies an explicitly socio-technical perspective on energy decarbonisation planning.

Energy policy is multifaceted, and there are complex interlinkages between the energy system as conceived by engineers, and with macro-scale societal and economic structures. Energy transitions cannot therefore be distilled down to narrow questions of technological configurations (Miller et al., 2013) without losing some of the bigger picture. The findings of this study show a clear requirement for the modelling community to integrate expertise from the social and political sciences alongside their traditional core disciplines of engineering and economics (Sovacool, 2014; Sovacool et al., 2015). Promising avenues for future research include more explicit modelling of behaviour in energy models (Li et al., 2015; Li and Strachan, 2017), better "bridging” between qualitative narratives and quantitative modelling (Geels et al., 2016; McDowall and Geels, 2016), and participatory modelling to better integrate decision-maker perspectives into the analytical process (Holtz et al., 2015; Strachan et al., 2016).

A number of interview participants commented on the challenge of setting a firm policy direction while allowing for flexibility in terms of how goals are achieved. The decision theory community has long advocated such an approach and cautioned against an over-reliance on formulating “optimal” strategies (Walker and Marchau, 2003). Assuming that the future can be predicted and designing policies accordingly, with only a limited number of variations, has been likened to “dancing on the top of a needle” (McInerney et al., 2012) producing solutions that are optimal “only if all the assumptions made about the future turn out to be correct” and which “may fail in the face of inevitable surprise" (Lempert, 2003). It is suggested that a more robust alternative is to implement a multi-stage or iterative decision making process where assumptions are revisited continually as uncertainties are revealed (Anadón et al., 2017; Swanson et al., 2010; Walker et al., 2010). This is sometimes conceived of as "dynamic adaptive" policymaking, with existing examples of these approaches being found in the flood risk planning (Haasnoot et al., 2013; Kwakkel et al., 2015) and transport (Marchau et al., 2010) domains. Some initial experiences in France and Germany suggest that such an approach could be transposed for application to energy decarbonisation pathway planning (Mathy et al., 2016). Exploring adaptive policymaking in the UK context should be a priority area for future research.

A significant fraction of interviewees reflected on the challenges faced in communicating uncertainty to decision-makers, even without the additional complexity associated with moving to a more socio-technical framing. Research shows that conventional climate policy communication strategies based on a cognitive information deficit model are increasingly ineffective, and that new alternatives are urgently required (Stoknes, 2014). Quantitative analysis has been found to only play a limited role in influencing decisions, as opinions are often largely guided by values, ideologies, worldviews and political orientation (Bosetti et al., 2017; Hornsey et al., 2016). Articulating compelling "visions" of the future energy system (Trutnevyte, 2014) and attaching energy and climate policies to strategic narratives (Bushell et al., 2015) may therefore be an increasingly important approach for science-policy discourse.

4.4.4 Critical reflection on study

The composition of the interview panel was limited by the authors' own access to different stakeholder groups, and those contacts provided by other participants. Many government participants who were willing to participate in the study, but fewer private sector companies. The views of business leaders, civil society, and academic research may therefore be underrepresented in this study. While the framing of the main research question around the uncertainties relating to the UK's long term climate policy target makes the strong involvement of government participants appropriate, it would have been fascinating to integrate views from a broader range of participants, such as institutional investors with an interest in long term asset management, venture capitalists, or innovators in areas such as information technology.

While an open-ended interview format was conducted, avoiding leading questions, it was found that most participants discussed uncertainties that have, for the most part, been well explored in existing literature (Watson et al., 2015). While around a third of interviewees called for an improved exploration of *radical or disruptive futures* (**O2**) in future analysis, only a few articulated what these might actually look like or involve. Only a handful of participants made explicit mention of potentially transformative socio-technical futures involving developments in machine intelligence, automation, big data, and the internet of things, that are becoming more common in horizon scanning studies (such as (Rohr et al., 2016)). It is possible that most of the participants are focused on the policy environment of the near future, with their perspectives strongly conditioned by existing frames, narratives, and the status quo, so the findings of the study must be viewed in that light.

As hoped for, the open-ended nature of questioning produced a wealth of discussion on diverse topics but was also challenging to structure and summarise. The authors found that many sub-themes could conceivably fit in different categories. For example, the issue of the *social mandate* (**P6**) could fit equally well as a societal or a political uncertainty. Likewise, the issue of new *technology adoption* (**S2**) clearly sits at the interface between multiple themes. However, the core findings of the study still stand.

4.5 Conclusions

Looking back 50 years ago, it may well have been fair to describe UK energy systems analysis and strategic planning as being largely conducted by engineers. Changes in the macro-scale landscape for energy policy over time, such as market liberalisation, has seen the perspectives of economists becoming fully integrated into policymaking. But the expertise of the wider socio-political sciences still remains largely outside of the formal decision process. This study confirms that energy system stakeholders are aware that numerous societal and political uncertainties are actually critical to future energy transitions. At the same time, many commented on how the more influential decision analysis tools used in this field tend to be narrowly focused on only the possible technological configurations of the future energy system, potentially overlooking issues such as behaviour and lifestyle change. Participants called for a broadening of the decision-making framework to incorporate qualitative narratives alongside quantitative analysis.

Mixing qualitative and quantitative methods is likely to increase the complexity of the decision making process. Formal models of the energy system are, by their nature, abstractions from an extremely complex reality (Mäki, 1992), and have both strengths and limitations as tools for thinking about the future. Interdisciplinary approaches that may be “inelegant from any single perspective, but robust because [they rely] on more than one epistemological and ethical foundation” (Rayner, 2012) are more likely to offer a means of charting a path forward under conditions of deep uncertainty. But harnessing such an approach requires a mature perspective on complexity and risk to be adopted by decision-makers. Under conditions of deep uncertainty, no amount of quantitative analysis is likely to produce a single “right” answer, and clear value judgements and preferences need to be brought to the table to enable decisions to be made.

A new approach means moving mainstream energy policy analysis away from an exclusive focus on techno-economic uncertainties. Policy design must escape from ‘caged’ thinking concerning what can or cannot be included in models, and therefore what types of uncertainties can or cannot be explored. Doing so requires a more inclusive approach that takes account of multiple disciplinary perspectives and solutions, while ensuring that decision support activity remains responsive to policy needs. An additional important research priority will be to explore if and how decarbonisation pathway planning can be moved from its current, largely static paradigm towards a more adaptive and responsive one.

This is no trivial task, as increased interdisciplinarity creates multiple challenges relating to research design, execution, interpretation, and communication, all of which require additional time and resources to overcome. These onerous requirements potentially place interdisciplinary innovation in direct tension with the desire from government for more rapid analysis that is easy to understand without specialist knowledge or training. But without it, the community risks underplaying future uncertainties, missing the solutions that are on offer from across the stakeholder community, and developing strategies that are not fit for purpose. Can the energy research community muster the courage and conviction to pioneer new ways of working, bridge between disciplinary silos and transform our field? Can we do so while remaining relevant and engaged with policymakers? These may prove to be the greatest uncertainties of all.

5. Assessing qualitative and quantitative dimensions of uncertainty in energy modelling for policy support in the United Kingdom

Abstract

Strategic planning for the low carbon energy transition is characterised by a high degree of uncertainty across many knowledge domains and by the high stakes involved in making decisions. Energy models can be used to assist decision makers in making robust choices that reflect the concerns of many interested stakeholders. Quantitative model insights alone, however, are insufficient as some dimensions of uncertainty can only be assessed via qualitative approaches. This includes the strength of the knowledge base underlying the models, and the biases and value-ladenness brought into the process based on the modelling choices made by users. To address this deficit in current modelling approaches in the UK context, the NUSAP (Numeral Unit Spread Assessment Pedigree) approach is used to qualify uncertainty in the energy system model, ESME. The research finds that a range of critical model assumptions that are highly influential on quantitative model results have weaknesses, or low pedigree scores, in aspects of the knowledge base that underpins them, and are subject to potential value-ladenness. In the case of the UK, this includes assumptions around CCS deployment and bioenergy resources, both of which are highly influential in driving model outcomes. These insights are not only crucial for improving the use of models in policy-making and providing a more comprehensive understanding of uncertainty in models, but also help to contextualise quantitative results, and identify priority future research areas for improving the knowledge base used in modelling. The NUSAP approach also promotes engagement across a broader set of stakeholders in the analytical process, and opens model assumptions up to closer scrutiny, thereby contributing to transparency.

Keywords

Uncertainty analysis; NUSAP; qualitative dimension of uncertainty; decarbonisation; energy systems modelling

5.1 Introduction

5.1.1 Energy and climate strategy under uncertainty

Strategic planning for the low carbon energy transition is characterised by a high degree of uncertainty across many knowledge domains and by the high stakes involved in making decisions. The future availability and costs of transition technologies, the political environment under which they may be deployed, and the role of changing societal preferences and individual behaviours are key uncertainties for decision makers to contend with, and which will impact numerous stakeholders (Li and Pye, 2018). As described in section 4.1.1, while the UK has long identified the need for the decarbonisation of the energy system, with some good progress made notably in the power generation sector (BEIS, 2017), strategic decisions in a number of critical sectors remain to be taken.

This type of challenge, where urgent near-term choices must be made in an environment where perfect information and universal agreement amongst key stakeholders is impossible to achieve, is characterised in the scientific literature as the domain of *post-normal science* (Funtowicz and Ravetz, 1993, 1990). This is in direct contrast to the definition of *normal science* by (Kuhn, 1962), where observations are used to iteratively resolve testable hypotheses through experimentation. The assessment of strategic options in a *post-normal science* context, such as long term energy policy, must contend with multiple epistemic uncertainties that arise from our imperfect knowledge, including those that can be quantified in modelling tools, but also those that are not easily quantifiable.

(Van Der Sluijs et al., 2005) argues that most quantitative-only approaches do not adequately deal with those dimensions of uncertainty that are non-quantifiable. These include the strength of the underlying knowledge base, the level of theoretical understanding of the processes modelled, and the value-ladenness coproduced by modellers themselves because of the requirement to make choices across key model assumptions. As an illustration, a quantitative analysis performed for a particular policy problem might produce modelling results which suggest that a given input parameter is highly influential on the distribution of costs of meeting a given objective. But what is typically missing from such an exercise is an assessment of the uncertainty arising from the strength of the knowledge base underpinning that quantified model outcome. Such non-quantifiable uncertainty, were it exposed to decision-makers, might reduce the perceived robustness of the model-derived quantitative insight, and lead to different conclusions for policy.

Approaches that recognise this multi-dimensional nature of uncertainty, as described in the next section, can provide decision makers with a more comprehensive understanding of uncertainty and improve the robustness of the resulting choices made. They help avoid quantitative-only approaches which only consider a "*restricted agenda of defined uncertainties – ones that are tractable*" (Wynne, 1992, p. 115). When faced with policy challenges in the *post-normal* domain, a broad approach to uncertainty assessment is vital. It is entirely possible that *"unquantifiable uncertainties dominate the quantifiable ones"* (Van Der Sluijs et al., 2005, p. 482) and excluding them from the analysis will risk giving decision makers a highly restricted perspective on the range of possible outcomes. The challenge is that uncertainties are numerous and appear, as per (Walker et al., 2003) typology, at different stages across the modelling process, from the problem framing itself, the selection of model input parameters, the structural design and process of defining relationships, and from the subjectivity of model users.

5.1.2 Existing approaches and knowledge gaps

Energy models are likely to continue to play a key role in ongoing energy transitions by providing the evidence base for planning policies on climate mitigation (Pye and Bataille, 2016), which in turn serve as key drivers behind many transitions towards sustainability (Markard et al., 2012). The Paris Agreement (United Nations, 2015a) recommends mid-century low emission strategies and states that individual signatories must provide regular updates on their strategic plans for low carbon development (Nationally Determined Contributions, NDCs), forcing a requirement for policymakers to assess low carbon energy transitions at the country-scale (Bataille et al., 2016). Energy models provide a clear framework for systematic experiments that explore the possible consequences of the multiple different options in systems that are otherwise difficult to grapple with (Holtz et al., 2015). However, the treatment of uncertainties in strategic analysis has had a number of limitations, and practitioners in the modelling community have repeated calls for increased use and improvement of methods for uncertainty analysis (Pye et al., 2015b, 2014; Usher and Strachan, 2012). As highlighted in chapter 4, this is mirrored by calls from strategy analysts, industry experts and government decision makers, who are cognisant of a broad spectrum of future uncertainties facing the energy transition and also the limitations of current modelling and scenario analysis practices to capture them (Li and Pye, 2018; McDowall et al., 2014).

Modelling practitioners are increasingly drawing from a range of more advanced quantitative techniques to assess uncertainties as a means of capturing more of the problem space in their work. Techniques found in the UK context include probabilistic analysis (Pye et al., 2015b, 2014), stochastic programming (Usher and Strachan, 2012), and modelling-to-generate-alternatives (MGA) (Li and Trutnevyte, 2017; Trutnevyte, 2016) using parameter uncertainty ranges supported through expert elicitation (Li and Pye, 2018; Usher and Strachan, 2013; Watson et al., 2015).

While valuable for opening up dialogue and highlighting the uncertain nature of the knowledge claims made in this field, none of the above techniques alone are able to adequately identify and assess those non-quantifiable dimensions of uncertainty discussed earlier. An innovative approach to assessing uncertainties in model-based analysis is the NUSAP system (Van Der Sluijs et al., 2005). NUSAP, or Numerical Unit Spread Assessment Pedigree, was first proposed by (Funtowicz and Ravetz, 1990), before undergoing substantial development and implementation in the Dutch Government's applied policy research institutes (Petersen et al., 2011). NUSAP retains the strengths of quantitative uncertainty assessment but brings a focus on the qualitative assessment of the quality or 'pedigree' of the underlying model assumptions. This framework, which includes both standard uncertainty analysis techniques but also assessment of non-quantifiable uncertainties, increases the robustness of emerging conclusions from models, providing decision makers with an enhanced understanding of the strengths and weaknesses of model insights.

5.1.3 Aims and objectives

In this chapter, it is demonstrated how practitioners can broaden the scope of strategic advice given to energy system decision makers by holistically considering both qualitative and quantitative dimensions of uncertainty using the NUSAP approach. For this research, a prominent UK energy systems model is used, the Energy Systems Modelling Environment (ESME) (Heaton, 2014), which is under active development and has been used for academic (Li et al., 2016; Pye and Daly, 2015), industry (ETI, 2015) and government (CCC, 2011b) applications. The application of the NUSAP protocol for assessing the qualitative dimension of uncertainty is described, including how this can be combined with insights from a quantitative mathematical sensitivity analysis (using the Morris Method).

The NUSAP system has been used before in diverse scientific fields such as the assessment of acid rain and transboundary air-pollution impacts, the global integrated assessment of climate policies, and the effects on human health of waste disposal practices (Kloprogge et al., 2011; Van der Sluijs et al., 2002; Van Der Sluijs et al., 2005; Vaughan and Gough, 2016). The life cycle assessment community have also effectively used pedigree scoring of underlying data assumptions, which is a key element of the NUSAP approach, to better recognise its impact on uncertainty (Ciroth et al., 2016; Weidema and Wesnaes, 1996). This is the first time such an approach has been applied to a national energy model used to inform thinking on energy transitions towards deep decarbonisation. Additionally, novel elements are incorporated into the NUSAP approach, such as the assessment of model pedigree in multiple time horizons.

The key research questions for this study were as follows:

- What are the key non-quantifiable uncertainties arising from limitations in the knowledge base underlying the ESME model?
- How do they inform and complement our understanding of uncertainty from quantitative uncertainty approaches, and what are the implications for strategic energy transition planning, in terms of policymaking and future research needs?

The chapter is structured as follows; in Section 5.2, the approach taken to the uncertainty analysis is first described. This includes descriptions of the NUSAP-based workshop used to elicit non-quantifiable uncertainties and of the Morris Method global sensitivity analysis that was used to explore the quantitative uncertainties. Section 5.3 presents the results from the workshop, while Section 5.4 provides a discussion of the results. The chapter concludes with recommendations for modelling uncertainty, particularly in support of decision-making, and a discussion on future research needs.

5.2 Research design and methods

In this section, the NUSAP approach is first described, followed by a brief overview of the model ESME, the subject of the approach. The selection of model assumptions to focus on is then described, and the process of designing and implementing a NUSAP workshop, to elicit an understanding of uncertainties in ESME.

5.2.1 NUSAP

The NUSAP approach[11] was proposed in 1990 (Funtowicz and Ravetz, 1990) and further developed to meet the need to revise the approach to uncertainty assessment following strong criticism of the Netherlands Environmental Assessment Agency, MNP,[12] in the late 1990s, on the credibility and reliability of the assumption and models used in environmental policy (Petersen et al., 2011; van der Sluijs, 2017). At the core of the approach is the recognition that uncertainty is multi-dimensional, with dimensions including technical (inexactness), methodological (unreliability), epistemological (ignorance) and societal (social robustness) (Van Der Sluijs et al., 2005). Quantitative uncertainty assessments, particularly those using global sensitivity analysis, typically representing the *technical* dimension, provide information on the uncertain quantifiable assumptions that have the greatest influence on the results (Saltelli et al., 2008).

However, missing from such assessments is information on the quality of the underlying knowledge base that allows users of the model results to form a view on the robustness of the emerging conclusions. Applying the NUSAP approach allows for scrutiny of the 'pedigree' or quality of model assumptions by a range of experts. Pedigree is judged based on scoring against multiple criteria, capturing different aspects of (non-quantifiable) uncertainty (Table 5.2). The term 'model

[11] NUSAP stands for Numeral-Unit-Spread-Assessment-Pedigree. 'Numeral' is the numbers used in the analysis; Unit is the units for the numbers; 'Spread' is the variance in the model outputs due to input uncertainty; 'Assessment' represents qualitative judgements about assumptions; and 'Pedigree' represents the strength of knowledge and use of knowledge in the analytical approach.

[12] MNP was merged with Netherlands Institute for Spatial Research (RPB) in 2008 to form the PBL Netherlands Environmental Assessment Agency (*Planbureau voor de Leefomgeving*)

assumption' relates to the following aspects of the model where uncertainty could manifest itself, and follows the typology proposed in (Walker et al., 2003) and subsequent PBL guidance (Petersen et al., 2013); i) model structure (relationships embedded in equations), and ii) model inputs, such as data, boundary conditions, and analysis framing.

For each model assumption considered, experts score against the selected criteria, as described in section 5.2.3. The resulting pedigree scores provide insights into qualitative dimensions of uncertainty, which can then be used to compliment the quantitative uncertainty analysis. A key strength of the approach is that both components can be brought together using a diagnostic diagram, as shown in Figure 5.1 (Refsgaard et al., 2007). The pedigree scores highlight the 'strength' of the model assumption, reflecting the methodological and epistemological limitations of the knowledge base, while the quantitative sensitivity analysis shows the influence of the model assumptions on the results via statistical methods.

The diagnostic diagram can be separated into four quadrants. In Q1, the influence of assumptions on model outputs is low, and the underlying knowledge base is strong, resulting in limited cause for concern. The same may also be true for Q3, where despite a weaker knowledge base, the influence of assumptions on outputs is low. In Q2, the assumptions have a strong effect on the overall modelled outcome, but the strong pedigree of the knowledge base can give decision makers confidence that the model is providing useful information to inform decisions about the real world system. In Q4, assumptions have high statistical influence over model outcomes, but a weak pedigree. This quadrant can be characterised as the 'danger zone'. In this region, what appears to be an important outcome from a quantitative perspective may need to be treated with caution as the quality of the knowledge underpinning the assumption has been revealed to be weak or contested. The application of this diagnostic diagram is further considered in the results (Section 5.3.3).

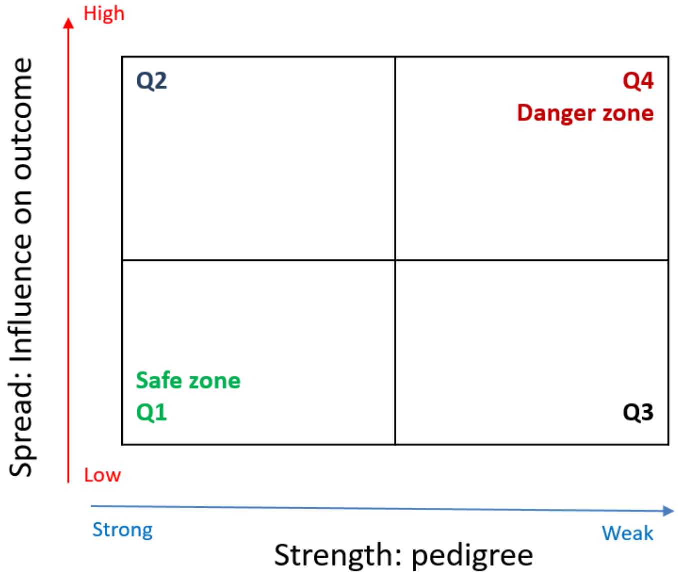

Figure 5.1. Diagnostic diagram used to combine quantitative and qualitative dimensions of uncertainty

Another important feature of the NUSAP approach is that it allows for in-depth scrutiny of model assumptions through expert stakeholder involvement, highlights the strengths and weaknesses of the model analysis (and areas to prioritise for improvement), and also explicitly clarifies the distinct areas of disagreement across assumptions. In effect, it provides greater transparency to the analytical process, for example through identifying a diversity of views on the strength of the underlying knowledge base, and the level of consensus across different assumptions. The evaluation of previous NUSAP exercises by participants has consistently highlighted broad agreement amongst stakeholders regarding their value (Van der Sluijs et al., 2002; Wardekker et al., 2008). However, the NUSAP process of eliciting expert perspectives via a workshop is time intensive and therefore not necessarily always appropriate in a fast-moving policy context. (Kloprogge et al., 2011) suggest therefore that it may be most appropriate to apply the NUSAP approach in high value analysis cases – for example, where decision stakes are high and uncertainty can have a large impact on policy development, and also in cases where societal controversies are prevalent. Hence, analysis for climate and energy policy is a good example of where such an approach can be highly relevant.

5.2.2 The ESME model

In this chapter, the NUSAP approach is applied to ESME[13], a regionally disaggregated model of the UK energy system, used to determine the role of different low carbon technologies for achieving the mid- to long-term climate mitigation goals set in UK legislation. A description of the model is provided in chapter 3, in section 3.2.1. The uncertainties around the future costs and performance

[13] Assumptions reviewed were in v4.1

of different technologies and resource prices are captured via a probabilistic approach, where multiple scenarios are generated to explore a wide range of pathways. A full list of the assumptions considered in this NUSAP exercise are provided in Table 5.1, with further background information on each in Appendix C2. A full description of the model is provided in (Heaton, 2014), while the data assumptions and sources are also published (ETI, 2016).

5.2.3 Selecting the model assumption for assessment

The large number of model assumptions, the structural complexity of the ESME model (which contains numerous equations), and the in-depth nature of the NUSAP assessment process meant that careful consideration was needed regarding which assumptions to prioritise during the workshop in order to keep the process manageable. The guiding principle was to focus the analysis on the most influential model assumptions. Following the practice observed in earlier NUSAP workshops (Van der Sluijs et al., 2002), a dual-layer approach was used for their selection; firstly, the model inputs which were ranked the highest in terms of their influence on model results (expressed in terms of the costs of meeting decarbonisation targets) were selected, based on two previously published global sensitivity analyses using ESME (Pye et al., 2015b; Usher, 2015). Such approaches allow for an understanding of 'how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input' (Saltelli et al., 2004, p. 45). One such approach is the Morris Method (Morris, 1991), also known as the Elementary Effects Method, which provides a computationally efficient means of screening a model in order to determine the set of input parameters to which the model solution is the most sensitive. A wide range of input parameters are first characterised as uncertain, and then subjected to the Morris Method sampling approach that captures the uncertainty space across the parameter value ranges. The ESME model is then run multiple times, in each case to meet the UK's climate legislation across the carbon budget periods and 2050 target. The sensitivity metrics are then calculated based on their influence on total system costs. This sensitivity analysis approach detailed in (Usher, 2015) was used here to inform the uncertainty analysis presented in the results section of this chapter, the approach for which is described in detail in Appendix C5.

Secondly, an interview was held with expert modellers from the Energy Technologies Institute (ETI), the developers of ESME, to elicit their views on what they considered to be the critical assumptions affecting the model output. Prior to the interview, participants were provided with an overview of the NUSAP approach, and the purpose of identifying key uncertainties for discussion at a workshop. The interview was exploratory in style (Li and Pye, 2018), with participants free to discuss any issues relevant to model uncertainty. This gave a broader perspective based on the developers' experience of using the model for different applications, and led to the inclusion in the workshop assessment of specific model features associated with analysis framing and model structure, which can also be considered within the NUSAP framework (Refsgaard et al., 2006).

Table 5.1 lists the model assumptions selected. Five were chosen on the basis of the global sensitivity analysis (GSA) and four from expert elicitation (EE) via the interviews with model experts, including two structural assumptions.

Table 5.1. Selection of assumptions for pedigree assessment

Assumption category	Assumption code	Assumption	Uncertainty location	Method of determination*
Resources	BioRES	*Bioenergy resource potential*: limits the level of domestic biomass available for use in the energy system	Input data	GSA
	BioEF	*Bioenergy emission factors*: reflecting assumptions around carbon neutrality, impacting on the attractiveness of bioenergy as a zero or low carbon source of energy	Input data / boundary conditions	EE
	GasPRC	*Gas resource costs*: based on UK Government projections reflecting international market prices	Input data	GSA
Technologies	CCSmbr	*Combined Cycle Gas Turbines (CCGT) w/ CCS build rate*: expressed as a constraint in the model as maximum capacity deployment per annum	Input data	GSA
	CCScap	*Combined Cycle Gas Turbines (CCGT) w/ CCS Capex*: expressed as expenditure requirement to install a unit of capacity	Input data	GSA
	NUCcap	*Nuclear Gen. III** Capex*: expressed as expenditure requirement to install a unit of capacity	Input data	GSA
Emissions accounting	NonCO2	*Non-CO_2 GHG emissions* (implicit in CO_2 trajectory): level of emissions that has an impact on the CO_2 target trajectory	Input data / boundary conditions	EE
Model structure	TchLRN	*Technology learning rates*: approach to incorporating projections in the model of the technology costs reductions over time, due to learning effects	Model structure	EE
	PerFOR	*Perfect foresight optimisation*: model formulation where all economic 'decisions' are made with a full knowledge of information relating to the future.	Model structure	EE

** GSA = global sensitivity analysis; EE = expert elicitation. ** Nuclear Gen III is a shorthand reference for third generation nuclear reactors, intended to represent the latest class of nuclear build designs, e.g. Areva's EPR, Westinghouse's AP1000*

The end result was a set of critical assumptions for modelling decarbonisation pathways, covering a range of different aspects of the modelling. It is also worth noting that issues not explicitly captured in this list could also form part of the elicitation process. For example, the capital costs of nuclear might not be considered the most important for this technology. Experts might consider planning, public acceptance, construction delay to be more important factors. Such opinions can be expressed during the engagement process.

5.2.4 NUSAP workshop for eliciting information on the qualitative dimension of uncertainty

A NUSAP workshop was held on 14th September 2017 to explore the qualitative dimensions of uncertainty across a range of assumptions used in the ESME model. In this section, the process of selecting experts for the workshop is described, followed by the approach to appraising the assumptions, and the process of running the workshop.

Expert selection

19 experts attended the NUSAP workshop, from a range of disciplinary backgrounds and professions, and all with different perspectives on modelling, including data providers, developers, and users of outputs. Just over half of the participants were from academia (across eight universities), with the other half equally split between government, industry, and other research organisations and institutes. All participants were primarily UK-based, although a number of the academic group had overseas affiliations.

Approximately 30 experts were originally contacted to be involved in the workshop. Determining invitations was based on the requirement for the workshop to include a mix of three different types of stakeholders: i) recognised subject experts on the model assumptions of focus; ii) experienced users of energy models who interact with the decision making community; and iii) users of energy model outputs in the decision making community. All three groups bring different perspectives on the use of models, and the knowledge base underpinning the different analyses undertaken.

Similar to other approaches to expert selection found in energy policy research (e.g. (Cox, 2016; Gillard, 2016)), the list of experts was based on purposive selection, identifying the relevant expert community. The resulting 19 experts who attended provided a broad range of expertise and a diverse range of perspectives on possible energy system developments, based on their disciplinary backgrounds and professional experience. Prior to the workshop, all participants were contacted and provided with an advance information pack that contained a description of the NUSAP concept, the list of assumptions for assessment, and the pedigree criteria and scoring framework. This was particularly to allow for familiarisation of the criteria definitions.

Criteria selection for pedigree assessment

Table 5.2 lists the criteria used to assess the pedigree of the model assumptions in Table 5.1. In broad category terms, the NUSAP assessment focuses on the methodological, epistemic, and societal dimensions to model pedigree. These criteria have been used in many previous NUSAP assessments; in particular, the research draws from (Van der Sluijs et al., 2002; Van Der Sluijs et al., 2005) on methodological and epistemological dimensions, and (Kloprogge et al., 2011) and (van der Sluijs and Wardekker, 2015) on the societal dimension. The methodological dimension focuses on uncertainty related to the perceived reliability of the estimates made for model inputs. The criteria for appraising reliability (in view of model purpose) considers how good a proxy a given assumption is, its empirical grounding, and whether it has been, or even if it can be, validated. The epistemological dimension focuses on areas of ignorance, in this case whether or not we think we have a sufficient and adequate theoretical understanding of the process to allow us to make meaningful assumptions about it.

The societal dimension recognises that the choice of model inputs is typically subjective, due to the different disciplinary backgrounds of model users, their political leanings, their preferences, whether there is limited information to inform assumptions, or whether there is wide range of possible choices that could be considered plausible. This *value-ladenness* is essentially unavoidable in sufficiently complex problems. Following the *post-normal science* tradition (as described earlier), NUSAP does not seek to reduce or minimise subjectivity, but instead considers that if there is a plurality of viewpoints and perspectives then they must be recognised, and properly recorded as part of the assessment, to better understand the bearing that this might have on the conclusions that can be drawn.

Five criteria focus on the methodological and epistemological underpinning of modelling assumptions. These include: the extent to which the model is a good *proxy* for the real world system, the quality of the *empirical basis* for assigning values to model parameters, the perceived *rigour* of the methods used to derive input values for models from available empirical data, the extent to which input *validation* has been carried out, and the extent to which the *theoretical understanding* of the real world process is viewed as providing a reliable basis for estimates. A further three criteria focus on the societal robustness of the assumptions made. These include the *choice space* for making assumptions (i.e. how different could plausible input values be from one another) the *justification* for the choice of value used and how defensible this is perceived to be by others and whether or not there is likely to be *agreement amongst peers* in choosing model parameter values.

Table 5.2. Pedigree criteria used in NUSAP assessment

Uncertainty dimension	Criteria	Description
Methodological	Proxy	The extent to which the assumptions that we use in the model are proxies for the reality that we seek to represent, given the purpose of the model. Examples include over simplifications, first order approximations, incompleteness.
	Empirical Basis	The degree to which observations, measurements and statistics are used to estimate a parameter.
	Rigour	Refers to the norms for methodological rigour in this process applied by peers. Well-established and respected methods for measuring and processing the data would score high on this metric, while untested or unreliable methods would tend to score lower.
	Validation	The extent to which assumptions have been cross-checked and validated against other observations and measurements
Epistemological	Theoretical Understanding	The extent to which our theoretical understanding of the real world processes provides a reliable basis for estimates
Societal	Choice Space	The degree to which alternative choices of assumptions could be made i.e. the degree to which other acceptable / plausible assumptions are available
	Justification	The degree to which the approximation made in the model can be justified as a reasonable, plausible or acceptable assumption, given one's understanding of the reality. Can these assumptions be defended?
	Agreement Amongst Peers	The degree to which the assumption made in the model (by the analyst) is likely to coincide with other experts in the field

Development of scorecards

To guide the expert assessment of pedigree and provide a common platform for discussion and intercomparison, a structured scoring system was provided (as per NUSAP practice). This was based on successful systems used in past NUSAP assessments but was specifically tailored to the featured model and the model parameters chosen for the assessment. Scores between 0 to 4, where 0 denotes a weak pedigree and 4 a strong one, could be given for each criterion discussed in Table 5.2, and applied to each model assumption listed in Table 5.1. For each score, a description was provided to guide the experts in making judgments on assumption pedigree. A full scoring matrix is provided in Appendix C1.

The research for this chapter added a novel component to the traditional NUSAP analysis process. Past assessments have typically explored the pedigree of models that explore research questions relating to the present day or the near future. However, the ESME model is designed to assess energy and climate policy pathways across a very long time horizon from 2010 to 2050, and clearly many of the assessment criteria outlined above in Table 5.2 can be interpreted differently when considering the recent past as compared to the far future. In the pedigree assessment therefore, a separate scoring is introduced for those assumptions relating to the model base year (2010) and those relating to the long term future (2050). In the case of CCS technologies, which are not commercially deployed at scale and accordingly do not have 2010 base year assumptions, the years 2030 and 2050 were considered. It was important to recognise the considerable differences in the underlying knowledge base in these near-to-mid term (2010/2030) and longer term time periods, and therefore the associated level of uncertainty.

The scorecard, for use by the experts, included a range of information for assisting in scoring, including a description of each of the model assumptions, how it was incorporated into the ESME model, and the mathematical ranking of the input assumptions in terms of how much they affect model outputs (where relevant) from previous global sensitivity analyses. The full set of scorecard templates used are provided in Appendix C2. A description of how the workshop was structured and how the scoring was undertaken is also provided in Appendix C2. This includes introducing the topics to the group, and allowing for question of clarification or understanding. Nevertheless, it should be recognised that there is inevitably differing levels of expertise within the group across the assumptions.

5.3 Results

Selected results from the NUSAP workshop are presented in this section. Some general observations from the aggregated results are first noted before a discussion of the individual criteria scores across the groups of assumptions, including resources, technologies, emissions accounting and model structure. The section concludes by describing a diagnostic diagram, which brings results from the workshop together with results from quantitative uncertainty analysis. Further detailed results, including the scoring by all participants for all of the individual assumptions from the workshop, are provided in Appendix C3.

5.3.1 Aggregate pedigree scores

Aggregate scores for the pedigree of assumptions were calculated based on averaging the five methodological and epistemological criteria from each expert. These scores were then averaged for each of the assumptions, to provide aggregate pedigree scores, as shown in Figure 5.2. Standard deviations provide an indication of divergence in score between experts. The three value-ladenness criteria focus on the nature, not the strength, of the assumptions and are therefore not included in the aggregation. A clear difference emerges in scores between time periods, with near-term scores always being higher than those for 2050, reflecting the lower levels of uncertainty across the knowledge base for the current energy system. This distinction is particularly strong for bioenergy resource (BioRES) and gas prices (GasPRC), where average scores in 2010 are typically around 3.0

and 3.5 respectively, compared to the ranges 1.0-2.0 and 1.5-2.0 in 2050. Recognising that pedigree decreases in future years is important when considering the robustness of model insights in the long term.

For current or near term assumptions (Figure 5.2a), high scores for BioRES and GasPRC are observed. Lower scores are found for bioenergy emission factors (BioEF), nuclear capital expenditure (NUCcap), and build rates of gas CCS plant (CCSmbr). For BioEF, this reflects uncertainty in the knowledge of emissions from a very diverse resource base, and the highly aggregated proxy representation of the resource in the model. The ESME model only distinguishes between average emission factors for domestic and imported biomass, whereas in reality, almost every single bioenergy resource stream (based on type, location, processing, transport, end use technology) will have different emission factors. Given the diversity of emission factors found across the resource base, this assumption was given a relatively low *proxy* score, while the possible range of plausible values (*choice space*) was viewed as large (section 5.3.2).

A lower score for NUCcap reflects the limited evidence on the costs of contemporary nuclear power plant designs, particularly given the small number of existing projects from which to draw from. This uncertainty was further reflected in the low scores for the choice space criteria (many respondents suggested that the plausible range for nuclear capital costs is wide) and the agreement amongst peers criteria (respondents suggested that there is only limited agreement amongst experts). Across all assumptions, CCSmbr scored lowest, perhaps predictably as an assumption relating to the year 2030. Additional reasons for the low pedigree score for CCSmbr include the limited evidence base from which to draw from, and the fact that the non-cost barriers that this constraint includes are poorly understood, such as the societal acceptability of large-scale CCS, and the political will behind any successful future deployment. Interestingly, workshop participants rated the model assumptions about the capital cost level for the same technology (CCScap) as scoring higher due to empirical evidence today on the costs of different components of the CCS system, based on existing projects, and a view amongst the experts that a stronger knowledge base underpins this assumption.

The average scores for all model assumptions being assessed in 2050, shown in Figure 5.2b are lower and much more clustered together than their equivalent scores for 2010, reflecting the increasing uncertainty in the longer term. The lack of spread between 2050 average scores (in the range of 1.4 to 2.2), and similar score variation between assumptions sees most experts suggesting a much weaker pedigree. For example, BioRES drops from a score of 3 in 2010 to 2 in 2050, reflecting expert views that future bioenergy resources are likely to be subject to multiple complex factors that are highly uncertain, around land use planning, competition between energy and food crops, and competition between the production of biomass for energy and the other non-energy uses of biomass (such as wood used in manufacturing). This weaker epistemic status of future values is not surprising; the implications of this for how decision makers think about model outputs is an important issue to further consider. For the CCS assumptions, the difference between the 2030 and 2050 scores is not marked, as the understanding of key parameters relating to this technology are uncertain at both points in time due to its low technology readiness level and the lack of real world examples where it has been deployed.

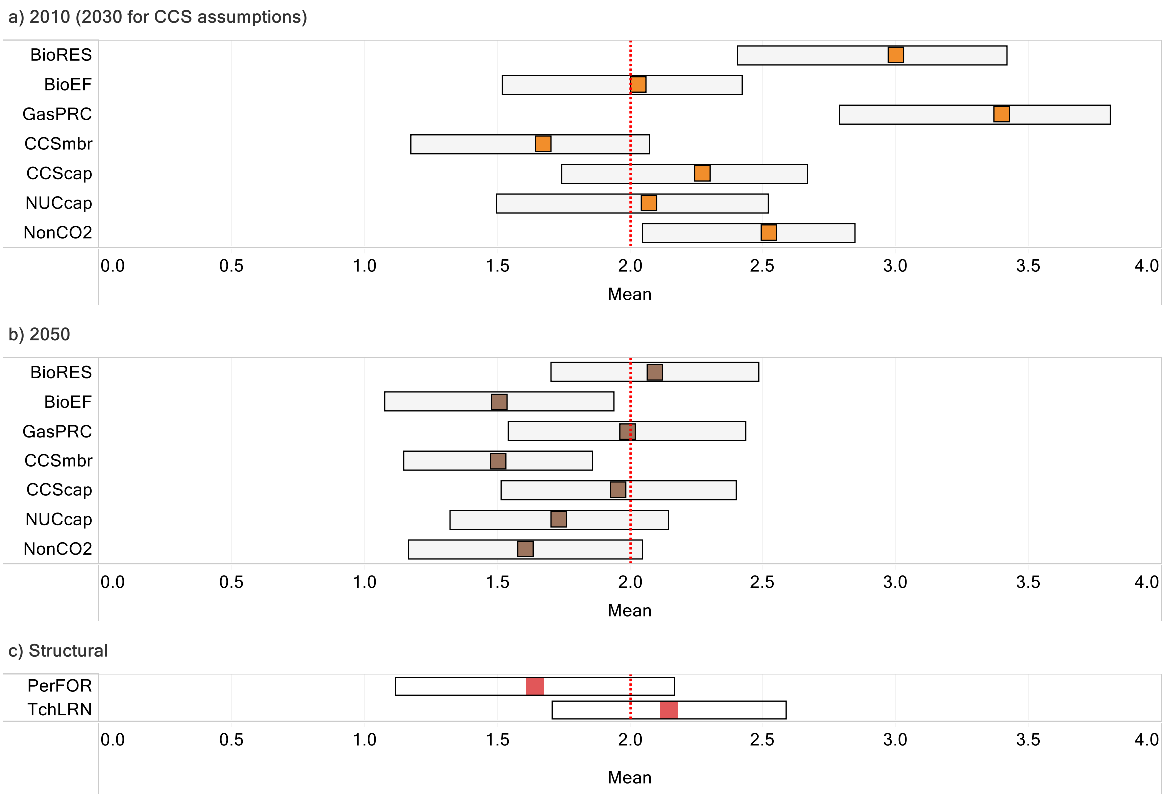

Figure 5.2. Mean aggregated pedigree scores
a) presents 2010 scores, except for the two CCS assumptions which relate to 2030. b) presents 2050 scores, and c) structural assumptions, technology learning and perfect foresight, which are both time independent. These pedigree scores show the mean and standard deviation of the participants mean scores based on the five pedigree criteria. The red line provides a reference point for comparison, as the central score value of 2. Model assumption labels are described in Table 5.1.

All assumptions see their relative scoring positions maintained between 2010 and 2050 with the exception of GasPRC and NonCO2. The level of non-CO_2 GHG emissions in the model is important because it determines the stringency of the cap on CO_2 emissions, which is the target that the ESME model tries to work towards (as covered earlier in Section 5.2.2). These future levels were considered much more uncertain by participants due to the many different factors influencing these emissions, from policy action, environmental factors such as land use management, and lifestyle choices around diets. On gas prices, the lower pedigree score (relative to other assumptions) in 2050 is related to multiple factors. These include uncertainty as to the how global supply and demand dynamics for natural gas play-out in future, given geo-political uncertainties, and the future potential role for gas in a future decarbonised energy system, which may be largely determined by the availability and deployment of CCS technologies.

Two structural assumptions are also shown in Figure 5.2b. “Technology learning” (TchLRN) is a term used to refer to how models capture future changes to technology costs resulting from factors like better and cheaper manufacturing processes (improvements over time). In the ESME model this is handled as an exogenous parameter i.e. the future cost pathways for key technologies are input assumptions that are decided in advance of the model being run. More complex approaches that link the change in technology costs to the level of technology deployment in the model are also possible. Experts’ comments reveal a sense of pragmatism here given the model purpose, scale and practices across the modelling community; ESME is a model of national scale, and the UK typically has not been observed to drive learning across energy technologies in recent years. Furthermore, the practicalities of endogenising domestic learning effects is technically challenging, with limited data to parameterise such an approach.

Conversely, the other structural assumption, perfect foresight (PerFOR), gains a lower score. “Perfect foresight” is a structural feature of the model whereby the pathway solutions generated are made by taking into account the various changes to technology performance and costs in all future time periods. A number of experts did not view this as a structural assumption to be replaced by an alternative formulation but rather a core part of the model framework. There was also concern as to why this was being subject to appraisal as perfect foresight was not intended to be representative of how real systems work given the behaviour of different actors, but is rather a basis for understanding the role of different technologies from a techno-economic perspective. With differences of opinion as to how this should be scored, a number of experts (5) decided not to, and therefore the distribution of pedigree scores shown for this assumption has a smaller number of data points than the other scores.

5.3.2 Pedigree scores by criteria and assumption

The aggregate pedigree scores are useful for providing a summary but mask the wide variation in how individual assumptions were scored against each criterion, as shown in Figure 5.3 to Figure 5.5. For example, these figures show the extent to which participants thought that the representation of bioenergy in the model (as a relatively small number of homogenous feedstocks) is a good *proxy* for reality, and the quality of the *empirical basis* used to generate estimates of that bioenergy resource.

Appendix C4 provides an alternative set of graphics, where the criteria for each model assumption are presented, instead of all assumptions for each criterion.

Of all the criteria, *validation* scores lowest in 2050 (range 1.0-1.5), reflecting that long-term model assumptions cannot be checked against real-word systems (Figure 5.3). For nearer term estimates, it is particularly useful to assess how well the modelled system is sense checked against current real-world system. For example, the *nuclear Capex* assumption (NUCcap) is the only assumption to have a score of less than 2.0, highlighting a potential weakness in validation against current nuclear projects, most of which are experiencing delays and incurring large cost-overruns. The *empirical basis* criterion, the degree to which observations, measurements and statistics are used to estimate a parameter has a similar pattern of scores to validation, albeit higher. Again, higher scores in 2050 are not obtainable as assumptions cannot be based on observations or measurements, but rather rely on estimates from other models (in a score range of 1.5-2.0). In 2010, scores are in the main between 2.5 and 3.5, where 3.0 represents a mix of observations and model-based estimates. As per the *validation* criterion, *empirical basis* scores for NUCcap and BioEF are lower, and are found closer to the central score of 2.0.

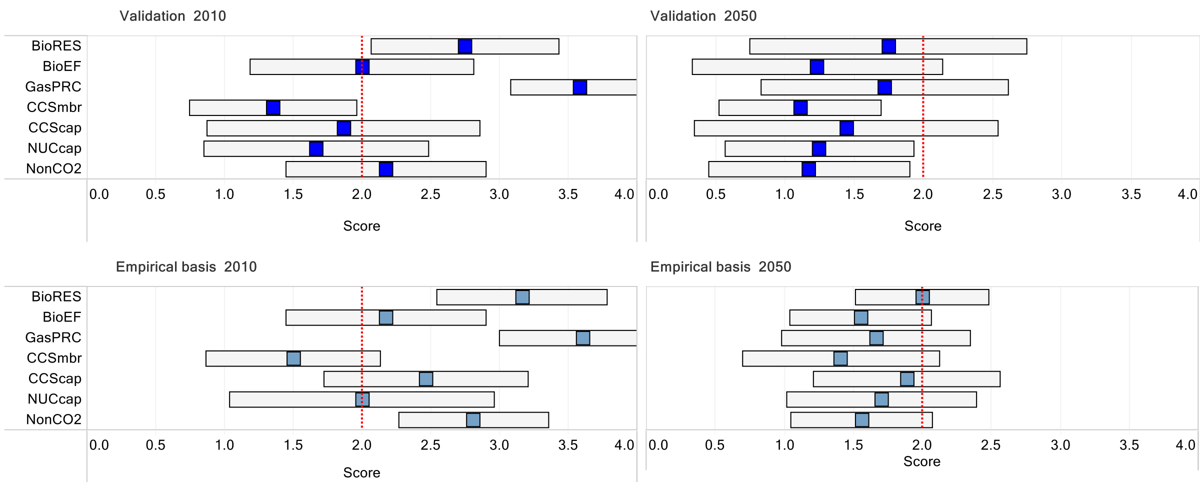

Figure 5.3. Mean and standard deviation for scores relating to validation and empirical basis criteria. The graphs on the left of the panel are for nearer term assumptions (2010, except 2030 for CCS) and on the right, for 2050. The red line provides a reference point for comparison, indicating the central score value of 2. Descriptions of the mode assumption abbreviations on the vertical axis can be found in Table 5.1. Scores across the structural assumptions can be found in Appendix C4 (Figure C4.3).

Methodological rigour and *theoretical understanding* (typically in the range of 1.5-2.5) in 2050 tend to score better than *validation* and *empirical basis* (Figure 5.4). These scores reflect a stronger pedigree based on the use of rigorous methods for deriving assumptions, and a reasonable level of understanding of how the real world works that allows these assumptions to be determined. Assumptions in 2050 are much more difficult to validate and empirically justify, so are understandably lower. The relative scores across assumptions reflect the aggregate pedigree scores in Figure 5.2. For 2010, only two assumptions (GasPRC / BioRES) with a score of over 3.0 were deemed to have 'good theoretical understanding' and a 'reliable method'. This highlights that for other assumptions, greater efforts may be needed to increase the pedigree with which the model represents base year conditions. NUCcap scores higher on *theoretical understanding* relative to other criteria, highlighting that for some assumptions, while a technology may be well understood, corresponding model estimates may still be poorly validated and have limited empirical grounding (as discussed above).

For the *proxy* criterion, or model representation of a given assumption, the scores in 2050 are clustered around a score of 2.0, described as a *moderate or acceptable representation*. It is notable that the two bioenergy assumptions score relatively lower against other assumptions under this criterion, reflecting the concern previously highlighted that the resource representation is too aggregated (as a single resource type) in the model. Given that the representation in the model of the different assumptions is the same in 2010 as it is in 2050, the divergence in scores is surprising, but perhaps reflects experts' view of the *proxy* criterion as relating to both model representation in terms of methodological approach and in terms of data availability.

Value-ladenness criteria - *choice space*, *justification*, and *agreement amongst peers* - provide insight into the potential for modeller bias and subjectivity when making assumptions. The 2050 scores, particularly for the criteria *choice space* and *agreement amongst peers,* suggests a much greater opportunity for individual values, biases and subjective judgements to enter the frame, for long term assumptions (Figure 5.5). This is intuitive; as the knowledge base underpinning assumptions weakens, there is less agreement amongst the expert community about the correct value range or appropriate structural assumptions to employ, and also a wider range of plausible choices that could be assumed in the model.

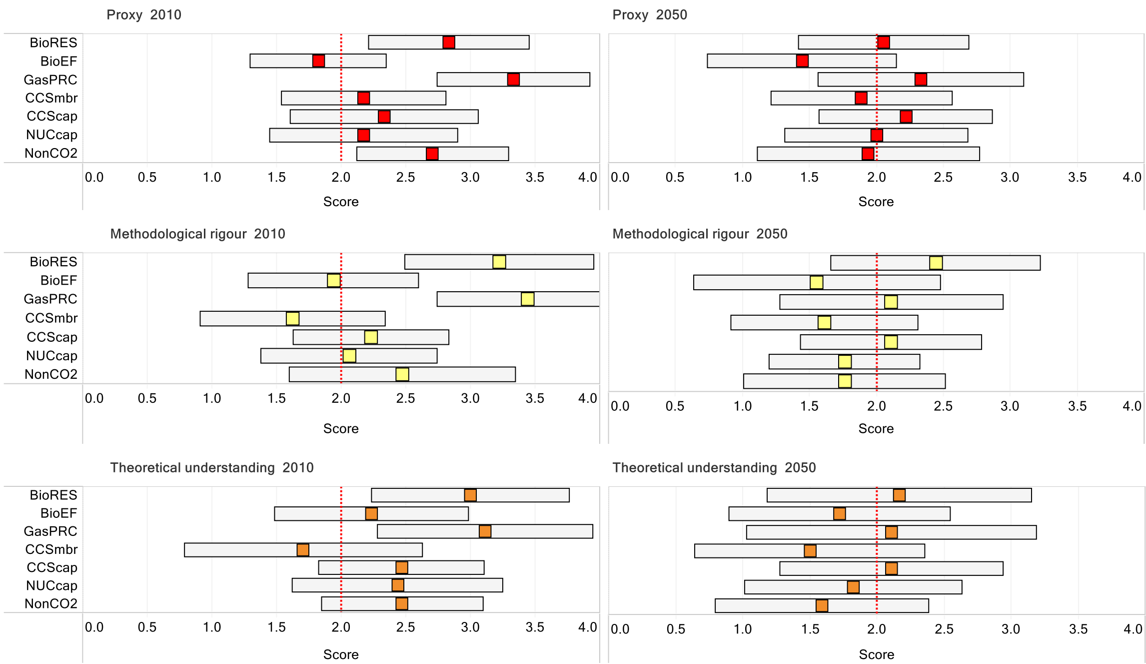

Figure 5.4. Mean and standard deviation for scores relating to proxy, methodological rigour and understanding criteria.

The graphs on the left of the panel are for nearer term assumptions (2010, except 2030 for CCS) and on the right, for 2050. The red line provides a reference point for comparison, indicating the central score value of 2. Descriptions of the mode assumption abbreviations on the vertical axis can be found in Table 5.1. Scores across the structural assumptions can be found in Appendix C4 (Figure C4.3).

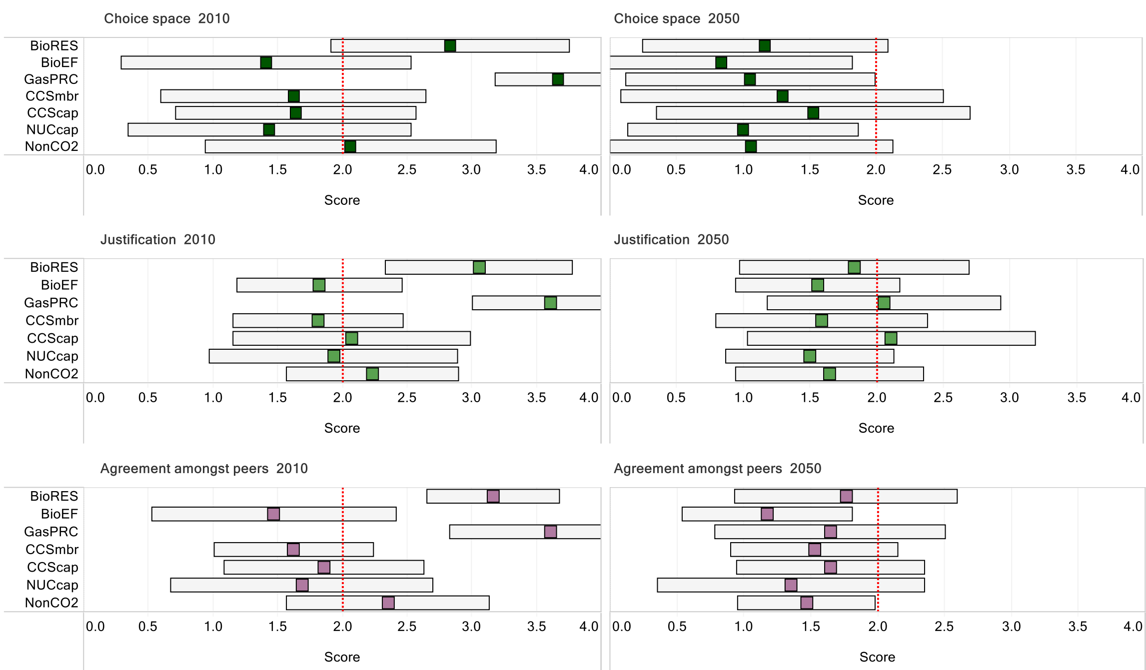

Figure 5.5. Mean and standard deviation for scores relating to choice space, justification and agreement amongst peers criteria.

The graphs on the left of the panel are for nearer term assumptions (2010, except 2030 for CCS) and on the right, for 2050. The red line provides a reference point for comparison, indicating the central score value of 2. Descriptions of the mode assumption abbreviations on the vertical axis can be found in Table 5.1. Scores across the structural assumptions can be found in Appendix C4 (Figure C4.3).

5.3.3 NUSAP diagnostic diagram

As described earlier, the NUSAP approach employs a diagnostic diagram to provide a comprehensive view of model uncertainty by bringing together insights on qualitative dimensions of uncertainty and from quantitative analysis. Figure 5.6 plots the aggregate pedigree scores (horizontal axis), based on the five pedigree criteria as in Figure 5.2, against the sensitivity measure (vertical axis), derived from a Morris Method global sensitivity analysis performed on the ESME model (Herman and Usher, 2017), which is further described in Appendix C5. The global sensitivity analysis reports the magnitude of the influence on the model results given movement over the full range of possible input values, providing a global measure of influence, or importance. The analysis here broadly replicates that undertaken by Usher (Usher, 2015), one of the two papers used to determine which assumptions to focus on for the NUSAP workshop (as described earlier in Section 5.2.3). The figure only includes the five data input parameters considered in the sensitivity analysis (see Figure C5.1, Appendix C5).

While the sensitivity analysis shows the strong influence of the CCS build rate assumption (CCSmbr) on the overall costs of decarbonising the UK energy system to hit 2050 climate targets, such an assumption scores weakest across the pedigree criteria. The assumption therefore lies in Q4, or the 'danger zone'. Such a result matters for decision makers, as the weaker pedigree score explicitly highlights the limits of knowledge underlying this assumption (not necessarily apparent just because an input assumption has a wide uncertainty range), and questions the robustness of any decisions supported by the quantitative analysis. The NUSAP analysis also highlights the large choice space that is possible in the future for this parameter, and limited consensus across experts. Two important conclusions from low scores are that further research and demonstration is needed to enhance the underlying knowledge base for CCS, which is limited, and that decision makers need to be circumspect about developing a strategy underpinned by this yet-to-be commercialised technology. While gas prices and biomass resource level have stronger pedigree scores in 2050, the significant impact of these parameters on the model solution suggests that additional research could help improve the pedigree of these model assumptions further. They perhaps merit stronger attention in future than assumptions about nuclear and CCS capex, which can be seen in Figure 5.6 to have less of an impact on the results of the sensitivity analysis.

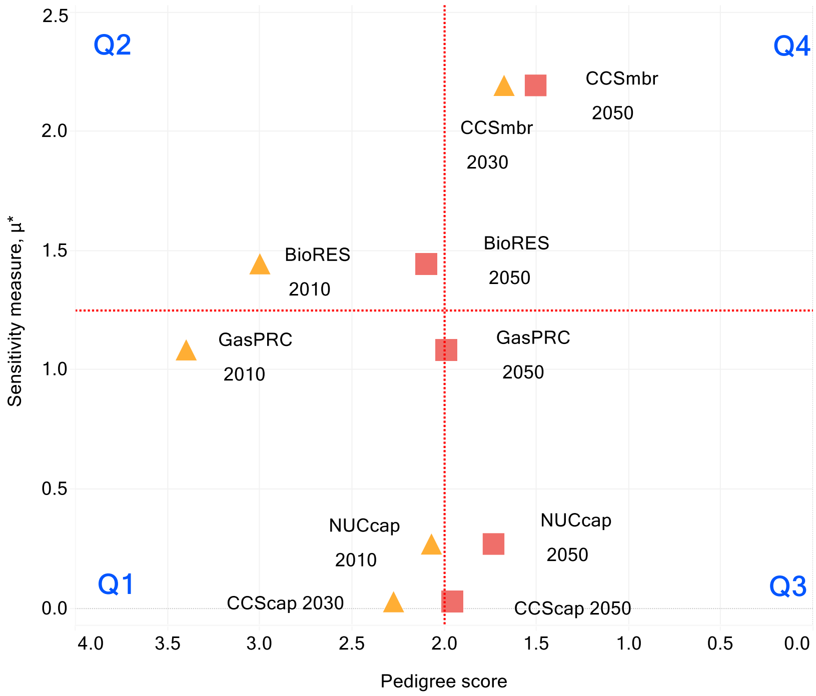

Figure 5.6. Diagnostic diagram to compare qualitative (pedigree scores) against quantitative uncertainties (sensitivity measure).
The sensitivity measure (based on the Morris Method approach) highlights the influence of the modelled uncertainty on the variance across the model objective function, the total discounted system costs.

The two model structural assumptions (technology learning rates, TchLRN, and perfect foresight optimisation, PerFOR) do not feature in the sensitivity analysis undertaken, nor do the assumptions NonCO2 and BioEF. This is because the emissions accounting for non-CO2 GHG emissions (NonCO2) is not an explicit model input assumption while emissions accounting that would capture bioenergy emission factors (BioEF), is not yet featured in the ESME simulation model. On NonCO2, there is evidence to suggest that this assumption, scoring 1.5 in 2050, could be in or near the danger zone (Q4). (Usher, 2015) considered the impact of changing the UK's emission reduction target, which non-CO_2 GHG emissions would impact, on the results, and found that this is the second most influential model parameter.

5.4 Discussion and conclusions

The application of the NUSAP approach to energy models such as ESME can help improve the modelling process by making clearer what the knowledge base behind model assumptions actually is, and its strengths and weaknesses. A key benefit of undertaking a NUSAP assessment is that the process specifies for decision-makers *which* model-based parameters are perceived to be particularly weak and exactly *how* they are weak. The diagnostic diagram in particular simplifies large amount of information into an easily digestible graphic for policy stakeholders, highlighting key findings from both the NUSAP workshop and quantitative analysis. Once recognised, decision makers can make better judgments about the robustness of quantitative insights from models, while modellers can seek to improve the transparency and quality of assumptions.

In this assessment, the pedigree scores highlighted which of the most influential model parameters had the weakest underlying knowledge bases (Q4 in Figure 5.6). It was found that some of the factors with a weak pedigree are those which crucially underpin elements of UK energy and climate policy. These include those on bioenergy (particularly in relation to emission factors), which is viewed as being critical for mitigation in hard to decarbonise sectors like aviation; the treatment of non-CO_2 emissions, which has a direct bearing on the stringency of CO_2 emission targets; and the possible deployment rates for natural gas fired power plant with carbon capture and storage (CCS). For CCS, the deployment assumption is highlighted as being found in the diagnostic diagram's 'danger zone' in Figure 5.6. This suggests that decision makers using this type of model should proceed with caution when drawing policy conclusions from model solutions that rely heavily on CCS.

The novel application of a NUSAP assessment that employs differentiated scoring for near and long-term assumptions has highlighted the weaker pedigree for assumptions in 2050, and their greater potential for value-ladenness. For nearer term assumptions, this points to an opportunity for strengthening pedigree through wider consultation with sector experts, development of model structure, and further research across different technologies. It also highlights those assumptions that are well understood, and where there is greater confidence in the knowledge base e.g. for gas prices and current bioenergy resource levels. For assumptions about longer term futures, the analysis highlights a need to recognise that these assumptions are fundamentally different from those relating to the present day, and that strengthening pedigree may not be an option. However, the recognition of a much weaker knowledge base is important in itself, for transparency to users of model outputs, to highlight the need for more research, and also the fundamental need for uncertainty analysis. This includes recognising the socio-political uncertainty that was highlighted by participants when scoring, particularly in relation to long term assumptions on gas prices, bioenergy resources and CCS deployment.

On value-ladenness, the criteria scores highlight that there are frequently many plausible choices that can be made for different assumptions, which often makes the justification of choices challenging, and also that there is sometimes disagreement amongst peers regarding which choices are appropriate. This confirms the need for more debate on specific model assumptions, for the transparency of choices to be increased, and for broadening the range of opinions to be tested, even those that are perceived as being outside of the 'mainstream'. Such insights were only gained through having a diverse set of stakeholders, in terms of discipline and organisational background, involved in the workshop scoring exercise.

Of equal interest to the specific findings of the study are the general insights from the process of undertaking the NUSAP workshop. Such a process allowed for extended consultation with a wide range of stakeholders, and revealed the logic and data behind critical model assumptions. While a formal evaluation of the workshop by the participants was not undertaken ex post, specific feedback from a range of stakeholders was that the workshop had succeeded in enhancing the understanding of the modelling approach, and the strengths and weaknesses across the underpinning assumptions. This suggests an opportunity for such a process to help engender higher levels of trust in the analytical process, and across the broader expert base. With this type of complex modelling often having been viewed as a black box in the past, opening up the detailed workings to critical scrutiny should contribute to the process of making energy systems analysis more transparent for decision makers (Cao et al., 2016; Pfenninger, 2017). This also helps avoid any risks of models gaining authority on or legitimising a specific position based on poor data and the opinions of analysts (Keepin, 1984; Wynne, 1984).

This constructive dialogue also allowed for participation in the modelling process by outside experts, and enabled the sharing of new perspectives that are often absent from conversations within established modelling teams, or for which the plurality of views are insufficiently recognised. The NUSAP workshop also provided key learning opportunities for those modellers who were present, forcing consideration of the strength of the relationships between elements of the modelled system and the real world system that it is trying to represent, partly as a result of the interactions with experts in specific domains of interest. It also provided the opportunity for modellers to learn about how model input and outputs are perceived and interpreted by others.

The ability of NUSAP to highlight the most critical uncertainties in models can also represent a structured method of selecting the most relevant dimensions for assessment in scenario-based analyses. This brings increased methodological rigour to the often chaotic and ad hoc process that characterise much scenario development activity (Bradfield et al., 2005; Martelli, 2001; Spaniol and Rowland, 2017) and potentially avoids the all-too-common situation where scenario-and-simulation exercises simply vary one or two parameters of interest without a thoroughly grounded understanding of whether these are really critical to influencing modelled outcomes.

This first foray into the application of this approach on a national model of this kind has thrown up a number of issues that future research should consider. First, there is an open question as to whether some of the qualitative assessment criteria employed worked equally well for both model input and structural model assumptions. It was observed that many participants who were comfortable using the pedigree scoring system for model inputs were at the same time unsure as to their applicability when it came to discussing model structural features. For example, as noted in the results, participants found it difficult to apply scoring for the *proxy* criterion when considering model perfect foresight, as this is not intended to directly represent real-world decision making. Nevertheless, it can be argued that the inclusion of structural parameters in addition to input parameters in this assessment enhanced the overall learning process for the workshop participants by forcing contemplation and discussion of the nature of the model and its relationship to reality in detail. Future work could consider how to integrate a wider set of model assumptions into the pedigree assessment, be they input assumptions, features of the model structure, or broader underlying socio-political assumptions being used in the model analysis. Second, a broader stakeholder base could have been consulted as part of the workshop, including a wider set of disciplines and more domain experts, for example on bioenergy, CCS, and gas markets. However, their absence was not by design but reflected the challenges of workshop organisation.

The NUSAP approach is clearly a time-intensive process that requires the active participation of a group of highly engaged stakeholders, and one that may well push up against the resource and time constraints of the policy making process. Despite this, for major new policy proposals or strategies, using energy models that encompass high complexity and large uncertainties, and which may not be well known, such an exercise is well worth the investment. The analytical process for such proposals will anyway require transparency, broad stakeholder engagement, transdisciplinary framing, scrutiny of assumptions, and recognition of uncertainty, all of which the NUSAP approach covers. Streamlining the NUSAP process to be more light touch would be extremely challenging. While it might be an attractive idea to develop a cut-down NUSAP approach that might fit better with the policy making timetable, all of the elements described in this example approach are actually needed to strengthen the science-policy interface.

A key recommendation is that such an approach is integrated into government guidance on policy analysis, recognising the qualitative dimension of uncertainty and an approach to deal with it. For example, in the UK it could be integrated into the formal guidance document for the use of model-based evidence in government policy, the Aqua book (HM Treasury, 2015). The addition of the NUSAP approach to this guidance would enable practitioners to assess the strength of the knowledge base underpinning their analytical approaches, and reflect any implicit value ladenness in model outputs. If the time-pressure and demands of the policy cycle mean that this cannot be employed on a routine basis, then it should at least be used following the introduction of new analysis techniques to the decision-making process or especially in advance of using models for any major policy decisions. To do otherwise would risk stripping quantitative model outputs of their qualitative context, with the result that decision makers may find themselves flying blind.

In conclusion, the NUSAP approach allows for the recognition of non-quantifiable uncertainties that are often co-produced as part of a highly inter-disciplinary modelling process. Whilst providing a more comprehensive pathway for uncertainty assessment, the approach also enhances the modelling process by facilitating both engagement with outside experts and enabling the necessary scrutiny of model assumptions. Given the importance of uncertainty assessment in modelling for public policy, not only in the UK but internationally, a stronger recognition of non-quantifiable uncertainty, and its inevitable coproduction in the policy assessment process, as well as techniques for addressing it, are all important elements to integrate into formal guidance

6. Technology interdependency in the United Kingdom's low carbon energy transition

Abstract

The role of different technologies in a future low carbon energy system is determined by numerous factors, many of which are highly uncertain. Their deployment may be a function of dependency on other technologies, or competition, or wider system effects. In this chapter, using a UK example, the patterns of interdependency between technologies are explored using a hierarchical clustering approach across multiple scenarios. The analysis finds that technologies compete in some instances, often on costs, cluster because they co-depend on each other, or emerge under all conditions, as robust options. Crucially, the broader scenario framing around CCS availability and climate policy stringency strongly influences these interdependencies.

Keywords

Energy system models; scenario clustering; technology interdependency; low carbon pathways

6.1 Introduction

6.1.1 Contending with technology-related uncertainties in low carbon transitions

The diffusion of new technologies to enable the transition to a low carbon energy system is subject to numerous uncertainties. Many countries are grappling with the options available to move energy supply to one that is zero emission (Bataille et al., 2016), where different solutions emerge depending on factors relevant to national circumstances and assumptions about technology commercialisation. The timescales for this transition are also squeezed, with Paris Agreement targets suggesting net-zero emissions by, or soon after, 2050 (Rogelj et al., 2015b). Therefore, decision makers have to contend with both technological uncertainty and short timescales, not suited for long term system transition (Smil, 2016), whilst moving beyond incremental policies to real structural change within socio-political constraints (Spencer et al., 2017).

Determining the future role of technologies used across the energy system is an important exercise for a number of reasons. Firstly, it can help demonstrate the plausibility of different technology pathways to decision makers. This is important in the context of deep decarbonisation by mid-century (Bataille et al., 2016), a timeframe that many countries have yet to fully consider but will increasingly need to, as per Article 4.19 of the Paris Agreement (United Nations, 2015a). Modelling analyses during the 2000s in the UK certainly helped determine multiple technology pathways that could deliver 60% (Marsh et al., 2003) and then 80% (Pye et al., 2008) reductions in GHGs, relative to 1990 levels. This provided an important evidence base that provided confidence for, and underpinned, climate action legislation. Secondly, it can orientate the research and policymaking community in a certain direction, pointing to technology focus areas for R&D and demonstration budgets. A recent example has been the increase in research on greenhouse gas removal (GGR) technologies, with the UK research council, NERC, launching a large programme of work.[14] This research direction is very much in response to the ubiquitous deployment of such technologies in energy systems analysis, notably from Integrated Assessment Models (IAMs) (Fuss et al., 2014; Vaughan and Gough, 2016).

However, many of the prospective technologies for the low carbon transition may be conceptual, partially demonstrated and at a very early stage of technology readiness, or only playing a niche role in the current system. This means large uncertainties exist concerning the role that technologies play, driven by many different factors. Take the example of solar; when (Lewis, 2007) discussed its prospects, highlighting some of the key barriers for widespread use, including costs of $0.25-0.30 per kilowatt-hour (kWh) compared to other generators at $0.03-$0.05, he, like key scenario providers such as the IEA, would have had difficulty envisaging this technology now competing with fossil generation 10 years later.

The question is how do the many technologies recognised as important for the low carbon transition play out together in the same system? The uncertainty around R&D, commercialisation, policy support, and social acceptability means that there are numerous eventualities in terms of system design and technology portfolios. Taking the prevalent example of CCS included in many climate mitigation scenarios (Rogelj et al., 2018a), this is subject to all such uncertainties, including techno-economic factors (Koelbl et al., 2014). Their impact on technology deployment will have different degrees of influence on the role of alternative competing technologies. This raises the question of how technologies or technology groupings interact, and whether they enable others, or compete. Possible examples are easy to identify (e.g. in a severely carbon constrained world and without CCS, would steam methane reforming be possible for hydrogen generation?), whilst others may be less obvious. Furthermore, inter-temporal dependencies may emerge, where specific technologies and their use in the system rely on earlier deployment of others.

6.1.2 Characterising technology uncertainties in energy modelling

Improved performance and cost reduction across technologies and their deployment in different societies is complex, and covered extensively in the fields of technology innovation and socio-

[14] NERC GGR Research programme, http://www.nerc.ac.uk/research/funded/programmes/ggr/

technical transitions (Gallagher et al., 2012; Geels, 2005; Smil, 2016). However, energy system models, such as that used in this study, typically make simplifying assumptions about the improvements in costs and performance based on exogenous single factor learning curves, and historical precedents in terms of deployment. In other words, there is limited attempt to model other factors, such as the innovation and learning process in national scale modelling, largely due the analysis scale and the complexity of process.

Without endogenising these effects, it is still possible to capture the uncertainty of the assumptions on technology learning and deployment in the energy system context, using different approaches. These approaches can provide a view of the many different system configurations, and help to understand the interdependency between technologies across the system. Most UK modelling analyses have focused on the development of traditional scenario analysis to explore distinctive low carbon transitions, either for the system as whole (ETI, 2015; Watson et al., 2018) or for specific sectors (Barton et al., 2018; Brand et al., 2018; Chaudry et al., 2015). The use of uncertainty techniques have been less widely applied to scenario analysis (Usher and Strachan, 2012), but are becoming increasingly recognised, both by researchers (Pfenninger et al., 2014) and decision makers (McDowall et al., 2014), as critical to facilitating more robust decision making. A recent review of the application of different uncertainty methods highlights some of the key modelling approaches deployed (Yue et al., 2018).

Global sensitivity analysis (GSA) is one such method, to assess and rank energy system uncertainties (see e.g. (Marangoni et al., 2017) for an integrated assessment modelling approach). In the UK context, (Fais et al., 2016a) employed this approach across binary technology and resource dimensions, in order to explore which low-carbon technologies and resources had most influence on energy system development under emission reduction targets and the interaction effects between different low carbon options. The analysis highlighted complementarities and substitutability between technologies, critical options that are robust to uncertainty, wider system effects, and path dependencies.

(Pye et al., 2015b) explored the potential for uncertainties across technologies and resources to undermine reduction targets, if policies were not robust to such uncertainties. The analysis also highlighted, via a GSA approach using multivariate regression analysis, which uncertainties had the largest influence on meeting decarbonisation goals. (Usher, 2015) undertook a similar analysis, using a GSA known as the Morris Method, to explore which model uncertainties across a range of technology and resource groups influenced the model solution the most. Similar to (Pye et al., 2015b), biomass resource availability and gas price proved to be highly influential, as did the CO_2 emission constraint.

While the above analyses focused on parametric uncertainty, other studies have been undertaken to explore uncertainty relating to model structure. The Modelling to Generate Alternatives (MGA) technique (Brill et al., 1982), with initial application in other fields, has been increasingly used for energy system analysis (DeCarolis et al., 2016; Price and Keppo, 2017). In the UK context, using a MGA technique, (Li and Trutnevyte, 2017) identified many possible near-optimal pathways to decarbonising the power sector, highlighting how system choices are strongly influenced by the model structure and formulation of optimality.

Different approaches to uncertainty assessment provide useful information about the impact of uncertainties on model results, and particularly from the GSA analyses, the ranking of uncertain assumptions based on solution influence. However, these analyses typically provide fewer insights into the explicit enabling or competitive relationships between technologies or technology families in different systems, and the impacts of deployment of one type of technology on another. The focus of this chapter is to explore the relationships between technology choices across different system pathways, to understand potential interdependencies.

6.1.3 Overview of the chapter

In this study, using the integrated energy systems model ESME, these issues are considered for the energy system transition in the United Kingdom, framed to meet the current policy goal of at least an 80% reduction in greenhouse gases (GHGs) in 2050 (HM Government, 2008). The research question tackled in this chapter is ‘Under a transition to a low carbon energy system, what technologies are typically deployed in combination or competition, and from these interdependencies, what are the insights for policy stakeholders?’ The interplay and interdependencies between different technologies and technology families is investigated by simulating a large number of plausible pathways under uncertainty. For example, for the deployment of technology X, influencing deployment may be the characteristics of technology X, those of technologies Y and Z, and / or the broader system e.g. carbon price signal, resource availability etc. To determine the extent to which Y and Z influence the deployment of X, clustering analysis is used across the many simulations.

This chapter is structured as follows; section 6.2 provides a description of the approach to modelling technology-focused scenarios and analysing interdependency between different groups. Results of the analysis are presented in section 6.3, followed by a discussion on the insights of the analysis for policy (section 6.4), and concluding comments (section 6.5).

6.2 Methodology

With the focus on technology interdependency in an energy system, the ESME model is used to run multiple scenarios based on a range of techno-economic uncertainties. These pathways are then analysed, using a hierarchical clustering approach, to analyse interdependency of technologies.

6.2.1 Modelling uncertainty

The ESME model (Heaton, 2014), is used due to its whole system representation and integrated structure, both of which are necessary to reveal interdependency between sector action and technology deployment. As described in chapter 3, the model is technology-explicit, thereby providing a sufficiently detailed representation of technology groups, to better understand the characteristics that enable deployment. Further information on the sector structure and data sources used in the model can be found in the ESME documentation (ETI, 2016).[15]

Within the ESME model, a number of scenarios are constructed using the inbuilt uncertainty characterisations across different techno-economic parameters, with a focus on costs, including capital expenditure (capex) and resource costs. Other uncertainties used for the scenario generation include specific technology build rates and biomass resource availability. Build rate uncertainty for CCS and nuclear in particular reflects that many other factors determine deployment in addition to cost, with such technologies not market-driven in the same way as, for example, renewables. Resource limits on domestic and imported biomass are also included. These assumptions are set out in Appendix D1.

Parameter ranges are established for mature (+/-10%), new (+/-30%), and novel / emerging (+/-50% or more) technologies (see Appendix D1). For example, a combined cycle gas turbine (CCGT) plant has a relatively narrow cost range, as it is well understood given its maturity, compared to the same plant with CCS, which has a much wider range. The range distribution is sometimes asymetric, where for a technology it is unlikely that one would observe cost increases to the same extent as reductions. It is worth noting that in this analysis the range of the uncertainty considered is more important than other characteristics of the distribution – the aim is to generate many scenarios with different parameter values, but not draw any conclusions about how likely specific combinations might be.

[15] The data input parameters are available at http://www.eti.co.uk/programmes/strategy/esme. Note that these data assumptions are for v4.3, and in the main, are consistent with the input assumptions for v4.2, which is the version used in this analysis. The key updates in v4.3 are shown in the 'change log' at the end of the document; all have been integrated into the version we are using (v4.2). Nuclear costs, and uncertainty distributions are based on this research (see Appendix D1), and therefore will differ from those published under the released v4.2.

The uncertainty distributions in 2050 are sampled using the Monte Carlo technique. For each simulation, values for intermediate years (prior to 2050) are determined based on interpolation back to the base year (2010) value based on an index using the shape of the original 2010 to 2050 trajectory. The interpolation of an uncertain value in 2050 back to 2010 is a simplification for reasons of model tractability. The increase or decrease in costs and build rates between now and 2050 will of course not follow a linear trajectory but may be subject to volatility over this time horizon, with sudden cost breakthroughs, or rapid increases or declines in deployment, often due to political driven policy change.

600 simulations are run, the number based on earlier analyses to determine coverage of the uncertainty space (Morgan et al., 1992). While most of the distributions are independent, some are correlated during the sampling procedure. This is to ensure that technologies that are similar in nature (for example, a light duty electric vehicle and an electric car) move in the same direction.

6.2.2 Scenario definition

The 600 Monte Carlo simulations are then modelled for a set of three scenarios (Table 6.1), resulting in 1800 model runs in total. The sample size of 600 is consistent to that used in previous ESME analyses that have similar set up in terms of input parameters defined as uncertain, and assigned probability distributions. Previous analyses include which used 500 simulations, (Pye et al., 2015b) which used 475, and (Pye et al., 2018) which used 640. The scenarios reflect major areas of uncertainty that are useful to hold constant due to their large impact on the system, in order to explore whether technology interdependencies change when a step change in the parameter values is introduced. Two scenario dimensions are represented – i) climate ambition, and ii) the availability of CCS.

Table 6.1. Scenarios for modelling

Scenario Name	Climate ambition*	Technology availability
NCCS (No CCS)	-80% GHG reduction in 2050 (rel. to 1990), -53% in 2030	All low carbon options except CCS
CP (Climate Policy)	-80% GHG reduction in 2050 (rel. to 1990), -53% in 2030	All low carbon options
F2R (‘Failure to ratchet’)	-64% GHG reduction in 2050 (rel. to 1990), -48% in 2030	All low carbon options

* The 2030 value includes international shipping and aviation emissions, sectors which are not included in the UK carbon budgets but which are included in the 2050 target. To ensure consistency, the 2030 reduction above is on the same basis as the 80% target, and include international transport emissions. This means that the reduction level is lower than the UK 5th Carbon Budget target of around 57% in 2030.

Both CP and NCCS meet the UK’s legislated climate ambition of at least an 80% reduction in GHGs in 2050, and the interim carbon budgets needed to deliver the long term target (CCC, 2017). The difference is that CP allows for large-scale CCS deployment, while NCCS does not. The testing of this assumption is important in the UK context, where CCS is often chosen because it offers a highly cost-effective pathway (ETI, 2015) and because the credibility of CCS and BECCS deployment at scale is coming under increasing scrutiny (Anderson and Peters, 2016; EASAC, 2018). F2R provides a lower climate ambition case, due to a 'failure to ratchet' ambition, to explore prospects for deployment under weakened ambition and therefore lower incentives for mitigation. The resulting level of ambition in 2050 is limited to the level of ambition required in 2030 the UK's 5th Carbon Budget. Both CCS availability and climate ambition are likely to lead to very differently configured systems, allowing us to observe whether different technology interdependencies emerge.

6.2.3 Clustering analysis

Clustering algorithms can be used to group scenario metrics based on information in the dataset about those metrics and their relationships (Tan et al., 2005). The objective is that cluster groups will have metric included that are similar to each other, and different enough to metrics in other groups. Given the research objective on technology interdependency, clustering is used to group metrics based on the strength of their correlation with each other. These are metrics that characterise the different pathways, for example the level of deployment of different technologies or level of use across energy resources. The correlation between such metrics allows us to observe, for example, whether certain technologies increase or decrease deployment simultaneously, whether their deployment moves in opposite directions or whether their deployment appears to be independent from each other.

Specifically, an agglomerative hierarchical clustering is used, which is a common clustering algorithm and has been applied, for example, in the energy and buildings field (Filippín et al., 2013; Ma et al., 2018). In this approach, clusters are nested meaning that they are merged successively. Each model metric is clustered with its closest neighbour, meaning where the strongest correlation is found. This cluster pair is then grouped with another, and so on, until a single cluster is reached that includes all metrics. This tree-like construction of nested sub-clusters can be visualised as a dendrogram, as shown in Appendix D3, representing the structure of the relationship between data metrics. The dendrograms use a dissimilarity metric to show strength of correlation, with a low value highlighting a higher positive correlation.

While clusters indicate where the deployment of technologies increase or decrease simultaneously, the algorithm used does not provide insight as to whether the deployment of individual technologies contributes to the energy system in a meaningful way. In other words, a cluster could include a power generation technology that barely contributes to overall electricity supply, together with a transport technology that is key for the transport sector. Therefore, further analysis of the results is required to complement the cluster analysis. It is also informative to determine negatively correlated metrics, to identify deployment of groups of technologies moving in opposite directions. To do this, a proximity matrix is constructed based on the correlations between any two clusters, represented by the mean of the metrics included.

In this chapter, the clustering approach is applied to two datasets. The first uses a range of metrics directly from the model, chosen for their representation of the main technologies and fuels deployed in pathway simulations. A second set of metrics is derived from the model outputs using a decomposition approach called logarithmic mean Divisa index (LMDI) (Ang, 2005). This method allows for an understanding of which drivers are responsible for the change in emission levels of different subsectors over time, including energy efficiency, conversion efficiency or decarbonisation of the energy supply. Decomposition approaches, such as LMDI, have been used for decades to study how changes in the level of a variable (e.g. emissions, energy use) can be attributed to the changes in its drivers (Ang, 2004), including in energy systems analysis (Chiodi et al., 2013; Förster et al., 2013; Kesicki, 2013). Both sets of metrics are listed and further described in Appendix D3.

6.3 Results

Here the results of the clustering analysis are presented, first discussing the LMDI clustering analysis, followed by the clustering of the direct model metrics.

6.3.1 Clustering of LMDI wedges

LMDI analysis provides an indicator of the contribution of different types of mitigation "wedges" (Pacala and Socolow, 2004) across sectors in any given simulation. These wedges allocate emission reductions across different sectors to three different types of measures *m*: (1) Reduction of energy demands (D_s) (2) improvements in efficiency (F_s/D_s, includes electrification effects) and (3) decarbonisation (carbon intensity of final energy), $CO_{2,s}/F_s$). The emissions for end use[16] sectors are thus expressed:

$$CO_{2,s} = D_s \cdot \frac{F_s}{D_s} \cdot \frac{CO_{2,s}}{F_s}$$

The LMDI formulation allows the allocation of mitigation efforts to individual "wedges", without leaving a residual. Mitigation between time t_1 and t_0, for a specific sector *s* and measure *m* can be calculated from:

[16] The equation remains the same for the conversion sector, but *Ds* in the above equation is replaced by the final energy output of the sector and F_s by the primary energy use of the sector.

$$\Delta CO_{2,s,m} = \frac{CO_{2,s,t_1} - CO_{2,s,t_0}}{\ln(CO_{2,s,t_1}) - \ln(CO_{2,s,t_0})} \cdot \ln(\frac{m_1}{m_0})$$

The distribution of relative contributions of measures (that contribute at least 10% of mitigation in at least one model run) in 2030 and 2050 are shown in Figure 6.1 for each scenario. Negative contributions suggest an increase in emissions, typically for energy service demands which rise over time and which the model cannot reduce.

Across the scenarios, the importance of electricity decarbonisation in both 2030 and 2050 (driving higher levels of electrification[17]) is evident. There are, however, also clear differences across the scenarios and the milestone years. Lack of any CCS applications and a stringent emissions target, for example, forces earlier power decarbonisation in all NCCS runs, whereas F2R, having the most flexibility of the three scenarios due to its lower target and full technology portfolio, can in some runs reduce the contribution from power sector decarbonisation down to 25% of the full mitigation effort. By 2050, much of this flexibility is gone and F2R relies even more on power sector decarbonisation than the other scenarios. Decarbonisation of the energy carriers used in industry is another key mitigation measures with a wide range of contributions across the scenarios and runs, contributing on average 20-30% by 2030 in the scenarios that allow CCS technologies. Without CCS, however, the carbon intensity generally increases, turning this mitigation wedge into a source of emissions in most NCCS runs. For F2R, this mitigation measure has a very wide range, contributing from -30% (i.e. being an emission source) to 65% of all mitigation by 2030. A mitigation wedge that shows both reductions (decarbonisation of process) and increases (higher output) is biofuel production (CBF), although most of the observed change is outside of the interquartile range. These effects are no longer evident in 2050, due to the diminishing role of biofuels in transport in the longer term.

Other mitigation measures generally contribute less and vary more across scenarios and milestone years than between simulation runs. The differences produced by scenario assumptions are greater than those based on the parametric uncertainty distributions. For example, in 2050, decarbonisation of passenger car fuels contributes 12 to 21% of mitigation in NCCS runs, but no more than 9% in all the simulation runs in the two other scenarios. In other words, all the uncertainties captured in the hundreds of CP and F2R runs did not lead to a run that would have as much passenger car decarbonisation as all of the NCCS runs did, highlighting how strongly discrete, key assumptions can

[17] For example, in NCCS system wide electricity use accounts for 14% of the total energy use in 2020, and between 52-62% in 2050.

change the model results. The small range of contributing mitigation wedges in 2050 and the limited variation in contribution across the scenario simulation sets, few meaningful results are observed from the cluster analysis. Most of the calculated wedges play an insignificant role by 2050 and thus can contribute little to the cluster analysis. Conversely, assessing the relationships between the key wedges becomes easier to do manually (see below). This highlights that the mitigation effort, at the sector level, is not that responsive to uncertainty, either as imposed via the scenarios or parameters, although the flexibility from less stringent targets does see more wedges under F2R.

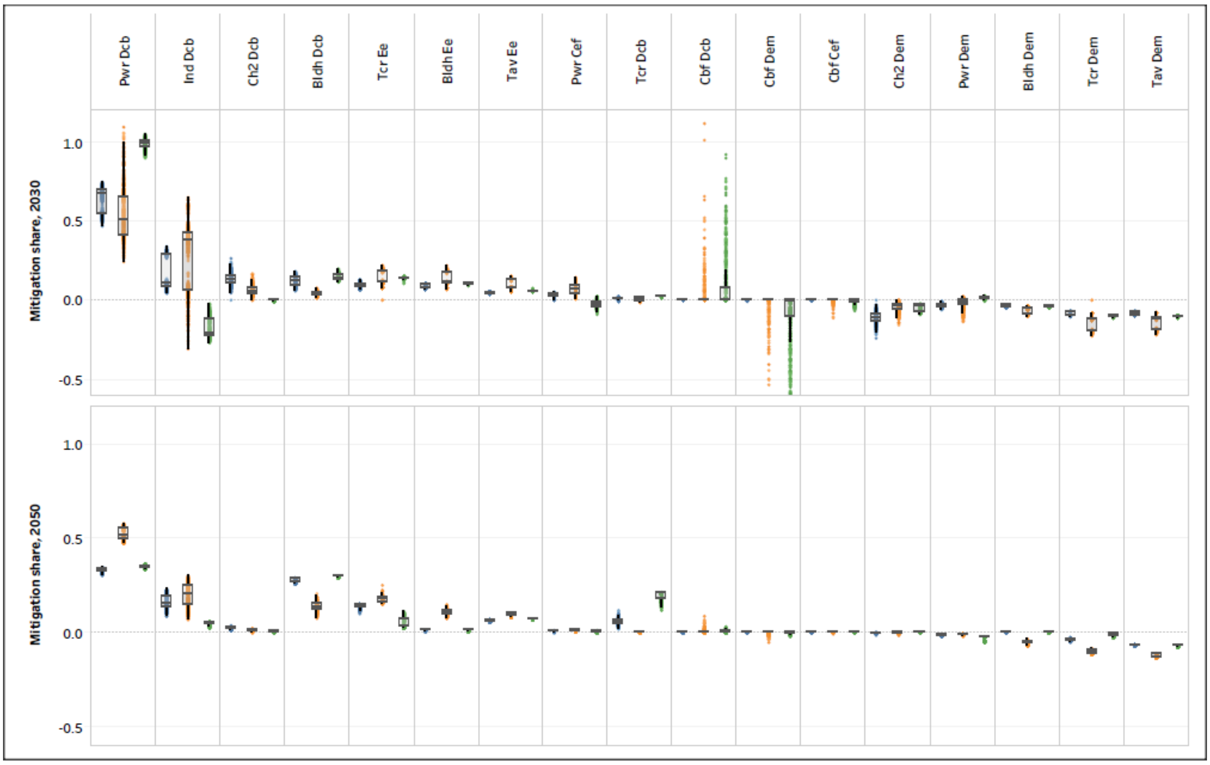

Figure 6.1. Contribution of different mitigation wedges to emission reduction in 2030 (upper panel) and 2050 (lower panel, NCCS = green, CP=Blue, F2R = orange).

Positive values represent a mitigation driver reducing emissions, and vice versa for negative value. The box corresponds to the inter-quartile range (IQR) and the whiskers represent the extent of values 1.5 times the IQR. Letters in the first part of the label denote sector [PWR=power; IND=industry; TCR=passenger cars; TAV=aviation; BLDH=building heat; CBF=biofuels production; CH2=hydrogen production], while second part denotes type of driver [EE=efficiency improvement; DEM=demand reduction; DCB=decarbonisation] [18]

However, the correlations between individual wedges (see Appendix D3), on which the clustering is based, reveal some useful insights. Focusing on wedges that contribute most, in both RM and NCCS, early power sector decarbonisation is strongly correlated with continued power sector contribution and heat decarbonisation in 2050, suggesting a path dependency for the power sector contribution. Interestingly, there is no link to early heat decarbonisation, suggesting that the transformation of the heating sector requires a longer timeframe than power sector decarbonisation due to slower

[18] Excluding outliers, i.e. data points that are at least 1.5 times the interquartile range above/below 3rd/2nd quartile. There are a handful of runs like this, but not many

deployment rates of low carbon options, and higher costs. Decarbonisation of fuels in the industrial sector by 2050, in turn, is negatively correlated with decarbonisation of heat in the residential sector and power sector decarbonisation in the scenarios in which CCS is available. This suggests that CCS brings with it some flexibility to target mitigation at different part of the system, but the wedge analysis alone does not reveal what specific technologies contribute to this dynamic, which are investigated in the following section.

6.3.2 Clustering of model metrics

From the more aggregated mitigation wedges, the anaylsis focus turns to the clustering of metrics taken directly from the modelling. These are listed in Appendix D2, and primarily consist of different energy technologies and resources, based on their use in the system (in generation or consumption terms). Based on the hierarchical approach, the resulting set of clusters in 2050 are shown for each scenario-based dendrogram in Appendix D3, with results presented in Figure 6.2 and Figure 6.3.[19]

Figure 6.2a shows six distinctive clusters under the No CCS (NCCS) scenario set of simulations. Where a cluster is negatively correlated to another cluster (based on a coefficient of less than -0.5), this is also indicated by a red arrow. The two largest clusters in terms of number of metrics, purple and orange, are negatively correlated. The purple cluster groups biomass resource levels with biofuel production for use in transport, including aviation, suggesting higher levels of biofuel production where biomass resource levels are higher. The orange cluster includes hydrogen use in the road transport sector and oil in aviation. The additional inclusion of cost metrics also suggests this is a higher cost cluster, due to use of electrolysis for hydrogen production, which is deployed when biofuel production is lower.

[19] While we pre-defined the algorithm to search for 10 clusters, the number is not crucial because the dendrogram (built based on the correlation coefficients) retains the same structure irrespective of the cluster number.

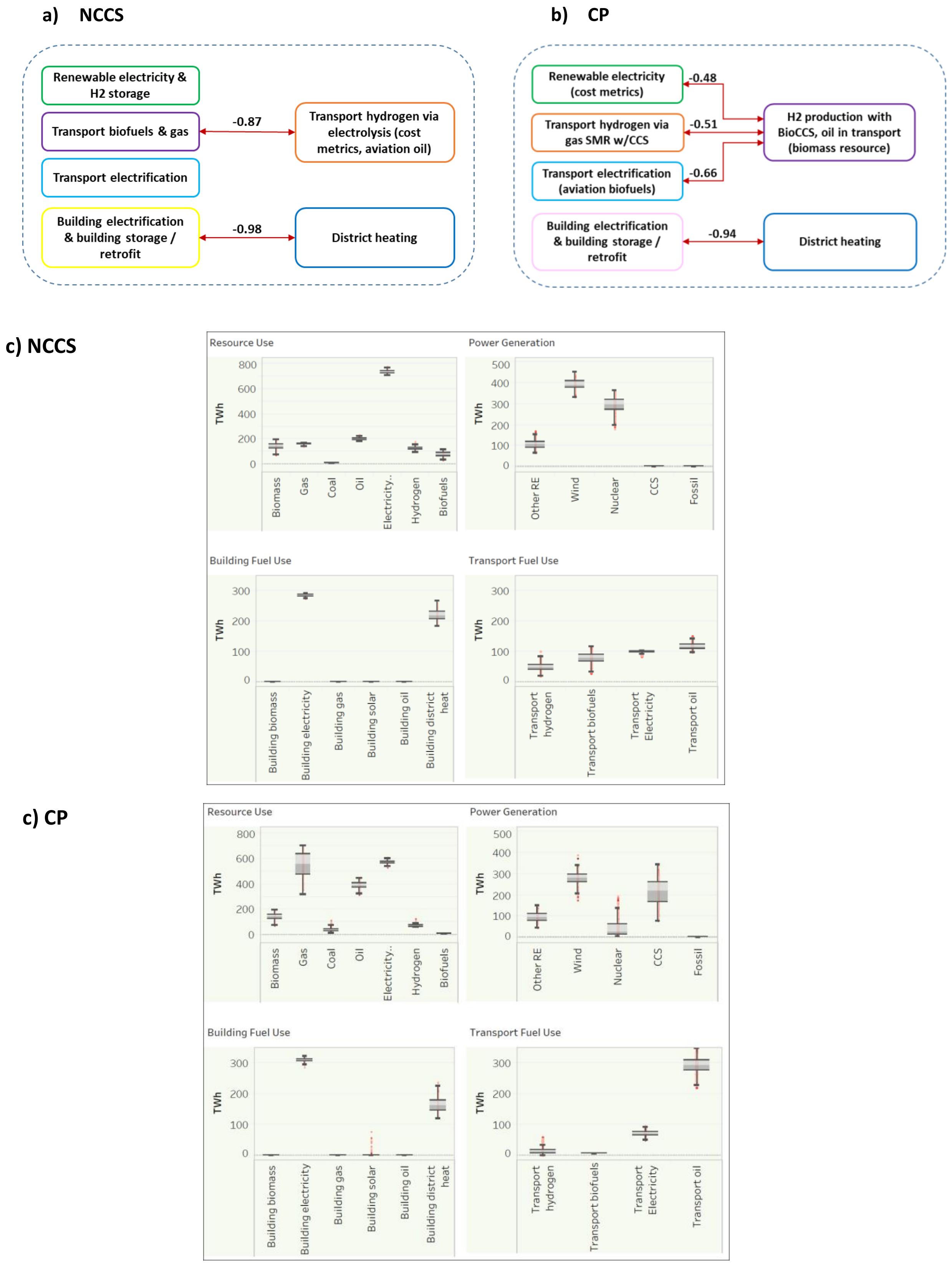

Figure 6.2. NCCS and CP scenario clusters (a-b) and results distribution (c-d) in 2050.
Clusters are identified in the top of the figure, with negative correlations shown by red connectors, the value indicating the correlation coefficient. More information on the technologies included in each cluster can be found in Appendix D3. The distribution of results underpinning the clusters are shown in the bottom part of the figure (c-d), with metrics (top left, going clockwise) on total energy use, power generation, building fuel use and transport fuel use.

Building sector clusters include district heating (blue) and building electrification (yellow), which are negatively correlated, suggesting competition between technologies. However, the level of electricity use is quite stable across simulations, with a low distribution so competition is based on marginal changes. The building electrification cluster includes heat storage in buildings, and building retrofits, both important to reduce demand and manage electricity loads, and improve building performance for heat pump uptake. The other two clusters include transport sector electrification (sky blue), and renewable generation (green). The absence of negative correlations for these clusters highlights that they are not 'crowded out' and are typically prevalent in most simulations, due to the increasing importance of electrification, particularly in the absence of CCS. This is particularly true of transport sector electrification, with limited results spread (as shown in Figure 6.2a box plot).

For the climate policy case with CCS availability (CP), the main difference in clusters, compared to NCCS, relates to hydrogen production, now produced using CCS (Figure 6.2b). A purple cluster reveals biomass availability associated with bioenergy-based H_2 production with CCS, and transport oil use, indicating that more bioenergy resource increases it use for H_2 production with CCS, in turn allowing headroom for transport emissions and more oil use. This cluster is negatively correlated with three other clusters including H_2 production and use in transport (orange), renewable generation (green), and passenger car electrification (sky blue). These include clusters with a stronger focus on end use sector mitigation in the transport sector (orange, sky blue), including biofuels in aviation, partly required when offsetting from BECCS is lower. The renewables cluster (green) is associated with costs metrics implying higher cost in higher renewable deployment cases. This is not because the unit generation cost of renewables is higher than alternatives but due to the more cost-effective system wide mitigation (offsetting) that CCS with bioenergy is able to provide. Similar to NCCS, the building electrification cluster (pink) is one that also sees heat storage in buildings and retrofitting to reduce energy requirements, and is again negatively correlated with the district heating cluster.

Finally, the F2R scenario assumes a weaker climate policy, based on 'failure to ratchet' ambition. As with the CP case, a cluster (brown) emerges to include H_2 production with CCS for use in industry, and transport oil use, enabled due to emissions headroom. This cluster is negatively correlated with the pink cluster, which includes transport biofuel use. However, the use of these fuels in this scenario are relatively low, so do not have a huge impact on the results.

Biomass availability and its use by industry are clustered (olive green) with gas use in buildings, indicating that higher mitigation efforts in industry see a reduction in the need for action in the building sector. This allocation of bioenergy, which differs from the higher allocation for use with

CCS under the CP case, suggests stringency has an important impact on resource allocation across sectors (as reflected in the discussion on flexibility across mitigation wedges). This cluster negatively correlates with the yellow cluster, which includes H_2 in industry, the electrification of buildings, and cost metrics. On the cost metrics, this is not surprising given how influential biomass resource availability is on system costs. Finally, the pale pink cluster includes gas CCS, and is negatively correlated with a non-CCS generation cluster (green), highlighting competition between generation types.

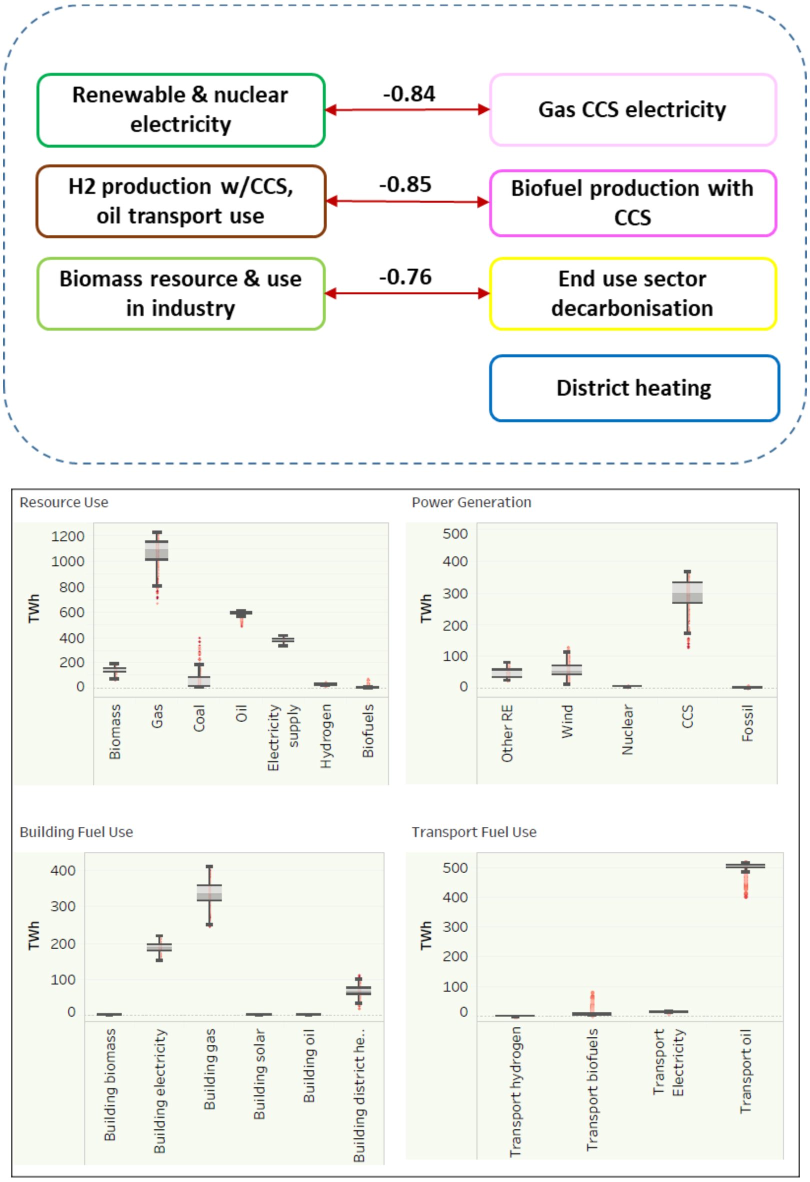

Figure 6.3. F2R scenario clusters (top) and results distribution (bottom) in 2050.
Clusters are identified in the left hand side of the figure, with negative correlations shown by red connectors, the value indicating the correlation coefficient. More information on the technologies included in each cluster can be found in Appendix D3. The distribution of results underpinning the clusters are shown on the lower part of the figure, with metrics (top left, going clockwise) on total energy use, power generation, building fuel use and transport fuel use.

6.4 Discussion

There are a number of insights that emerge from the clustering analyses. First, the approach provides a useful basis for understanding key interdependencies between different technologies and where these do not exist. Second, it highlights how the overarching scenario drivers appear to have a strong impact on patterns of technology interdependency. Third, the LDMI analysis highlights limited change in the pattern of sectoral contribution, and points to observed changes driven by scenarios rather than the uncertainty ranges across input parameters (as might be expected given the influence of the parameters represented in the scenarios).

6.4.1 Technology interdependency revealed

Whilst all technology options can be deployed in a given pathway, the clusters indicate what technologies move together and so are interdependent, and therefore would have a tendency to deploy at relatively higher levels together, and in such instances of high deployment, identify other technology groups that deploy at lower levels (where negative correlations are revealed). A clear example is for the buildings sector, where electrification is tied to building storage and retrofit, highlighting the requirement for the system to manage increasing intermittent supply and peak demand. The negative correlation with district heating suggests some competition between these systems depending on cost uncertainties. For both high ambition scenarios (NCCS, CP), these relationships hold.

Where CCS is not available (NCCS), three transport sector clusters emerge - biofuels, H_2 and electrification. The negative correlation between biofuels and H_2 clusters is driven by biomass availability, whereby higher availability leads to more biofuel production and use, and less H_2, which can only be produced via higher cost electrolysis. Where CCS is available, hydrogen from biomass gasification with CCS clusters with system oil use, and is negatively correlated with biofuel and electrification clusters. Dissimilar to NCCS, the H_2 production cluster here is most cost-effective, due to the biomass availability and system wide role of CCS in offsetting mitigation effort required in other sectors; hence the higher oil use in transport as CCS use increases.

For the power sector, analysis shows that wind generation always deploys at scale (between 40-50% of total generation in NCCS and CP), as the largest generation source in the absence of CCS, or in the top two generators where CCS is available, showing it to be fairly robust under all cases. In the NCCS case, renewable generation is clustered with H_2 storage, due to its role in production via electrolysis. Where CCS is available, renewable generation is negatively correlated with CCS-based clusters; in F2R and CP, CCS directly competes with renewable generation, and indirectly in CP by providing more emissions headroom due to offsets, meaning less renewable generation for low carbon electrification in end use sectors.

6.4.2 Scenario drivers influence on interdependency

The above insights on technology interdependency are clearly impacted by overarching scenario assumptions for CCS availability and climate ambition. This is evident in some quite distinctive cluster patterns; for example, bioenergy availability is clustered with H_2 production using CCS under CP, but with biofuels production in NCCS, while in F2R, biomass availability is associated with its use in industry. This is because such assumptions have strong system wide effects. CCS combined with bioenergy provides negative emissions, which can offset hard-to-treat sectors that would require higher cost mitigation options.[20] In addition, important low carbon energy production is also provided, such as hydrogen or electricity production. Even high CCS cost-low bioenergy simulations in CP are lower cost than any simulation in NCCS. CCS for example is valued by the system to the extent that it brings the marginal abatement costs of mitigation in 2050 down to an average £450 per tCO_2 (range £320-595) in CP, from £1500 (£885-2115) in NCCS. The value of CCS, particularly with bioenergy, is reflected in a range of other analyses, both at a national (Element Energy & Poyry, 2015; Fais et al., 2016a) and global level (Fuss et al., 2014).

Similarly, the lower ambition in F2R see costs of £38 per tCO_2 (range £34-42), meaning lower incentives for a range of technologies, although CCS still plays a role. The absence of CCS (in NCCS) means cost uncertainty matters less, as the system has reduced flexibility and has to take specific options with limited prospects for fossil fuels.

In addition to highlighting the difference, the robustness of some insights are evident by the fact that they do not change across the scenarios. For example, the higher cost clusters are in each case negatively correlated with the clusters with more biomass availability. This is due to the high value of biomass in the system and its influence on energy system costs (Pye et al., 2015b). The building electrification clusters always see a similar composition, and are negatively correlated with district heating in the CP and NCCS cases. The absolute changes across simulations are indeed limited by the building sector being the end use sector with near total decarbonisation by 2050. Another similarity across scenarios is that a renewable generation cluster is identified for each scenario, although its composition typically differs, as do the clusters to which it is negatively correlated. In the 'with CCS' scenarios, it is negatively correlated with CCS dominated clusters, while in NCCS, it is not negatively correlated with any clusters but with a single technology i.e. nuclear generation.

[20] Imported bioenergy is not fully carbon neutral, with 30% of total emissions from its use counted due to consideration of life cycle emissions. For domestic bioenergy, the accounted level is 10%.

The strength of scenario drivers also highlights that technology interdependency is more sensitive to broader analysis framing than the technology uncertainty ranges. This raises questions as to whether uncertainty ranges sufficiently cover a wide enough range or indeed the necessary types of system uncertainty.

6.4.3 Aggregation impacts on clustering results

While technology clustering (3.2) highlights how parametric uncertainty and scenario framing can reveal interdependency, the LMDI metrics suggest that these same uncertainties do not radically change the share of sector mitigation (i.e. technologies within the sector may change, but the total sector contribution does not). This either tells us something about the robustness of the results as to the level and timing of sector contribution, or suggests that the model is structurally pre-disposed to determining such patterns, despite the uncertainties introduced into the modelling. This lack of variation across wedges results in clustering being ineffective. As most simulations rely on a handful of key mitigation wedges, most wedges become meaningless for the clustering and the dimensions of the analysis are reduced to a level at which clustering does not provide much benefit. Conversely, focusing on the key wedges, it is possible to identify very strong correlation between specific wedges, which reinforce the relationships observed in the technology clustering. Additional observations are that scenario drivers have a stronger effect on the distributions than the technology level uncertainties, reinforcing the idea that the uncertainty distributions may be limited in range, and to the assumptions to which they apply.

6.5 Conclusions

This type of analysis provides decision makers with insights on the interdependencies of technologies, arising from competition on cost (electrification versus district heating), co-dependence (electrification plus storage), or system wide effects (absence or inclusion of key technologies e.g. CCS, policy ambition). Understanding interdependency in a system is important; it helps identify what technologies work together and which tend to compete, under different system level conditions. It also provides insights into why technology deployment may be low, if negatively correlated to a competing technology deployed at scale.

The negative correlations between biomass availability and higher cost clusters highlight the strong influence of this commodity on costs. Similarly, the negative correlation between CCS with bioenergy clusters and other end use options (in the CP case), for example for transport sector decarbonisation, highlight how such options might be significantly reduced by the inclusion of another (such as CCS). This type of approach therefore provides enhanced understanding of multiple pathways under uncertainty, through clustering options and revealing negative correlations.

There are a number of specific insights for UK policy. First, the prevalence of CCS, due its cost-effectiveness, suggests it is a critical technology to develop and scale. This is an important message – it is a clear opportunity. However, the inclusion of CCS also hides other solutions, reducing the diversity of option type, and delaying their deployment. There is a danger that the pervasive effect of this technology on the wider system as shown by this analysis is not fully recognised, which is problematic given the real risks of it not scaling in a timely fashion. It is not simply an alternative electricity generation option but one that can offset action in end use sectors (via BECCS), allow for a slower transition away from fossil fuels, and delays direct mitigation in end use sectors like transport. Arguably this analysis shows the need for robust action, given CCS' influence and risks of non-delivery, to ensure options that allow for dynamic policy making as the situation evolves (Mathy et al., 2016). Notably, recent Government projections perhaps underlie fading optimism as to the role CCS can play in the next 20 years, with almost no deployment envisaged prior to 2035 (BEIS, 2018).

Second, interdependencies are strongly influenced by biomass resource assumptions. It is important to observe that this commodity has huge value in the analysis, and that its allocation varies markedly for given climate ambition and CCS deployment. Third, renewable electricity deployment levels appear less impacted by system level or technology uncertainty, highlighting the robustness of this technology as a major player for electricity generation in the long term. This is not the case for nuclear, which is much more dependent on the scaling or not of CCS. Given that wind generation is proven with rapidly falling costs, it appears an extremely robust option, which makes lack of UK government support for onshore wind all the more questionable.

Finally, the interdependency shown by clusters highlights some important insights on planning policy actions in parallel. High building electrification requires thinking about building efficiency and storage to allow for strong deployment of heat pumps. Hydrogen production is only cost-effective alongside CCS, allowing for gas steam methane reforming (SMR) technology or the opportunity to generate negative emissions via BECCS. Importantly, negative correlations between clusters do not indicate that policy makers need to take an either-or decision, but rather what technology groups may compete under different system configurations.

Whilst useful insights for policy, it is also worth highlighting the limitations of this type of techno-economic modelling. System choices are driven by rational economic choices and perfect information, with limited consideration of other barriers. In reality, there are a range of other factors that will influence deployment of different technologies, particularly in the socio-political domain. For example, many technologies are subject to political influence, such as onshore wind planning barriers in the UK and support for nuclear, or the lack of support for nuclear and push for renewables in Germany (Cherp et al., 2017). Community acceptance is an oft cited additional factor, linked to influencing the political agenda (Enevoldsen and Sovacool, 2016). Other technologies have received very little support in the past due to range of governance and social factors e.g. district heating (Bush et al., 2016). Therefore, the implementation of different strategies for decarbonisation will need policies designed that further consider some of the key issues around barriers, including convenience, choice and acceptance.

Reflecting on the analysis, future efforts could focus on widening both the existing uncertainty ranges and the type of uncertainties included in the simulations e.g. climate policy incentives, energy demands. It is interesting how narrow some of the results ranges were – and the comparative strength of the scenario drivers. It would also be informative to consider scenario exploration techniques that gave stronger insights into the determinants of different clusters (Rozenberg et al., 2014). In summary, the use of clustering for enhanced understanding of how technologies interplay or not in a system context adds to the toolbox of modelling approaches that can assist decision makers.

7. Conclusions

The overall aim of this thesis is to assess how innovative approaches to energy modelling can enhance decarbonisation analyses, by improving the assessment of uncertainty, and through meaningful engagement with stakeholders during the analytical process. In this concluding section, the contributions of the different chapters to this central question are summarised, based on the findings of the research papers. They follow the flow described in the thesis introduction (section 1.4) of first setting out the strategic decarbonisation challenge that models need to inform. Secondly, how current practice can provide useful insights for decision makers. And finally, how approaches can be more innovative, in moving practice towards stronger engagement, a broader understanding of uncertainty, and improved modelling methods. The section concludes with recommendations for both the research community as to how to take the research agenda forward, and for policy, concerning how modelling can better support low carbon strategy development.

7.1 The modelling challenge of energy system deep decarbonisation

As argued in chapter 1 of this thesis, countries have to contend with a hugely ambitious transition to a low carbon energy system, which needs to occur over a relatively short timescale, be implemented by numerous actors, and contend with high levels of uncertainty. (Pye et al., 2017) illustrates how modelling can provide insights on the decarbonisation challenge under critical uncertainties. It first concludes that Paris Agreement ambition necessitates a net-zero CO_2 emissions energy system around the middle of the century, and more ambitious action in the near term than currently envisaged. The implications for target setting are clear for the UK; a net-zero target date to be established, and a trajectory that ensures stronger near term action, particularly in phasing out fossil fuels and ramping up action in end use sectors such as buildings and transport. Without both appropriate near and long term target setting, poor investment choices could result that do not deliver the necessary emission reductions. This conclusion has particular resonance for countries revisiting their NDC pledges under the UNFCCC prior to 2020.

The model analysis also highlight some key uncertainties. The first is very much a political one, with questions emerging about the level of ambition a country adopts, given the uncertainty in the size of the global carbon budgets, and questions of ethics concerning fair allocation of such a budget. The second relates to technology and resources, notably around bioenergy, CCS and the role of negative emissions. Due to the system benefit of BECCS, combining bioenergy with CCS to derive negative emissions, these are high uncertainty-high impact assumptions in the model, which need to be recognised and considered by decision makers when developing strategy. Third, the analysis also implies profound disruption on the demand side in the near term under the most ambitious case (an equity-based share of a 1.5°C global budget), if such ambition is to be achieved. In view of this, key issues raised for modelling include i) consideration of uncertainties outside of the model that are non-quantifiable, notably socio-political uncertainties, ii) understanding of the implications of large critical sources of uncertainties that impact strategy, and iii) given supply-side constraints, sufficiency of focus on demand side opportunities and implications.

There is also a clear role for modelling in reflecting 'feasibility' of ambition, a key motivation of this research. Modelling deep decarbonisation helps bridge the gap between the international political rhetoric of what is desirable and an evidence-based national level assessment of what could be achieved. For example, for the UK, the analysis suggests that without a sharp fall in demand for energy or radical breakthroughs in sequestration technologies, realising a net-zero energy system prior to 2050 would appear improbable, or at best, requires radical and immediate action across all sectors and a rapid shift away from fossil fuels.

7.2 Current practice of modelling decarbonisation strategy under uncertainty

Scenario analysis remains the mainstay of energy system modelling, where a small set of distinctive storylines or technology sensitivities are modelled in turn. These analyses have played a significant role in providing insights about system transition, and in turn informing strategy around multiple objectives including decarbonisation, energy security and affordability. However, a key criticism is that they fail to capture the multiple uncertainties of the future, and how such uncertainties play out together. There are a range of approaches for more systematic representation of uncertainty in energy system models, but based on a review in (Yue et al., 2018) , these have been underused.

Chapter 3 of this thesis describes the application of Monte Carlo analysis (MCA) alongside scenario analysis to explore the role of natural gas in a decarbonising system. This is one of the more challenging strategic issues facing UK government, given the high reliance on gas across all sectors of the economy. The analysis shows that gas will not aid emission reductions in the near term, due to the lack of higher carbon-intensive fuels to displace. It could have a role in the future, for electricity generation and hydrogen production, but this would be contingent on CCS at scale. Without CCS, 2050 gas use would be at 10% of its 2010 level but with CCS, natural gas levels of 50-60% of the 2010 levels could be enabled. The dependency of the future role of natural gas to CCS needs to be carefully considered, to avoid choices around infrastructure that could risk asset stranding and lock-in to higher fossil futures.

The mixed approach of using MCA with scenario analysis strengthens the methodology by partially dealing with the weakness of the other approach. In a less complex model like ESME, MCA can be run to capture a much broader range of uncertainties, and provide a more systematic assessment of under what conditions different pathways emerge for natural gas. Scenario analysis in UKTM allows for wider socio-political considerations using strong narratives that also help communicate the issues arising around the role of natural gas.

7.3 Innovating modelling approaches

Chapters 4 to 6 focus on determining how modelling approaches can be further developed, given the large-scale challenge of deep decarbonisation, and high levels of uncertainty around the future transition of energy systems. Chapter 4 considers the perspectives of stakeholders involved in energy and climate strategy in the UK, recognising that they represent a diversity of worldviews and positions on the many options that could be taken, and the uncertainties besetting such options.

Using semi-structured interviews with experts from government, industry, academia, and civil society, the research reveals a diversity of views on the most critical uncertainties, how they can be mitigated, and how the research community can develop approaches to better support strategic decision-making. While socio-political dimensions of uncertainty are discussed by experts almost as frequently as technological ones, there exists divergent perspectives on the role of government in the transition and whether or not there is a requirement for increased societal engagement. On improving modelling for decision support, the challenge is that many of the areas of uncertainty fall outside of the model boundary, and the focus remains on the narrow technological domain that models capture.

There is therefore the need for a new approach to uncertainty assessment that overcomes analytical limits to existing practice, is more flexible and adaptable, and which better integrates qualitative narratives with quantitative analysis. The process of engagement in this research also highlights the multiple perspectives that exist, shaped by different disciplinary backgrounds, current professions, value systems, and experiences. Recognising this and reflecting these perspectives through a more participatory approach to framing and focusing modelling analyses, has the potential to produce analyses that capture broader uncertainty, wider expertise, and engender buy-in. However, engagement needs to be done in a way that ensures decision support activity can remain responsive to policy needs. This is no trivial task, as increased interdisciplinarity creates multiple challenges relating to research design, execution, interpretation, and communication, all of which require additional time and resources to overcome. These requirements potentially place interdisciplinary innovation in direct tension with the desire from government for more rapid analysis that is easy to understand without specialist knowledge or training.

In response to the challenges identified in chapter 4, chapter 5 explores how an interdisciplinary mix-methods approach to modelling decarbonisation pathways can address the engagement deficit often seen in analyses, help elicit uncertainty that sits outside of the techno-economic domain of models, while retaining the insights from quantitative statistical approaches such as global sensitivity analyses. Taking a post normal science perspective, the NUSAP approach provides a structured framework for elicitation of uncertainty embedded in model assumptions, and the potential value ladenness underpinning them. The elicitation process with stakeholders finds that statistically influential assumptions on quantitative model results can have poor knowledge based underpinning, as measured by low pedigree scores, and are subject to potential value-ladenness. This particularly applies to assumptions around CCS deployment and bioenergy resources, both of which are highly influential in driving model insights. The approach also highlights the increasing uncertainty in the longer term, and provides valid questions about the structural assumptions in the model e.g. perfect foresight, and exogenous technology learning. In understanding the robustness of the knowledge base that underpins the modelling results, further efforts can focus on improved understanding of such assumptions.

Important as the modelling insights are, the actual process of undertaking the approach itself is also hugely beneficial. Such a process allows for extended engagement with a wide range of stakeholders, and reveals the logic and data behind critical model assumptions, allowing for renewed consideration by modellers. Feedback from stakeholders was that the process had enhanced understanding of the modelling approach, and the strengths and weaknesses across the underpinning assumptions, suggesting it brings opportunities to engender higher levels of trust in the analytical process, and across the broader expert base. With this type of modelling often being labelled ‘black box’, opening up the detailed workings to critical scrutiny should contribute to making analyses more transparent for decision makers, and avoid risks of models gaining authority on or legitimising a specific position based on poor data and the opinions of analysts.

In view of the perspectives in chapter 4, this approach grounded in post-normal science thinking, is important for capturing uncertainties outside of narrow techno-economic framing, whilst promoting meaningful engagement recognising the many perspectives and multiple expert opinions on the plethora of issues considered in decarbonisation pathways analysis.

Chapter 6 also brings an innovation in approaches to modelling decarbonisation pathways, by recognising that the options deployed in future systems often coevolve with other options, and emerge due to wider system conditions. This idea of option dependency has not been systematically explored in many papers; to do so, a clustering algorithm approach is applied in this analysis. A range of insights on the interdependencies of technologies, arising from competition on cost (electrification versus district heating), co-dependence (electrification plus storage), or system wide effects (absence or inclusion of key technologies e.g. CCS, policy ambition) can help decision makers identify what technologies work together and which tend to compete, under different system level conditions. It also provides insights into why technology deployment may be low, if negatively correlated to a competing technology deployed at scale. For example, the negative correlations between biomass availability and higher cost clusters highlight the strong influence of this commodity on costs. Similarly, the negative correlation between CCS with bioenergy clusters and other end use options (in the CP case), for example for transport sector decarbonisation, highlight how such options might be significantly reduced by the inclusion of another (such as CCS).

Key insights for UK policy, but with application elsewhere, include the pervasive influence of CCS due to its cost-effectiveness under stringent constraints. While highlighting the benefit of developing and scaling this technology, there are clear risks; it can 'hide' other alternative pathways, reducing the diversity of options in the system, and delaying the deployment of other options. There is a danger that the pervasive effect of this technology on the wider system, as shown by this analysis, is not fully recognised, which is problematic given the real risks of it not scaling in a timely fashion. Second, interdependencies are also strongly influenced by biomass resource assumptions, with a high system value on this commodity, and that its allocation varies markedly for given climate ambition and CCS deployment. Third, renewable electricity deployment levels appear less impacted by system level or technology uncertainty, highlighting the robustness of this technology as a major player for electricity generation in the long term. This is not the case for nuclear, which is much more dependent on the scaling or not of CCS. Given that wind generation is proven with rapidly falling costs, it appears an extremely robust option, which makes lack of UK government support for onshore wind all the more questionable.

Finally, the interdependency shown by clusters highlights some important insights on planning policy actions in parallel. High building electrification requires thinking about building efficiency and storage to allow for strong deployment of heat pumps. Hydrogen production is only cost-effective alongside CCS, allowing for gas SMR technology or the opportunity to generate negative emissions via BECCS. Importantly, negative correlations between clusters do not indicate that policy makers need to take an either-or decision, but rather what technology groups may compete under different system configurations.

7.4 Aligning modelling to the needs of decision makers

All of the chapters in this thesis relate to the use of modelling to inform energy and climate strategy. There are some clear insights that emerge around how to better align modelling to the needs of decision makers. These include i) the representation of uncertainty, ii) understanding model uncertainty, iii) recognising sources of uncertainty outside of the model boundary, and iv) meaningful engagement with stakeholders.

The nature of the challenge of deep decarbonisation means high levels of uncertainty due to scale of transition, rate of change required, and the multiple actors involved who have a stake in the process. This means that modelling must represent this uncertainty to allow decision makers to explore the range of possible pathways – and be able to develop robust, adaptive strategies to contend with this. This is well illustrated in chapters 2 and 3, in exploring different pathways for UK system decarbonisation, and the radically different futures that can emerge.

However, it is also important that modellers can provide insights into what are the most influential uncertainties. A decision maker might see a large ensemble of scenario pathways, reflecting the distribution of plausible outcomes, but have limited insight into what uncertainties matter the most. Techniques such as global sensitivity analysis (used in chapter 5) and clustering analysis (chapter 6) can provide important insights into what drives different outcomes. In addition to modellers needing to be able to determine the influence of uncertainty in the model, there also needs to be a recognition of uncertainty not included in the model, usefully illustrated by the NUSAP exercise (chapter 5) and the expert interviews (chapter 4). Otherwise there is a danger that modellers convey a sense of having provided a comprehensive analysis of uncertainty by nature of using a specific quantitative approach.

Finally, the research suggests a need for more robust engagement with a diverse stakeholder group to i) allow for stronger participation, engendering trust and buy-in through greater transparency, ii) to gain wider expertise particularly given the interdisciplinary nature of the decarbonisation challenge, and iii) to challenge and scrutinise the assumptions in the model, and the thinking of the modelling analysts.

Guidance for modelling has been led by the Dutch Environmental Agency PBL, which embodies the above requirements, and which could usefully be adopted and adapted for other institutions undertaking decarbonisation analysis using energy models.

7.5 Directions for the future research agenda

The research presented here has also produced a number of avenues for further research. Chapter 2 highlights the challenge of net-zero strategies and the implications across different sectors. Models will need to focus more research on mitigation in hard-to-treat sectors that no longer have room to emit, options for offsets, and the rates of change that might be required. Modelling also needs to better reflect the options on the demand side (given the supply side focus of many such models) and the uncertainty embedded in the demand drivers. Without this, there is a risk of focus only on the supply side, and under increased stringency, too much emphasis on risky and untested options e.g. carbon dioxide removal (CDR) options.

In chapter 3, on the role of natural gas, key areas for future research include the contentious issues of methane leakage, and the geo-politics of international markets versus domestic energy security. Issues around methane leakage both in domestic production and from imports need further research, as do the geo-political implications of import dependency in a changing market. On modelling approaches, this research highlights the benefit of using multiple approaches to tackle uncertainty issues, and a focus on more research to understand the use of multiple linked methods.

Chapter 4 highlights the need for a greater diversity of perspectives to be included in analyses, with an observed bias in favour of public sector participants. Future research would benefit from stronger representation of the views of business leaders, and civil society, and other actors including institutional investors with an interest in long term asset management, venture capitalists, or innovators in areas such as information technology. There is also scope in future research on uncertainty perspectives to try and highlight more radical or disruptive futures. Only a handful of participants made explicit mention of potentially transformative socio-technical futures involving developments in machine intelligence, automation, big data, and the internet of things that are becoming more common in horizon scanning studies. This was perhaps because participants were focused on the policy environment of the near future, with their perspectives strongly conditioned by existing frames, narratives, and the status quo, so the findings of the study must be viewed in that light.

Chapter 5, following the application of the NUSAP approach, reflects on a number of issues that future research should consider. First, there is an open question as to whether some of the qualitative assessment criteria employed worked equally well in the context of energy system models, for both model input and structural assumptions. For example, many participants who were comfortable using the pedigree scoring system for model inputs were at the same time unsure as to their applicability when it came to discussing model structural features. For example, as noted in the results, participants found it difficult to apply scoring for the *proxy* criterion when considering model perfect foresight, as this is not intended to directly represent real-world decision making. Nevertheless, there was value in the inclusion of structural parameters as it enhanced the overall learning process for the workshop participants by forcing contemplation and discussion of the nature of the model and its relationship to reality. Future work could consider how to integrate a wider set of model assumptions into the pedigree assessment, be they input assumptions, features of the model structure, or broader underlying socio-political assumptions being used in the model analysis. Second, a broader stakeholder base could have been consulted as part of the workshop, including a wider set of disciplines and more domain experts, for example on bioenergy, CCS, and gas markets. However, their absence was not by design but reflected the challenges of workshop organisation. Finally, there would be merit in further research as to how best such an approach could be used in the time constrained policy making process.

Finally, in chapter 6, future research efforts could focus on widening both the existing uncertainty ranges and the type of uncertainties included in the simulations e.g. climate policy incentives, energy demands. It is interesting how narrow some of the results ranges were, and the comparative strength of the scenario drivers. It would also be informative to consider scenario exploration techniques that gave stronger insights into the determinants of different clusters.

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Appendices

Appendix A. Supplementary information for Chapter 2

Appendix A1. Analysis set-up

Implementation of scenario sensitivity analysis

The analysis undertaken in UKTM (described in section 2.3) has been framed by four UK budget levels. These have been determined by first taking the low and high values from a global carbon budget range of 590-1240 $GtCO_2$ that has a 66% probability of limiting warming to 2°C. The UK share is then determined based on an allocation approach (as described below), which is applied to the global budget values. The resulting UK budget levels provide a range of stringency, with 590 Equity being most stringent and 1240 Inertia being least stringent. For each of the four UK budget levels, 16 model runs were performed, based on the combination of the 4 model sensitivities (2x2x2x2), resulting in a total of 64 model runs. The scenario sensitivity framework is shown below, in Figure A1.1.

A policy case has also been defined, based on the targets that exist under the current UK legislative framework. As per the carbon budget cases, this was also run for the 16 combinations of sensitivities. All model runs assumed UK domestic mitigation efforts only, with no option for offsetting, in line with the broad guidance from the UK's statutory climate advisor, the Committee on Climate Change (CCC).

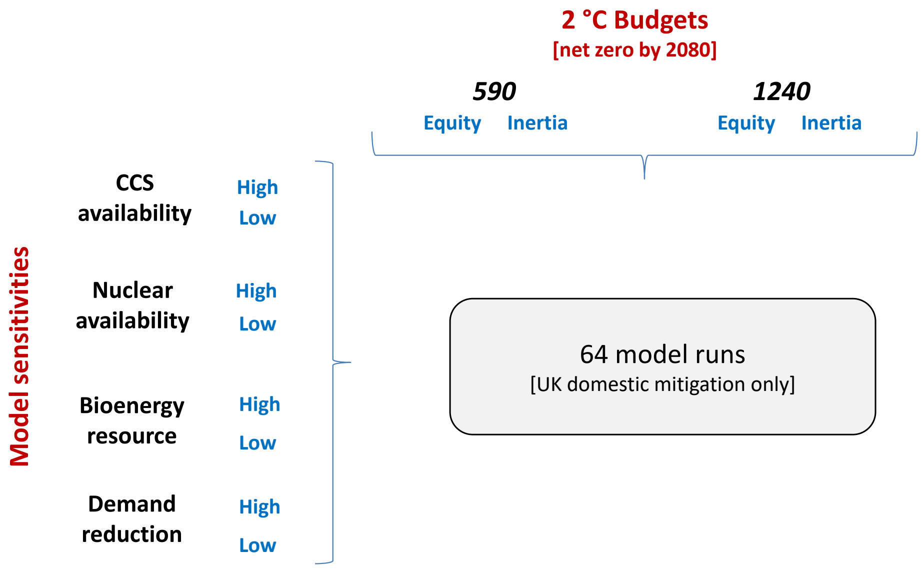

Figure A1.1. Scenario sensitivity framework

Carbon budget level and allocation

The carbon budget range of 750-1400 $GtCO_2$ (from 2011) to limit temperature increases to 2°C (66% probability) is sourced from the IPCC AR5 Synthesis Report. It is the range recommended in (Rogelj et al., 2016b) of 590 – 1240 $GtCO_2$, adjusted to start from 2015. The 1.5 °C (50% probability) range was also considered in the analysis scoping phase but discounted from inclusion due to its stringency, particularly at the lower end of the range (as shown in Figure A1.2). The 1.5 °C (33% probability) range was not considered as it is broadly captured by the low end of the 2°C (66% probability) range.

In order to allocate the global carbon budget to individual countries, the methodology set out in (Raupach et al., 2014) is followed. This allocates a share of the global budget to the UK, based on two approaches – i) equity, where allocation is on an equal per-capita basis, giving 0.8% of the total and ii) inertia, where the UK share is determined by its 2010 share of global emissions, at 1.5%. For the *equity* case, UN population projected estimates for 2040 are used (United Nations, 2015b). 2040 is when the global population hits 9 billion, as per the assumptions in (Raupach et al., 2014). The allocation in the *inertia* case is based on the share of emissions in 2010, using the global estimates of emissions from the Global Carbon Project (Le Quéré et al., 2015). The *blend* approach that results in weighted, intermediate cases between these two endpoints has been included as a sensitivity case, and presented later in this appendix.

In each case, no adjustments to budget allocation have been made based on GDP, or historic attribution of emissions, factors often considered in budget sharing principles. Regarding the former option, this is because both GDP and emissions are correlated with development status, and switching between one or the other has only a moderate impact on implied mitigation rates and therefore budget sharing (Raupach et al., 2014). Incorporation of historical emissions on the other hand has a significant effect on developed nations, making their required mitigation rates near impossible, while giving comparatively little benefit to developing countries and so they are not included.

In applying an allocation method in the analysis, no political judgement is being made about whether the UK government would choose a particular budget level or not, given the actions of others nations and their relative ambition. This analysis reflects the approach taken by successive UK governments since the Climate Change Act in 2008, which has been characterised by reviewing the evidence for the necessary global ambition to meet a limit of 2°C warming objective (a 'required by science' perspective), considering the type of ambition that the UK subsequently would need to take as a developed country, planning for this to be achieved predominantly by domestic action (CCC, 2015a). On the latter point, the UK climate advisors, the CCC, did leave open the possibility for the use of limited offsets to meet the 2050 target, but provide advice on the basis of domestic action only, due to the likely scarcity of offsets in a decarbonising world, and their high price. On this latter point, the implicit assumption based on the allocation method is that other countries are likely to be subject to similar allocation rules, and therefore the analysis is undertaken in the context of a world that is moving towards deep decarbonisation of the energy system.

Figure A1.2 illustrates the number of years left at current emissions levels for each of the UK budgets, based on the global carbon budget value and allocation method. For example, the low end of the 2°C range (590 $GtCO_2$) based on an equity allocation (black coloured bar) gives the UK just under 8 years at current emission levels, based on a cumulative budget from 2015 of 4 $GtCO_2$ (value in red).

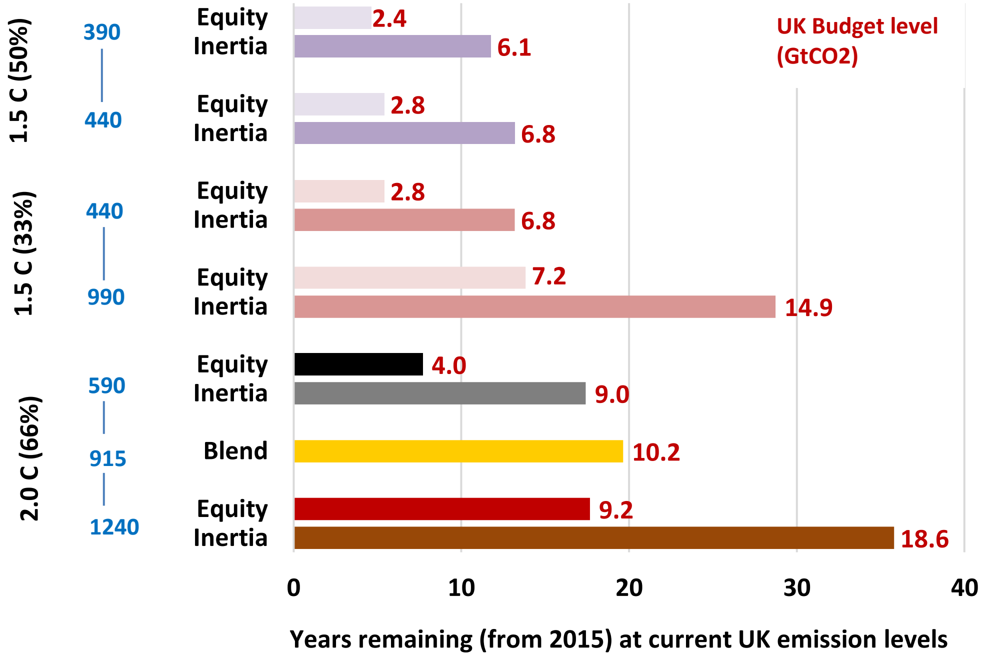

Figure A1.2. Years remaining (from 2015) at current UK emission levels under different approaches to carbon budget allocation (based on (Raupach et al., 2014)**).** Blue values on the vertical axis denote the global budget range associated with the temperature objective. Red label values represent the determined UK budget based on global budget and allocation method.

For the purposes of accounting in the UKTM model, the CO_2 budgets are implemented between 2015-2100 as cumulative constraints. The cumulative budget approach leaves the model free to determine the timing of emissions reductions on a cost-optimality basis, allowing a trade-off between early action with higher costs, and later action with lower costs (due to the effects of discounting). While the cumulative budget approach has been taken, it is assumed that a net-zero target must be achieved by 2080 at the latest, although in most cases, with the exception of 1240 Inertia, it is achieved before this date. The choice of 2080 reflects the assumption that developed nations may be required under future international obligations to achieve net-zero significantly in advance of 2100 in order to allow headroom for developing countries to transition at a slower rate. This is in line with the principles laid out in Article 2 and Article 4 of the Paris Agreement.

In implementing budgets in UKTM, no allowance is permitted for net negative emissions accounting. For the modelling, this choice means that while negative emissions technologies (NETs) can be part of the solution in achieving a net-zero position, they cannot provide additional flexibility to the system by taking the accounting system into negative balance. The primary motivation for this approach is to ensure bioenergy with Carbon Capture and Storage (BECCS) (as the only NET in the model) is deployed as a means of offsetting emissions that cannot be mitigated by other means (as shown in Figure A2.2), rather than as a system wide mechanism for delaying action in the near term, based on providing additional headroom in the future. This is particularly important given the uncertainties already inherent in scaling this type of technology (Anderson and Peters, 2016). As can be seen from Figure A2.3b, BECCS already provides a significant amount of negative emission benefit to the system. This is an area for additional research, which would be informative in respect of the additional flexibility and cost impacts that net negative emissions accounting could provide.

The UK policy case, to which the budget cases are compared, is based on the current climate legislation in the UK. This includes carbon budgets in 5-year steps covering the period out to 2032, and a long term target for 2050, which is a reduction of at least 80% in GHGs relative to 1990 levels (CCC, 2015a). These targets are all in expressed in levels of GHG emissions. Therefore to derive a UK policy trajectory in terms of CO_2 emissions only, needed for comparison to the carbon budget cases, an earlier scenario assessment was used (Pye et al., 2015a). Effectively, this provided the trajectory for CO_2 reductions, based on system wide GHG targets. The effective reduction level in 2050 for CO_2, at around 87%, was then held constant to 2100. This assumption was used to illustrate the pre-2050 choices in the absence of more stringent targets post-2050.

Low carbon technologies: nuclear and CCS

Global model exercises show that when commercially available, high deployment levels of these technologies are observed under stringent climate targets, particularly Carbon Capture and Storage (CCS). For the UK, the deployment of these technologies has also been shown to be crucial in achieving cost-effective decarbonisation across many analyses (ETI, 2015; Pye et al., 2015b).

To capture the considerable uncertainties, two cases are differentiated as scenario sensitivities. The high case is broadly in line with current UK government assumptions. Nuclear energy can contribute a maximum of 33 GW to electricity generation, while CCS technologies in electricity generation, industry and hydrogen production are commercially available from 2020 (in line with the core scenario from past government strategy plans (HM Government, 2011)). In addition, an annual growth constraint of 10% is applied for all CCS technologies. In the low cases, the available nuclear potential is reduced to 15 GW (i.e. close to the currently installed 11 GW), in order to reflect possible constraints in the UK with respect to the financial feasibility and public acceptance[21] as well as the water resource requirements of nuclear energy (Konadu et al., 2015). Similarly, given the immaturity and current political uncertainty regarding CCS technologies in the UK,[22] their availability in the low cases is delayed to 2040 and the growth constraint is lowered to 5% per year.

Bioenergy resource

For the UK energy system, assumptions regarding the availability of bioenergy have been shown to have the largest impact on both the feasibility and the costs of meeting ambitious decarbonisation goals (Pye et al., 2015b). However, the future availability of bioenergy, both for domestic resources and imports, and their sustainability are highly uncertain.

For this analysis, the input assumptions on the bioenergy potentials and costs are based on the Committee on Climate Change's (CCC) Bioenergy Review for the UK (CCC, 2011a). In the high case, the CCC Extended Land Use scenario is applied with the total bioenergy potential growing to about 1300 PJ in 2030, compared to a current consumption of about 300 PJ (covering both imports and domestic resources of dedicated energy crops, forestry and agricultural residues as well as waste). This potential is then held constant until 2050 (in contrast to the CCC report where falling bioenergy imports are expected). In the low case, the projection for the domestic biomass resources is based on the CCC Constrained Land Use scenario, assuming lower crop yields and tighter social and environmental constraints on biomass production. Moreover, the UK is assumed to be unable to import any bioenergy resources from 2020 onwards, limiting the available biomass to around 380 PJ per annum over the model horizon.

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[21] Hinkley Point C will cost customers at least £4.4bn, Jowit, J. and Carrington, D. (2015). https://www.theguardian.com/environment/2015/oct/29/hinkley-point-c-nuclear-power-station-cost-customers-4bn

[22] UK cancels pioneering £1bn carbon capture and storage competition, Damian Carrington (2015). https://www.theguardian.com/environment/2015/nov/25/uk-cancels-pioneering-1bn-carbon-capture-and-storage-competition

Energy service demand levels

UKTM has a set of exogenous energy service demand levels that are based on UK government projections to 2050 and are in line with average annual growth rates of 2.1% for GDP and 0.4% for population based on the DECC EEP model (DECC, 2014b) and ONS projections (Office for National Statistics, 2013). For this analysis, the UKTM demand drivers are extended until 2100 starting from the ONS population projections (Office for National Statistics, 2013) with very low population growth of 0.2% between 2050 and 2100, and the assumption that GDP growth rates gradually fall from 1.9% p.a. in 2050 to 0.8% in 2100.

Different approaches are then applied to extend the sector demand projections. For the residential sector, demand for space heating, hot water and non-heat services are, as before 2050, mainly based on the number of households. In the transport sector, the underlying projections (DfT, 2015) demonstrate relatively high growth rates prior to 2050. After 2050, passenger transport demand is directly linked to population growth, while freight transport is linked to GDP with the assumption of a falling GDP elasticity to take increasing decoupling effects into account. In the services sector, commercial demands are a function of commercial GVA growth, which is projected to fall from 2% p.a. in 2050 to 1% p.a. in 2100, and a falling GVA elasticity, whereas the drivers for the public energy services demands are assumed to stay constant after 2050. In the industrial sectors, the average annual growth observed between 2040 and 2050 is also applied for the period until 2100, leading to some considerable decreases in the output level of energy-intensive industries.

Built into the analytical framework is the option for endogenous demand response to energy service prices. Behavioural response to changes in prices are endogenised (compared to equivalent prices in a reference case with no climate constraint), and provides a crucial policy mitigation lever in those sectors where technology-based solutions are costly, limited or exhausted. Any reductions in demand resulting from price increases are fed into the model algorithm as a welfare loss. Low and high own-price elasticity assumptions have been used for the sensitivity range. The absolute limits of demand reduction have been set at 15% in the low case and 40% in the high case, (as compared to the fixed projected demand levels). A detailed explanation of the price elasticity assumptions and model implementation can be found in (Pye et al., 2014).

Appendix A2. Additional scenario analysis

Assessment of a central budget case

In addition to the spread of UK carbon budgets derived for this chapter, a central budget option was also assessed to explore what type of reduction trajectory might emerge, and how this compared to the other budget options. It could be argued that a ‘middle-of-the-road’ type approach could be one that is most likely to be adopted by decision makers.

The central budget option, labelled 915 Blend takes the median value of the global budget range, 915 GtCO2, and allocates a UK share (of 1.1%) based on the hybrid ‘blend’ approach in (Raupach et al., 2014), using a 50:50 weighting applied to the inertia and equity approaches. The estimated budget of 10.2 GtCO_2 is shown in Figure A1.2, and is about 1 Gt higher than 1240 Equity / 590 Inertia. The modelled trajectory is shown in Figure A2.1; in the most part, the trajectory lies below the policy case, although the difference is less than that observed for 1240 Equity. The trajectory reaches a net-zero position between 2070 and 2075, 5-10 years later than in 1240 Equity.

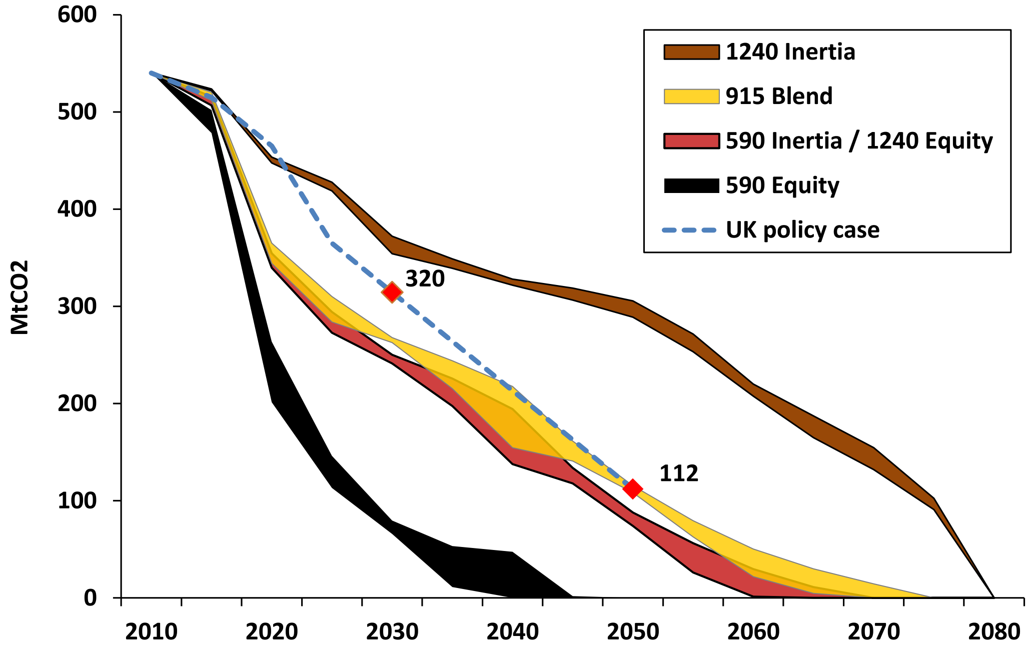


Figure A2.1. Net CO_2 emissions under the 2 °C (66% prob.) carbon budget range, based on *Equity* and *Inertia* allocations. The red markers show CO_2 emissions indicative of the UK Government's 5th carbon budget (2030) and the Climate Change Act 2008 (2050). Trajectories are based on all feasible runs that did not include the backstop mechanism. Note that *590 Inertia* is has the same trajectory as *1240 Equity*.

The challenge of achieving net zero CO_2 emissions

The 590 Equity case is particularly challenging to achieve, and a large fraction of the model runs under this budget were found to be infeasible, so they were not included in the results presented. Figure A2.2 shows the infeasibility level of the 590 Equity case, based on the share of runs requiring the high cost mitigation backstop mechanism at a given point in time, and the characteristics of those runs. This is a technology that is priced significantly higher than any other mitigation option in the model, at £10,000 /tCO_2, and its selection effectively indicates that the model solution is infeasible. Its only function is to remove a tonne of CO_2 out of the system at the above stated price. The earlier the backstop is introduced, the more critical the common assumptions of that scenario set. By 2020, over 30% of runs are infeasible due to an insufficient ability to deploy CCS technologies. In 2030, this is over 50%, due to a low bioenergy resource in addition to low CCS deployment. By 2050, almost 70% of runs are infeasible, all of which have at least a low bioenergy resource constraint, in combination with other assumptions. Those few runs that are assessed as being feasible all assume high bioenergy resource availability and the ability to deploy high levels of CCS.

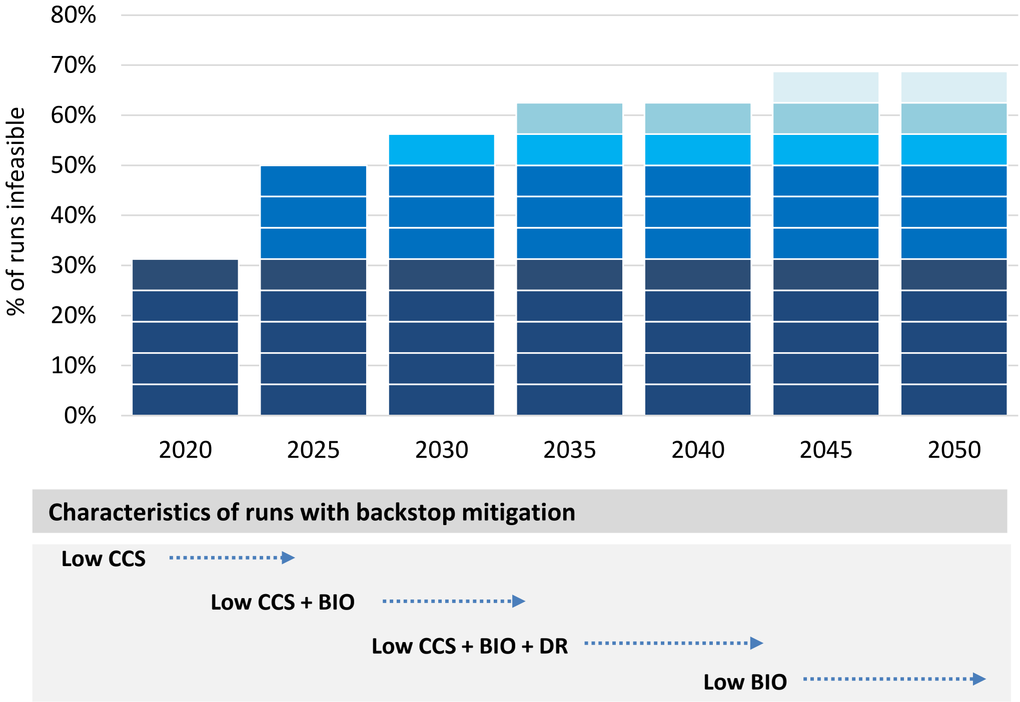


Figure A2.2. Model run infeasibility under the 590 Equity case. The shares of runs that are characterised as 'infeasible' reflect those where the backstop mechanism is chosen. This increases over time in line with the budget stringency, with 70% of sensitivities infeasible by 2050. None of these runs are presented in the results in chapter 2. [***Model case labels*** – DR=demand reduction, NUC=Nuclear, CCS=Carbon Capture and Storage, BIO=Bioenergy resource]

It is useful to explore the levels of residual emissions that remain in those model runs that have been assessed as infeasible e.g. those runs that only solve by deploying the backstop mechanism. While 70% of runs were infeasible under the 590 Equity case, this figure was at 50% under the other three carbon budget cases. This generally occurred where a low bioenergy resource assumption was used, resulting in the net-zero target not being achieved by 2080 or beyond.

Residual emissions in the 1240 Equity model runs that do not achieve the net-zero target in 2080 are shown in Figure A2.3. Other budget cases show similar patterns. As can be seen from the figure, the transport sector is the single most dominant contributor to residual emissions in all cases. Transport emissions typically comprise 65% aviation (predominantly international), 20% shipping (predominantly international), and 15% road freight. Other sectors that do not reach full decarbonisation include specific industry sectors (IND), emissions from non-energy fuel use (NEU), and specific process emissions (PRC). Emissions from the building sector do not feature in the residual as they are able to reach full decarbonisation in all assessed scenarios.

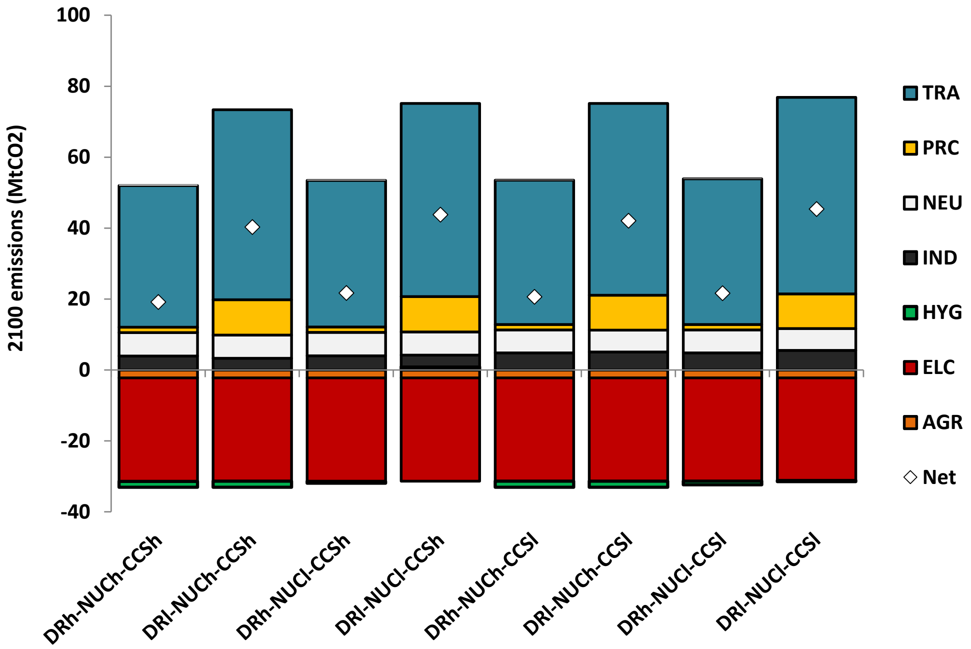


Figure A2.3. Residual emissions under the *1240 Equity* case in 2100. The white markers show the net emission level, which is above zero and therefore not meeting the zero emissions target. In other words, the positive emissions level from a range of sectors is greater than the negative level (below the horizontal axis).
[***Model case labels*** – DR=demand reduction, NUC=Nuclear, CCS=Carbon Capture and Storage; Labels followed by 'h' and 'l' refer to high and low; Legend labels –TRA=Transport, PRC=Processes, NEU=Non energy use, IND=Industry, HYG=Hydrogen, ELC=Power generation, AGR=Agriculture, Net=Net emission level]. Further detail on sector definitions can be found in the Methods section of Chapter 2.

Deployment of CCS technologies

Under the Equity cases, the median deployment of CCS before and after 2050 is larger than observed in the Policy case. This stronger role for CCS reflects both the increased stringency of the carbon budget, leading to stronger pre-2050 deployment, and the requirements for net zero, needing stronger post-2050 deployment (Figure A2.4a). The drop in CO_2 captured between 2040 and 2050 is due to the CCS sensitivities undertaken, with half of the runs assuming delayed CCS commercialisation until 2040.

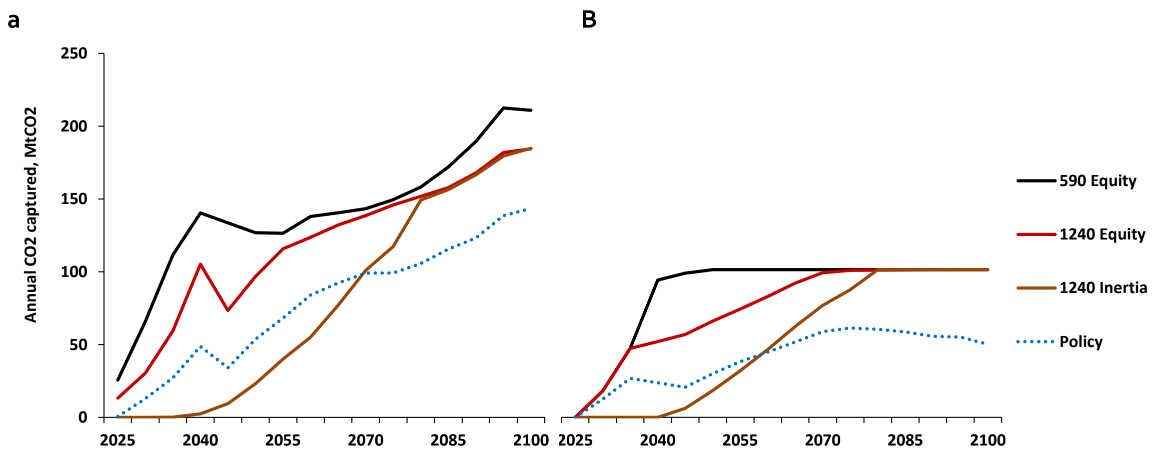


Figure A2.4. a) Annual median CO_2 capture level by budget case, 2025-2100; b) Annual median CO_2 capture level by budget case from BECCS, 2025-2100

The contribution by BECCS, the only negative emissions technology included in the model, is shown in Figure A2.4b. It shows the importance of BECCS to the model solution, and rapid scale up by the 2040s under the Equity cases. The criticality of this technology to achieving a net-zero system is illustrated by the difference between the Policy case, where a net-zero requirement is not achieved, and the other budget cases. At the point at which the different scenarios reach net-zero, BECCS is deployed at the model limits, at around 100 $MtCO_2$, a limit based on assumptions about the availability of CCS and bioenergy resources. BECCS is primarily used to deal with the residual emissions shown in Figure A2.3. There are of course key uncertainties inherent in the role of BECCS. In UKTM, the model allows for redeployment of bioenergy towards BECCS to maximise its value under the climate budget constraint. However, in reality, non-modelled system constraints may make this difficult, such as switching all bioenergy sources to a specific sector or application. Furthermore, large uncertainties are inherent in the bioenergy resource estimates outlined above. More work is ongoing in the UK on the potential for BECCS and other NETs (Smith et al., 2016), to allow for a more robust assessment of the role of such technologies.

Finally, it is important to recognise that the deployment of NET options are a function of their cost and availability, the mitigation options that could be foreseen for reducing the residual emissions, and the underlying drivers of demand for energy services. Firstly, as stated, the only NET in the model is BECCS; other options could be foreseen that could play a role in achieving a net-zero system (Smith et al., 2016). At the time of the analysis, it was judged that information to characterise the costs and performance of NETs other than BECCS was not sufficient. Secondly, other emission reduction options not included in the model could address the residual emissions, rather than having to offset via negative emissions. This could be via policies to tackle rising demand directly e.g. aviation taxes or other technical options such as gains in aviation efficiency, increased use of biofuels etc. Biofuels for aviation are available in the model, but the assumed costs are high relative to those for BECCS, and therefore the model targets bioenergy for use in BECCS. Thirdly, further assessment of alternative underlying demand drivers (economic growth, population etc.) could show a very different demand profile across sectors, either decreasing or increasing the stringency of the assumed budgets.

Appendix A3. Economic implications of carbon budgets

In a model such as UKTM, the marginal abatement cost reflects the cost of reducing the marginal (or last) unit of CO_2 under the emissions constraint. It is generated as a dual value in the model solution from the constraint, and can also be interpreted as the increase in the total system cost from a unit increase in the constraint stringency. The marginal value reflects any costs captured in the system, namely capital, operation and maintenance, fuel and any welfare losses associated with demand reduction. It is important to note that the marginal cost reflects the optimal situation, whereby all energy service demands are satisfied at a given point in time to ensure partial equilibrium of the system, and at the lowest possible cost, given the system constraints, including the cap on emissions.

The financial impact of rapid action under the 590 Equity case prior to 2030 is shown in Figure A3.1, where the marginal costs are around £1800/tCO_2. That the model has perfect foresight, energy markets in equilibrium, and limited actor inertia, but still sees such high marginal cost values for CO_2, reflects the extreme mitigation challenge that this case represents, particularly in the near term. This extreme mitigation challenge is characterised by a system that has to stay within a small carbon budget but which lacks the necessary timescale to allow for full commercialisation and scaling of deployment for low carbon technologies.

By 2050, the marginal costs of abatement are in the region of £400-550/tCO_2, across all cases except 1240 Inertia, dropping by 2080, as the system transition stabilises. This is not observed in the 1240 Inertia case, where a relatively modest mitigation rate to 2070 is followed by a sharp decline in the decade that follows to meet the net zero target.

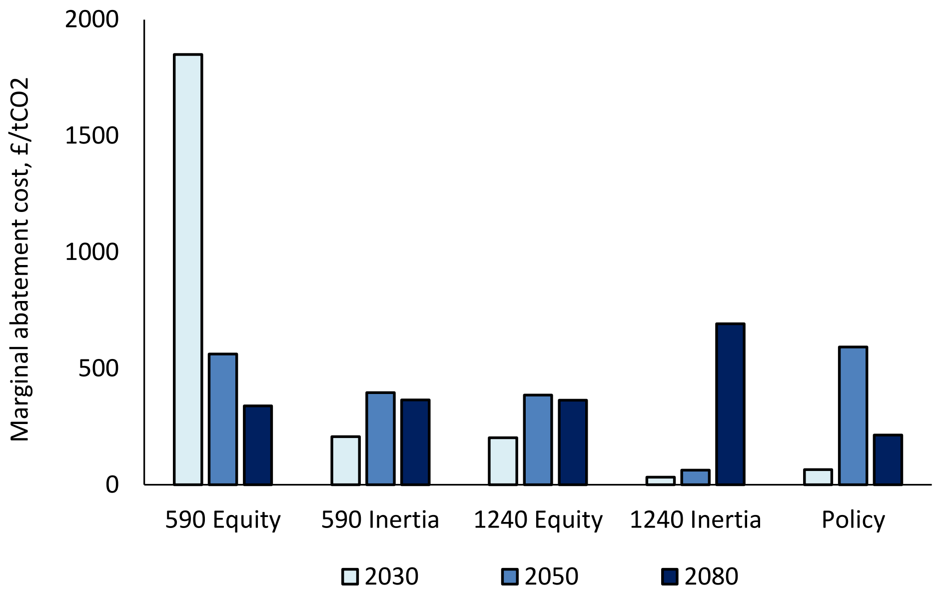


Figure A3.1. Averaged marginal abatement costs across budget cases

The additional costs of the transition are strongly dependent on the uncertainties considered; Figure A3.2 shows the change in total cumulated system costs for the 1240 Equity case, compared to the policy case median. The scenario sensitivities, all of which assume high bioenergy resource, show that restricting CCS availability has the strongest impact on system costs with an increase of £130 billion (labelled 'Low CCS') compared to the scenario with most optimistic high assumptions 'All high assumptions'), followed by demand reduction at £60 billion ('Low demand reduction') and nuclear at £35 billion ('Low nuclear').

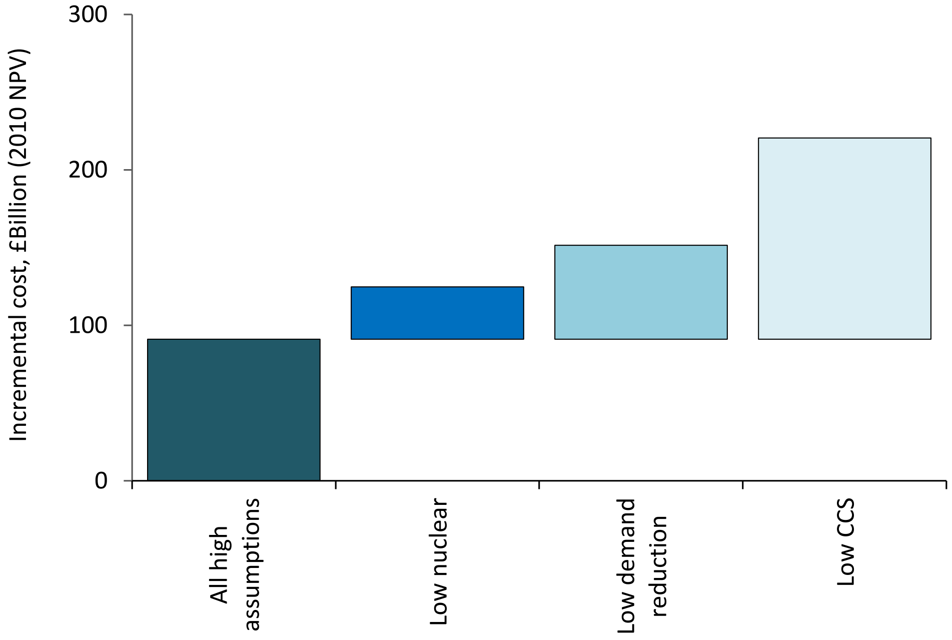


Figure A3.2. Cost differences for 1240 Equity sensitivities versus Policy Case (median)
The additional costs of different sensitivities are compared to a most favourable case, where assumptions are all high (labelled All high assumptions). Each sensitivity holds one of the assumptions low to explore the incremental cost above the Policy case. The All high assumptions case is the difference in discounted total systems costs compared to the median policy case.

Appendix B. Supplementary information for Chapter 3

Appendix B1. Description of models

UKTM

The national UK TIMES energy system model (UKTM) has been developed at the UCL Energy Institute over the last two years as a successor to the UK MARKAL model (Kannan et al., 2007). It is based on the model generator TIMES (The Integrated MARKAL-EFOM System), which is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) (Loulou and Labriet, 2007).

UK MARKAL was largely developed by UCL within UKERC, and was used as a major underpinning analytical framework for UK energy policy making and legislation from 2003 to 2013 (CCC, 2008; DECC, 2011c; DTI, 2007; Ekins et al., 2011), and UKTM continues to perform this role as the central long-term energy system pathway model used for policy analysis at the former Department of Energy and Climate Change (DECC) and the Committee on Climate Change (CCC). It has been used for DECC's analysis of the 5th Carbon Budget, which sets the limit on GHG emissions in the UK for the period from 2028 to 2032 (DECC, 2016). With the aim to increase the transparency in energy systems modelling and to establish an active user group – including key decision makers – an open source version of UKTM is being prepared that will be updated on a regular basis.

UKTM is a technology-oriented, dynamic, linear programming optimisation model representing the entire UK energy system (as one region) from imports and domestic production of fuel resources, through fuel processing and supply, explicit representation of infrastructures, conversion to secondary energy carriers (including electricity, heat and hydrogen), end use technologies and energy service demands. Like other models of this type, as noted above, it minimizes the total welfare costs (under perfect foresight) to meet the exogenously given sectoral energy demands under a range of input assumptions and additional constraints and thereby delivers an economy-wide solution of cost-optimal energy market development.

The model is divided into three supply side sectors (resources & trade, processing & infrastructure and electricity generation) and five demand sectors (residential, services, industry, transport and agriculture). All sectors are calibrated to the base year 2010, for which the existing stock of energy technologies and their characteristics are taken into account. A large variety of future supply and demand technologies are represented by techno-economic parameters such as the capacity factor, energy efficiency, lifetime, capital costs, O&M costs etc. Moreover, assumptions are laid down concerning energy prices, resource availability and the potentials of renewable energy sources, etc. UKTM has a time resolution of 16 time-slices (four seasons and four intra-day times-slices). In addition to all energy flows, UKTM tracks CO_2, CH_4, N_2O and HFC emissions. The model structure is illustrated in Figure B1.1. For more information on UKTM, see (Daly et al., 2015; Fais et al., 2016a; Pye et al., 2017, 2015a).

On gas resources, three supply steps are given for each of the four reserve types with different cumulative potential and extraction costs, thus establishing resource supply curves with 12 steps. The reserve types include i) located reserves, ii) reserves growth, iii) new discovery, and iv) shale gas. Each resource step is associated with an activity in 2010 (calibrated to the DUKES energy balances, (DECC, 2011a)), a cost of activity, and the cumulative reserves (total resource availability in PJ over the model horizon, based on BUEGO (McGlade and Ekins, 2014). The auxiliary gas use for extraction is taken into account (based on the DUKES energy balances, assuming that 75% of auxiliary gas consumption is used for production and 25% for transmission network operation). In addition, GHG emissions from leakage and flaring during fossil fuel extraction are modelled in UKTM (based on data from the GHG Inventory (DECC, 2013)).

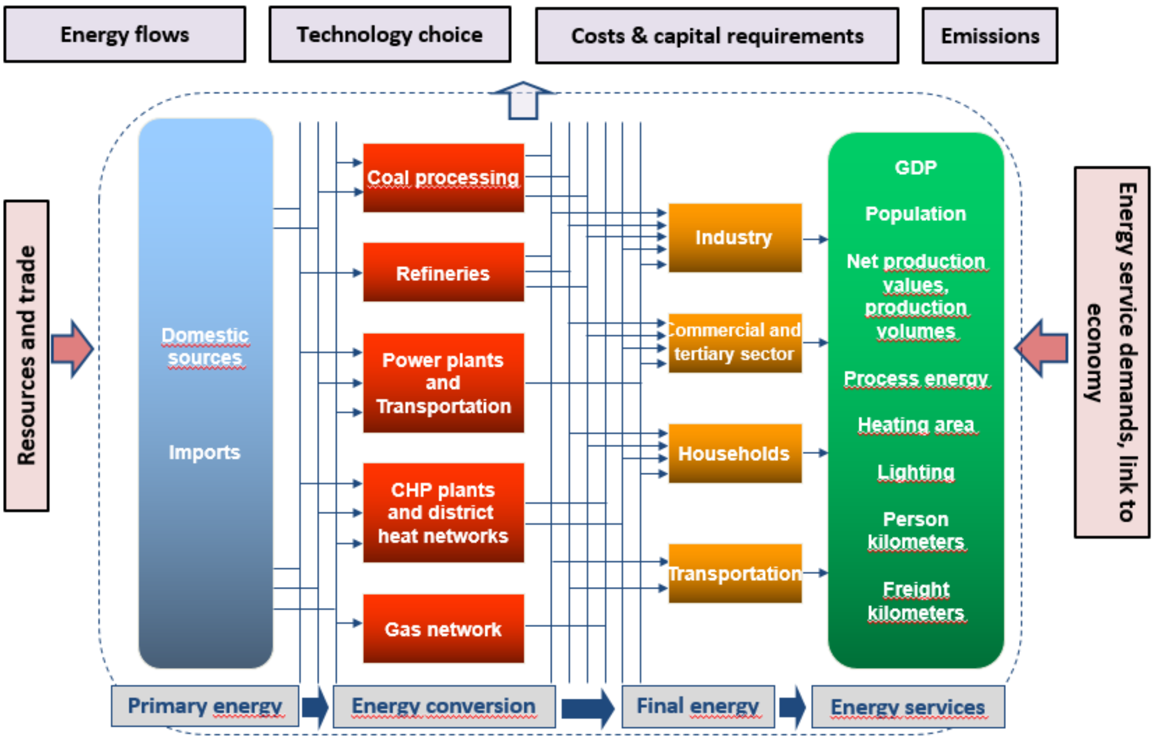


Figure B1.1. Schematic of features of UKTM. Adapted from Remme et al. (2002)

Sector	Description
Resources and trade	Includes potentials and cost parameters for domestic resources and traded energy products. For fossil fuels, assumptions are mainly based on results from the global energy system model TIAM-UCL (Anandarajah et al., 2011), while the assumptions on bioenegy potentials are aligned with the CCC's Bioenergy Review and the Extended land use scenario (CCC, 2011a).
Energy processing	Covers all energy conversion processes apart from electricity generation, including oil refineries, coal processing, gas networks, hydrogen production, bioenergy processing as well as CCS infrastructure.
Power generation	Represents a large variety of current and future electricity generation technologies as well as storage technologies, the transmission grid and interconnectors to Continental Europe and Ireland. The technology assumptions are mostly aligned with DECC's Dynamic Dispatch Model (DDM) (DECC, 2012).
Residential	Domestic housing is divided into existing and new houses. In addition to a large portfolio of heating technologies for the two main energy service demands of space heating and hot water, other services like lighting, cooking and different electric appliances are represented. The technology data is based on various UK-focused building studies, including (Bergman and Jardine, 2009), (Davies and Woods, 2009), (Radov et al., 2009), and (Element Energy & Energy Saving Trust, 2013).
Services	As per residential structure, but stock divided into low- and high-consumption non-domestic buildings. The technology data is based mostly on the same UK-focused building studies mentioned for the residential sector.
Industry	Divided into 8 subsectors of which the most energy-intensive ones (iron & steel, cement, paper and parts of the chemicals industry) are modelled in a detailed process-oriented manner (Griffin et al., 2013), while the remaining ones are represented by generic processes delivering the different energy services demands. The demand projections are aligned with the DECC Energy and Emissions Projections model (EEP).[23]
Transport	Nine distinct transport modes are included (cars, buses, 2-wheelers, light goods vehicles, heavy goods vehicles, passenger rail, freight rail, aviation and shipping). For road transport, the demand projections are based on the road transport forecasts 2013 (DfT, 2013) and the technology parameters are mainly sourced from (Ricardo-AEA, 2012).
Agricultural and land use	Represents, in addition to processes for the comparatively small fuel consumption for energy services, land use and agricultural emissions as well as several mitigation options for these emissions (Moran et al., 2008).

Table B1.1. UKTM sector descriptions

ESME

ESME (Energy Systems Modelling Environment), developed by the Energy Technologies Institute (ETI), is a fully integrated ESM, used to determine the role of different low carbon technologies required to achieve the UK's mitigation targets. The model has been used in this capacity by the UK Department for Energy and Climate Change (DECC) and the UK Committee on Climate Change (CCC) (CCC 2011, CCC 2013, DECC 2011). Built in the AIMMS environment, it uses linear programming to assess cost-optimal technology portfolios. The uncertainty around cost and performance of different

[23] This model is used to produce the UK energy and emission projections, the latest of which can be found at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/368021/Updated_energy_and_emissions_projections2014.pdf. The industry demand projections are not publically available but were provided by DECC on request.

technologies and resource prices is captured via a probabilistic approach, using Monte Carlo sampling techniques. The focus of uncertainty is on technology investment costs in the power and transport sectors, fuel costs and resource potential e.g. biomass imports. The characterisation of uncertainty, implemented in ESME v3.2 which was used in this research, is described in detail in (Pye et al., 2015b).

The representation of energy demand sectors is typical of other ESMs, with representation of power generation, industry, buildings and other conversion sectors e.g. biofuel production, hydrogen production. The model endogenously determines how to meet these demands in a cost-optimal manner, through investment in end use technologies (including efficiency measures), and the production and supply of different energy forms. In the household sector, a rich characterisation of low carbon technologies is provided, particularly for heat pumps, district heating (incl. infrastructure) and building fabric retrofit. The transport sector also incorporates key low carbon technologies, and the different infrastructure required to deliver alternative fuels e.g. electricity charging infrastructure and hydrogen networks. The industry sector is characterised more simply, focusing on efficiency gains, fuel switching measures and carbon capture and storage (CCS). Transformation sectors (power generation, hydrogen production, biofuel production) represent the key low carbon technologies, and associated infrastructures (to enable inter-node transmission). Primary resource supply is characterised by commodity price and resource availability, with no distinction between imports and domestic indigenous production (except for biomass), and no explicit representation of resource and upstream sectors.

On GHG emissions accounting, ESME accounts for CO2 but not other greenhouse gases (GHGs). Therefore, the CO2 emissions constraints applied in the model exogenously assume the level of non-CO2 GHG levels in future years, taking account of expected abatement, with necessary adjustments made to the CO2 target. In this version of the model, a non-CO_2 GHG level of 55 $MtCO_2e$ is assumed in 2050, based on (CCC, 2010), allowing for 105 $MtCO_2$ of CO_2. A more detailed description of the ESME model can be found in (Heaton, 2014), while an overview of the ESME data sources is provided in (ETI, 2016).

Appendix B2. Description of UKTM scenarios

The first, called **'Abandon'** assumes that climate change policy is downgraded in importance during the late 2010s. The Climate Change Act is repealed in 2021, partly due to political opposition to the short-term costs of decarbonisation at a time of continued austerity, and partly due to a failure by the international community to implement the ambitious deal agreed in Paris in 2015. This means that further limits on emissions beyond the 3rd carbon budget (2018-22) are not implemented. The UK maintains its commitment to international trade and integration with international energy markets. However, because of a relative lack of emphasis internationally on moving away from fossil fuels, and consequently higher overall demand, the price of fossil fuels is relatively high in this scenario. Despite the repeal of the Climate Change Act, because of a desire to 'sweat' current assets and to ensure a continued commitment to EU Directives, the existing pledge that no new unabated coal power plants are to be constructed remains.

The second, **Insular,** scenario also assumes that climate change policy is downgraded in importance during the late 2010s. The Climate Change Act is repealed in 2021, for similar reasons to Abandon, which again means that further limits on emissions beyond the 3rd carbon budget are not implemented. As a reaction to economic problems at home and the perceived failure of international markets and institutions, UK citizens vote to leave the EU. It also shifts towards a more inward looking energy policy with, for example, much less electricity connection to the European continent. Strict limits are placed on imports in favour of domestic fossil fuel (including new coal) and renewable resources, and prices of fossil fuels are relatively high as a result.

The **Affordable** scenario continues with commitment to climate change targets well into the 2020s, but with an impression that the world is not acting sufficiently quickly to reduce emissions, this commitment starts to falter. This results in a lack of agreement on the 5th carbon budget (2028-32) because of the perceived high costs of meeting progressively challenging targets and so only the 4th carbon budget (2023-27) is met. The UK shifts away from any ambition to take a leadership position on climate change, and progressively argues for the EU to play a following role in international negotiations. Policies to support the deployment of renewables are progressively scaled back as is policy support for nuclear and CCS.

In the **Maintain** scenario, the UK continues its commitment to climate change targets (i.e. 80% GHG emissions reduction by 2050). The 5th carbon budget is agreed, broadly in line with Committee on Climate Change advice. Part of the reason for this is a relatively strong climate agreement in Paris and significant progress by many countries towards meeting their commitments. This drives down the costs of many low carbon technologies and energy efficiency measures and starts to remove trade barriers. This includes CCS technologies which are successfully commercialised and 'rolled out' alongside other low carbon technologies. Since the world shifts away from carbon-intensive fuels, particularly coal, fossil fuel prices remain relatively low.

The **Maintain (tech fail)** scenario is similar to Maintain, but there is a failure of efforts to commercialise CCS technologies. More emphasis is therefore placed on other forms of mitigation to meet UK targets such as renewables, nuclear power and energy efficiency.

Some of the key assumptions that vary across each of the above scenarios are set out in Table 3.2. The scenarios with 2050 emissions reduction targets are also required to keep within a cumulative level of emissions between 2028 (the end of the 4th carbon budget period) and 2050. This ensures that there is a steady progression towards the 2050 target and is used as a proxy for future carbon budgets to be set by the Committee on Climate Change. The cumulative constraint is constructed on the basis of a linear decrease from the maximum emissions level in 2028 to the level required in 2050. For example, **Maintain** has maximum emissions in 2028 of 430 Mt CO_2-eq and 160 Mt CO_2-eq in 2050. A linear decline between these dates yields total emissions of 6750 Mt CO_2-eq, which is therefore imposed as a cumulative limit on emissions between these dates in this scenario.

The above scenarios can be visualised with respect to the 'Energy Trilemma' (World Energy Council, 2015) of the interplay and tensions between the goals of emissions reduction (decarbonisation), 'keeping the lights on' (energy security), and the affordability of energy for consumers (called 'equity' in the WEC version of the trilemma). It is noteworthy that the UK lost its AAA rating in the 2015 WEC benchmarking exercise because the rising cost of electricity at the time reduced its 'equity' score to a B.

Figure B2.1 shows a diagram of the Energy Trilemma, positioning in which represents policy priorities within each scenario, rather than the assumed result of any scenario[24]. In **Abandon**, for example, the repeal of the Climate Change Act, a failure to support or allow the cheapest forms electricity production, no efforts to mitigate emissions globally and an assumption that energy prices will be high mean that the scenario would potentially fail to fully achieve any of the trilemma

[24] A comprehensive analysis of the implications of these scenarios for energy security and affordability is beyond the scope of this report. A separate UKERC project is underway that is analysing the security implications of these scenarios.

objectives. Therefore, it is equidistant from all the corners of the diagram. **Insular, Affordable** and **Maintain** concentrate primarily (though not exclusively) on one of the main goals, and so are located towards the corners of the diagram. However, there is, for example, a slightly greater emphasis on emissions mitigation in **Affordable** than in **Insular** (since the former is required to fulfil the 4th carbon budget while the latter is not), meaning that it is positioned slightly closer to the 'decarbonisation' corner. **Maintain (tech fail)** is placed slightly along the 'security' axis but also further from the 'affordability' corner than **Maintain**. **Maintain (tech fail)** excludes CCS, but still needs to meet decarbonisation objectives. It is therefore likely that there will be more emphasis on domestic renewable and efficiency measures rather than importing fossil fuels for use in centralised power plants.

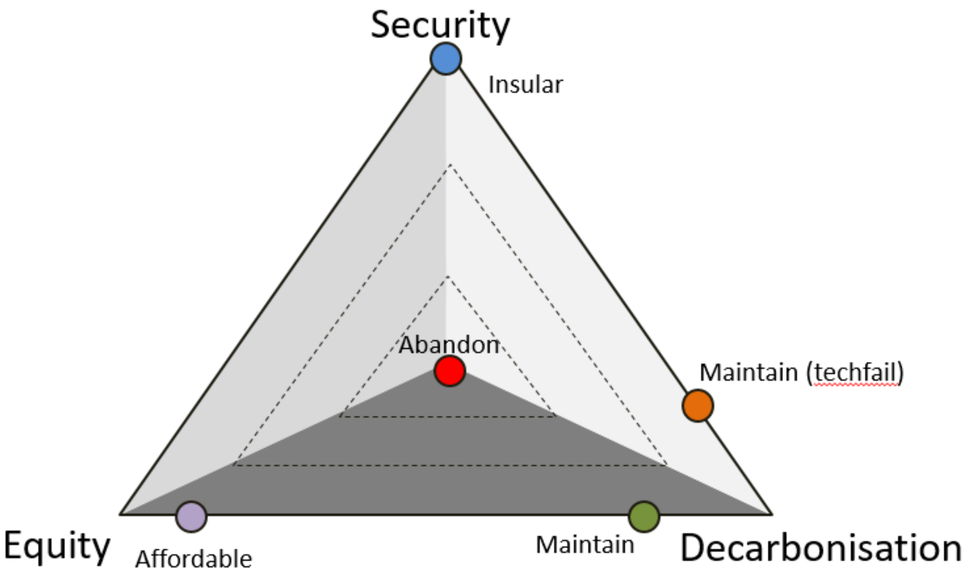


Figure B2.1. The location of UKTM scenarios within the energy trilemma

Appendix C. Supplementary information for Chapter 5

Appendix C1. NUSAP assessment criteria and scoring descriptions

Uncertainty dimension	Criteria	Description	Criteria scores				
			4	3	2	1	0
Methodological	Proxy	The extent to which the assumptions that we use in the model are proxies for the reality that we seek to represent, given the purpose of the model. Examples include over simplifications, first order approximations, incompleteness.	Exact representation	Good representation	Moderate or acceptable representation	Weak representation	Poor representation
	Empirical basis	The degree to which observations, measurements and statistics are used to estimate a parameter.	Observation	Mix of observations and model-based estimates	Model estimates only	Educated guess	Crude speculation
	Rigour	Refers to the norms for methodological rigour in this process applied by peers. Well-established and respected methods for measuring and processing the data would score high on this metric, while untested or unreliable methods would tend to score lower.	Best available practice	Reliable method; very few concerns	Acceptable method but questions on reliability	Preliminary or experimental methods with no clear view of reliability	No discernible rigour in the method, grave concerns
	Validation	The extent to which assumptions have been cross-checked and validated against other observations and measurements	Huge database of reliable sources	Compared with numerous reliable sources	Limited validation with only a few reliable sources	Weak validation, questions on reliability of sources	No validation
Epistemological	Theoretical understanding	The extent to which our theoretical understanding of the real world processes provides a reliable basis for estimates	Extremely strong theoretical understanding	Good understanding	Generally understood but lack of complete consensus	Poorly understood	Crude speculation
Value-ladenness	Choice space	The degree to which alternative choices of assumptions could be made i.e. the degree to which other acceptable / plausible assumptions are available	No alternatives	Only a few acceptable/plausible alternatives	Small or limited range of alternatives	Moderate range of alternatives	Extremely wide range of alternatives
	Justification	The degree to which the approximation made in the model can be justified as a reasonable, plausible or acceptable assumption, given one's understanding of the reality. Can these assumptions be defended?	Fully justified	Strong justification	Acceptable justification	Weak justification	Completely speculative
	Agreement amongst peers	The degree to which the assumption made in the model (by the analyst) is likely to coincide with other experts in the field	Complete or near-complete agreement	High degree of agreement, with some variation	Some disagreement possible, there are a few competing schools of thought	Low degree of agreement, contentious subject	No agreement or almost no agreement, extremely controversial

Appendix C2. Description of workshop structure, and NUSAP scoring card information

At the start of the full day workshop, the concept of NUSAP was introduced, and the motivation for applying it to the UK energy and climate policy field. An overview of the ESME model was also presented, to provide context for participants when assessing the assumptions and crucially for understanding the model design and purpose, an important consideration when judging the pedigree of the model assumptions. Finally, given the importance of understanding what each of the criteria specifically meant, and how to approach the scoring, an example assessment of a model data input (not listed in Table 5.1), the capital expenditure for a combined cycle gas turbine (CCGT), was presented.

The workshop then took the format of three working sessions with breaks in between. At the beginning of each working session a set of ESME model parameters was presented to the participants using the descriptions set out in the scoring cards, copies of which can be seen below. The assumptions behind the model representation of each parameter were explained to the group in plenary by an expert ESME user or developer, with an opportunity for clarification questions to be taken from the audience. Participants were then split into four discussion groups for each working session. For each session, the composition of the groups was changed in order to avoid experts only being subjected to the same set of perspectives. Each group always included a facilitator with an understanding of the scoring criteria and an expert user of the ESME model who was familiar with the way in which each model parameter was implemented and the underlying assumptions supporting these choices. Group discussions then followed for each assumption, providing an opportunity to hear different perspectives but not draw consensus. Following this 5-10 minute exchange, participants then scored the pedigree criteria independently. Three model assumptions from Table 5.1were discussed and subsequently scored in each of the sessions.

The NUSAP scorecards used in the workshop are presented below.

1. Domestic biomass resource potential	**Name:**
	Disciplinary background:

Definition:

This parameter constrains the level of domestic biomass available for use in the energy system. The available biomass (central estimate) increases from 101 PJ in 2010 to 432 PJ in 2050. These estimates of maximum UK production, based on analysis using ETI's Biomass Value Chain Model (BVCM) are considered economical and sustainable, whilst not displacing UK food production. The biomass resource, which is not distinguished by feedstock type, can be allocated across the energy system, to the sectors where it is most optimally used.

	2010, 2050 value:	**2050 range over which sensitivity was tested:**
Biomass resource potential [PJ]	101, 432	+/- 50%
Biomass resource potential [TWh]	28, 120	+/- 50%

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	Pye et. al (2015)
Rank	2	2

Scores [Note that all the cards used in the workshop included this scoring matrix, shown here for illustrative purposes]

		2010					2050						Additional comments
Criteria		4	3	2	1	0	4	3	2	1	0		
Proxy	Exact											Poor	
Empirical basis	Observation											Speculative	
Methodological rigour	Best available											None	
Validation	Many sources											None	
Theoretical understanding	Agreed											Speculative	
Choice space	Wide											None	
Justification	Full											Speculative	
Agreement amongst peers	Complete											None	

2. Biomass emission factors	Name:

Definition: Assumptions about the emission factor associated with domestic and imported biomass are important as this will impact on the attractiveness of bioenergy as a zero or low carbon source of energy. In addition, it will also impact on the negative emissions credit when bioenergy is used in CCS applications (Bioenergy with CCS, or BECCS). For example, a higher level of emissions assumed for biomass means that BECCS is a less effective mitigation option.

For domestic biomass, the growth phase credit is set at 90%, with 10% assumed to be lost to agricultural practices, processing and transportation. For imported biomass, the growth phase credit is 70%, with 30% emissions across the aforementioned sources.

	2010, 2050 value:	**2050 range over which sensitivity was tested:**
Domestic biomass emissions credit [%]	90	Not subject to uncertainty analysis
Imported biomass emissions credit [%]	70	Not subject to uncertainty analysis

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	**Pye et. al (2015)**
Rank	n/a	n/a

3. Gas resource cost	Name:

Definition: Cost estimates are based on the central gas price scenario on the Government fossil fuel price projections. From *BEIS 2016* – 'key uncertainties concern how LNG supply will evolve in longer term depending on Asian market demand; and the impact of Russian, Norwegian and North African production on the European market'. The basic approach is to use a supply curve (from Wood Mackenzie) and demand from IEA NPS, and determine price level.

	2010, 2050 (£2010 basis) value:	**2050 range over which sensitivity was tested:**
Price (p/kWh)	1.5, 2.73*	+/- 50-60%
Price (p/therm)	44, 79	
Price ($/mmbtu)	6.6, 12	

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	**Pye et. al (2015)**
Rank	3	1

* Note current central projection (based on updated forecasts is 1.83 p/kWh (or 54 p/therm)

4. CCS maximum build rate	Name:

Definition: CCS options are available across the model in power production, industry, hydrogen production and biofuel production. The uptake of CCS is a function of the limits on build rate and the relative economic attractiveness of the option. The most prevalent CCS technology was CCGT w/ CCS, for which the assumptions and sensitivity analysis relate. This technology utilises post-combustion carbon capture, with a 95% assumed capture rate. Maximum build rates permit CCS build from 2030 at commercial scale. This assumption is sourced from internal project analysis. The MM sensitivity analysis applied a +/-50% variation on the 2050 estimate. [NB. Industrial CCS was not considered in the sensitivity analysis].

For CCGT w/CCS:

	2030, 2050 value:	**2050 range over which sensitivity was tested:**
Build rate (GW)	1, 2	1, 3

CCS availability also highlighted as crucial via the EE, based on scenario analysis (with a binary setting of available or not) that has shown the importance (in terms of costs) of CCS as an available option. This is binary setting was not captured in the sensitivity analysis.

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	**Pye et. al (2015)**
Rank	20	n/a

5. CCS capex	Name:

Definition: As noted above, the uptake of CCS is a function of the limits on build rate and the relative economic attractiveness of the option (versus other LC technologies). CAPEX estimates are derived from an extensive research programme undertaken by the ETI (*Next Generation Capture Technologies: Benchmarking* (CC2001) and *Next Generation Capture Technologies 2 Gas Capture* (CC1008)). Note that cost reductions are not contingent on the deployment of the technology, but rather completely independent.

For CCGT w/CCS:

	2010, 2050 (£2010 basis) value:	**2050 range over which sensitivity was tested:**
Capex (£/kW)	1300, 971	+/- 50%

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	**Pye et. al (2015)**
Rank	12	[Not ranked]

6. Nuclear Gen. III Capex	Name:

Definition: Nuclear capital cost and build rate both impact on the deployment of nuclear in the long term. Here the focus is on III generation power stations, with Capex determined via ETI expertise and stakeholders, and build rates based on data from the ETI project *Power Plant Siting Study*. A cumulative capacity constraint is set at 35 GW, although has not been subject to sensitivity analysis.

In the latest version of ESME, IV gen. and SMR have been added in. However, III gen. potential in the model still dominates as having the largest potential and contribution to nuclear generation.

	2010, 2050 (£2010 basis) value:	**2050 range over which sensitivity was tested:**
Capex (£/kW)	3800, 3040	+/- 40%

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	Pye et. al (2015)
Rank	8	4

7. Non-CO_2 GHG emissions (implicit in CO2 trajectory)	Name:

Definition: Under the UK CCA (2008), total GHG emissions have to be less than 160 $MtCO_2e$ in 2050. For this year, the modelling exogenously assumes that non-CO_2 GHGs will constitute 55 $MtCO_2e$, requiring that total CO_2 emissions (including international transport) do not exceed 105 $MtCO_2e$. In 2010, non-CO_2 emissions (CH_4 & N_2O) stood at 89 $MtCO_2e$, and were 75 $MtCO_2e$ in 2014.

The 2050 non-CO_2 GHG level constitutes a 70% reduction relative to 1990 levels. This is based on assessment (by the CCC) of options that could lead to further reductions in methane emissions from waste, agriculture and other source sectors.

	2010, 2050 value:	**2050 range over which sensitivity was tested:**
Emissions level ($MtCO_2e$)	89, 55	Not subject to uncertainty analysis

Rank in Sensitivity Analysis (*all sensitivity analysis results are in relation to discounted system costs*)

	Usher (2015)	Pye et. al (2015)
Rank	n/a	n/a

8. Exogenous representation of technology learning	Name:

Definition: This assumption relates to how technology learning is formulated in the model, and is typical of similar bottom-up models. In ESME, the change in cost and performance of a technology is exogenously set, implicitly taking account of technology innovation and commercialisation, and therefore a range of factors including global developments.

While the assumptions used across different technologies are informed by a range of data sources, the uncertainty here relates to the way the model represents the process. While global factors cannot be modelled explicitly, there may be the potential for learning effects from R&D, demonstration projects and commercial deployment in the UK for specific technologies e.g. offshore wind, hydrogen infrastructure, electric vehicles. These are not captured dynamically, based on deployment.

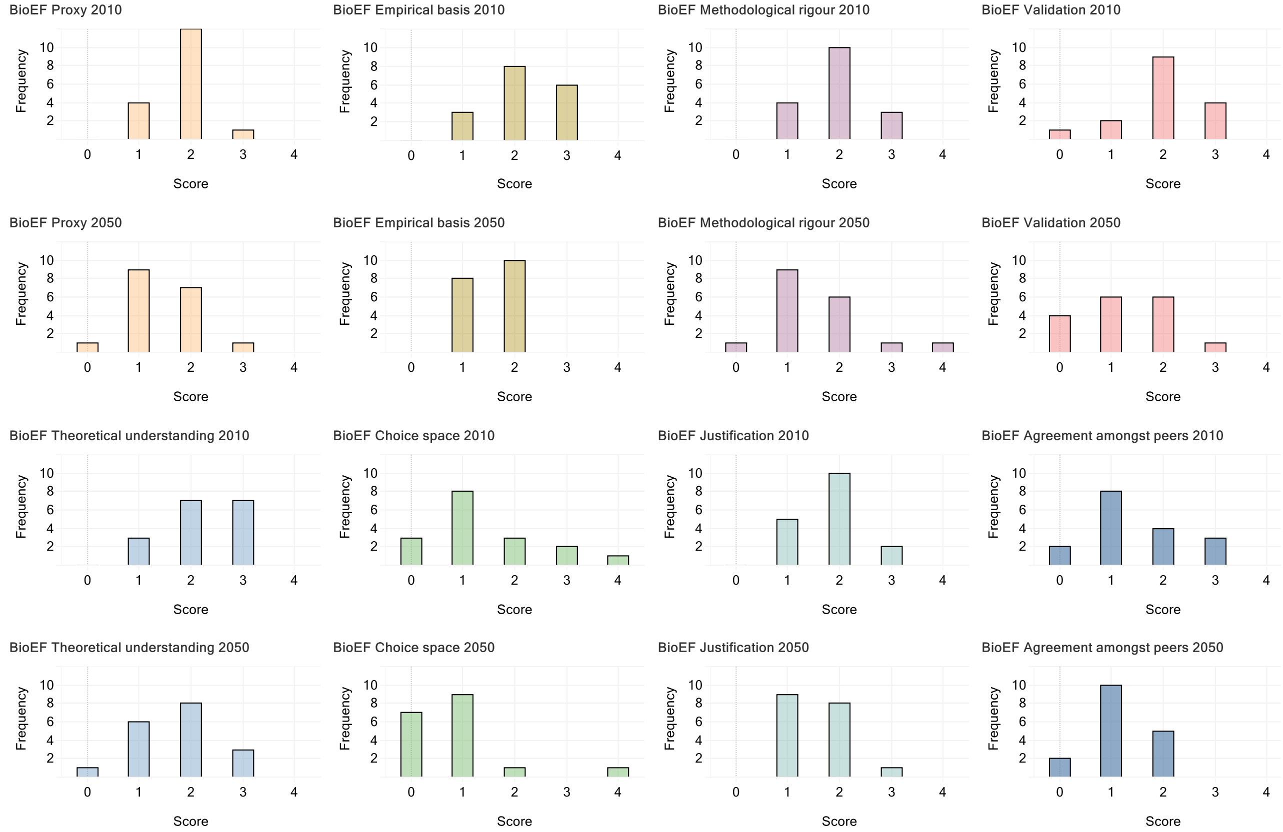
9. Perfect foresight	Name:

Definition: Perfect foresight formulation means that all economic 'decisions' are made with a full knowledge of all information relating to the future. This means that no agents in the system are subject to new information or unforeseen surprises, as all information is held at any given point in time. The formulation is such that technology costs, demand level, and commodity prices revealed in 2050 are all known in 2010. This therefore avoids over investment, and potential stranding of different assets, and allows for optimality in any given solution.

Such a formulation can be useful for determining cost-effective technology pathways, so long as there is a recognition that these emerge under a set of specific assumptions e.g., a commodity price trajectory, user constraints, technology learning assumptions. The perspective on this structural assumption is likely to be informed by the purpose of the modelling. Specific techniques employed to disrupt this formulation (and explore structural uncertainty) include introducing myopia e.g. solving incrementally for 1-2 periods at a time, stochastic programming, where uncertainty is resolved only at a future point in time, or by 'fixing' specific investment levels for future periods.

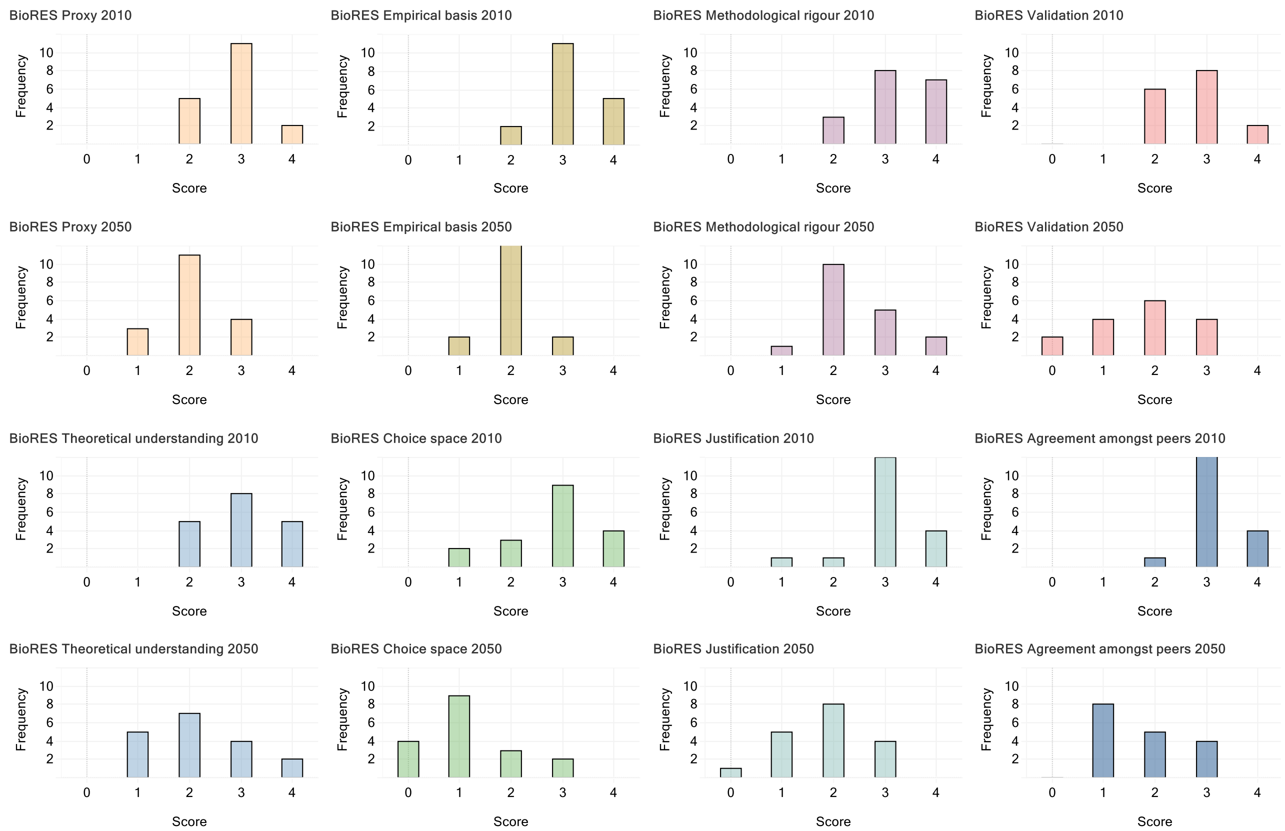
Appendix C3. NUSAP workshop pedigree scores by model assumption

Figure C3.1. Frequency plots for criteria scores across model assumptions: biomass resource potential. For each criteria, the 2010 score plots are shown directly above the 2050 score plots.



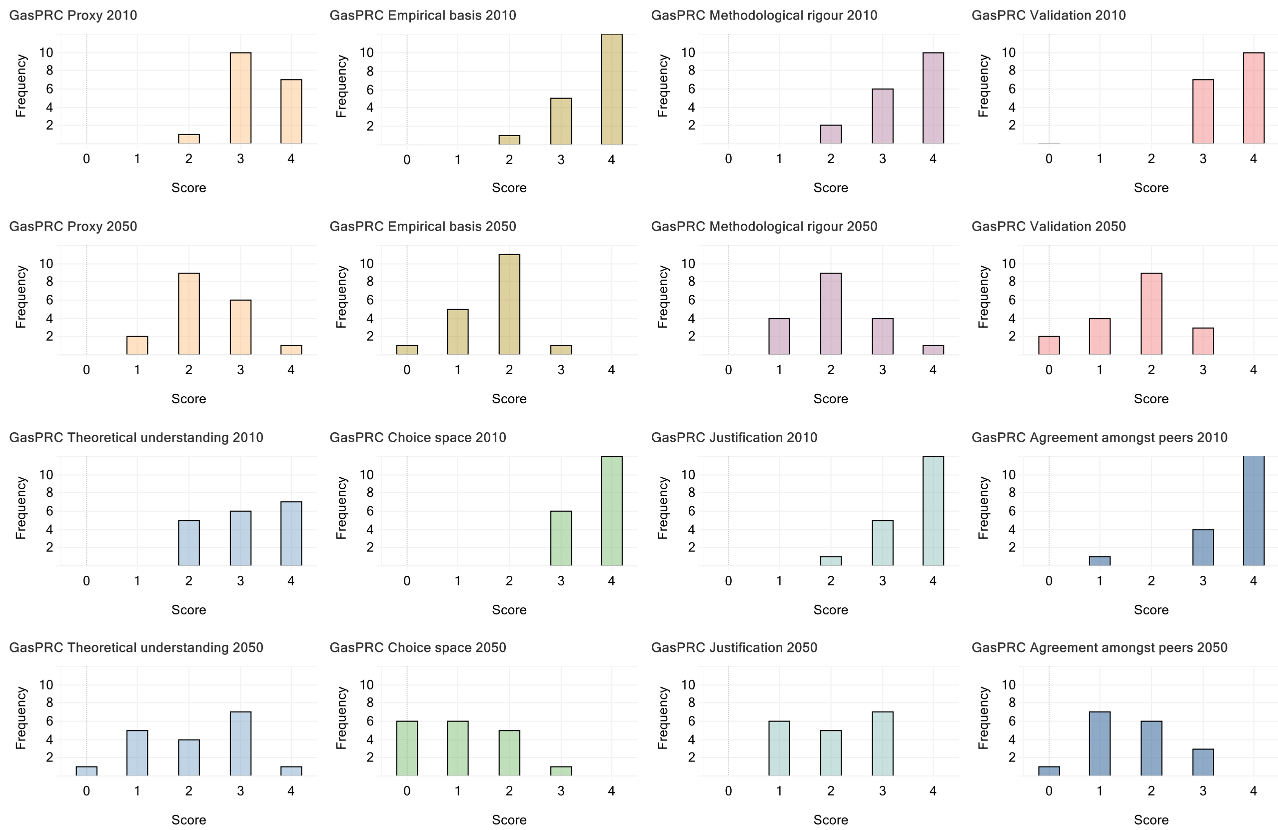
Criteria		No of experts providing a specific score (and mean)												
		2010						2050						
		0	1	2	3	4	μ	0	1	2	3	4	μ	
Proxy	Poor representation	0	0	5	11	2	2.8	0	3	11	4	0	2.1	Exact representation
Empirical basis	Crude speculation	0	0	2	11	5	3.2	0	2	14	2	0	2.0	Observation
Rigour	No discernible rigour in the method, concerns	0	0	3	8	7	3.2	0	1	10	5	2	2.4	Best available practice
Validation	No validation	0	0	6	8	2	2.8	2	4	6	4	0	1.8	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	0	5	8	5	3.0	0	5	7	4	2	2.2	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	0	2	3	9	4	2.8	4	9	3	2	0	1.2	No alternatives
Justification	Completely speculative	0	1	1	12	4	3.1	1	5	8	4	0	1.8	Fully justified
Agreement amongst peers	No agreement, extremely controversial	0	0	1	13	4	3.2	0	8	5	4	0	1.8	Complete or near-complete agreement

Figure C3.2. Frequency plots for criteria scores across model assumptions: biomass emission factor. For each criteria, the 2010 score plots are shown directly above the 2050 score plots.



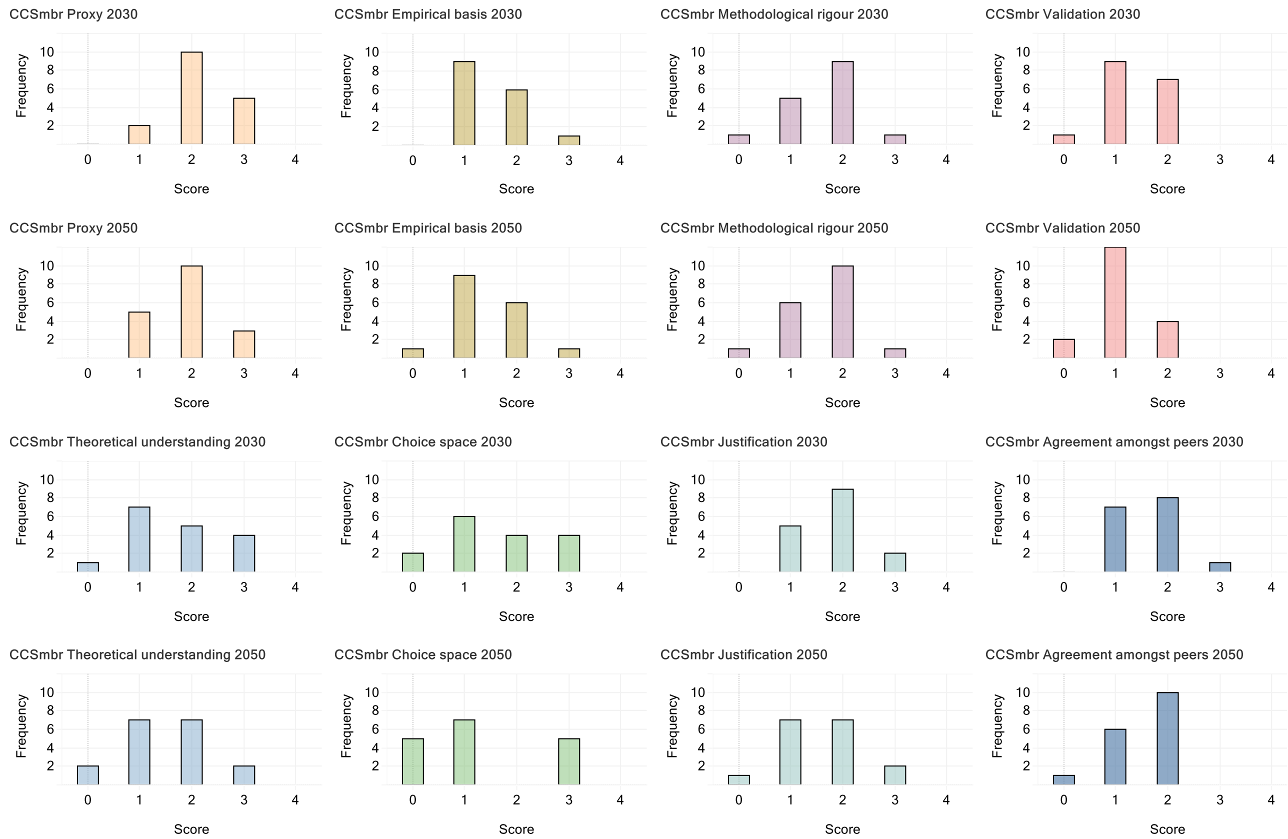
Criteria		No of experts providing a specific score (and mean)												
		2010						**2050**						
		0	**1**	**2**	**3**	**4**	**μ**	**0**	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation	0	4	12	1	0	1.8	1	9	7	1	0	1.4	Exact representation
Empirical basis	Crude speculation	0	3	8	6	0	2.2	0	8	10	0	0	1.6	Observation
Rigour	No discernible rigour in the method, concerns	0	4	10	3	0	1.9	1	9	6	1	1	1.6	Best available practice
Validation	No validation	1	2	9	4	0	2.0	4	6	6	1	0	1.2	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	3	7	7	0	2.2	1	6	8	3	0	1.7	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	3	8	3	2	1	1.4	7	9	1	0	1	0.8	No alternatives
Justification	Completely speculative	0	5	10	2	0	1.8	0	9	8	1	0	1.6	Fully justified
Agreement amongst peers	No agreement, extremely controversial	2	8	4	3	0	1.5	2	10	5	0	0	1.2	Complete or near-complete agreement

Figure C3.3. Frequency plots for criteria scores across model assumptions: gas prices. For each criteria, the 2010 score plots are shown directly above the 2050 score plots.



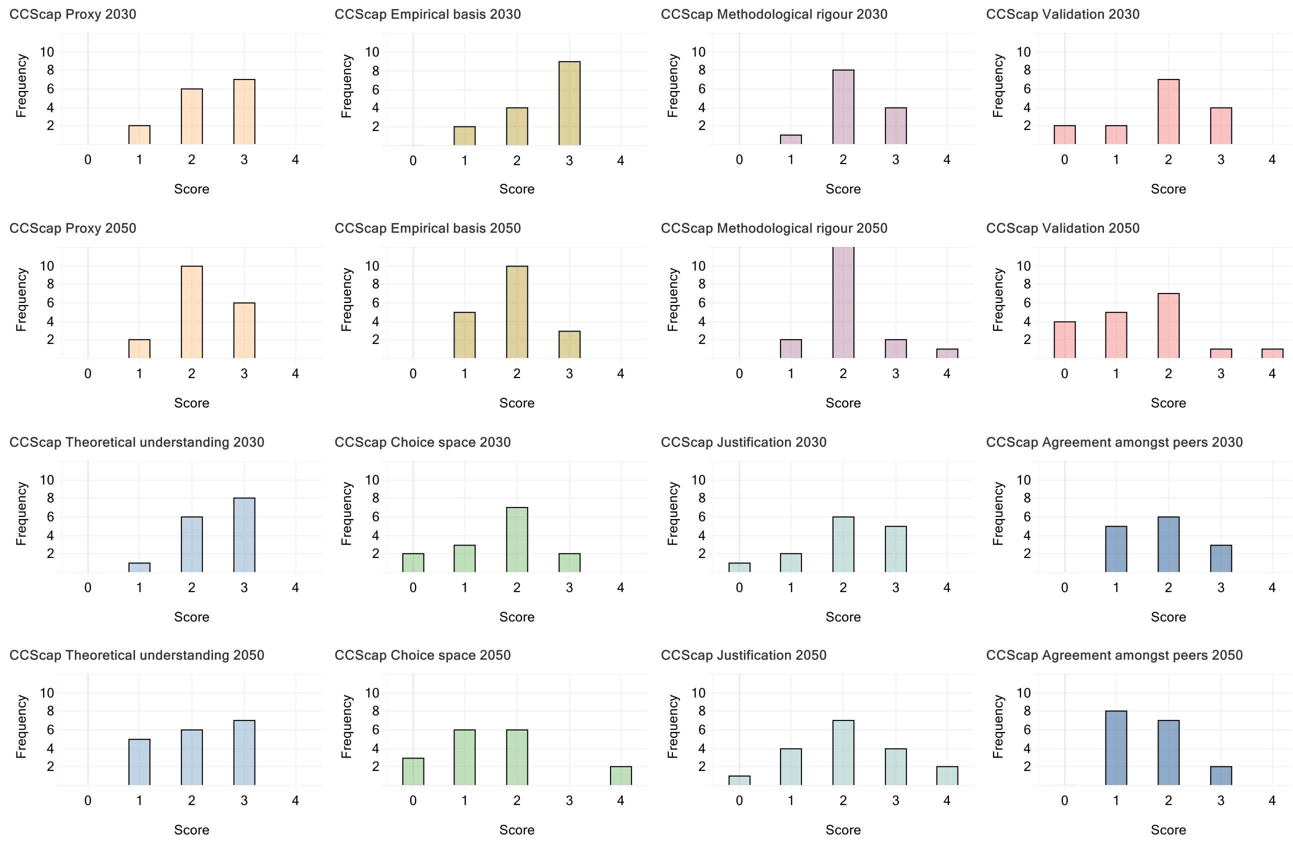
Criteria		No of experts providing a specific score (and mean)												
		2010						**2050**						
		0	**1**	**2**	**3**	**4**	**μ**	**0**	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation	0	0	1	10	7	3.3	0	2	9	6	1	2.3	Exact representation
Empirical basis	Crude speculation	0	0	1	5	12	3.6	1	5	11	1	0	1.7	Observation
Rigour	No discernible rigour in the method, concerns	0	0	2	6	10	3.4	0	4	9	4	1	2.1	Best available practice
Validation	No validation	0	0	0	7	10	3.6	2	4	9	3	0	1.7	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	0	5	6	7	3.1	1	5	4	7	1	2.1	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	0	0	0	6	12	3.7	6	6	5	1	0	1.1	No alternatives
Justification	Completely speculative	0	0	1	5	12	3.6	0	6	5	7	0	2.1	Fully justified
Agreement amongst peers	No agreement, extremely controversial	0	1	0	4	13	3.6	1	7	6	3	0	1.6	Complete or near-complete agreement

Figure C3.4. Frequency plots for criteria scores across model assumptions: CCGT with CCS maximum build rate. For each criteria, the 2030 score plots are shown directly above the 2050 score plots.



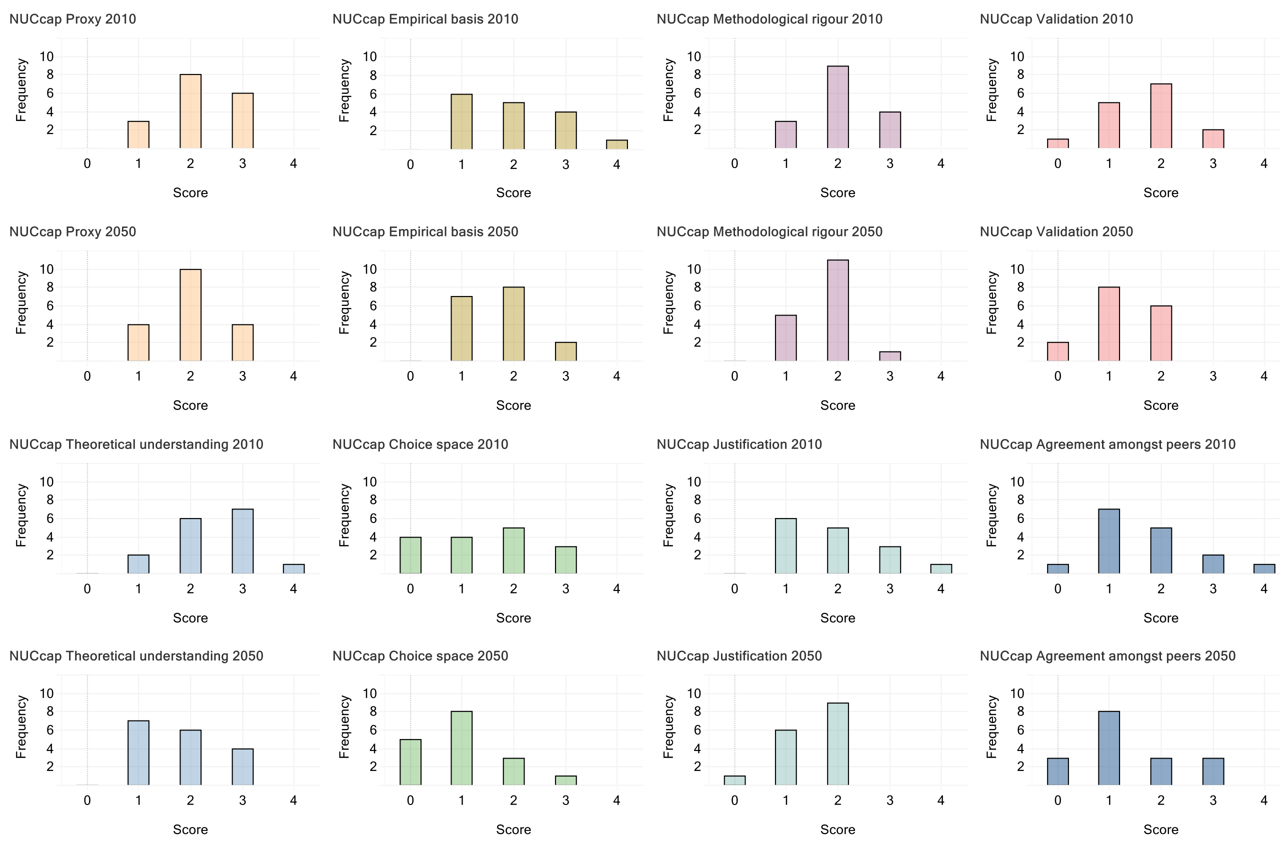
Criteria		No of experts providing a specific score (and mean)												
		2030						**2050**						
		0	**1**	**2**	**3**	**4**	**μ**	**0**	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation	0	2	10	5	0	2.2	0	5	10	3	0	1.9	Exact representation
Empirical basis	Crude speculation	0	9	6	1	0	1.5	1	9	6	1	0	1.4	Observation
Rigour	No discernible rigour in the method, concerns	1	5	9	1	0	1.6	1	6	10	1	0	1.6	Best available practice
Validation	No validation	1	9	7	0	0	1.4	2	12	4	0	0	1.1	Huge database of reliable sources
Theoretical understanding	Crude speculation	1	7	5	4	0	1.7	2	7	7	2	0	1.5	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	2	6	4	4	0	1.6	5	7	0	5	0	1.3	No alternatives
Justification	Completely speculative	0	5	9	2	0	1.8	1	7	7	2	0	1.6	Fully justified
Agreement amongst peers	No agreement, extremely controversial	0	7	8	1	0	1.6	1	6	10	0	0	1.5	Complete or near-complete agreement

Figure C3.5. Frequency plots for criteria scores across model assumptions: CCGT with CCS capital expenditure level. For each criteria, the 2030 score plots are shown directly above the 2050 score plots.



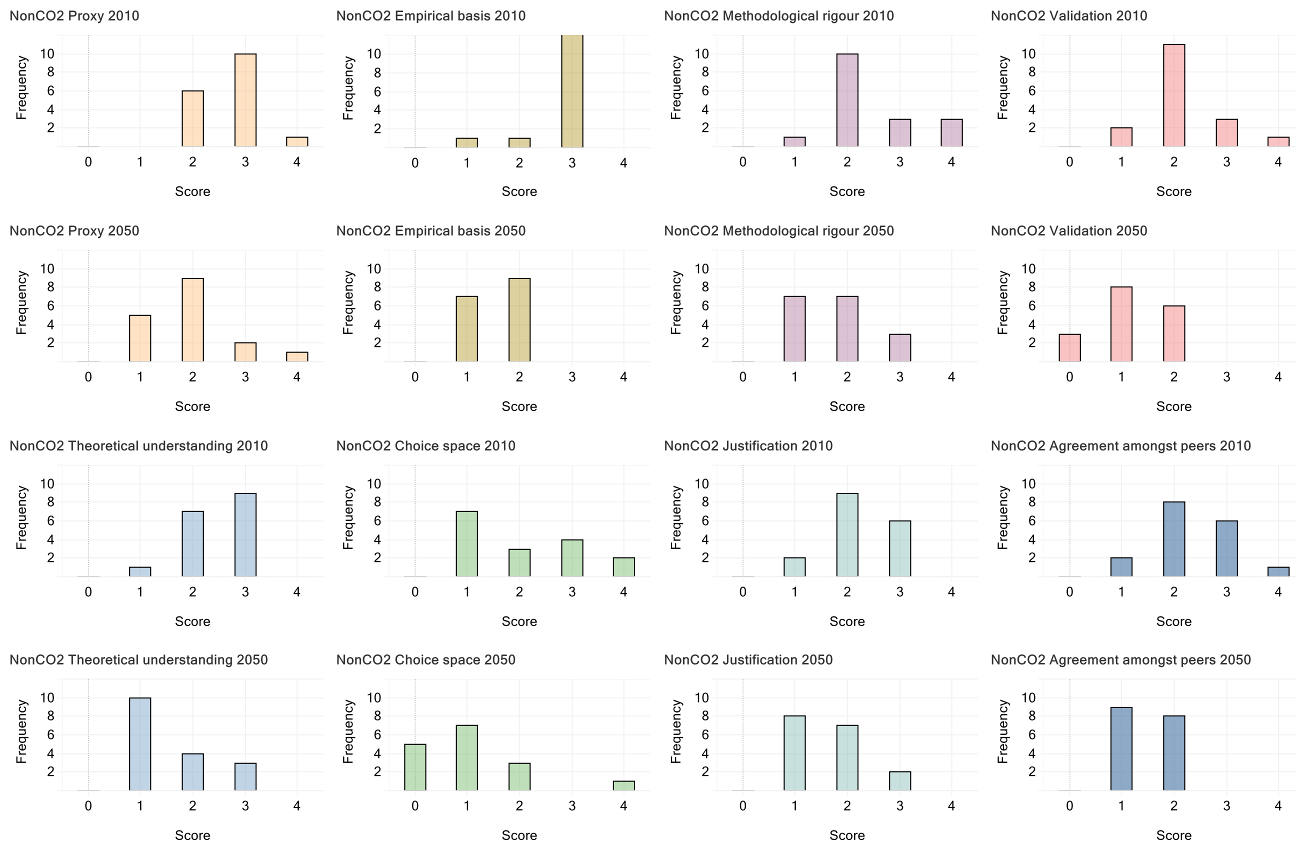
Criteria		No of experts providing a specific score (and mean)												
		2030						**2050**						
		0	**1**	**2**	**3**	**4**	**μ**	**0**	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation	0	2	6	7	0	2.3	0	2	10	6	0	2.2	Exact representation
Empirical basis	Crude speculation	0	2	4	9	0	2.5	0	5	10	3	0	1.9	Observation
Rigour	No discernible rigour in the method, concerns	0	1	8	4	0	2.2	0	2	13	2	1	2.1	Best available practice
Validation	No validation	2	2	7	4	0	1.9	4	5	7	1	1	1.4	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	1	6	8	0	2.5	0	5	6	7	0	2.1	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	2	3	7	2	0	1.6	3	6	6	0	2	1.5	No alternatives
Justification	Completely speculative	1	2	6	5	0	2.1	1	4	7	4	2	2.1	Fully justified
Agreement amongst peers	No agreement, extremely controversial	0	5	6	3	0	1.9	0	8	7	2	0	1.6	Complete or near-complete agreement

Figure C3.6. Frequency plots for criteria scores across model assumptions: Nuclear Gen III capital expenditure level. For each criteria, the 2010 score plots are shown directly above the 2050 score plots.



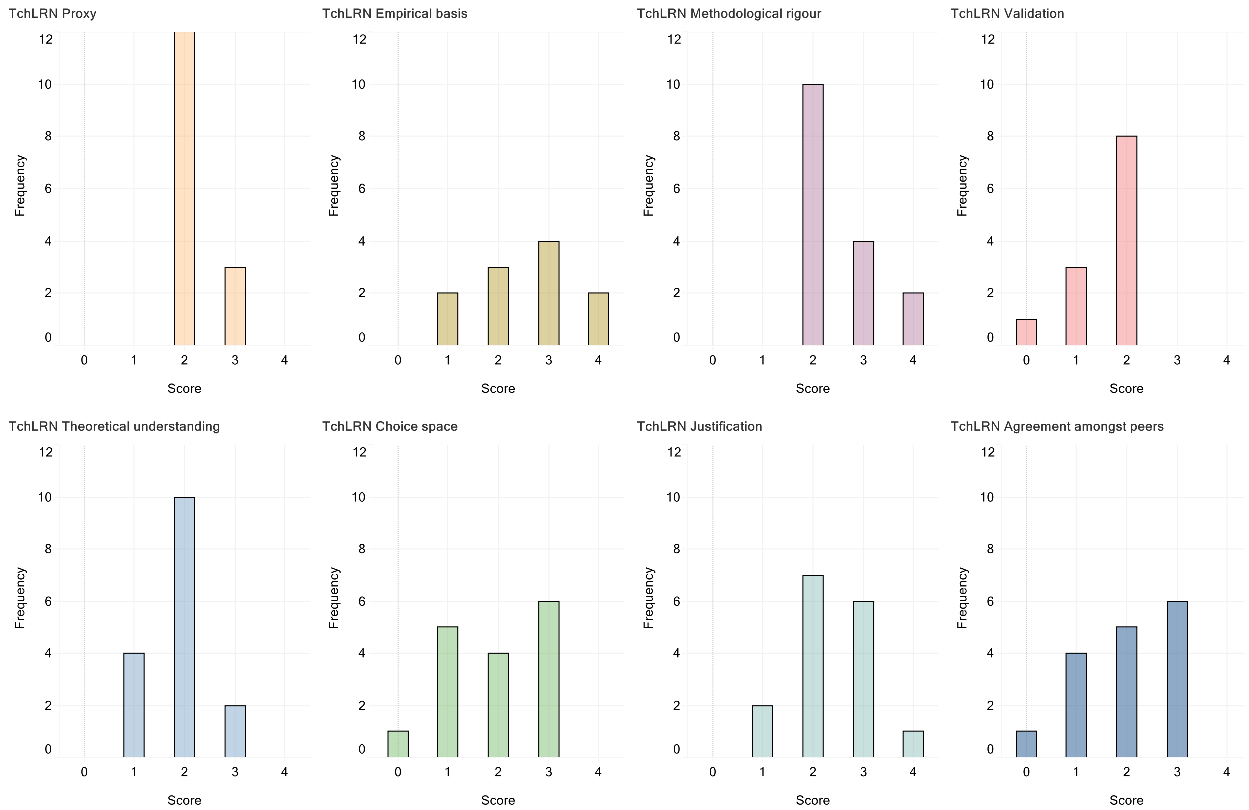
Criteria		No of experts providing a specific score (and mean)												
		2010						**2050**						
		0	**1**	**2**	**3**	**4**	**µ**	**0**	**1**	**2**	**3**	**4**	**µ**	
Proxy	Poor representation	0	3	8	6	0	2.2	0	4	10	4	0	2.0	Exact representation
Empirical basis	Crude speculation	0	6	5	4	1	2.0	0	7	8	2	0	1.7	Observation
Rigour	No discernible rigour in the method, concerns	0	3	9	4	0	2.1	0	5	11	1	0	1.8	Best available practice
Validation	No validation	1	5	7	2	0	1.7	2	8	6	0	0	1.3	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	2	6	7	1	2.4	0	7	6	4	0	1.8	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	4	4	5	3	0	1.4	5	8	3	1	0	1.0	No alternatives
Justification	Completely speculative	0	6	5	3	1	1.9	1	6	9	0	0	1.5	Fully justified
Agreement amongst peers	No agreement, extremely controversial	1	7	5	2	1	1.7	3	8	3	3	0	1.4	Complete or near-complete agreement

Figure C3.7. Frequency plots for criteria scores across model assumptions: Non-CO2 emissions level. For each criteria, the 2010 score plots are shown directly above the 2050 score plots.



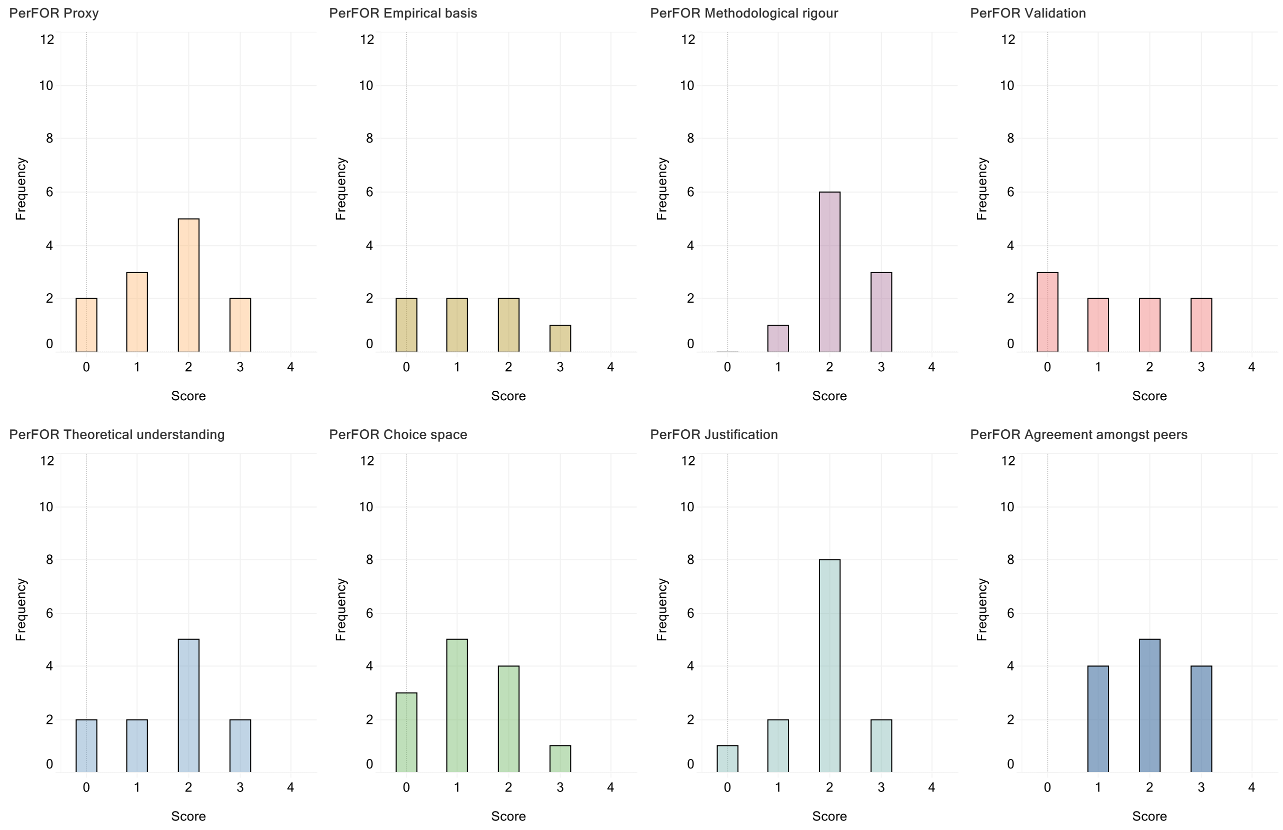
Criteria		No of experts providing a specific score (and mean)												
		2010						**2050**						
		0	**1**	**2**	**3**	**4**	**μ**	**0**	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation	0	0	6	10	1	2.7	0	5	9	2	1	1.9	Exact representation
Empirical basis	Crude speculation	0	1	1	14	0	2.8	0	7	9	0	0	1.6	Observation
Rigour	No discernible rigour in the method, concerns	0	1	10	3	3	2.5	0	7	7	3	0	1.8	Best available practice
Validation	No validation	0	2	11	3	1	2.2	3	8	6	0	0	1.2	Huge database of reliable sources
Theoretical understanding	Crude speculation	0	1	7	9	0	2.5	0	10	4	3	0	1.6	Strong theoretical understanding
Choice space	Extremely wide range of alternatives	0	7	3	4	2	2.1	5	7	3	0	1	1.1	No alternatives
Justification	Completely speculative	0	2	9	6	0	2.2	0	8	7	2	0	1.6	Fully justified
Agreement amongst peers	No agreement, extremely controversial	0	2	8	6	1	2.4	0	9	8	0	0	1.5	Complete or near-complete agreement

Figure C3.8. Frequency plots for criteria scores across model assumptions: exogenous approach to technology learning.



Criteria		No of experts providing a specific score (and mean)												
								Not year specific						
								0	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation							0	0	13	3	0	2.2	Exact representation
Empirical basis	Crude speculation							0	2	3	4	2	2.5	Observation
Rigour	No discernible rigour in the method, concerns							0	0	10	4	2	2.5	Best available practice
Validation	No validation							1	3	8	0	0	1.6	Huge database of reliable sources
Theoretical understanding	Crude speculation							0	4	10	2	0	1.9	Strong theoretical understanding
Choice space	Extremely wide range of alternatives							1	5	4	6	0	1.9	No alternatives
Justification	Completely speculative							0	2	7	6	1	2.4	Fully justified
Agreement amongst peers	No agreement, extremely controversial							1	4	5	6	0	2.0	Complete or near-complete agreement

Figure C3.9. Frequency plots for criteria scores across model assumptions: perfect foresight formulation.



Criteria		No of experts providing a specific score (and mean)												
								Not year specific						
								0	**1**	**2**	**3**	**4**	**μ**	
Proxy	Poor representation							2	3	5	2	0	1.6	Exact representation
Empirical basis	Crude speculation							2	2	2	1	0	1.3	Observation
Rigour	No discernible rigour in the method, concerns							0	1	6	3	0	2.2	Best available practice
Validation	No validation							3	2	2	2	0	1.3	Huge database of reliable sources
Theoretical understanding	Crude speculation							2	2	5	2	0	1.6	Strong theoretical understanding
Choice space	Extremely wide range of alternatives							3	5	4	1	0	1.2	No alternatives
Justification	Completely speculative							1	2	8	2	0	1.8	Fully justified
Agreement amongst peers	No agreement, extremely controversial							0	4	5	4	0	2.0	Complete or near-complete agreement

Appendix C4. NUSAP scores (mean and St. dev.) for each criterion, by assumption

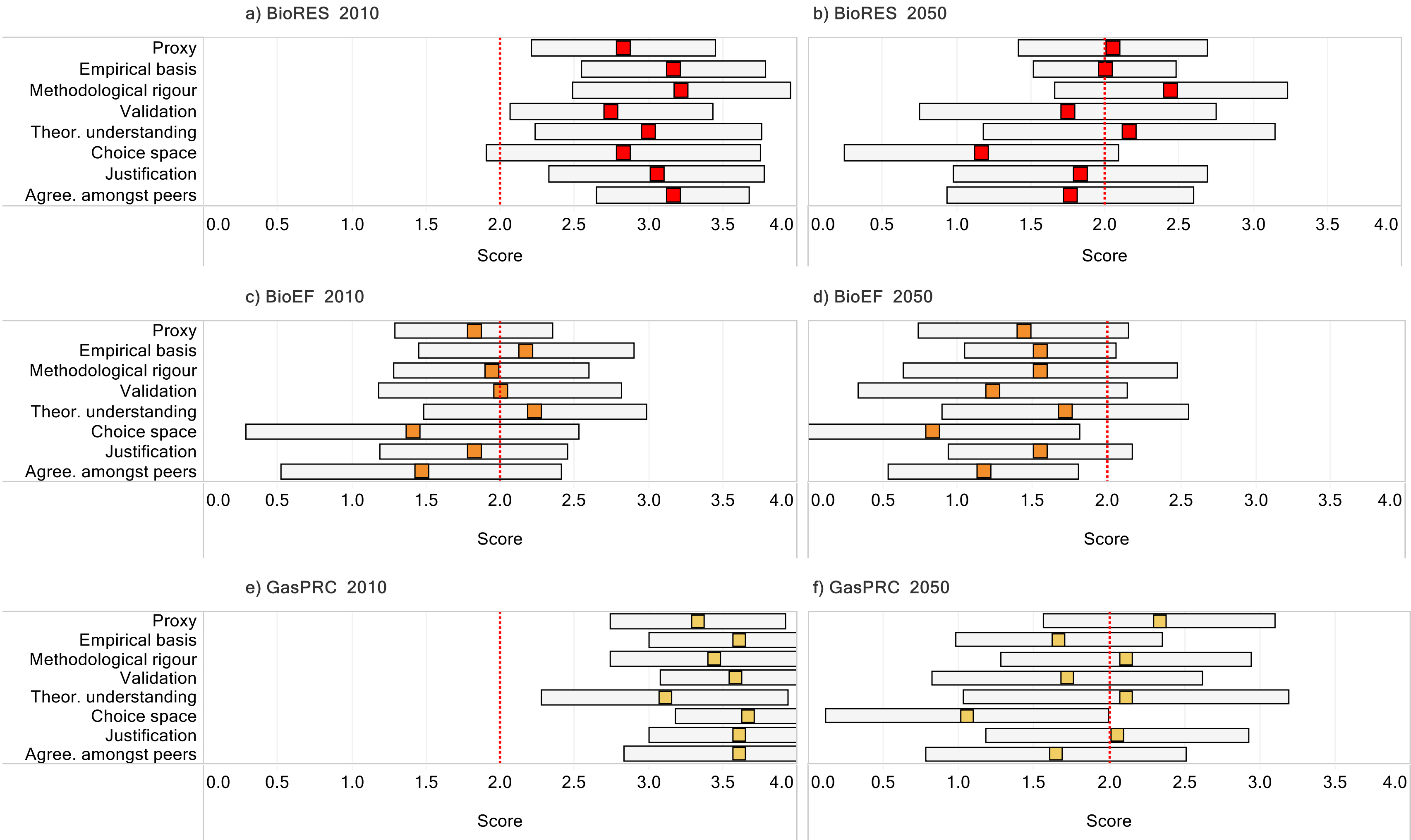


Figure C4.1. ***Mean and standard deviation for scores relating to resource assumptions.*** The graphs on the left of the panel are for current assumptions (2010) and on the right, for 2050. The red line provides a reference point for comparison, indicating the central score value of 2.

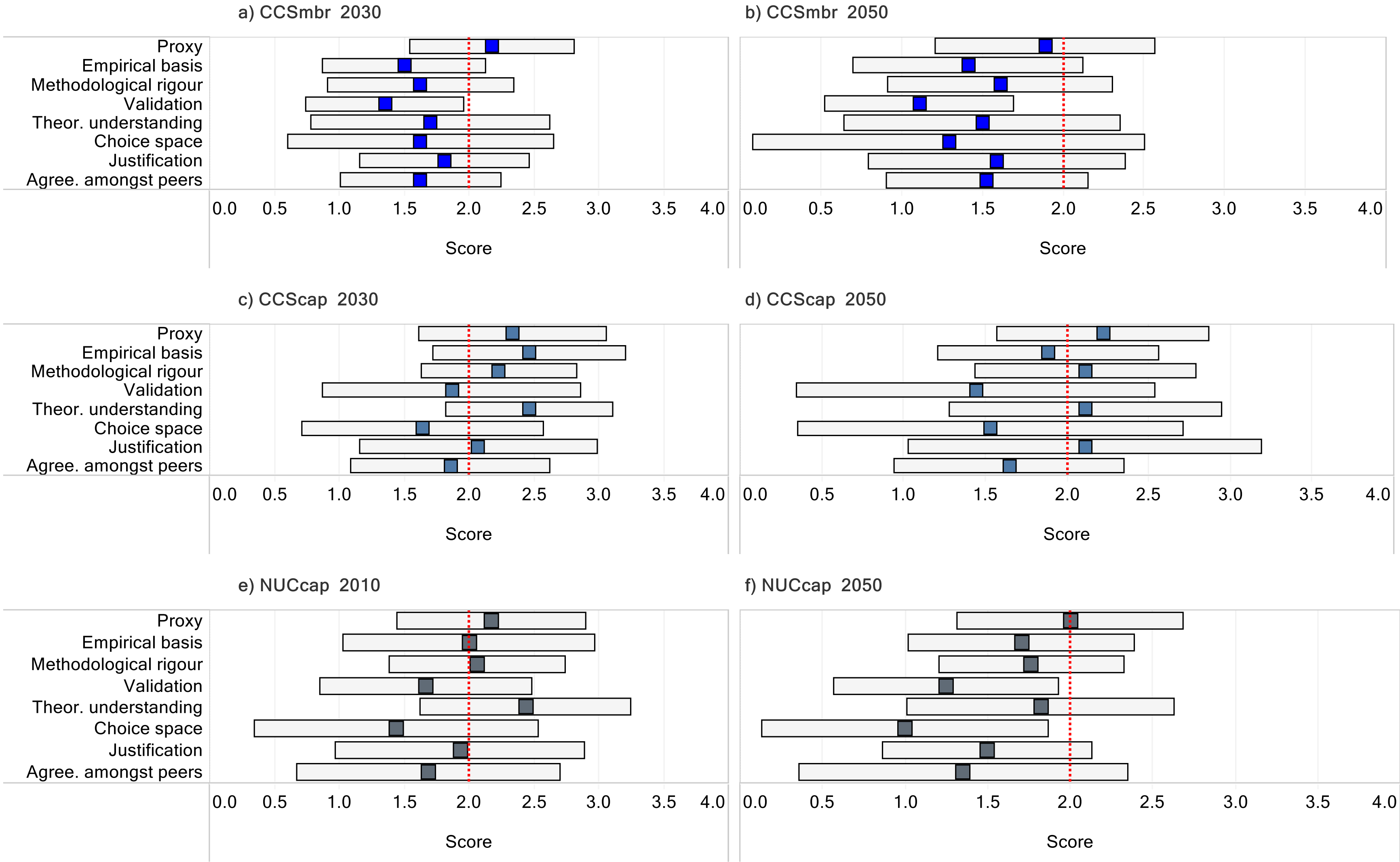


Figure C4.2. ***Mean and standard deviation for scores relating to technology assumptions.*** The graphs on the left of the panel are for nearer term assumptions (2010 for NUC, 2030 for CCS) and on the right, for 2050. The red line provides a reference point for comparison, indicating the central score value of 2.

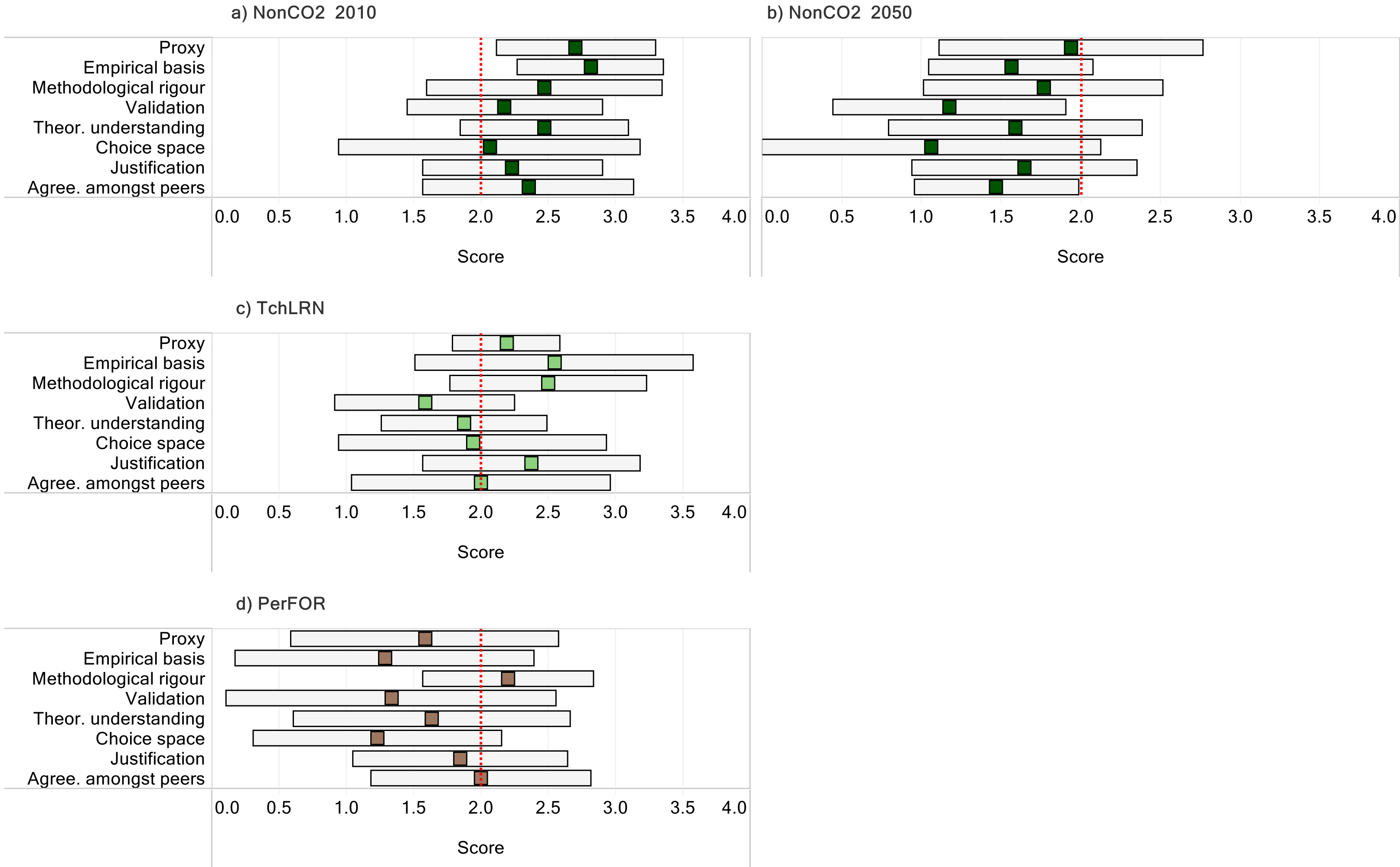


Figure C4.3. ***Mean and standard deviation for scores relating to emissions accounting and structural assumptions.*** For emissions accounting (top of panel), the scores are for 2010 (left) and 2050 (right) assumptions. Structural assumptions (bottom of panel) are time independent. The red line provides a reference point for comparison, indicating the central score value of 2.

Appendix C5. Description of the Morris Method used in diagnostic diagram

In section 5.3.3, a diagnostic diagram has been developed that combines the information on qualitative uncertainties elicited during the NUSAP workshop with modelling analysis from running the ESME model, to explore the impact of quantitative uncertainty on meeting UK decarbonisation goals. Here the quantitative analysis feeding into that diagnostic diagram is described.

The quantitative uncertainty analysis undertaken is based on an approach to sensitivity analysis known as the Morris Method (Morris, 1991). Such approaches allow for an understanding of 'how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input'(Saltelli et al., 2004). The Morris Method, also known as the Elementary Effects Method, provides a computationally efficient means of screening a model to determine which input parameters the model solution is most sensitive to. For the purposes of this exercise, the objective is to understand the influence of input uncertainty on the costs of decarbonisation. This choice of output metric is important as the model is driven by the objective of minimising costs. It is useful for a decision maker who wants to find cost-effective pathways to better understand what input parameters might impact on this objective, and to develop research and policy direction accordingly.

The Morris Method is implemented in the ESME model as described in detail in a paper by (Usher, 2015). Note that all simulations are undertaken to meet the UK GHG emission reductions legislated, which leads to an 80% reduction in 2050, relative to 1990. Uncertain input parameters are first grouped together, with ranges defined for each, negating the need for probability distributions. The input ranges are then discretized into a grid, defined by a number of levels (p) based on dimensions determined by the number of input factors (k). Trajectories (N) are then randomly generated which are used to sample across this multi-dimensional space. These trajectories need to be independent from each other to cover the uncertainty space of the inputs.

For a given trajectory, a starting value for each input k is selected from the defined value range. In the next step a value for one variable is changed, with all other inputs fixed, with the change in model outcome 1 compared to the starting point. A second variable is then changed, with the first variable kept at its changed value, and all other inputs at their starting value, with the model outcome 2 compared to outcome 1. This is repeated until all inputs are changed. This process is repeated for all trajectories, which crucially have different starting points (as described in chapter 4 in (Van der Sluijs et al., 2002)). Elementary effects are calculated by comparing the change in input parameter values from the generated trajectories, with the change in the output result of interest, for example the overall system costs, as used in this research. This Morris Method analysis was implemented in ESME using the python library SALib (Herman and Usher, 2017), using an approach based on that by (Campolongo et al., 2007). The following analysis set-up, resulting in 640 simulations, was as follows: p = 4, k = X, N = 10.

The results are shown in Figure C5.1 below. The input parameters to which the model is most sensitive are ranked, with length of the bar chart values showing the influence on the variance in the output metric, total system costs. It highlights that the top four parameters – CCS build rate, biomass resource level, gas price and oil price - can explain the majority of the variance. The error bars also provide important information, with larger bars suggesting interactions between parameters or an indication of non-linear effects.

Interactions between model input parameters can be explained by thinking through examples of the effect of different parameter values. In the ESME model, the imposition of a low build rate for CCS would require a substitute low-carbon technology to meet the demand for energy services subject to a constraint on emissions. However, a constraint on CCS also reduces the availability of BECCS, diverting the use of biomass to residential heating which is the next most cost-effective mitigation option in the model. On the other hand, high availability of CCS with a constraint on biomass pushes the model to seek a different portfolio of mitigation options.

Non-linear effects are also evident in the effect of constraints upon the cost of mitigation. For example, constraints on technologies force the model to choose a cocktail of ever more costly and exotic technologies resulting in an exponential increase in total energy system cost.

The four main variables, CCS build rate, biomass resource availability, the cost of liquid fuels and gas, account for much of the variability in total energy system cost. In fact, there is a almost exponential relationship between most and leave influential variable. Thus the 1st and 4th ranked variable are significantly different in their influence, while 5th and 10th are very similar in their influence on the model cost. A considerable number of model inputs have little, if any influence on model outputs, raising the opportunity to remove them from the model. For example, under scenarios in which a stringent emissions constraint is imposed upon the model, technologies such as PC (pulverised) and IGCC (integrated gasification combined cycle) coal are not chosen by the model due to the large emissions.

The role of transport related parameter variables is indicative of the major role played by cars in the UK energy system. Note that the total system cost in ESME includes the capital cost of private road vehicles. Likewise, the role of liquid fuel sources, predominantly used in the transport sector in the first half of the model horizon (out to 2030) makes the model highly sensitive to changes in the cost of petrol.

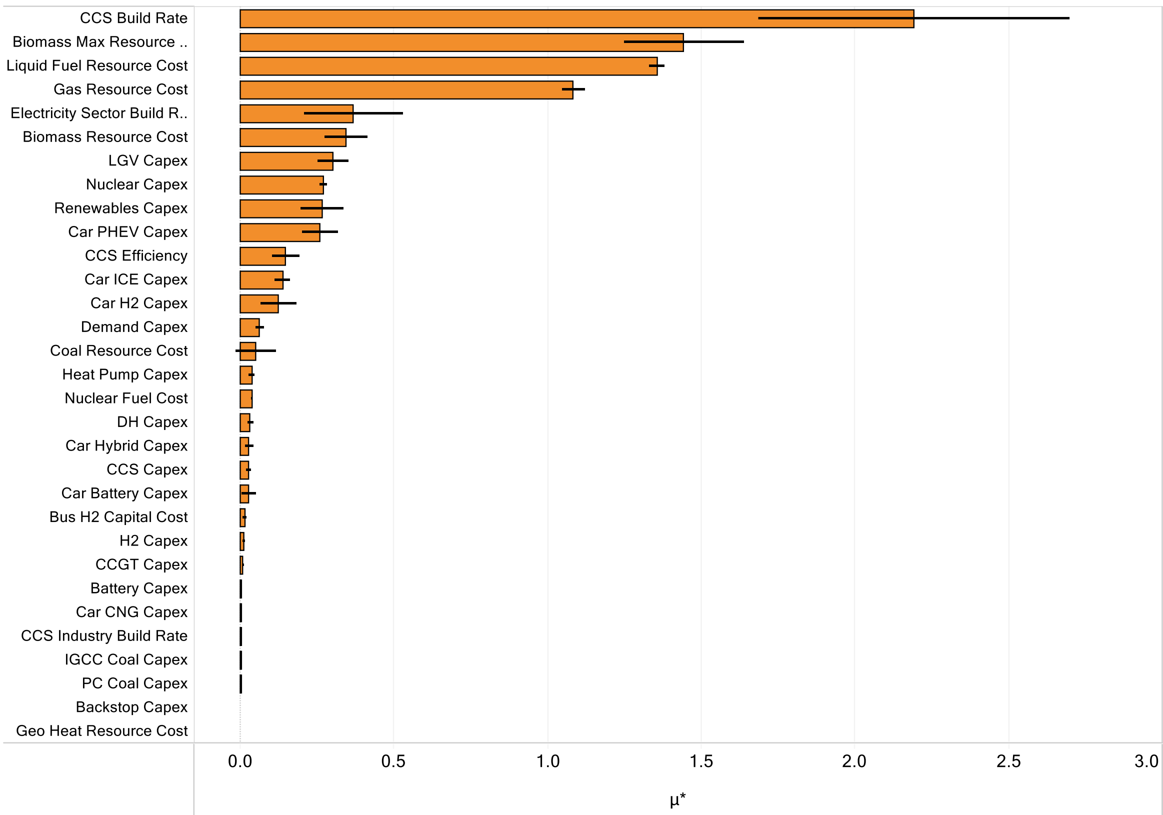


Figure C5.1. Results of Morris Method analysis, ranking the most important input parameters in relation to the variance in the output metric discounted system costs

Appendix D. Supplementary information for Chapter 6

Appendix D1. Uncertainty parameterisation

The table below lists the input parameters subject to uncertainty distributions, with the distribution range in the right hand columns. Further information on the data input parameters can be found at http://www.eti.co.uk/programmes/strategy/esme. Note that these data assumptions are for v4.3, and in the main, are consistent with the input assumptions for v4.2, which is the version used in this analysis. The key updates in v4.3 are shown in the 'change log' at the end of the document; all have been integrated into the version that is being used (v4.2). Nuclear costs, and uncertainty distributions are based on this research, and therefore will differ from those published under the released v4.2.

The focus of the uncertainty assessment is on costs of technologies and energy commodities. Annual maximum build rate uncertainties are also applied to nuclear and CCS technologies whose deployment are subject to many additional factors e.g. planning, social acceptability, political support. The uncertainty distributions in 2050 are sampled using the Monte Carlo technique. For each simulation, values for intermediate years (prior to 2050) are determined based on interpolation back to the base year (2010) value based on an index using the shape of the original 2010 to 2050 trajectory.

Table D1.1. Model input parameter assumptions, and uncertainty ranges

			Values			2050 distribution range	
Technology type	**Technology**	**Parameter type**	**2010**	**2050**	**Units (£/unit for cost parameters)**	**Low**	**High**
Storage	Battery - Li-ion	Capital Cost	668	267	kWh	-50%	50%
	Battery - NaS	Capital Cost	241	229	kWh	-10%	10%
	Compressed Air Storage of Electricity	Capital Cost	10	10	kWh	-30%	30%
	Flow battery - Redox	Capital Cost	443	266	kWh	-50%	50%
	Flow battery - Zn-Br	Capital Cost	280	252	kWh	-10%	10%
Power	Biomass Fired Generation	Capital Cost	2417	2357	kW	-10%	10%
	CCGT	Capital Cost	589	496	kW	-10%	10%
	CCGT with CCS	Capital Cost	997	777	kW	-42%	60%
	Gas Macro CHP	Capital Cost	562	489	kW	-10%	10%
	Geothermal Plant (EGS) Electricity & Heat	Capital Cost	9507	8556	kW	-50%	50%
	Geothermal Plant (HSA) Electricity & Heat	Capital Cost	25869	23282	kW	-30%	30%
	Geothermal Plant (HSA) Heat Only	Capital Cost	1459	1313	kW	-10%	10%
	H2 Turbine	Capital Cost	590	500	kW	-10%	10%
	IGCC Biomass	Capital Cost	1911	1507	kW	-50%	50%
	IGCC Biomass with CCS	Capital Cost	4069	2661	kW	-50%	50%
	IGCC Coal	Capital Cost	1827	1369	kW	-30%	30%
	IGCC Coal with CCS	Capital Cost	2343	1719	kW	-25%	100%
	Incineration of Waste	Capital Cost	1712	1472	kW	-10%	10%
	Nuclear (Gen III)	Capital Cost	6000	4200	kW	-20%	50%

	Nuclear (Gen III)	Max annual build rate	1000	2000000	kW	-90%	25%
	Nuclear (Gen IV)	Capital Cost	6000	4200	kW	-20%	50%
	Nuclear (Gen IV)	Max annual build rate	100	240000	kW	-90%	25%
	Nuclear (small modular reactor, or SMR)	Capital Cost	6500	6500	kW	-20%	50%
	Nuclear (small modular reactor, or SMR)	Max annual build rate	100	1200000	kW	-100%	20%
	Offshore Wind (fixed)	Capital Cost	3000	1500	kW	-30%	15%
	Offshore Wind (floating)	Capital Cost	3000	1261	kW	-30%	15%
	Onshore Wind	Capital Cost	1489	1250	kW	-30%	30%
	PC Coal	Capital Cost	1565	1326	kW	-10%	10%
	PC Coal with CCS	Capital Cost	2868	2232	kW	-42%	60%
	Severn Barrage	Capital Cost	2330	2330	kW	-30%	50%
	Solar PV (Domestic)	Capital Cost	3300	673	kW	-30%	30%
	Solar PV (Farm)	Capital Cost	1400	449	kW	-30%	30%
	Tidal Range	Capital Cost	3030	2580	kW	-50%	50%
	Tidal Stream	Capital Cost	1890	1050	kW	-50%	50%
	Waste Gasification	Capital Cost	3750	3750	kW	-50%	50%
	Waste Gasification with CCS	Capital Cost	5800	5800	kW	-50%	50%
	Wave Power	Capital Cost	7810	3540	kW	-50%	50%
Fuel production	Biodiesel Production	Capital Cost	168	168	kW	-30%	30%
	Biokerosine Production	Capital Cost	219	219	kW	-50%	50%
	Biopetrol Production	Capital Cost	883	641	kW	-30%	30%
	Biopetrol Production with CCS	Capital Cost	883	671	kW	-30%	30%
	H2 Plant (Biomass Gasification with CCS)	Capital Cost	1204	828	kW	-50%	50%
	H2 Plant (Biomass Gasification)	Capital Cost	1061	763	kW	-50%	50%
	H2 Plant (Coal Gasification with CCS)	Capital Cost	950	698	kW	-50%	50%
	H2 Plant (Electrolysis)	Capital Cost	1266	611	kW	-30%	30%
	H2 Plant (SMR with CCS)	Capital Cost	553	459	kW	-50%	50%
	SNG Plant (Biomass Gasification with CCS)	Capital Cost	1209	831	kW	-50%	50%
	SNG Plant (Biomass Gasification)	Capital Cost	969	764	kW	-50%	50%
Transport	Bus (BEV)	Capital Cost	182574	117300	vehicle	-50%	50%
	Bus (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	152920	112579	vehicle	-30%	30%
	Bus (Dual Fuel Direct)	Capital Cost	146002	108100	vehicle	-30%	30%
	Bus (Dual Fuel Port)	Capital Cost	146002	110300	vehicle	-30%	30%
	Bus (Flywheel Hybrid)	Capital Cost	138085	110615	vehicle	-30%	30%
	Bus (Gas SI Flywheel Hybrid)	Capital Cost	148570	109252	vehicle	-30%	30%
	Bus (Gas SI)	Capital Cost	141002	104400	vehicle	-30%	30%
	Bus (Hybrid)	Capital Cost	224700	156600	vehicle	-30%	30%
	Bus (Hydrogen FCV)	Capital Cost	520000	153800	vehicle	-50%	50%
	Bus (ICE)	Capital Cost	130000	106400	vehicle	-10%	10%
	Bus (Wireless PHEV)	Capital Cost	165000	112700	vehicle	-30%	30%

	Car Battery (A/B Segment)	Capital Cost	18200	7567	vehicle	-10%	75%
	Car Battery (C/D Segment)	Capital Cost	25373	13161	vehicle	-10%	75%
	Car CNG (A/B Segment)	Capital Cost	10667	8186	vehicle	-10%	10%
	Car CNG (C/D Segment)	Capital Cost	16781	12949	vehicle	-10%	10%
	Car Hybrid (A/B Segment)	Capital Cost	10348	6125	vehicle	-10%	15%
	Car Hybrid (C/D Segment)	Capital Cost	15603	9146	vehicle	-10%	15%
	Car Hydrogen FCV (A/B Segment)	Capital Cost	33064	8192	vehicle	-10%	75%
	Car Hydrogen FCV (C/D Segment)	Capital Cost	52221	14234	vehicle	-10%	75%
	Car Hydrogen ICE (A/B Segment)	Capital Cost	29927	9207	vehicle	-10%	50%
	Car Hydrogen ICE (C/D Segment)	Capital Cost	47488	14847	vehicle	-10%	50%
	Car ICE (A/B Segment)	Capital Cost	7631	5662	vehicle	-10%	10%
	Car ICE (C/D Segment)	Capital Cost	11123	8456	vehicle	-10%	10%
	Car PHEV (A/B Segment)	Capital Cost	17710	6832	vehicle	-10%	25%
	Car PHEV (C/D Segment)	Capital Cost	26594	10328	vehicle	-10%	25%
	HGV (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	97212	64767	vehicle	-30%	30%
	HGV (Dual Fuel Direct)	Capital Cost	92228	59253	vehicle	-30%	30%
	HGV (Dual Fuel Port)	Capital Cost	81807	58143	vehicle	-30%	30%
	HGV (Flywheel Hybrid)	Capital Cost	81109	60965	vehicle	-30%	30%
	HGV (Gas SI Flywheel Hybrid)	Capital Cost	83286	62200	vehicle	-30%	30%
	HGV (Gas SI)	Capital Cost	71807	56698	vehicle	-10%	10%
	HGV (Hydrogen FCV)	Capital Cost	1728053	455325	vehicle	-10%	75%
	HGV (ICE Euro 6)	Capital Cost	72337	57578	vehicle	-10%	10%
	LGV (BEV)	Capital Cost	65865	21200	vehicle	-10%	75%
	LGV (Dual Fuel Direct)	Capital Cost	39140	38640	vehicle	-10%	10%
	LGV (Dual Fuel Port)	Capital Cost	38140	37640	vehicle	-10%	10%
	LGV (Gas SI)	Capital Cost	31120	30620	vehicle	-10%	10%
	LGV (Hybrid)	Capital Cost	30290	16680	vehicle	-10%	10%
	LGV (Hydrogen FCV)	Capital Cost	84780	25737	vehicle	-10%	75%
	LGV (Hydrogen ICE)	Capital Cost	81911	28773	vehicle	-10%	50%
	LGV (ICE)	Capital Cost	21871	15350	vehicle	-10%	10%
	LGV (PHEV)	Capital Cost	36335	17050	vehicle	-10%	25%
	MGV (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	61302	43621	vehicle	-30%	30%
	MGV (Dual Fuel Direct)	Capital Cost	59721	38369	vehicle	-30%	30%
	MGV (Dual Fuel Port)	Capital Cost	56350	40050	vehicle	-30%	30%
	MGV (Flywheel Hybrid)	Capital Cost	49446	39621	vehicle	-30%	30%
	MGV (Gas SI Flywheel Hybrid)	Capital Cost	52339	41928	vehicle	-30%	30%
	MGV (Gas SI)	Capital Cost	46350	36597	vehicle	-30%	30%
	MGV (Hydrogen FCV)	Capital Cost	1728053	455325	vehicle	-10%	75%
	MGV (ICE Euro 6)	Capital Cost	44779	35643	vehicle	-30%	30%
Buildings	District Heating (HD)	Capital Cost	3376-7059	3376-7059	dwelling	-30%	30%
	District Heating (MD)	Capital Cost	5818-9906	5818-9906	dwelling	-30%	30%

	District Heating (LD)	Capital Cost	8365-12903	8365-12903	dwelling	-30%	30%
	Retrofix (LD)	Capital Cost	16363	10187	dwelling	-20%	10%
	Retrofix (MD)	Capital Cost	11904	7284	dwelling	-20%	10%
	Retrofix (HD)	Capital Cost	7629	4917	dwelling	-20%	10%
	Retroplus (LD)	Capital Cost	25495	18237	dwelling	-20%	10%
	Retroplus (MD)	Capital Cost	18974	13608	dwelling	-20%	10%
	Retroplus (HD)	Capital Cost	14765	10246	dwelling	-20%	10%
	Heat Pump (Air Source, Hot Water)	Capital Cost	750	585	kW	-30%	30%
	Heat Pump (Air Source, Space Heat)	Capital Cost	750	585	kW	-30%	30%
	Heat Pump (Ground Source, Hot Water)	Capital Cost	1200	936	kW	-30%	30%
	Heat Pump (Ground Source, Space Heat)	Capital Cost	1200	936	kW	-30%	30%
	Heat Pump (Large Scale Marine)	Capital Cost	300	300	kW	-30%	30%
	Solar Thermal (Domestic non south facing)	Capital Cost	3046	2264	kW	-50%	50%
	Solar Thermal (Domestic south facing)	Capital Cost	1616	1249	kW	-50%	50%
Resources	Biomass Importing	Max build rate	1.08E+10	3.40E+10	kWh	-100%	200%
	Biofuel Imports	Resource Cost	6.01	5.46	p/kWh	-31%	50%
	Biomass Imports	Resource Cost	1.94	2.27	p/kWh	-21%	58%
	Coal	Resource Cost	0.78	0.61	p/kWh	-22%	51%
	Gas	Resource Cost	1.41	1.86	p/kWh	-39%	16%
	Liquid Fuel	Resource Cost	4.62	4.20	p/kWh	-31%	50%
	Nuclear	Resource Cost	0.16	0.34	p/kWh(th)	0%	39%
	UK Biomass	Resource Cost	1.87	1.87	p/kWh	-30%	30%
	UK Biomass	Max Resource Quantity	1.89E+10	1.17E+11	kWh	-30%	30%
	Industry CCS	Max annual build rate	1	100000	industrial units	-90%	50%
	Other CCS	Max annual build rate	100	20000000	kW	-90%	50%

Appendix D2. Metrics used in clustering analysis

These following metrics used in the technology clustering analysis (section 6.3) are taken directly from the model results, and consist of different energy technologies and resources, based on their use in the system (in generation or consumption terms).

Table D2.2. Model scenario metrics using in technology clustering analysis

Metric	Units	Abbreviation
Marginal abatement cost	£/tCO2	SYS-MCC
Total discounted costs	£bln	SYS-TDC
Biomass system wide consumption	TWh	RSR-BIO
Coal system wide consumption	TWh	RSR-COA
Electricity system wide consumption	TWh	RSR-ELC
Gas system wide consumption	TWh	RSR-GAS
Oil system wide consumption	TWh	RSR-OIL
Wind generation level	TWh	ELC-WND
Nuclear generation level	TWh	ELC-NUC
CCS generation level	TWh	ELC-CCS
Other renewable generation level	TWh	ELC-ORE
Fossil generation level	TWh	ELC-FOS
Building bioenergy consumption	TWh	BLD-BIO
Building electricity consumption	TWh	BLD-ELC
Building gas consumption	TWh	BLD-GAS
Building oil consumption	TWh	BLD-OIL
Building district heating consumption	TWh	BLD-DH
Building solar energy consumption	TWh	BLD-SOL
CCS in biofuel production	MtCO2 captured	CCS-BFL
CCS in hydrogen production	MtCO2 captured	CCS-H2
CCS in industry	MtCO2 captured	CCS-IND
CCS in power generation	MtCO2 captured	CCS-ELC
BECCS in biofuel production	MtCO2 captured	CCSB-BFL
BECCS in hydrogen production	MtCO2 captured	CCSB-H2
BECCS in industry	MtCO2 captured	CCSB-IND
BECCS in power generation	MtCO2 captured	CCSB-ELC
Retrofitted dwellings	000s dwellings	DWL-RTR
Imported biofuel	TWh	BFP-IMP
Domestic biofuel production	TWh	BFP-DOM
H2 production by biomass gasification with CCS	TWh	H2-BCCS
H2 production by coal gasification with CCS	TWh	H2-CCCS
H2 production by electrolysis	TWh	H2-ELC
H2 production by gas steam methane reforming (SMR) with CCS	TWh	H2-GCCS
H2 production by gas steam methane reforming (SMR)	TWh	H2-GAS
Industry bioenergy consumption	TWh	IND-BIO
Industry coal consumption	TWh	IND-COA
Industry electricity consumption	TWh	IND-ELC
Industry gas consumption	TWh	IND-GAS

Industry hydrogen consumption	TWh	IND-H2
Industry oil consumption	TWh	IND-OIL
H2 storage	GWh	STR-H2
Building level storage	GWh	STR-BLD
District heating storage	GWh	STR-DH
Imported biofuel	TWh	BFL-IMP
Domestic biofuel production	TWh	BFL-DOM
Aviation & shipping - gas	TWh	TAS-GAS
Aviation & shipping - oil	TWh	TAS-OIL
Aviation & shipping - biofuel	TWh	TAS-BFL
Cars - electricity	TWh	TCAR-ELC
Cars - gas	TWh	TCAR-GAS
Cars - H2	TWh	TCAR-H2
Cars - oil	TWh	TCAR-OIL
Cars - biofuels	TWh	TCAR-BFL
Heavy goods vehicles - electricity	TWh	THGV-ELC
Heavy goods vehicles - gas	TWh	THGV-GAS
Heavy goods vehicles - H2	TWh	THGV-H2
Heavy goods vehicles – oil	TWh	THGV-OIL
Heavy goods vehicles - biofuels	TWh	THGV-BFL
Light goods vehicles - electricity	TWh	TLGV-ELC
Light goods vehicles - H2	TWh	TLGV-H2
Light goods vehicles - oil	TWh	TLGV-OIL
Light goods vehicles - biofuels	TWh	TLGV-BFL
Other transport - electricity	TWh	TOTH-ELC
Other transport - gas	TWh	TOTH-GAS
Other transport - H2	TWh	TOTH-H2
Other transport - oil	TWh	TOTH-OIL
Other transport - biofuels	TWh	TOTH-BFL

This following LDMI derived mitigation wedges provide an indicator of the contribution of different types of mitigation across sectors. These wedges allocate emission reductions across different sectors to three different types of measures: (1) Reduction of energy demands (2) improvements in efficiency and (3) decarbonisation.

Table D2.3. LMDI metrics using in mitigation wedge clustering analysis

Sector	Mitigation wedge	Abbreviation
Buildings – heat	Demand reduction	BLDH_DEM
Buildings – heat	End use efficiency	BLDH_EE
Buildings – heat	Decarbonisation	BLDH_DCB
Industry	Demand reduction	IND_DEM
Industry	End use efficiency	IND_EE
Industry	Decarbonisation	IND_DCB
Transport – aviation	Demand reduction	TAV_DEM
Transport – aviation	End use efficiency	TAV_EE
Transport – aviation	Decarbonisation	TAV_DCB
Transport – car	Demand reduction	TCR_DEM
Transport – car	End use efficiency	TCR_EE
Transport – car	Decarbonisation	TCR_DCB
Transport – road freight	Demand reduction	TFR_DEM
Transport - road freight	End use efficiency	TFR_EE
Transport - road freight	Decarbonisation	TFR_DCB
Transport – shipping	Demand reduction	TSP_DEM
Transport – shipping	End use efficiency	TSP_EE
Transport - shipping	Decarbonisation	TSP_DCB
Power generation	Conversion efficiency	PWR_CEF
Power generation	Decarbonisation	PWR_DCB
Conv - biofuel production	Decarbonisation (based on FE)	CBF_DEM
Conv - biofuel production	Conversion efficiency	CBF_CEF
Conv - biofuel production	Decarbonisation	CBF_DCB
Conv - district heating	Decarbonisation (based on FE)	CDH_DEM
Conv - district heating	Conversion efficiency	CDH_CEF
Conv - district heating	Decarbonisation	CDH_DCB
Conv - H2 production	Decarbonisation (based on FE)	CH2_DEM
Conv - H2 production	Conversion efficiency	CH2_CEF
Conv - H2 production	Decarbonisation	CH2_DCB
Conv - Other	Decarbonisation (based on FE)	COT_DEM
Conv - Other	Conversion efficiency	COT_CEF
Conv - Other	Decarbonisation	COT_DCB

Appendix D3. Technology clustering results

The following tables describe the clusters of technologies under each of the scenarios, and the negatively correlated clusters. These are the results presented in section 6.3.

Table D3.1. NCCS cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5

Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Purple	Transport biofuels and gas	System wide biomass and gas use; domestic biofuel production and use across modes; oil and gas us in freight (in addition to biofuels)	Orange (-0.87)
Sky blue	Transport electrification	Electricity use across road transport (passenger and freight)	None
Green	RE with H_2 storage	Wind and other renewables; H_2 storage	None (but strong with nuclear generation)
Blue	District heating	District heating (and storage). Clustered with 2 metrics of transport biofuel use but weak correlation.	Yellow (-0.98)
Yellow	Building electrification	Electrification of the building stock; storage capacity in buildings (hot water); building retrofit; nuclear generation.	Blue (-0.98)
Orange	H_2 for transport	H_2 production via electricity; H2 in passenger road transport; cost metrics; oil in aviation; system wide oil use	Purple (-0.87)

Table D3.2. CP cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5

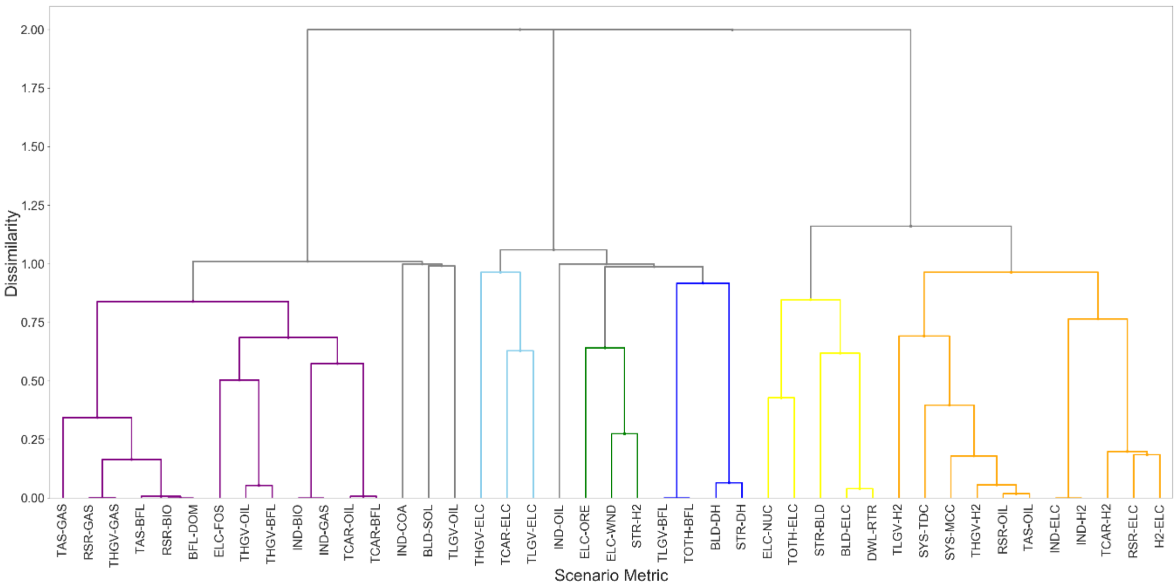
Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Orange	H_2 production with gas for transport	H_2 production (via gas SMR) and use in the transport sector.	Brown (-0.51)
Green	Renewable generation	Renewable power generation options, costs metrics, selected transport electrification.	Brown (-0.48)
Sky blue	Passenger car electrification	Passenger transport electrification; system electricity; aviation biofuels.	Brown (-0.66)
Brown	H_2 with bio CCS, car oil use	Biomass resource; H_2 production with CCS & bioenergy; oil in cars; system oil use; H2 and oil use in industry.	Orange (-0.51), Green (-0.48), Sky blue (-0.66)
Pink	Building electrification, power gen. w/ CCS	Electrification of buildings – as per the description in Table D3.1; CCS in power sector, and system gas use.	Blue (-0.94)
Blue	District heating	District heating (and storage). Clustered with transport biofuel use but weak correlation.	Pink (-0.94)

Table D3.3. F2R cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5

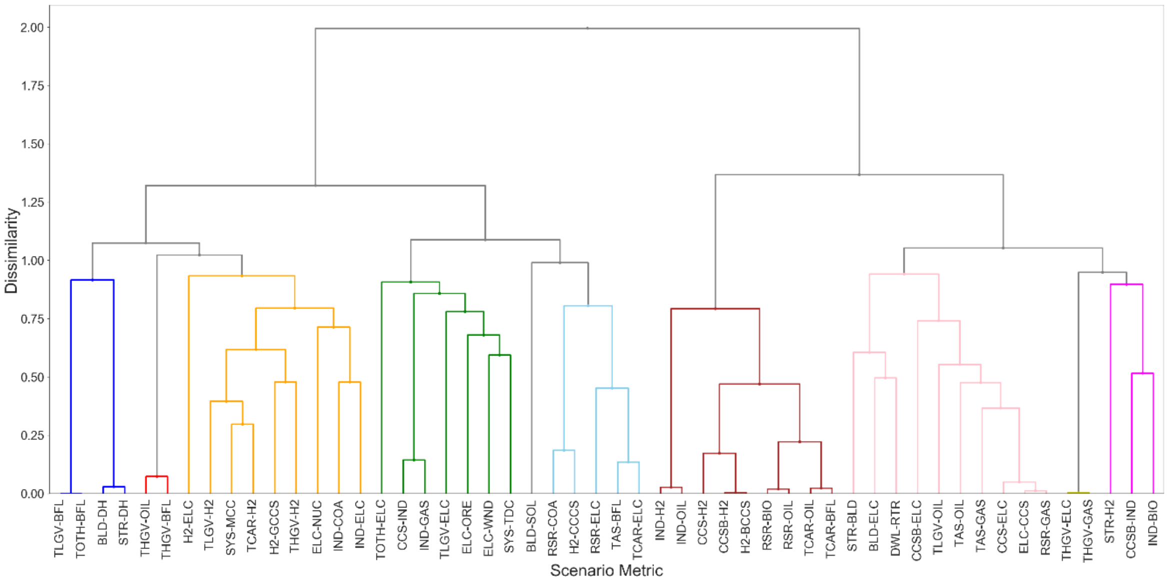
Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Green	Non-CCS generation	Generation types including nuclear, wind and other renewables	Pale pink (-0.84)
Pink	Biofuel production (w/ CCS)	Biofuel production with use across the transport sector	Brown (-0.85)
Brown	H_2 with CCS, transport oil use	As per brown cluster under CP (Table D3.2), except for biomass resource.	Pink (-0.85)
Olive green	Biomass resource	Biomass availability; industry biomass; gas use in buildings.	Yellow (-0.76)
Yellow	End use sector decarbonisation	System electricity; building sector electrification; H_2 in industry; system costs.	Olive green (-0.76)
Pale pink	Gas CCS	System gas use; electricity generation with CCS (as in pink CP cluster).	Green (-0.84)
Blue	District heating	District heating (and storage). As in NCCS / CP, clustered with transport biofuel use but weak correlation.	

The following figures show the dendrograms based on the technology clustering analysis by scenario. The different colours in the figures denote the clusters, based on a predetermined ten cluster set. The dissimilarity score, at the lowest level between two metrics, is estimated as (1 – [correlation coefficient between two metrics]), with very low values suggesting a high positive correlation. As clusters begin to grow through aggregating individual metrics/subsets of metrics, the dissimilarity value is recalculated to represent the relationship between two clusters, instead of the relationship between individual technologies in the two clusters. A dissimilarity score of 2 between two larger clusters indicates that there is a higher chance that a technology in one cluster will have a negative correlation with a technology in the other cluster.

a) NCCS



b) CP



c) F2R

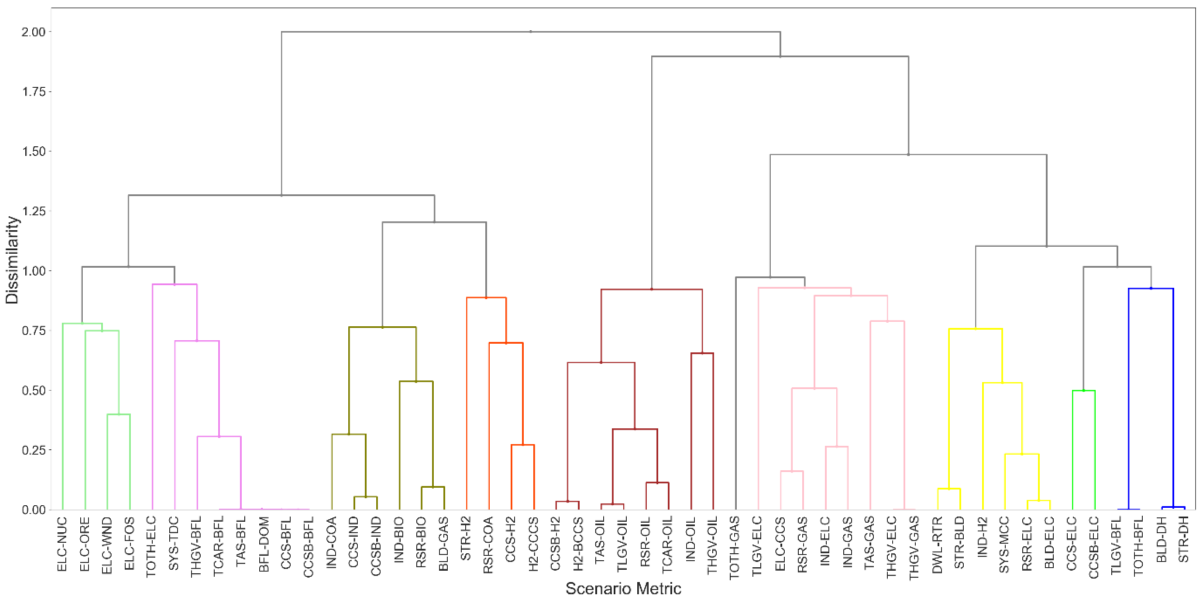


Figure D3.1. Hierarchical clustering dendrogram of ESME simulations in 2050 for each scenario. Note that the lower the dissimilarity score, the stronger the positive correlation. The low dissimilarity scores for pairs of industrial fuels reflect very limited variation between simulations and are excluded from the results descriptions.

Appendix D4. Correlations between mitigation wedges

NCCS

	BLDH_EE(30)	BLDH_DCB(30)	IND_DCB(30)	TAV_DEM(30)	TCR_DEM(30)	TCR_EE(30)	PWR_DCB(30)	CBF_DEM(30)	CBF_DCB(30)	BLDH_DCB(50)	TCR_EE(50)	TCR_DCB(50)	PWR_DCB(50)
BLDH_EE(30)		-0.03	-0.94	-0.97	-0.97	0.76	0.95	-0.06	0.06	0.95	0.66	0.13	0.80
BLDH_DCB(30)	-0.03		-0.25	-0.16	-0.17	0.07	-0.02	0.03	-0.04	0.15	0.07	0.00	0.20
IND_DCB(30)	-0.94	-0.25		0.98	0.97	-0.79	-0.93	0.03	-0.03	-0.98	-0.62	-0.22	-0.88
TAV_DEM(30)	-0.97	-0.16	0.98		1.00	-0.77	-0.95	0.05	-0.05	-0.99	-0.65	-0.16	-0.86
TCR_DEM(30)	-0.97	-0.17	0.97	1.00		-0.72	-0.95	0.05	-0.05	-0.98	-0.66	-0.12	-0.85
TCR_EE(30)	0.76	0.07	-0.79	-0.77	-0.72		0.70	-0.03	0.03	0.78	0.44	0.49	0.67
PWR_DCB(30)	0.95	-0.02	-0.93	-0.95	-0.95	0.70		-0.03	0.03	0.95	0.58	0.20	0.88
CBF_DEM(30)	-0.06	0.03	0.03	0.05	0.05	-0.03	-0.03		-0.98	-0.05	-0.07	0.10	0.00
CBF_DCB(30)	0.06	-0.04	-0.03	-0.05	-0.05	0.03	0.03	-0.98		0.05	0.07	-0.09	0.00
BLDH_DCB(50)	0.95	0.15	-0.98	-0.99	-0.98	0.78	0.95	-0.05	0.05		0.62	0.22	0.88
TCR_EE(50)	0.66	0.07	-0.62	-0.65	-0.66	0.44	0.58	-0.07	0.07	0.62		-0.47	0.46
TCR_DCB(50)	0.13	0.00	-0.22	-0.16	-0.12	0.49	0.20	0.10	-0.09	0.22	-0.47		0.28
PWR_DCB(50)	0.80	0.20	-0.88	-0.86	-0.85	0.67	0.88	0.00	0.00	0.88	0.46	0.28	

CP

	BLDH_EE(30)	BLDH_DCB(30)	IND_DCB(30)	TCR_EE(30)	PWR_DCB(30)	CH2_DEM(30)	CH2_DCB(30)	BLDH_DCB(50)	IND_DCB(50)	TCR_EE(50)	TCR_DCB(50)	PWR_DCB(50)
BLDH_EE(30)		-0.03	-0.94	0.76	0.95	-0.41	0.46	0.95	-0.80	0.66	0.13	0.80
BLDH_DCB(30)	-0.03		-0.25	0.07	-0.02	-0.06	0.07	0.15	-0.13	0.07	0.00	0.20
IND_DCB(30)	-0.94	-0.25		-0.79	-0.93	0.32	-0.37	-0.98	0.87	-0.62	-0.22	-0.88
TCR_EE(30)	0.76	0.07	-0.79		0.70	0.00	0.05	0.78	-0.83	0.44	0.49	0.67
PWR_DCB(30)	0.95	-0.02	-0.93	0.70		-0.33	0.37	0.95	-0.84	0.58	0.20	0.88
CH2_DEM(30)	-0.41	-0.06	0.32	0.00	-0.33		-1.00	-0.33	-0.13	-0.58	0.68	-0.12
CH2_DCB(30)	0.46	0.07	-0.37	0.05	0.37	-1.00		0.38	0.07	0.60	-0.65	0.17
BLDH_DCB(50)	0.95	0.15	-0.98	0.78	0.95	-0.33	0.38		-0.87	0.62	0.22	0.88
IND_DCB(50)	-0.80	-0.13	0.87	-0.83	-0.84	-0.13	0.07	-0.87		-0.31	-0.61	-0.86
TCR_EE(50)	0.66	0.07	-0.62	0.44	0.58	-0.58	0.60	0.62	-0.31		-0.47	0.46
TCR_DCB(50)	0.13	0.00	-0.22	0.49	0.20	0.68	-0.65	0.22	-0.61	-0.47		0.28
PWR_DCB(50)	0.80	0.20	-0.88	0.67	0.88	-0.12	0.17	0.88	-0.86	0.46	0.28	

F2R

	BLDH_EE(30)	IND_DCB(30)	TAV_EE(30)	TCR_EE(30)	PWR_DEM(30)	PWR_CEF(30)	PWR_DCB(30)	CBF_DEM(30)	CBF_CEF(30)	CBF_DCB(30)	CH2_DEM(30)	CH2_DCB(30)	BLDH_EE(50)	BLDH_DCB(50)	IND_DCB(50)	TAV_EE(50)	TCR_EE(50)	PWR_DCB(50)
BLDH_EE(30)		-0.94	0.97	0.76	-0.12	0.17	0.95	-0.06	-0.06	0.06	-0.41	0.46	0.54	0.95	-0.80	0.69	0.66	0.80
IND_DCB(30)	-0.94		-0.98	-0.79	0.25	-0.33	-0.93	0.03	0.03	-0.03	0.32	-0.37	-0.44	-0.98	0.87	-0.74	-0.62	-0.88
TAV_EE(30)	0.97	-0.98		0.77	-0.19	0.22	0.95	-0.05	-0.05	0.05	-0.39	0.44	0.45	0.99	-0.84	0.73	0.65	0.86
TCR_EE(30)	0.76	-0.79	0.77		-0.34	0.25	0.70	-0.03	-0.03	0.03	0.00	0.05	0.37	0.78	-0.83	0.54	0.44	0.67
PWR_DEM(30)	-0.12	0.25	-0.19	-0.34		-0.38	-0.28	-0.11	-0.11	0.11	-0.33	0.31	0.28	-0.25	0.42	-0.28	0.06	-0.38
PWR_CEF(30)	0.17	-0.33	0.22	0.25	-0.38		0.20	-0.01	-0.01	0.01	0.04	-0.02	0.05	0.29	-0.31	0.25	0.16	0.28
PWR_DCB(30)	0.95	-0.93	0.95	0.70	-0.28	0.20		-0.03	-0.03	0.03	-0.33	0.37	0.40	0.95	-0.84	0.74	0.58	0.88
CBF_DEM(30)	-0.06	0.03	-0.05	-0.03	-0.11	-0.01	-0.03		1.00	-0.98	0.16	-0.17	0.01	-0.05	-0.02	-0.01	-0.07	0.00
CBF_CEF(30)	-0.06	0.03	-0.05	-0.03	-0.11	-0.01	-0.03	1.00		-0.96	0.16	-0.17	0.01	-0.05	-0.02	-0.01	-0.07	0.00
CBF_DCB(30)	0.06	-0.03	0.05	0.03	0.11	0.01	0.03	-0.98	-0.96		-0.15	0.16	-0.02	0.05	0.02	0.01	0.07	0.00
CH2_DEM(30)	-0.41	0.32	-0.39	0.00	-0.33	0.04	-0.33	0.16	0.16	-0.15		-1.00	-0.27	-0.33	-0.13	0.04	-0.58	-0.12
CH2_DCB(30)	0.46	-0.37	0.44	0.05	0.31	-0.02	0.37	-0.17	-0.17	0.16	-1.00		0.29	0.38	0.07	0.01	0.60	0.17
BLDH_EE(50)	0.54	-0.44	0.45	0.37	0.28	0.05	0.40	0.01	0.01	-0.02	-0.27	0.29		0.37	-0.33	0.27	0.37	0.29
BLDH_DCB(50)	0.95	-0.98	0.99	0.78	-0.25	0.29	0.95	-0.05	-0.05	0.05	-0.33	0.38	0.37		-0.87	0.76	0.62	0.88
IND_DCB(50)	-0.80	0.87	-0.84	-0.83	0.42	-0.31	-0.84	-0.02	-0.02	0.02	-0.13	0.07	-0.33	-0.87		-0.82	-0.31	-0.86
TAV_EE(50)	0.69	-0.74	0.73	0.54	-0.28	0.25	0.74	-0.01	-0.01	0.01	0.04	0.01	0.27	0.76	-0.82		0.27	0.76
TCR_EE(50)	0.66	-0.62	0.65	0.44	0.06	0.16	0.58	-0.07	-0.07	0.07	-0.58	0.60	0.37	0.62	-0.31	0.27		0.46
PWR_DCB(50)	0.80	-0.88	0.86	0.67	-0.38	0.28	0.88	0.00	0.00	0.00	-0.12	0.17	0.29	0.88	-0.86	0.76	0.46	

Figure D4.1. Correlations between mitigation wedges in RM (top panel), NCCS (middle panel) and F2R (bottom panel). Wedges for 2030 and 2050 both are given and only the ones with at least 10% share for the milestone year in at least one run are included. Correlations above 0.8 and below -0.8 are highlighted. Fill colours indicate over 10% share in at least one run for 2030 only (yellow), for 2050 only (blue) or for both 2030 and 2050 (green).